AN IDIOGRAPHIC ANALYSIS OF TRAIT INTEGRATION PROCESSES IN IMPRESSION FORMATION

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ABSTRACT

AN IDIOGRAPHIC ANALYSIS OF TRAIT INTEGRATION
PROCESSES IN IMPRESSION FORMATION

By

Eileen G. Thompson

This research was designed to examine a number of models of attribute integration within an impression formation paradigm. The adequacy of the major existing models of trait integration--the summation model, congruity theory, Wyer's trait redundancy model, and Anderson's equal-weighting version of integration theory--were discussed in terms of their ability to account for impression formation phenomena. The adequacy of the theories of attribute organization underlying these models was examined with respect to research in the broader area of attribute structure, including studies in the areas of implicit personality theory and cognitive complexity.

A theory of information processing--Configurational Consistency Theory--which is based upon a multidimensional conception of evaluative attribute organization was presented. A set of models of the impression formation process were derived within the framework of this theory. These models and the previously developed models of trait integration were compared in terms of their ability to predict the qualitative and quantiative features of the data from the current impression formation experiment.

The current study was conducted on a highly idiographic basis. Stimuli for the impression formation task were chosen individually for each subject on the basis of multidimensional analyses of patterns of attribute usage. In addition, model parameters were estimated on an individual basis, and each of the models was tested in terms of its accuracy in predicting each subject's responses.

Twenty-seven students enrolled in an upper-level honors psychology course served as subjects for the study. The majority of the instruments used in the study were presented on computer terminals. To obtain measures of the multidimensional structure of attribute usage the subjects were given two tasks. In the first task each subject rated 40 of his or her own acquaintances on 40 semantic differential scales. A separate factor analysis of this data was performed for each subject to obtain the major trait dimensions used in these ratings. In the second task the subjects rated the distance in meaning between pairs of evaluative traits. A multidimensional scaling was performed on this data for each subject to examine the dimensionality of these distance measures.

The stimuli for the impression formation task were chosen from these individual analyses of trait structure. For each subject, three salient trait dimensions were chosen. Three trait words were chosen as representing each pole of each of these dimensions, resulting in the choice of 18 trait adjectives for each subject. Sets of two and three traits were prepared from these adjectives so as to fit in one of two categories: Coincident trait sets consisted of traits which loaded on the same pole of the same dimension, and noncoincident trait sets consisted of adjectives, all of the same valence, loading on different dimensions.

The subjects were instructed to consider the attribute information as originating from one of two sources. The subjects receiving internal instructions were told to consider the trait sentences as judgments they had themselves made about the person. Subjects receiving external instructions were told to consider the stimuli as descriptions provided by an acquaintance. All subjects rated each hypothetical stimulus person on a 21 point scale of degree of predicted liking.

An analysis of variance performed on this data indicated that a set-size effect occurred in all conditions and that this set-size effect was highly linear. A substantially greater set-size effect was found for noncoincident than for coincident trait sets. Type of instructions did not affect the results. The major general features of this analysis provided support only for those models of trait integration which predict a set-size effect and which distinguish between redundant or synonymous and nonredundant or nonsynonymous traits in their formulations.

Tests of goodness of fit for each of the models were performed individually for each subject. Among the models requiring no parameter estimation from the data, the simple averaging and congruity models predicted observed values most accurately. All models hypothesizing some form of summation process overestimated the extremity of responses. Among the models including an estimated multiplicative parameter, two models in particular showed an excellent fit to the data--the Wyer redundancy model and the CCT approximation model. The Anderson equal-weighting model, requiring the estimation of two parameters from the data, did not provide an accurate a fit to the data relative to the other models tested.

Using the criteria that an adequate model of the trait integration process should predict both the qualitative and quantitative qualities of the data, the conclusion was drawn that the Wyer redundancy and CCT approximation models provided the best account of the trait integration process. Models based on the concept of a single evaluative dimension of judgment failed to account for the effects due to trait coincidence, redundancy or synonymity.

A further test of the multidimensional CCT formulation involved prediction of the responses to single trait stimuli. CCT predicts that these responses will be a function of loadings of traits on the dimensions, importance of the dimensions, and rating of the self on these dimensions. This formula was found to be an excellent predictor of the single-trait judgments--a type of prediction lying outside the range of other attribute integration models. This finding was regarded as further support for the utility of a multidimensional conception of attribute organization in studying the attribution process.

AN IDIOGRAPHIC ANALYSIS OF TRAIT INTEGRATION PROCESSES IN IMPRESSION FORMATION

By

Eileen Gail Thompson

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Of the terrible doubt of appearances,
Of the uncertainty after all, that we may be deluded,
That may-be reliance and hope are but speculations after all,
That may-be identity beyond the grave is a beautiful fable only,
May-be the things I perceive, the animals, plants, men, hills, shining
   and flowing waters,
The skies of day and night, colors, densities, forms, may-be these
   are (as doubtless they are) only apparitions, and the real something
   has yet to be known,
(How often they dart out of themselves as if to confound me and
   mock me!
How often I think neither I know, nor any man knows, aught of
   them,)
May-be seeming to me what they are (as doubtless they indeed but seem)
   as from my present point of view, and might prove (as of course
   they would) nought of what they appear, or nought anyhow, from
   entirely changed points of view;
To me these and the like of these are curiously answer'd by my lovers,
   my dear friends,
When he whom I love travels with me or sits a long while holding me
   by the hand,
When the subtle air, the impalpable, the sense that words and reason
   hold not, surround us and pervade us,
Then I am charged with untold and untellable wisdom, I am silent,
   I require nothing further,
I cannot answer the question of appearances or that of identity
   beyond the grave,

But I walk or sit indifferent, I am satisfied,
He ahold of my hand has completely satisfied me.

Walt Whitman
"Of the Terrible Doubt of Appearances"
Calamus
Leaves of Grass, 1888

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CHAPTER I

REVIEW AND THEORETICAL DEVELOPMENT

Much of the current theoretical and empirical work in cognitive social psychology has focused upon the role played by traits or attributes in information processing and in cognitive organization. This work has involved the building of complex models of attribute combination and usage, particularly in the area of person perception. Studies of impression formation, in particular, have revolved around formulations which predict responses to the communication of sets of attributes, based upon judgments made concerning these attributes in isolation. However, the models of attribute organization which underlie this theoretical development are often poorly articulated. In addition, these underlying models typically fail to take into account the empirical evidence stemming from studies of implicit personality theories concerning the complexity of attribute organization.

It is the purpose of the present research to compare the existing models of attribute integration--and, by implication, the underlying theories of attribute structure--within the impression formation paradigm. In addition, a multidimensional theory of attribute organization is outlined, and models of the impression formation process are derived from this theory. The predictions of these models for attribute judgments are compared with those of the existing models. The models examined in this study were tested in terms of their ability to account for qualitative features of the impression formation data and on the basis of their accuracy in predicting impression formation judgments on an individual-subject basis.

I. Impression Formation: The Phenomena and the Models

The investigation of processes used to integrate attribute information generally has been conducted by examining what have been termed impression formation judgments. In the typical impression formation task, subjects are presented with lists of trait adjectives assumed to characterize imaginary persons. Subjects are then required to make judgments of liking or global evaluation for these stimulus persons. These judgments are examined in an attempt to determine how multiple "bits" of attribute information are processed.

The use of this type of experimental task as the major source of data in the research areas labeled "impression formation" and "person perception" suggests that the models derived from this research apply quite broadly to information processing as it relates to interpersonal interaction. These experimental procedures are most appropriately used to investigate the specific question of how individuals process information about other persons when this information is presented solely in trait form. In fact, from the present theoretical perspective, one might conceptualize three categories of person perception or impression formation. The first category is self-perception or what might be considered first-person perception and concerns the processing of introspective material. In this type of processing, the information to be dealt with concerns one's interpretations of one's own thoughts and actions. The second category of person perception might be termed <u>direct</u> impression formation or second-person perception and concerns the processing of information about other people resulting from direct contact with these others. Here the sources of information tend to be primarily relational in nature: the processor forms impressions based upon the interactions of the object-people with other objects and people in the environment. Based upon this information, the processor makes inferences concerning the underlying traits and attributes of the object-people which may be used to summarize and/or explain the relational information observed.

The third category of person perception might be termed <u>indirect</u> impression formation or third-person perception, and it is based upon communicated information. At this level, the investigator is concerned with the ways in which the processor deals with information about object-people when this information is received as a communication from others. When this information is presented in trait form, the present theory suggests that these traits are summaries or explanations of relational information that have already been processed by the communicator. That is, when a subject is given the information that an object-person is "warm," this information is regarded as secondary or derived, both in the sense that the object person is not directly observed and in the sense that "warm" is itself the product of someone's attribution process and is a summary of observed relationships and interactions.

These distinctions between levels of information in person perception, along with the theoretical assumption that trait attributions are a result of the processing of directly observable and inferred relations, will be discussed further in the sections concerned with models of attribute structure. It is important to make the point here that theories or models of the impression formation process are concerned with ways in which people process a particular type of information about other people. Moreover, from a point of view which assumes that an individual assigns traits to people through some process of attribution rather than by direct observation, models of impression formation must be examined within the context of assumptions about this underlying attribution process.

A. Linear Evaluative Models of Trait Integration

The majority of the models dealing with the integration of attribute information assume, either implicitly or explicitly, that evaluation is unidimensional. That is, the assumption is made that there exists a single evaluative dimension, along which specific traits may be placed, which determines their evaluative favorability. Thus, in predicting judgments of the favorability or likability of trait combinations it is necessary simply to obtain the measurement of each trait's position on this evaluative dimension and then to combine these measures according to specified sets of combination rules. Traits that are equally favorable are interchangeable in these formulations. For the purposes of information integration according to these models, the "meaning" of a trait is determined simply by its evaluative favorability.

The single-evaluative-dimension models have typically followed the linear form,

$$R = C + \sum_{i=0}^{n} w_i S_i \qquad (1)$$

where R is the liking or evaluative response; S_i is the evaluative scale value of the ith trait stimulus; w_i is the weight attached to the ith trait stimulus; and C is an additive constant.* The models have differed primarily in terms of restraints placed upon the weights as well as on the question of the existence of some initial impression which is to be integrated with the stimuli presented.

The question of the treatment of the weights in this general formulation has revolved around the question of adding versus averaging the trait stimuli. Stated in the most simple terms, the issue is one of whether evaluative scale values of individual traits are summed or averaged when a judgment is made to a set of these traits. In general, the adding models suggest that whenever the attributes in a set all have the same evaluative sign, the evaluative response to the set will be more polarized than the response to any of the single traits. In addition the larger the number of traits (of the same valence) in a

*In discussing these models, this paper is concerned specifically with patterns of attribute combination. Many of the theories use the formulations in a broader sense to predict patterns of combination of attitudes, psychophysical judgments, etc. Evidence pertaining to such use of the models is not included here. These formulas also assume ratio scale properties for the rating scales, with S_i presumed to equal S_i-O_r where O_r is the origin of the scale. Wyer (1969) compares several of these models treating O_r as a parameter to be estimated independently or as a free parameter to be estimated from the data. These results will be discussed subsequently. It is important to note here that $(S_i$-$O_r)$ may be substituted for S_i in these formulas if the ratio scale assumption is not desired.

set, the greater will be the polarity of the response. Any model of the form of equation 1 in which the weights of the trait stimuli sum to more than one may be termed an adding model.

In a specific version of the adding model, Fishbein (1963) suggested that attitudes toward objects could best be predicted by a model in which the evaluations of components of that object are directly summed. Fishbein's model may be represented by the formula

$$A_0 = \sum_{i=1}^{n} B_i A_i \qquad (2)$$

where A_0 is the attitude toward the complex stimulus object; B_i is the probability of an association between the object, <u>0</u>, and the ith concept (attribute); and A_i is the evaluative rating of the ith concept (attribute). Since the impression formation task states that 0 has attributed i with certainty, and thus $B_i = 1$ for all i, this formula may be restated

$$R = \sum_{i=1}^{n} S_i \qquad (3)$$

for use in most impression formation paradigms.

As an adding model, this formulation makes both of the general predictions stated above. In addition, by assuming unit weight, it predicts (1) that the evaluative response to a set of stimuli will equal the sum of the responses to the components, and (2) that the response to a set of stimuli possessing the same evaluative scale value will be a linear function of the number of stimuli in the set.

Impression formation models may be classified as averaging models if the weights in the formula in equation 1 are required to sum to one. In its simplest form, the averaging model may be expressed as

$$R = \frac{1}{n} \sum_{i=1}^{n} S_i \tag{4}$$

This model predicts that the judgment made for a set of attribute stimuli will equal the mean of the responses to the single traits.

A more complex averaging model is the model developed from Osgood and Tannenbaum's (1955) congruity theory. The congruity formulation suggests that evaluative attribute scale ratings are averaged, with each weighted according to its evaluative polarity. Thus

$$R = \frac{S_1/S_1/}{/S_1/+/S_2/} + \frac{S_2/S_2/}{/S_1/+/S_2/} \tag{5}$$

where $/S_1/$ is the absolute value of S_1, or the degree of polarization of the attribute, independent of its valence. This formula suggests that more polarized attributes will contribute disproportionately to the global evaluation or liking rating, relative to less polarized attributes. The congruity model predicts that the overall response is a fairly complex function of S_1 and S_2 if these attributes are of the same evaluative sign, while it is simply a function of the sum of the two attribute scale values if these are opposite in sign. The congruity formulation is thus basically a weighted averaging model, with attribute weights determined by their polarity. In general, any averaging model which predicts judgments to sets of attribute stimuli based solely upon the responses to the individual stimuli predicts

(1) that the rating of the response to the set will always lie between the extremes of the ratings of the responses to the single attributes, and (2) that the response to sets of traits which have the same evaluative polarity will not be affected by the number of traits in the set.

Comparisons between adding and averaging models can be carried out either by investigating the general predictions of each model type or by examining the goodness of fit of the numerical predictions of the specific models. Investigations of the general predictions have focused on two issues. The first concerns the relationship between the response to a set of traits equal in polarity and valence and the number of traits in the set. Adding models predict more polarized judgments to larger trait sets--a set size effect--while the simple averaging models do not. In fact, the set size effect is a highly stable phenomenon in the impression formation literature. It has been demonstrated in both between-subjects designs (Sloan and Ostrom, 1974) and within-subjects designs (Fishbein and Hunter, 1964; Anderson, 1965, 1967, 1968a, 1971; Podell and Amster, 1966; Levin and Schmidt, 1970; Levin, Schmidt, and Norman, 1971) and with sets ranging in size up to 32 traits. Those studies comparing more than two set sizes have uniformly found the set size effect to be a negatively accelerated function of the number of traits in the set, rather than the linear function predicted by the adding models. The use of a rating scale with fixed end points in all of these studies other than the Anderson (1965) experiment must be considered as a possible source of this non-linearity.

The second issue used as a general test in comparing adding and averaging models concerns the effect of the addition of moderate to more extreme information. In this situation the averaging models predict a response intermediate between the single-attribute ratings, while the adding models predict a response more extreme than either of the single trait ratings. On the whole, the averaging position has been supported in tests of the competing hypotheses. Anderson (1965, 1968a); Hendrick (1968); Hendrick, Franz, and Hoving (1975); and Warr (1974) all found that the addition of moderately polarized traits to a list of extremely polarized traits decreased the polarity of the evaluative response. Lugg and Gollob (1973), however, obtained support for the adding position on this issue. Rather than asking subjects to rate the stimulus persons on a scale of likability, Lugg and Gollob presented subjects with a highly polarized piece of information, followed by a same-signed moderately polarized piece of information and asked whether the second piece of information led them to like the person described more, less, or just the same. The majority of the subjects in this study gave the adding response.

Studies comparing the goodness of fit of the numerical predictions of these adding and averaging models have tended to support the adding models. These results are difficult to interpret, due to the methodological complexity of these studies and the nature of the measures of goodness of fit. Three of these studies were designed to compare Fishbein's adding model with the congruity model (Anderson and Fishbein, 1965; Anderson, 1970; and Cooper and Crano, 1974). In each of these studies, the stimulus information was presented in the form of paragraphs about a named hypothetical person in which the attributes were embedded rather than simply as attribute statements. The evaluative responses used as independent and dependent variables consisted of the sums of a set of semantic differential ratings. In each case, the evaluative response to the person described by the paragraph was predicted on the basis of ratings of the embedded traits in isolation rather than from ratings of paragraphs containing each trait embedded singly. In addition, the Fishbein predictions used measures of the belief that the person described actually possessed each of the traits used in the overall experiment. Thus in some cases, traits were included in the predictive equation (Equation 2) which were not contained in the actual descriptions received by the subject. Thus the Fishbein predictions are based on substantially more pieces of information than are the congruity predictions. In each of these studies, the Fishbein adding model received substantial support, while the congruity model did not.

In a study by Wyer (1969), a simple adding model (Equation 3) was compared with the congruity model in terms of predictions in a standard impression formation task. In this experiment, a linear transformation (with least squares slope and intercept parameters) of the simple adding predictions accounted for a greater percent of the variance in observed values than a similar transformation of the congruity predictions. Thus, this study provides additional support for the adding models.

In general, it appears that an adequate model of attribute integration must be able to predict both a set size effect for sets of traits which are of equal valence and polarity and an averaging effect for sets containing moderate and extreme traits of the same valence. In terms of the adding and averaging models as they are described above, such predictions appear irreconcilable. However, Anderson has proposed a model which suggests a modification of the attribute averaging process so as to account for the set size effect. This model assumes that subjects begin the impression formation task with an initial impression, I_0, of the stimulus person. It is then assumed that this presumably relatively neutral initial impression is combined with the weighted averages of the scale values of the attributes presented. Thus for a set of n attribute statements, in which all attributes have the same evaluative scale value, S_1, and the same weight, W_1,

$$R_n = \frac{nw_1 S_1 + w_0 I_0}{nw_1 + w_0} \tag{6}$$

where w_0 is the weight associated with I_0. As long as I_0 is less polarized than S_1, a set size effect is predicted. Moreover, according to this model, the magnitude of the set size effect is a negatively accelerated function of the number of attributes presented with S_1 as the limit of R_n. For attribute sets containing stimuli which differ in scale value, the formula for Anderson's model is

$$R_n = \frac{nw_1 \sum_{i=1}^{n} S_i + w_0 I_0}{nw_1 + w_0} \tag{7}$$

This model then accounts for the averaging effect resulting from the addition of moderate to extreme trait information and predicts the existence of the set size effect, as well as suggesting that this function will take the form which has typically been demonstrated empirically.

In addition to the support received for this model from its ability to predict the above phenomena, empirical support in the form of tests of goodness of fit also has been obtained. Anderson himself has not performed such investigations--rather than estimate parameters and test the model numerically, he has preferred to focus on the use of analysis of variance to examine the more general predictions, in keeping with his theories concerning the issue of functional measurement. Two studies, however, do provide such tests. Cooper and Crano (1974) report the use of what they term a "simple-average" model, which is equivalent to equation 7. In this model, the subject's pretest attitudes toward the person described (the initial impression) is averaged with the evaluation of the traits presented. Crano and Cooper found this model to be equivalent in fit to the Fishbein model and thus superior to the congruity formulation. In the study referred to above, Wyer (1969) found the Anderson model to be the best predictor of the models tested. However, using least squares procedures to estimate I_0 and w_1 for this model, Wyer found the I_0 parameter estimates to be extremely positive, more positive than the most extreme scale value of the individual stimuli. Not only does this contradict Anderson's statement that the initial impression should be relatively neutral, it makes the I_0 parameter theoretically useless in accounting for the set size effect.

Because of its ability to account for the set size effect, the averaging of extreme and moderate information, and its prediction of the shape of the set size curve, Anderson's model is clearly the most widely accepted model of the impression formation process at this time. It is clear from Wyer's (1969) data, however, that the numerical form of the model and the meaning of its parameters require further investigation. Anderson's model has also been criticized indirectly by Hodges (1973). Hodges points out that Anderson's comparison of his weighted-averaging models against the summation model essentially involves a comparison between a relatively complex model with several parameters and a very simple model. Hodges suggests that complex adding models could be developed, which would also account for the impression formation data reported.

Warr (1974) has, in fact, proposed an impression formation model which combines the summation and the averaging processes. Warr's model suggests that when two traits have different evaluative implications (i.e., a broad "range" of evaluation), their evaluative ratings are averaged, with greater weight being placed on the more polarized attribute. However, when the evaluative ratings of two attributes are highly similar, their ratings summate, resulting in the set-size effect. Thus Warr proposes essentially a dual process conception. Specifically, he regards a low-range compound (one in which evaluative ratings are similar) as a single attribute, likely to have an extreme value and not in need of "integration" (averaging). Warr suggests that models of information integration should be required only for sets of stimuli with a larger range of evaluation. The comments by Hodges and the model proposed by Warr suggest that more complex adding models than those currently proposed could become serious contenders with Anderson's weighted-averaging model in accounting for the impression formation data. In fact, however, several models of the impression formation process which are currently receiving empirical and theoretical attention are those which are based on an entirely different model of attribute use--the simple category model.

B. Simple Category Models: Problems of Redundancy

The notion of a single evaluative dimension suggests that traits which have the same evaluative rating are indistinguishable in use or in "meaning." Thus if "honest" receives a rating of 9 on an evaluative scale ranging from -10 to +10, it is no more "identical" to "truthful" (+9) than to "kind" (+9). Similarly, dishonest (-9) should be no more inconsistent with "kind" than with "honest." Thus there is no basis, given the assumption of a single evaluative dimension, for a discussion of the effects of other aspects of meaning similarity among attributes upon evaluative ratings. In fact, however, the issue of the "similarity in meaning" or "redundancy" of traits has played an important role in recent studies of the impression formation process.

A number of different criteria for the definition of redundancy or meaning similarity have been used in impression formation studies. Schmidt (1969) required subjects to rate stimulus persons based on a combination of trait and behavioral information. Redundant sets were defined as stimulus combinations in which the adverb modifying the behavior was directly derived from the trait presented. Judgments from highly related stimulus sets were consistently less extreme than those from the low-related sets.

A number of studies defining redundancy in terms of trait overlap or trait cooccurrence have obtained results that consistently show redundancy of stimuli as reducing the magnitude of the evaluation response. Dustin and Baldwin (1966) obtained redundancy ratings by asking subjects to indicate the degree to which a person who possessed trait A was also likely to possess trait B. The three experiments in this study showed a reduced set size effect due to stimulus redundancy. Wyer (1968) defined redundancy as the conditional probability of occurrence of B given A. Once again, redundant attributes were found to produce a smaller set size effect. Using a somewhat more complex set-theoretic notion of redundancy, Wyer (1970) estimated redundancy from the degree to which the conjunctive probability of the occurrence of 2 traits, P_{AB}, exceeded the product of their unconditional probabilities of occurrence ($P_A P_B$). Redundancy of traits was found to decrease the polarity of the evaluative judgment. Using Hays' (1958) measure of trait implication as well as measures of trait cooccurrence, Kaplan (1971) found less extreme judgements for redundant trait sets and also found a reduced set size effect for redundant traits. Phillips, et al. (note 4) obtained similar results, using normative measures of trait synonymity to select synonymous and nonsynonymous trait sets. Only one study (Feldman, 1968) has found trait redundancy to increase the extremity of responses.

This general finding that redundancy, defined in various ways, reduces the polarity of the judgment for a set of traits makes intuitive sense on information processing grounds: The more "new" information that is presented by an attribute statement, the greater effect it should have on the overall judgment. Within the linear-evaluative framework, Schmidt (1969) has proposed a mechanism for dealing with this redundancy issue. He has suggested that redundancy may affect the Andersonian weights of the stimuli in the combination process. According to this formulation, if a subsequent item of information is similar in meaning to a prior item of information, the weight of the subsequent item is decreased. This conception departs from the equal-weighting assumption prsented in equation 7 and requires the following formula:

$$R_n = \frac{\sum_{i=1}^{n} w_i S_i + w_0 I_0}{\sum_{i=1}^{n} w_i + w_0}$$

This model does provide a means of accounting for the observed redundancy effects. Moreover, Anderson has used an unequal-weighting model in order to explain order effects and valence effects in impression formation data.

Such a solution is somewhat unsatisfactory, however, in that the determination of redundant items falls outside the underlying model of evaluative attribute structure. Thus an extra theoretic aspect of meaning is allowed to play a major role in evaluative judgments.

One structural representation of attribute organization which allows for the consideration of redundancy as a structural variable is the simple category model proposed by Wyer (1974a) in his theory of information processing. In this representation, attributes are considered not as points on an evaluative dimension but rather as categorizers of objects. Attributes are simply defined as categories which determine the classification of objects into other categories. According to this model, redundancy can be defined in terms of the overlap of categories. Two attributes are redundant to the extent that elements which fall into one category are likely to fall into the other category as well. Redundancy can then be discussed in set-theoretic terms.

Wyer (1969) proposed a specific model of the impression formation process which stems from such a conception. According to this model, the overall evaluation of a set of traits will be equal to the sum of the scale values of the attributes minus the sum of the redundancies between the attributes. Since symmetry of redundancy is not assumed (the degree to which A implies B is not assumed to be equivalent to the degree to which B implies A), this model takes the form

$$E_{(AB)} = (1 - \frac{P_{A/B}}{2})E_A + (1 - \frac{P_{B/A}}{2})E_B, \tag{9}$$

where E_A and E_B are the evaluative scale values of traits A and B respectively, and $P_{A/B}$ is the conditional probability that trait B applies, given trait A. It is possible to obtain estimates of the conditional probability values independently, by asking subjects to indicate the degree to which each trait presented implies each other trait. Thus, this formulation has no free parameters (other than estimation of scale origin). Mathematically, this model is a weighted-adding model. Wyer found this formulation to account well for his impression formation data, with substantially more accuracy than that provided by the congruity formulation. While Wyer did find Anderson's weighted-averaging model to be superior to equation 9 in fitting the data, Anderson's model has two free parameters; and the best-fitting values of the parameters in Anderson's model were contrary to Anderson's theoretical statements, as was noted above. Other studies conducted by Wyer (1968, 1970) have provided further evidence in support of his model.

Models similar to Wyer's, also based on set-theoretic notions of trait redundancy, have been proposed by Dustin and Baldwin (1966) and by Warr and Smith (1970). Dustin and Baldwin's model,

$$E_{AB} = w_1 E_A + w_2 E_B - w_3 R_{AB} \tag{10}$$

is, for a given set of traits, a weighted adding model with a subtractive constant. The rationale for the estimation of the weights in this model is unclear--if the weights vary with particular traits and trait orders, the number of parameters would exceed the number of data points. If w_1 is assumed to equal w_2, the model is a linear function of Wyer's model, using a somewhat different measure of redundancy.

Warr and Smith (1970) have proposed a set of models derived directly from set-theoretic operations. These models are based on Hays' (1958) conception of trait implication, which defines trait centrality as the extent to which a trait implies other traits without itself being implied. The Hays formulation is used to define measures of trait salience and inter-trait distance. The last of the six set-theoretic models proposed by Warr and Smith is conceptually similar to the models proposed by Wyer and by Dustin and Baldwin, in that the degree of trait redundancy serves as a subtractive function from the sum of individual trait ratings. In tests of their models, Warr and Smith found this formulation to be a better predictor of trait set judgments than models based upon averaging or simple summation. It should be noted that the averaging and summation models tested in this study included measures of trait salience in the equations.

Wyer (1974a) has stated in general terms a theory of impression formation which is consistent with the simple-category set-theoretic model of attribute organization.

> First consider two adjectives, A and B. Theoretically, there is a subjective distribution of objects described by each adjective along the category scale used to record evaluations, and the evaluations based upon this adjective alone is estimated by the expected value of the distribution of objects described by it. The group of objects described by both A and B is the conjunction of these distributions, and therefore the evaluation of a single object described by A and B is the expected value of this conjunction. Unfortunately, the exact nature of the conjunctive distribution cannot be inferred from the expected values of the component distributions alone. Nor can it be determine *a priori* from the component distributions without making some simplifying assumptions (p. 307).

Thus these models must focus on questions concerning the conditional probabilities of attribute distributions. Since symmetry of these conditional probabilities cannot be assumed, according to the simple category model, these formulations must be complex, and they require a great deal of independent information concerning conditional probabilities of trait implication. Moreover, as the number of traits to be combined increases, the complexity of the formulations and the amount of conditional probability information required is increased excessively.

II. Models of Attribute Organization: The Theories and the Evidence

The models of impression formation discussed in the previous section have been based upon either the single evaluative dimension conception of attribute organization or on the simple category notion.

The support received for the various models in impression formation studies has been summarized. It is relevant for the purpose of the current study to examine not only the empirical evidence directly relating to these models of attribute combination but also that evidence germane to the underlying conceptions of attribute organization. It is the author's position that any model of a specific process must be evaluated not only in terms of its ability to predict the outcome of that process but also in terms of the adequacy of the underlying theory to account for a broader range of phenomena. For this reason, the discussion in the present section focuses upon theoretical and empirical work in the broad area of patterns of attribute organization.

A major early study in patterns of attribute structure involved a series of experiments on impression formation conducted by Asch (1946). This study was designed to examine the effect of certain personal attributes, or traits, upon patterns of trait description. Working within a Gestalt framework, Asch was concerned with the effects of the inclusion of various traits in person descriptions on the meanings of other traits in the descriptions. Asch focused on the notion of attribute centrality, regarding as "central" those attributes which contribute disproportionately to person perception. This view of attributes as forming a kind of global whole of meaning that is not directly derivable from the separate qualities of the attributes has not received further attention in attribute research until relatively recently.

Asch's work was criticized on methodological grounds by Wishner (1960), who argued that the "centrality" of a trait, in terms of its influence on other trait descriptions, is due primarily to the correlation between the "central" trait and other traits in the descriptive list. Wishner argued that attribute lists could be constructed so as to manipulate centrality effects, and was largely successful in demonstrating such manipulations.

The notion that interattribute correlations are descriptive of attribute organization has served as the basis of much of the factor-analytic study of attribute use. The extensive work by Osgood, Suci, and Tannenbaum (1957) on patterns of attribute organization is based on such a principle. Using factor-analytic methods, these authors found in a wide-ranging series of studies that three highly stable attribute dimensions--evaluation, potency, and activity--form the basis of a three-dimensional space which is sufficient to describe a wide variety of concepts.

This empirical support for the unitary nature of evaluation has served as the base for that research which assumes that evaluative attributes may be ordered on a single continuum in terms of their valence and degree of polarization. This work includes not only the single-evaluative-dimension impression formation models but also a number of other attribute-consistency models of attitude organization and change (cf. Phillips and Thompson, note 3, Chapter IV). Rosenberg's affective-cognitive consistency theory, Fishbein's models of beliefs, attitudes and behavior, and Osgood and Tannenbaum's general congruity conception all adopt the position that the evaluative scale scores of objects and/or attributes may be combined in such a way as to predict attitude development and change. The predictive capacity of these models, along with the research program of Osgood et al., indicates the power of the single-evaluative-dimension conception.

In contrast to the work by Osgood, et al., a number of studies of the factor structure underlying attribute use have failed to find a unitary evaluative dimension. A study by Phillips (reported in Phillips and Thompson, note 3) demonstrated the stability and differential susceptibility to manipulation of two evaluative dimensions. Studies by Berlo and Lemert (1961), Reed (1972), Kuusinen (1969), and Price (note 5) also found multiple evaluative dimensions. To a certain extent, the discrepancies between these studies and those reported by Osgood, et al., reflect a difference in methodology as discussed by Miron (1972). Miron suggests that variance due to individual differences be eliminated in such studies by averaging over subjects prior to performing the factor analysis. Phillips and Thompson (note 3) argue that such a methodology results in a factor structure that maps the gross features of linguistic usage but which may be inappropriate for predicting attribute dimensions used by subjects in making inter-item judgments. Phillips and Thompson suggest that a more appropriate procedure for investigating individual attribute usage involves averaging scores over concepts to eliminate concept variance. Alternatively an acceptable procedure would entail performing the factor analysis on trait usage individually for each subject.

Evaluation, potency, and activity do appear to form the basis of the space used to determine the cultural definition of words, as these factors are most often found when individual variance is eliminated and concept variance is used as the basis of the factor analysis. However, use of variance contributed by individual differences in attribution suggests that multiple evaluative dimensions are used by people in making judgments about cognitive entities.

The notion of multiple evaluative attribute dimensions has also been supported in a number of studies of implicit personality theory which have analyzed attribute structure using dimensionality-based procedures. Rosenberg, Nelson, and Vivekananthan (1968) used multidimensional scaling to examine the intrinsic dimensionality of trait usage. These writers found that a two-dimensional solution provided an excellent fit to subjects' judgments, with the dimensions interpretable as intellectual good/badness and social good/badness. Studies by Rosenberg and Jones, (1972), and Jones and Rosenberg, cited in Rosenberg and Sedlak (1972), also involved the multidimensional scaling of attributes. In these experiments, a multidimensional depiction of evaluative traits also was required.

Much of the work in cognitive complexity has also used analysis procedures which assume a multidimensional organization of evaluative attributes. Dimensionality of the evaluative attribute space is regarded in many of the complexity formulations as a major component of cognitive differentiation. The focus of this research differs from that of the implicit personality research, with less emphasis placed upon the interpretation of evaluative dimensions and greater emphasis placed upon individual differences in the number of dimensions used in evaluative judgments.

A number of measures of individual dimensionality have been developed within the context of complexity research. Those instruments which have received the widest usage include the Bieri measure, based upon Kelly's (1960) Role Construct Repertory Test; variations of the factor-analytic procedures developed by Ware (1958); and a number of measures of dimensionality developed by Scott (1969). These dimensionality measures are discussed in some detail in Phillips and Thompson (note 3). Recent unpublished research by these authors has shown substantial correlations between a number of measures of dimensionality, over a broad range of concepts and for various groups of subjects.

The complexity studies have raised another issue which is basic to the consideration of models of attribute organization. Much of this research suggests that attribute dimensionality differs across domains of objects. Osgood et al., (1957), found the EPA factor structure to hold for a large number of diverse concepts, ranging from common nouns, to art objects, to sonar signals. Scott (1974) however, found differences in dimensionality between the domains of acquaintances, family activities, nations, self, groups and organizations, and schools. Signell (1966) found differences in the influence of age on attribute dimensionality in the domains of persons and nations. A number of studies (Tripodi and Bieri, 1966; Todd and Rappoport, 1964; and Hanno and Jones, 1973) have found dimensionality differences in judgments concerning different types of reference persons. Moreover, the large number of research studies generated to test the vigilance hypothesis (Miller and Bieri, 1965; Irwin, Tripodi, and Bieri, 1967; Miller, 1968; Soucar, 1970, etc.) have indicated consistent dimensionality differences between the domains of close and distant persons.

The third theoretical conception of attribute structure which has received general theoretical attention is the simple category model developed by Wyer. As was noted in Section I, Wyer defines attributes as categories that determine the classification of objects. This formulation specifically rejects the dimensional notion of attributes. The research conducted within this framework treats "continuous" evaluative rating scales as ordered sets of discrete categories. As was noted above, such a translation allows for the investigation of relationships between attributes in terms of the subjective probabilities of class membership. Wyer (1974) summarizes a substantial body of research relevant to the translation of scale values into categories and to the use of subjective probabilities in representing attribute structure. This work focuses particularly upon the tendency of attribute integration to parallel the laws of probability. Interestingly, a portion of the research conducted within this framework has focused on issues similar to those raised initially by Asch (1946) on the "change of meaning" in attributes as a result of the trait context. Conditional probabilities of category membership have been used by Wyer and Watson (1969) and Wyer (1974b) to explore these context effects. The support obtained by Wyer for his theoretical conception suggests that the simple category notion presents an alternative to the dimensional representations of attribute structure. The choice between these forms of representation of attribute organization thus must be made on the basis of the theoretical power provided by the various conceptions.

In order to provide a basis for further examination of this issue, it is appropriate to delineate more clearly the precise assumptions underlying each approach. Such a discussion, including the evidence pertaining to various aspects of these underlying models, is presented in detail in Phillips and Thompson (note 3, Chapter III). This discussion is summarized below:

A. The Simple Category Model

The simple category model of attributes treats attributes simply as discrete categories. According to this model, stimuli are interpreted by assigning them to various cognitive categories. The assertion that "x is honest" simply indicates that x is a member of the set of "honest" elements. Membership of an element in one or several cognitive categories may serve as a criterion for membership in another category. For example, membership in the categories, "kind elements" and "honest elements," may determine that an element belongs in the "sincere" category. Such a model of elements as categories does not preclude quantification of attributes. Scale values of attributes may themselves be associated with categories. Wyer (1973) has demonstrated empirically that subjects' attribute scale ratings correspond to the distribution of elements over a set of ordered attribute categories.

The simple category model treats independence of attributes simply in terms of the degree of overlap of category membership. In this model, the enumeration of attributes-in-use, together with specification of category redundancy, is required to describe an individual's attribute organization.

B. The Dimensional Model

The traditional representation of attributes, tied to a dimensional model, treats attributes as more or less continuously valued bi-polar variables. According to this representation, attributes can be considered as vectors in some n-dimensional space. Zajonc (1968) defines psychological dimensions in the following way:

> A psychological dimensions is one's capacity to map consistently a set of responses onto a collection of stimuli that is itself ordered. A specific act of "perceiving" or "cognizing" a given stimulus object or event is regarded as involving the projection of the stimulus onto a set of psychological dimensions, and thereby attributing to it one value from each of these dimensions. These projected values, attributes, are the elements of the cognitive structure under analysis. They are what is commonly understood by the traits, characteristics, qualities, etc., of the object, event, or concept as the person perceives them (p. 328).

The representation of attributes as bi-polar scales leads to the conception of attributes as lines or vectors in some multidimensional space. Cognitive elements may then be represented as points in this space. Since every point in the space may be shown to have a projection on each line in the space, the projection may be thought of as the value of the cognitive element represented by that point on each of the attributes represented by the vectors. Given a set of such vectors in some space, it is possible to determine some minimum (nonunique) set of orthogonal vectors which span, or form the basis of, this space. The number of these vectors constitutes the dimensionality of the space; and these vectors may themselves be regarded as the critical subset of attributes required to describe the set of cognitive elements.

Such a model is assumed in the use of factor analytic or multidimensional scaling techniques to analyze the intrinsic dimensionality of attribute data. In either case the data are interpreted in terms of dimensions or factors, with associated weights. The use of rotation in the factor analysis of such data attempts to select some set of orthogonal vectors which offer maximum interpretability of the dimensions in the solution.

The theory underlying the use of the dimensional model in the work of Osgood, et al. assumes that a single set of attribute dimensions applies to all cognitive elements. It is possible, however, to postulate a dimensional model of attribute structure which does not require such a restriction. Such a model--a domain-specific dimensional model--suggests that cognitive elements may be divided into categories on the basis of some set of characteristics, with possibly differing sets of attribute dimensions being used within each category. Thus an individual may group cognitive elements into domains on the basis of some set of characteristics or on the basis of proximity in experience and may then use a different dimensional attribute structure within each domain. Such an assumption underlies most of the work in the area of implicit personality theory, where the focus is on the structure of the attributes used to characterize person-elements. Thus in dealing with the area of impression formation we are concerned with the structure of attributes used specifically within the domain of "people."

Within the general category of dimensional models of attribute organization the _unidimensional evaluative models_ assume that within the attribute space there is a single dimension which constitutes the basis for evaluation. Knowledge of a given cognitive element's position on this dimension provides sufficient information to determine the individual's evaluative response to that element. In contrast, the <u>multidimensional evaluative models</u> assume the existence of multiple evaluative dimensions within the attribute space. According to this conception, in order to examine an individual's response to information it is necessary to examine the implication of that information along the multiple evaluative dimensions. It is then necessary to examine how a cognitive element's position in this multidimensional attribute space affects or becomes translated into a general "evaluative" response.

The implicit personality theory literature cited above makes a strong case for the development of a multidimensional model of attribute organization applicable to the general area of person perception. Such a model must deal with the question of how information is processed in terms of the multidimensional attribute space and with the way in which the cognitive organization determines the individual's response. A theory of cognitive processing developed by Phillips and Thompson (note 3), Configurational Consistency Theory, provides the framework for such a model. Following a review of those impression formation studies which have been based upon a multidimensional conception of evaluation, this theory and its application to the impression formation process will be explored.

III. A Multidimensional Model of Attribute Integration

A. Multidimensional Evaluation and Impression Formation

Considering the extensive research in implicit personality theories that has been conducted using multidimensional-evaluative models, surprisingly little research in impression formation has used this model as a framework. Two studies have been conducted to test the effects of manipulating attribute traits which load on particular dimensions on different types of evaluative judgments. Zanna and Hamilton (1972) conducted an impression formation study in which polar attributes loading on one evaluative dimension were presented in the context of attributes loading on a separate dimension. For example, the social-dimension attributes "warm" and "cold" were presented in the context of four positive intellectual traits, while polar attributes on the intellectual dimension--"industrious" and "lazy"--were presented in the context of four positive social traits. The stimulus persons were then rated on 20 trait inference scales, including traits from both the social good/bad and intellectual good/bad dimensions (as defined from the work of Rosenberg et al., 1968). The results of this study indicated that manipulation of information on one dimension affected trait inferences on that dimension alone. In a similar study, Hamilton and Fallot (1974) again varied the content of person descriptions in terms of the social and intellectual desirability dimensions. In this experiment, the dependent variable was the predicted degree of "liking" and of "respect" for the person described. The trait information loading on the social good/bad dimension was found to have a greater influence on liking judgments, while the intellectual good/bad trait manipulations had a greater effect on respect judgments.

In a somewhat more complex study, Bryson (1974) suggested that attention to the multidimensionality of the evaluative process could help to resolve the issues surrounding (1) the adding versus averaging controversy, and (2) the discrepant results regarding the facilitative or reductive effect of trait redundancy on responses. Bryson examined the dimensionality of the evaluative trait space used in the processes involved in the impression formation task by performing a principal components factor analysis on the evaluative ratings for a number of single traits, chosen to represent two evaluative dimensions--sociability and responsibility. Bryson isolated five factors, the first of which was identified as general evaluation. Rotation of the first two factors produced the expected sociability and responsibility dimensions, each similarly related to the unrotated first factor. Bryson then examined responses to redundant sets (sets of traits containing attributes from either the social or responsible dimension only) and to nonredundant sets (sets containing both types of attributes). In general, the results indicated that redundancy reduced the polarity of responses on the general evaluative dimensions, while it facilitated extreme responses on the dimensions upon which the redundant traits loaded most heavily. The valence of the traits presented interacted with this general trend, however.

Anderson has suggested that integration theory (the set of weighted-averaging models) may be applied to a multidimensional conception of the impression formation process by applying the weighted-averaging model to each dimension in turn. Such a suggestion is adequate for studies of the type done by Zanna and Hamilton and Hamilton and Fallot, in which separate responses are associated with each dimension. The question confronted by the Bryson article concerns the way in which these separate dimensional responses are combined in order to arrive at a single evaluative or liking response.

Bryson's work offers a suggestion for the type of multidimensional model required to deal with the effects of intraset trait interrelations on global evaluative responses. In terms of redundancy of attributes, Bryson found that reproducing evaluative scores solely on the basis of a single evaluative factor would have resulted in more extreme values for nonredundant than redundant sets, an effect which has received widespread empirical support. Reproduction of the evaluative scores directly from the specific evaluative factor on which the redundant traits loaded would have shown a facilitative effect for redundancy, as was found by Feldman (1968).

B. CCT Models of Impression Formation: The Idiographic, Multidimensional Approach

Configuration Consistency Theory (CCT) as a theory of information processing, provides an approach for examining the process of the translation of multidimensional evaluative information into an affective response to the object. Taken as a whole, CCT is a broad and complex theory designed to deal with a number of areas relating to cognitive structure and processing. A detailed exposition of the theory is presented in Phillips and Thompson (note 3). An overview of the major assumptions and formulations of the theory which are applicable to the issue of the processing of attribute information will be presented here. Several models of attribute integration will then be derived from this theoretical basis.

CCT proposes that the translation of multidimensional evaluation into an affective (liking) response to the object being judged follows from a postulated correspondence between experienced relations between objects and the attribution process. That is, CCT assumes a particular set of correspondence rules between the way in which a person represents the observation of relationships between people, objects, etc., in his or her world and the evaluative judgments made by the person conccerning those objects. In turn, these evaluative attributions then affect the individual's assumptions and hypothesis about other interobject relationships. The basic assumptions of the theory revolve around the notion that people structure cognition in a way that allows them to account for and explain the reality around them.

CCT proposes a theoretic structure which consists of three parts--categories or domains of cognitive elements, a multidimensional space of attributes in which the elements exist as points, and a network of interelement affective relations. The relational network is presumed to be the fundamental unit of the system. The individual is assumed to represent as elements in the cognitive space the objects, events, people, etc., which are the material of cognition. The interconnections between these external objects in the world of experience are represented by the individual as relational bonds between the elements. These relations are assumed to be relatively direct encodings of experience--thus, the relational network is referred to in the theory as the <u>experiental component</u> of the cognitive system.

It should be noted here that CCT makes a distinction between affective relations, described above in terms of the experienced interconnections between elements, and attributional evaluation, which will be described below. While the valence of affective relations and evaluation typically are congruent, this is regarded as a function of a motive to maintain consistency rather than as evidence that a unitary process is represented. The experience of "liking" (a relational bond) a person or an object which is negatively evaluated (cigarettes, "my untrue love," the person who is "so friendly he makes me uncomfortable") may be inconsistent and infrequent but it is not impossible. Previous research, particulary in the area of attitudes, has failed to distinguish between affective relations and evaluation. This distinction is essential to CCT.

The set of affective relations between all of the cognitive elements in a domain may be represented as a relational network such as that proposed by Cartwright and Harary (1956) in their extension of balance theory to multi-element structures. Such a conception is described graphically by Rosenberg (1968):

> Let us imagine a finite but vast space. Within it are located hundreds (thousands?) of object-concepts, each of these being a verbal (or other symbolic) representation of a person, institution, policy place, event, value standard or any other "thing." . . . Represent each of these object-concepts as a little metal disk. Between these disks run strings which tie them together, two at a time. Red strings indicate a negative or disjunctive relationship. . . . Green strings indicate a positive or conjunctive relationship . . . (p. 79).

This graph theoretic depiction of the network of interitem relations may be translated directly into a matrix representation of the relational network, in which cell i_j of the matrix represents the experienced affective relationship between element i and element j. It is then possible to discuss the structural properties of the relational network in terms of the mathematical properties of this relational matrix.

Within any domain, the elements are assumed to be arranged in some multidimensional evaluative attribute space. The position of a given element in this space determines the projection of this element on the evaluative dimensions which define that space. The characteristics of this attribute space and the placement of elements within it are assumed to result from an attempt on the part of the person to account for the pattern of interelement relationships. This position is similar to that adopted by Kelly, 1955, in that attributes are assumed to serve a "constructive" rather than an informative function. While relations are assumed to be the relatively direct representations of interactions between objects in the real world, attribution is assumed to be a derived process designed to explain or account for the encoded relational network. That is, the theory assumes that evaluative attributes are not immediately perceived as properties of elements but rather that they are derived as explanations of relational observation. A similar position has been stated by Mischel (1973):

> Traits are constructs which are inferred or abstracted from behavior. When the relations between the observed behavior and the attributed trait are relatively direct, the trait serves essentially as a summary term for the behaviors that have been integrated by the observer (p. 262) and
>
> Thus while the traditional personality paradigm views traits as the intraphysic <u>causes</u> of behavioral consistency, the present position sees them as the summary terms (labels, codes, organizing constructs) applied to observed behavior (p. 264).

These means by which the process of attribution explains or accounts for the representation of interitem relations is determined by a structural parallelism between the relational matrix and the multidimensional attribute space. It is this parallelism which provides a basis for the CCT definition of cognitive consistency. To the extent that the relational network precisely determines the attribute space, the network--the experiential subsystem--can be fully reproduced by the attribute space--the explanatory subsystem. To the degree that such a reproduction is possible, the person's cognitive structure in that domain may be said to be consistent. Departures from ideal fit of the two systems are experienced as degrees of inconsistency--as failures to explain or account for the "facts" of experience.

The calculus of reproduction which allows for an assessment of the goodness of fit of the two subsystems utilizes the mathematical properties of each subsystem. The relational matrix, R*, which represents the set of interrelations among the elements in a domain may be characterized in terms of its dimensionality, equal to its rank. The number of characteristic vectors required to generate R* defines the dimensionality of the matrix. Attributional consistency deals with the correspondence between the ratings (or projections) of the elements on the attribute dimensions and the specific eigenvectors of the matrix of interitem relations. As individual is attributionally consistent in a given domain to the extent that the evaluations of the elements on the various attribute dimensions correspond to the entries in the eigenvectors of the relational matrix. That is, if $\{E_K\}$ is a vector representing the evaluations of the n elements in the domain on the kth evaluative attribute dimension, then the entries in $\{E_K\} = [e_1, e_2, \ldots e_i, \ldots e_n]^T$ should correspond to the entries in one of the eigenvectors E_K of the relational matrix, R*. Attributional consistency thus requires that the number of evaluative dimensions must equal or exceed the number of eigenvectors of R* and requires in addition the matching of the entries in the corresponding vectors.

For the unidimensional case, Phillips (1967) demonstrated that balance (in the strong sense, with null relations regarded as imbalanced) implies that R* be of rank 1--that is, that R* be reproducible from a single eigenvector. Phillips demonstrated empirically that the entries of the dominant eigenvector of the relational matrix corresponded to element evaluations. Thus, attributional consistency was found, in general, to hold. In the unidimensional case, attributional consistency may be defined by the following equation:

$$r_{ij} = \lambda e_i e_j \tag{11}$$

where r_{ij} represents the affective relation between elements i and j; e_i represents the evaluation of the ith element on the single attribute dimension; and λ is a weighting factor, the eigenvalue associated with the single eigenvector of R*.

According to CCT, the existence of multiple orthogonal evaluative dimensions implies that R*, which is of rank m, may be spectrally decomposed into m rank 1 matrices, each reproducible from a single eigenvector. Thus

$$R^* = R_1^* + R_2^* + \ldots R_k^* + \ldots + R_m^*$$

where

$$R_k^* = \lambda_k E_k E_k^T$$

R_k^* is a rank 1 matrix which results from multiplying the kth eigenvector of R* by its transpose and then by its associated eigenvalue. Each of the m eigenvectors of R* is, of course, orthogonal to each other eigenvector.

If consistency is to exist in this domain, the individual must use at least m (orthogonal) attribute dimensions to make judgments concerning the n elements in the domain. If the n elements are represented as points in the attribute space, each of the m attribute dimensions may be represented as a vector consisting of the projections of each of these n elements on the dimension. Thus each dimension may be represented by the set of evaluations of the n elements on this dimension,

$$\{E_K\} = [e_{1k}, e_{2k}, \ldots, e_{ik}, \ldots, e_{nk}]^T$$

For attributional consistency to hold, these m orthogonal vectors representing the attribute dimensions, $\{E_1\}$, $\{E_2\}$, ..., $\{E_k\}$, ... $\{E_m\}$, must correspond to the eigenvectors of R*. Thus R* may be reproduced from the evaluations of the n elements on the m attribute dimensions, and

$$R^* = \lambda_1 \begin{bmatrix} e_{11} \\ e_{21} \\ \vdots \\ e_{i1} \\ \vdots \\ e_{n1} \end{bmatrix} [e_{11}, e_{21}, \ldots, e_{i1}, \ldots e_{n1}]$$

$$+ \lambda_2 \begin{bmatrix} e_{12} \\ e_{22} \\ \vdots \\ e_{i2} \\ \vdots \\ e_{n2} \end{bmatrix} [e_{12}, e_{22}, \ldots, e_{i2}, \ldots e_{n2}]$$

$$+ \\ \vdots$$

$$+ \lambda_k \begin{bmatrix} e_{1k} \\ e_{2k} \\ \vdots \\ e_{ik} \\ \vdots \\ e_{nk} \end{bmatrix} [e_{1k}, e_{2k}, \ldots, e_{ik}, \ldots e_{nk}]$$

$$+ \\ \vdots$$

$$+ \lambda_m \begin{bmatrix} e_{1m} \\ e_{2m} \\ \vdots \\ e_{im} \\ \vdots \\ e_{nm} \end{bmatrix} [e_{1m}, e_{2m}, \ldots, e_{im}, \ldots e_{nm}]$$

This condition of attributional consistency may be represented by the multidimensional form of equation 11,

$$r_{ij} = \sum_{k=1}^{m} \lambda_k e_{ik} e_{jk} \tag{12}$$

where e_{ik} is the evaluation of the ith element on the kth attribute dimension and λ_k is the "weight" of the kth attribute dimension (equivalent to the eigenvalue associated with the eigenvector which corresponds to the kth attribute dimension).

If two elements are located as points in the attribute space for a given domain, then equation 12 may be used to predict the affective relation between them, based upon their evaluations (the projections of the points) on the m orthogonal attribute dimensions and based upon the relative weights associated with these dimensions. If one element is the self, _s_, it is thus possible to predict the affective relation between _s_ and any person i who is also an element in the domain. From equation 12,

$$r_{si} = \sum_{k=1}^{m} \lambda_k e_{sk} e_{ik}. \tag{13}$$

This equation leads to the prediction that when _s_ and _i_ are both elements in a domain (and thus are points in an attribute space), _s_ will have a maximal degree of liking for person i to the extent that the evaluations of both are maximally polarized and of the same valence on each dimension.* Thus for a given level of self-evaluation on a

The assumption is made here that the λ's are ≥ 0 for each attribute dimension. Such an assumption fits with the _reflexive model_ of CCT which assumes positive values for the diagonal elements of R. The implications of negative eigenvalues for interpersonal relations, according to a model of CCT which allows irreflexivity, are discussed in detail in Phillips and Thompson, Chapters VII and VIII.

particular dimension, r_{si} will be maximized when the evaluation of person i is highly polarized on the same side of the origin as s's self-evaluation. For an individual who rates the self as positive on all evaluative dimensions, the degree of liking for i will be a direct function of the positivity of the evaluation of i on each of these dimensions.*

In the case of direct person perception, based on the observation of the object person's interrelations with other objects of experience, equation 12 may be applied directly to predict the set of consistent attributions which are likely to be made about the person. These attributions are determined by the person's interactions with already evaluated elements. If the direct contact has not involved the formation of an affective relational linkage between s and i, the nature of such a link can be predicted by the same equation. As an example, suppose I have observed person i interacting with people I know at a party and have heard person i state his or her approval of various ideas, issues etc. I have not actually interacted myself with this person. Based on my encoding of the interactions I observed and based on my existing evaluations of the other elements involved in this interaction, I am able to "place" person i at a relatively

*Since CCT assumes normalization of evaluation vectors to unit length, e_{ik} and e_{sk} are not strictly independent. For a domain containing a relatively large number of elements, these two evaluations may essentially be treated as independent variables. In a domain consisting of p and i only, however, liking will be maximized to the extent that both elements are rated identically on each dimension. The implications of number of elements in a domain for evaluation and interpersonal attraction are discussed in Phillips and Thompson, Chapter VIII.

consistent point (in terms of equation 12) in my attribute space. Based on these attributions and upon my evaluation of myself on my evaluative dimensions, I can then make predictions about r_{si}--for example, expecting to like this person a great deal.

The impression formation task used in the research discussed in Section I presents greater difficulties in the application of the theory to the prediction of liking judgments. In this task, the information presented is not in the form of observed interactions. Instead the subject is presented with attribute judgments. In the standard impression formation paradigm, subjects are simply presented with sets of traits, are told that the traits "describe a person," and are asked to predict "how much they would like a person so described." The source of the trait judgment is unspecified. That is, it is unclear whether subjects are to make the judgment in terms of how they would feel about a person whom they themselves would describe in this way or whether they are to rate the person as though an external source were providing the description. In other experiments (cf. Brewer, 1968; Cooper and Crano, 1974), the trait statements are presented in letter of recommendation form. In this case, it is clear that the trait statements have been made by an external source and that the subjects are processing the results of another person's attribution process.

Preliminary research conducted by Thompson and Phillips (Thompson, note 6) indicates that trait information presented to subjects in the form of statements made by an acquaintance about a third person is regarded as somewhat ambiguous. In this experiment, subjects were presented with a set of statements about a person which they were instructed to regard as statements made by either a liked or a disliked acquaintance. The statements received were either in trait or relational form--"She is quarrelsome" or "She picks fights over nothing," for example. The relational statements given were selected on the basis of their consistent encoding of the corresponding trait statements in an earlier set of studies. Judgments of predicted liking for the object person were clearly affected by the interaction between type of statement and liking for the person giving the information. The judgments for trait stimuli were responsive to a balance effect while those for relational statements were not. That is, when trait statements were given, subjects given positive or negative information from a disliked source responded more neutrally than when the source was liked. This effect did not occur when the information presented was relational. Information in trait form was apparently regarded as less objective than equivalent relational information, and thus judgments were more strongly affected by evaluation of the source of information. A study by Rodin (1972), which investigated the effectiveness of trait versus behavioral statements as encoders of information, obtained similar results. The presentation of characteristic traits of a person did not provide sufficient information to identify the person, while the presentation of typical behaviors did provide such information.

This issue concerning the ambiguity of trait information arises within the context of CCT's assumption that evaluative attributes serve a constructive or explanatory function. Since the characteristics of the attribute space are assumed to be derived from relational experience, individuals would be expected to have different attribute structures. The number and content of the attribute dimensions, the relationships between specific trait vectors and these dimensions, and the placement of elements along the trait vectors would all be expected to vary on an individual basis. This issue of individual differences in trait organization has not been resolved in the implicit personality research. While several studies of trait usage have attempted to assess individual difference variables (Kuusinen, 1969; Hamilton, 1970) much of the work on attribute organization has relied exclusively on the analysis of grouped data. The cognitive complexity literature does tend to support the notion of quantitative, if not qualitative, differences in attribute structure. Several studies (Shrauger and Patterson, 1974; and Wish, Deutsch, and Biener, 1970) have indicated individual differences in the content of attribute dimensions, in several domains. As Schneider (1973) notes:

> It is relatively easy to show that individuals differ in their implicit personality theory, but there has been limited success relating such differences to traditional personality variables (pp. 304-305).

Thus the argument has been made that predicted liking judgments based upon presented trait stimuli are not equivalent to such judgments based on the observation of actual interactions or to judgments based on the presentation of relational information. This is not meant to imply that the impression formation paradigm is highly artificial or that it has no analog in the information processing tasks of everyday life. In fact, people do attempt to communicate with other people about "target persons" in the form of trait statements. "Just wait until you meet X--he's such a bright, friendly, intelligent person" is not in any sense an atypical type of communication among friends and acquaintances. Thus the attempt to develop models of how such information is processed is certainly of interest.

In the impression formation task, person S (the subject) receives and is about to process the statement, "Person i is trait A." Let us begin by assuming the following: S has a trait vector in his or her multidimensional attribute space which is labeled trait A. S is willing to assume that either (1) the experimenter (E) knows what S means by trait A and expects S to process this information as though person i is someone whom S has actually evaluated as possessing this trait, or (2) the source of this communication (either E or "the acquaintance," or the writer of the letter of recommendation, etc.) has a vector for trait A which means the same thing to the source, in terms of S's attribute dimensions, as it means to S. In this latter case, then, the assumption is that S is willing to accept the source's evaluation of person i as directly translatable into S's evaluation of this person. Under either of these assumptions, S is able to locate person i as a point on the vector representing trait A with complete certainty. Person i is now a point in S's evaluative space. The position of person i on each evaluative dimension is determined simply by the projection of this point on each dimension. Equation 12 then determines r_{si}, the predicted liking relation between S and person i.

This outcome may be illustrated by a concrete example. Suppose that S has a 3-dimensional attribute space containing dimensions which might be labeled: (1) "intelligent-unintelligent," (2) "friendly-unfriendly," and (3) "reliable-unreliable." This space contains a vector labeled "bright-dull" which is "closest" to (has its highest loading on) dimension 1 but which also loads on dimensions 2 and 3. S receives the communication "Person i is bright" and places Person i at the positive endpoint of the "bright" vector. The projection of the point corresponding to person i on each of the dimensions is simply

$$e_{ik} = \cos_{kA} \cdot F_A$$

where $\cos_{kA}$ represents the cosine of the angle between vector A and dimension k and where F_A represents the position of person i on vector A. Equation 12 may then be stated for this case as

$$r_{si} = \sum_{k=1}^{3} \lambda_k e_{sk} \cos_{kA} \cdot F_A$$

Questions concerning the processes of information integration arise when S is presented with two or more pieces of trait information. If the trait vectors are entirely coincident, then person i may be located unambiguously in the attribute space as a single point. If the trait vectors are not coincident, person i is represented by multiple points whose projections on at least one of the attribute dimensions differ from one another. In this case, it is necessary to identify the process by which these differing projections are integrated. Any of the unidimensional evaluative models of trait integration discussed previously may be applied separately to each dimension in arriving at a decision about the unambiguous placement of person i on each dimension as input into equation 12.

Let us assume that the ambiguity concerning the placement of person i on a given dimension is resolved through a simple averaging process:

$$e_{ki} = \frac{1}{n} \sum_{T=1}^{n} \cos_{kT} \cdot F_T \tag{14}$$

where T represents the trait vectors, and n represents the number of trait stimuli presented. In the case of two traits, A and B,

$$e_{ki} = \frac{\cos_{kA} \cdot F_A + \cos_{kB} \cdot F_B}{2}$$

Substitution of equation (14) into equation (12) results in a simple averaging model of trait integration. That is, $E_{AB} = 1/2\ (E_A + E_B)$, etc. These assumptions are thus clearly unsatisfactory, due to the failure of such a model to predict set size effects under any circumstances.

The problem of dealing with the set size phenomenon may be met by adopting the strategy suggested by Anderson and applying the Anderson equal-weighting model separately to each dimension. Such an application involves the assumption that there exists an I_0 or initial impression parameter for each evaluative dimension. In this case,

$$e_{ki} = \frac{\sum_{T=1}^{n} w_1\ (\cos_{kT} \cdot F_T) + w_0 I_{0k}}{nw_1 + w_0} \tag{15}$$

This model predicts a combinatorial process which is essentially equivalent to that predicted by Anderson's unidimensional model. A set size effect is predicted for univalent, equal-polarity trait sets, while an averaging process is predicted in the case of the addition of moderate to extreme information. Like Anderson's model, however, this formulation fails to make differential predictions for sets of information which differ in redundancy.

In a multidimensional model of attribute organization, redundancy may be defined in terms of the relationship between trait vectors. Entirely redundant vectors are those which are coincident in the space. Two vectors are coincident if the angle between them is zero. Thus the cosine of the angle between a pair of vectors may be used as a measure of redundancy--the greater the cosine, the greater the degree of redundancy between the traits. Equivalently, redundancy may be defined in terms of the pattern of loadings on the attribute dimensions which define the space--two vectors which have the same loadings on all of the orthogonal dimensions are coincicent.

Models which deal with attribute relevance: The nonexplicit projection models. The optimal multidimensional model of attribute integration should take into account the degree of redundancy--as defined above--within the trait sets. In order to develop such a model, it is necessary to reexamine the assumptions discussed above. In the multidimensional analysis of trait information processing to this point we have assumed that the experimental subject treats a single piece of trait information in something like the following way: "Person is is trait A. That means that person i is completely defined by trait A and that the position of person i on trait A is sufficient to explain all relationships between person i and other elements in the domain." This is equivalent to interpreting "Person i is smart" as "Person is is smart and that's all he or she is."

Let us reconsider the example discussed above in which S has the three attribute dimensions "intelligent-unintelligent," "friendly-unfriendly," and "reliable-unreliable." S receives the statement, "Person i is bright." S's vector labelled "bright" has a high loading on dimension 1, and small loadings on dimensions 2 and 3. What is likely to be going on in this case is that S is processing the information in the following way: "Person i is bright. Therefore I can be fairly certain that he or she is located near the positive extreme of the intelligent dimension. <u>Until I get more information</u>, I will assume that person i is relatively neutral in friendliness and reliability since bright is not highly related to these dimensions." If S then receives the statement "Person i is bright and dependable," the processing is likely to take the following form: "I now have the information that S is both bright <u>and</u> dependable. Dependable implies an extreme rating on the reliable dimension because of its high loading while bright implies an extreme rating on the intelligent dimension. The small loadings for "bright" on dimension 2 and for "dependable" on dimension 1 do not require that I average a neutral rating with the extreme ratings to locate person in on each dimension. Instead, the small loadings simply mean that those vectors are not good predictors for locating the person on those dimensions. The projection of "bright" on dimension 2 and "dependable" on dimension 1 should be discounted for this reason."

The question then becomes one of how to systematize such a process. We might consider first the situation in which all attributes presented to the subject are represented by vectors which are exactly coincident with one or another of the subject's attribute dimensions. Let us assume that trait A and trait B are coincident with dimension 1, trait D with dimension 2 and trait G with dimension 3. We can then treat the statement "Person i is trait A" as locating person i on dimension 1 only. In the case of three dimensions, this may be represented as person i being located somewhere on a plane surface that intersects dimension 1 at A and which is parallel to the other two dimensions. When S is asked to make a liking judgment for person i, this judgment may be represented by the formula

$$r_{Si/A} = \lambda_1 e_{S1} A + \lambda_2 e_{S2} E\ (e_{i2}) + \lambda_3 e_{S3} E\ (e_{i3}) \tag{16}$$

where $r_{Si/A}$ represents the liking judgment based on the trait A statement and $E\ (e_{ik})$ represents the expected value of person i's position on dimension k when no information relevant to that dimension has been presented. This expected value may be assumed to be either (1) neutrality or (2) the position of "the average person" on this dimension--an I_{0k} parameter value. Under the first assumption, equation 16 becomes

$$E_{Si/A} = \lambda_1 e_{S1} A \tag{17}$$

while under the second assumption,

$$E_{Si/A} = \lambda_1 e_{S1} A + \lambda_2 e_{S2} I_{02} + \lambda_3 e_{S3} I_{03} \tag{18}$$

The equivalent formulas for prediction of liking judgments when trait D or G is presented alone are given below:

$$E_{Si/D} = \lambda_2 e_{S2} D. \tag{19}$$

Alternatively

$$E_{Si/D} = \lambda_1 e_{S1} I_{01} + \lambda_2 e_{S2} D + \lambda_3 e_{S3} I_{03}. \tag{20}$$

$$E_{Si/G} = \lambda_3 e_{S3} G \tag{21}$$

or

$$E_{Si/G} = \lambda_1 e_{S1} I_{01} + \lambda_w e_{S2} I_{02} + \lambda_3 e_{S3} G. \tag{22}$$

When S is presented with two traits, each coincident with a different dimension, S is then able to locate person i's position on these two dimensions, being completely uncertain about person i's position on the third. In the three dimensional case, this is equivalent to locating person i on a line which has projections on dimensions 1 and 2 at points A and D respectively and which is parallel to dimension 3. This may be represented by the following equation:

$$r_{Si/AD} = \lambda_1 e_{S1} A + \lambda_2 e_{S2} D + \lambda_3 e_{i3}\ E\ (e_{S3}) \tag{23}$$

Replacing E (e_{S3}) by either zero or I_{03},

$$r_{Si/AD} = \lambda_1 e_{S1} A + \lambda_2 e_{S2} D \tag{24}$$

or

$$r_{Si/AD} = \lambda_1 e_{S1} A + \lambda_2 e_{S2} D + \lambda_3 e_{i3} I_{03}. \tag{25}$$

Examination of the relationships between equations 17, 19, and 24 indicated that, according to these assumptions

$$r_{Si/AD} = r_{Si/A} + r_{Si/D} \tag{26}$$

while equations 18, 20, and 25 show that if E (e_{ik}) is assumed to equal I_{0k} rather than zero,

$$r_{Si/AD} = r_{Si/A} + r_{Si/D} - (\lambda_1 e_{S1} I_{01} + \lambda_2 e_{S2} I_{02} + \lambda_3 e_{S3} I_{03}) \tag{27}$$

This formulation thus takes the form of an adding model (with a subtractive constant in the case of equation 27) when the pieces of trait information presented each are coincident with different attribute dimensions. In the case of trait A and B, both of which load on the _same_ dimension, the projections are assumed to be averaged to arrive at e_{i1}. Thus

$$r_{Si/AB} = \lambda_1 e_{S1} \frac{A+B}{2} \qquad \text{or} \tag{28}$$

$$r_{Si/AB} = \lambda_1 e_{S1} \frac{A+B}{2} + \lambda_2 e_{S2} I_{02} + \lambda_3 e_{S3} I_{03}. \tag{29}$$

This assumption leads to the prediction, using either equation 38 or equation 29 that

$$r_{Si/AB} = 1/2\ (r_{Si/A} + r_{Si/B}).$$

In general, then, this conceptualization is based on the idea that each trait statement which presents information about person i's location on a dimension for which no previous information has been available _will take the place of_ the expected value for that dimension.

That is, the expected value of the projections of all the points in the domain on a given dimension is used in equation 12 if no relevant information is available. Once such information is available, the use of the expected value in making the judgment is replaced by (not averaged with) the result of the new information.

Extended beyond the specific case presented in equations 17 through 29, such a model predicts the following: Information which is entirely nonredundant, that is, information presented in the form of traits whose vectors are each perfectly coincident with a different attribute dimension will be added (with a subtractive constant if the assumption that $E\ (e_{ik}) = I_{0k}$ is adopted) in arriving at a judgment based upon sets of these traits. Information which is entirely redundant, that is, information which is presented in the form of traits whose vectors are all perfectly coincident with the same attribute dimension will be averaged in arriving at judgments for these trait sets.

The distance-weighting model. The formulation presented above is less than satisfactory for two reasons. First, it fails to deal with trait sets containing traits whose vectors are neither entirely orthogonal nor entirely coincident. If "effective" loads .6 on the "intelligent-unintelligent" dimension and .5 on the "reliable-unreliable" dimension, it would be highly arbitrary to treat this trait as locating person i precisely on the former dimension and providing no information at all on the latter. In addition, the geometry of the model is unsatisfactory. Any point on a vector, being a point in the space, has projections on all dimensions in the space. A point on a vector which is coincident with one dimension has a projection on the other two dimensions, even though that projection is at the zero point. Thus to talk about a trait statement as locating person i in a plane in the space rather than at a point is to adopt a notion similar to that used by Scott (1969), which states that points need not have "explicit" projections on all dimensions. This idea implies a geometry which does not fit with the attempt by CCT to deal with cognitive structure in terms of multidimensional Euclidean spaces.

It is possible to resolve this issue and at the same time retain the flavor of the model discussed above by incorporating the idea that the angular distance between a vector and a dimension affects the contribution of the projection to the overall judgment. That is, we may propose a mechanism which weights the projection of a trait on each dimension according to the closeness of the trait vector to that dimension. If "bright" loads highly on "intelligent-unintelligent," its projection on this dimension will receive a high weight in determining e_{ik}. "Bright's" low loadings on "friendly-unfriendly" and "reliable-unreliable" mean that while its projections on these dimensions won't be entirely disregarded (or considered nonexplicit), they will receive a low weight in the combinatorial process. The proposed model, then, is a weighted averaging model, where the weight of a projection on a dimension is inversely proportional to the angular distance between the trait vector and the dimension. As a weighting factor, this model uses the cosine of the angle between the trait vector and the dimension. For sets of traits, each of which is perfectly coincident with one of the attribute dimensions (i.e., where all cosines are equal to either 1 or 0), this model will make the same predictions as the nonexplicit projection model discussed above with E $(e_{ik}) = 0$.

The general formula for this distance-weighting model may be stated in the following form:

Let θ_{Tk} equal the angle between the vector for trait T and dimension k.

Let T_k equal the projection of trait T on dimension k.

Let w_{Tk}, the distance-weighting factor, equal cos θ_{Tk}.

A subject S, for whom the attribute space for the relevant domain has m orthogonal dimensions, is presented with n pieces of trait information about person i, each of which is represented by a vector in S's attribute space. The final value for person i on dimension k, resulting from the information integration process, is determined by the following formula:

$$e_{ik} = \frac{\sum_{T=1}^{n} w_{Tk} T_k}{\sum_{T=1}^{n} w_{Tk}} \tag{30}$$

That is, the value of person i on dimension k is a weighted average of the projections of the n traits on dimension k, where each trait projection is weighted by a function of the distance between the corresponding trait vector and the dimension.

Then from equation 12:

$$r_{Si/T=1.....n} = \sum_{k=1}^{m} \lambda_k e_{Sk} \frac{\sum_{T=1}^{n} w_{Tk} T_k}{\sum_{T=1}^{n} w_{Tk}} \tag{31}$$

Let us consider the special case in which k=3 and each of the three traits is perfectly coincident with a different attribute dimension. Then

$$\begin{array}{llllll}
w_{A1}=1 & A_1=F_A & w_{D1}=0 & D_1=0 & w_{G1}=0 & G_1=0 \\
w_{A2}=0 & A_2=0 & w_{D2}=1 & D_2=F_B & w_{G2}=0 & G_2=0 \\
w_{A3}=0 & A_3=0 & w_{D3}=0 & D_3=0 & w_{G3}=1 & G_3+F_C
\end{array}$$

That is, for trait T, coincident with dimension k, the cosine of that trait vector with dimension k is 1, and the cosine of the vector with all other dimensions is zero. The projection of T on k, T_k, is equal to the distance of the trait along the trait vector from the origin, that is, to F_T. The projection of T on all dimensions to which it is orthogonal is zero.

It is thus the case from equation 31 that

$$r_{Si/A} = \lambda_1 e_{S1} F_1$$

$$r_{Si/D} = \lambda_2 e_{S2} F_2$$

$$r_{Si/G} = \lambda_3 e_{S3} F_3$$

Since, from equation 31, $r_{Si/AD} = \lambda_1 e_{S1} F_1 + \lambda_2 e_{S2} F_2$, it is apparent that

$$r_{Si/AD} = r_{Si/A} + r_{Si/D}. \tag{32}$$

It is also the case that

$$r_{Si/DG} = r_{Si/A} + r_{Si/D} + r_{Si/G}. \tag{33}$$

In general, the model predicts that when a set of attributes are represented by vectors, each of which is coincident with a different dimension, the likability judgment for the set will equal the sum of the likability judgments for the individual traits.

Considering the case in which two trait vectors are coincident with the same dimension,

$w_{A1}=1$	$A_1=F_A$	$w_{B1}=1$	$B_1=F_B$
$w_{A2}=0$	$A_2=0$	$w_{B2}=0$	$B_2=0$
$w_{A3}=0$	$A_3=0$	$w_{B3}=0$	$B_3=0$

it is once again the case that

$$r_{Si/A} = \lambda_1 e_{S1} F_A \quad \text{and}$$

$$r_{Si/B} = \lambda_1 e_{S1} F_B.$$

Since

$$r_{Si/AB} = \lambda_1 e_{S1} \left(\frac{F_A + F_B}{2}\right)$$

it is the case that

$$r_{Si/AB} = \frac{r_{Si/A} + r_{Si/B}}{2} \tag{34}$$

In general, when a set of attributes are represented by vectors, all of which are coincident with the same dimension, the likability judgment for the set will equal the average of the likability judgments for individual traits.

The use of this multidimensional model suggests a definition for trait redundancy or trait synonymity, as was noted above. When two traits are represented by vectors which have a small angular distance between them, they may be said to be highly redundant or highly synonymous. In factor-analytic terms, synonymous traits would be those which have the same pattern of factor loadings across all dimensions. A pair of traits may be said to be maximally nonredundant or nonsynonymous to the extent that the vectors representing them approach orthogonality. In general, the distance-weighting model predicts that for traits of the same valence, the magnitude of the set size effect will be a direct function of the nonredundancy of the traits in the set. For perfect synonymous, a strict averaging prediction is made. For perfect, univalent nonsynonyms, a strict adding prediction is made. The more nonsynonymous the traits in a set, the greater the set size (summation) effect should be.

For univalent sets of traits chosen without regard for synonymity or redundancy, this model would predict a set size effect, with polarity of judgments being a negatively accelerated function of the number of traits in the set. This is the case because a randomly chosen set of traits of relatively small size is unlikely to contain highly redundant traits. However, since the dimensionality of attribute spaces is limited--typicall falling in the range of 2 to 6 dimensions in most cognitive complexity studies--large sets of traits must necessarily be characterized by increased redundancy and a reduction in the additive contribution of additional traits.

The distance-weighting model thus appears to have considerable potential as a model of attribute integration. Among randomly chosen univalent, equally polarized trait sets, a negatively accelerated set size curve is predicted. When synonymity or redundancy is varied, a greater set size effect is predicted for nonredundant than for redundant sets. Each of these predictions fits the findings obtained in prior studies. The distance-weighting model predictions concerning the addition of moderate to extreme trait sets vary according to the degree of coincidence of the trait vectors. An averaging effect is predicted if the traits load on the same dimension; an adding effect is predicted if they load on different dimensions. Since trait redundancy has not typically been used as a variable in studying the moderate-extreme effect, the relationship between prior data and these predictions is not clear.

Two features of the general class of CCT models should be noted. First, each of the models discussed in this section has been based upon equation (12)

$$r_{Si} = \sum_{k=1}^{m} \lambda_k e_{Sk} e_{ik}$$

in which S's liking for i is assumed to be the dependent variable and in which S's self-evaluations on the attribute dimensions in the domain are important independent variables. None of the models of the impression formation process discussed earlier have dealt with self-evaluations as variables, although a substantial literature exists on the relationship between attraction, similarity, and self-evaluation (Deutsch and Solomon, 1959; Dittes, 1959; Dutton and Arrowood, 1971; Skolnick, 1971; Dutton, 1972). CCT definitely makes the prediction (within the assumption of positive weights for the dimensions) that S will expect to like other people who are evaluated favorably on the same dimensions on which S rates himself or herself favorably. This prediction holds only for studies that use a measure of the expected <u>affective relation</u> for person i as the dependent variable. When S is asked to rate person i on overall favorability or on particular evaluative scales, equation 12 does not apply. The process of combining trait ratings to arrive at global evaluative judgments or to infer other specific attributes is treated by CCT as a different type of information processing and will not be dealt with in this study.

The second general feature of the CCT models which should be emphasized relates to the theoretical assumptions concerning the idiographic nature of cognitive structure. Attributes are considered to be explanatory constructs in the cognitive system, derived by each individual to explain the relational features of that individual's representation of his or her own experience. While cultural patterns of linguistic usage are expected to contribute to some commonality in features of attribute structure, individual differences in the number of dimensions and the trait vectors loading on the dimensions are predicted. The CCT models may show some power in predicting judgments for sets of traits chosen as coincident or noncoincident based on the results of multidimensional analysis of grouped data. For instance, from Rosenberg et al's. (1968) multidimensional scaling analysis, CCT could be used to classify traits as synonymous or nonsynonymous in terms of loadings on the social good-bad and intellectual good-bad dimensions. The CCT models would then predict averaging within synonymous sets and adding within nonsynonymous sets. The maximum power of the theory, however, comes into play when trait sets are classified as synonymous or nonsynonymous based on coincidence or non-coincidence within each individual subject's cognitive structure. This requires that the dimensional analysis of trait usage be performed on the individual subject level.

In the initial set of assumptions, stated at the beginning of this section, the situation was described as one in which S accepts the trait statements as descriptive of the attributions he or she has made or would make. As was noted above, the instructions in most impression formation studies have failed to specify to the subject whether the trait statements are to be considered as descriptions provided by an external source or as descriptions which the subject should consider as his or her own. The distinction between these two interpretations of the information situation is particularly important in light of CCT's emphasis on individual differences in attribute structure. If, in fact, attribute meaning is culturally defined, with individuals sharing the same basic attribute dimensions and the same placement of trait vectors in the attribute space, then the source of information is not important. If I can assume that everyone means the same thing I mean by an attribute, then it should not matter who is providing the trait descriptions. The evidence indicating that there is ambiguity in the communication of attributional information, (Thompson and Phillips, Thompson, note 6; Rodin, 1972) suggests, however, that the source of the information may make a difference.

The nature of possible effects of internal vs. external source of attribute information may be explored within the CCT framework. Brewer (1968) discussed degree of certainty as a possible factor in impression formation, particularly in explaining the set size effect. If, in fact, subjects take into account the possibility that the source of information may have a different meaning for a trait than their own, this may be reflected in uncertainty. This uncertainty may then be reflected in less extreme liking judgments. It may in fact be the case that if a subject receives the statement "Person A is smart," the cognitive response may be "There is an area of some size in my attribute space which corresponds to what other people may define as 'smart.' Because of my uncertainty about the precise point at which person i should be placed, I will give a somewhat neutral response." Under these circumstances, sets of highly coincident traits may not really be redundant in terms of the information which they convey. Receiving multiple pieces of coincident attribute information may in fact increase one's certainty that "person i is what *I define* as smart." If this is the case, Brewer's hypothesis that increased certainty leads to more extreme responses suggests that a set size effect may occur in the case of entirely coincident traits if the subjects is uncertain that the source of the trait statements defines the traits (relative to S's attribute dimensions) in the same way S does.

As was discussed previously, prior studies of impression formation have either been unclear about whom the subjects were to consider as the source of the information, or they have specified the externality of the source. The studies have not attempted to direct the subjects to consider the trait descriptions as their own attributions and make judgments on this basis. The CCT models discussed in this section have assumed that subjects are, in fact, treating the descriptions as directly equivalent to their own attributive judgments. The effects of uncertainty in the case of an external source of information would be expected to modify the predictions of the CCT non-explicit projection model and the distance-weighting model in the case of totally coincident traits. If subjects are directed to treat the trait statements as their own attributions then no set size effect would be predicted for perfectly coincident trait sets. However, if the descriptions are presented as statements made by an external source and if this externality leads to uncertainty which moderates the polarity of the judgment, then additional perfectly coincident traits should reduce uncertainty, and increase judgment polarity. Thus some set size effect would be predicted even for perfectly coincident traits when the experimental stimuli are attributed to an external source.

It is clear from the review of the previous literature and from the discussion of the application of Configurational Consistency Theory that the impression formation paradigm may be used to examine a number of important theoretical issues relating to the processing of interpersonal information. The present study is designed to examine these theoretical issues in a comprehensive way, using a highly idiographic approach. The study focuses on both examination of general predictions stemming from the various classes of models and on an intensive examination of the goodness of fit of the specific models themselves. Following from the assumptions made by CCT concerning properties of attribute structure, stimuli for this study were chosen individually for each subject based on the dimensional properties of that subject's patterns of attribute usage. In testing each of the models discussed in this chapter, parameters were measured or estimated on an individual basis. The tests of goodness of fit of the models were also performed separately for each individual. The study was designed to provide an intensive examination of the processes involved in the integration of attributive information at the individual level. The hypotheses stemming from the various classes of models and the formulas to be used to test the models in the specific design used in this study are presented in Chapter II.

CHAPTER II

THE PREDICTIVE MODELS TO BE TESTED

The formulas and general predictions of the models of attribute integration which are to be tested in this study have been presented within a theoretical framework in Chapter I. What remains is to present the form for the application of these models to the specific paradigm used in this study.

The current set of experiments was designed as a test of the effect of trait redundancy on the set size effect and as a test of the goodness of fit of many of the models discussed in Chapter I. The study was highly idiographic--it involved the preliminary collection of an extensive set of data for each subject on patterns of trait usage and judgments concerning trait meaning. Stimuli for the impression formation study were selected for each subject on the basis of dimensional analyses of this preliminary data. A three-dimensional model of attribute organization was adopted for this study. From the n dimensions required to represent each subject's evaluative attribute space, three clearly defined dimensions were chosen. Three bipolar trait scales with high loadings on each dimension were then selected. The study thus involved nine trait vectors including three groups, each consisting of three relatively coincident vectors. Since there was a trait fixing each end (positive and negative valence) of each vector, this process resulted in the choice of 18 trait stimuli for each subject.

One hundred sixty-two univalent sets of one, two, and three trait adjectives were prepared for each subject from the 18 traits. The two- and three-trait sets were chosen so as to contain traits which were either highly coincident (which load on the same attribute dimension) or highly noncoincident (with each trait in the set loading on a different dimension). The selection and preparation of the stimuli are discussed in detail in Chapter III.

The study was designed to allow for the use of (1) an analysis of variance to examine the general predictions made by the various classes of models, and (2) tests of goodness of fit to examine each model's ability to predict the judgments for two-and three-trait sets from the single-trait judgments. The factors in the ANOVA included set size, coincidence of the traits within the set, and trait valence. In addition, the study was designed to allow for the examination of the effects of type of instructions on these factors and their interactions.

Two sets of instructions were prepared for the impression formation task. The first set were internal instructions, directing the subjects to consider the trait statements as attributions which they themselves have made about the person, based on interactions with this person. In the external instructions, the subjects were instructed to consider the statements as descriptions about a person whom they have not met given by an external source. The subjects were divided randomly into two groups, with all subjects taking the instrument twice, once under each set of instructions. The first group received the internal instructions first, then the external instructions. For the second group, the order was reversed. In the ANOVA, the effect of type of instructions was assessed by examining the interaction between the order of instructions and first or second administration of the instrument.

Based upon this description of the experimental paradigm employed in this study, the application of each of the models to this experimental design will be discussed below. The specific models to be tested are classified according to their theoretical basis. For each class of models, the hypotheses concerning the ANOVA results will first be stated. The formulas used to predict the ratings for the two- and three-trait sets from the ratings for the single traits will then be presented.

I. Adding Models

The adding models to be tested in this study are based on equation 3

$$R_{ADD} = \sum_{T=1}^{n} S_T$$

which predicts that the liking judgment for a set of traits will equal the sum of the ratings of the single traits in the set (or the appropriate end point of the scale if the absolute value of the sum exceeds the absolute value of this end point).

In terms of the ANOVA, these models predict that ratings will be a linear effect of set size. The coincidence of the trait vectors should not affect the magnitude or shape of this set size function. From this theoretical position, there is no reason to expect that valence, order of instructions, time (first or second administration) or any interactions among these variables will have any significant effect.

To set up the formulas for the experimental paradigm used in this study, let us state the following: Let A, B, C.....I represent the nine positive traits and let J, K, L.....R represent the negative traits chosen for a subject. Let A, B, C represent positive traits with high loadings on dimension 1; D, E, F, positive traits with high loadings on dimension 2; and G, H, I, positive traits with high loadings on dimension 3. A corresponding grouping will apply for the negative traits. Let formulas concerning traits A, B, and C be considered as applying to all coincident trait sets. Let formulas concerning traits A, D, and G be considered as applying to all noncoincident trait sets.

For a number of the models presented here, parameters to be estimated from the data have been included in the formulas. These estimated parameters have been included for two reasons. First, it is the purpose of this study to examine the nature of the process of attribute integration. In several cases, the existing models representing some general theories of this process are extremely simple. The inclusion of additional parameters in derivations from these models allows for an examination of the adequacy of more complex versions based on the same theoretical principles. Secondly, the specific models discussed in Chapter I differ among themselves in the amount of information used and the number of parameters estimated from the data. A formulation which requires the estimation of two parameters is almost certain to provide a better fit to the data than a model for which 0 or 1 parameter is to be estimated. For the purposes of making judgments concerning the adequacy of the theoretical conceptions underlying each of the models, it is useful to examine models requiring the estimation of an equivalent number of parameters.

It must be noted, as well, that scaling assumptions are involved in tests of the goodness of fit of predictions. As long as strictly correlational procedures are used to compare the models, only interval scaling is assumed, and the inclusion of strictly multiplicative or additive parameters will not affect such measures. However, for the purposes of examining measures of absolute deviation between predicted and observed values, scaling assumptions must be taken into consideration. Due to the nature of the stimulus selection procedures used in this study (based upon semantic differential scaling, with a specified neutral point), ratio scale measurement was assumed. The adequacy of this assumption will be examined subsequently, in terms of the intercept of the regression of predicted on obtained values. Within the ratio scale assumption, the use of multiplicative parameters to modify the general forms of the equations of many of the models may be justified. Such parameters allow for an equitable comparison between the simple general models and those models which include an estimated multiplicative parameter on theoretical grounds.

Three specific models in the class of adding models will be tested in this study in terms of the goodness of fit between predicted and observed values for each multiple-trait set, for each subject.

The 0-parameter adding model. Applying equation 3 to all trait sets,

$$R_{AB} = R_A + R_B$$

$$R_{AD} = R_A + R_D$$

$$R_{ABC} = R_A + R_B + R_C$$

$$R_{ADG} = R_A + R_D + R_G$$

The 1-parameter adding model. A multiplicative constant, to be estimated by a least squares procedure, is included in the above formulas. The inclusion of these parameters provides for a more adequate comparison between the adding process and the processes implied by models which include such multiplicative parameters on theoretical grounds.

$$R_{AB} = C_1 \ (R_A + R_B)$$

$$R_{AD} = C_1 \ (R_A + R_D)$$

$$R_{ABC} = C_1 \ (R_A + R_B + R_C)$$

$$R_{ADG} = C_1 \ (R_A + R_D + R_G)$$

The 2-parameter adding model. This model involves two separate multiplicative, least-square parameters--one (C_1) for coincident sets and another (C_2) for noncoincident sets. The value of these parameters may be used as one measure of the effect of trait coincidence on processing.

$$R_{AB} = C_1\ (R_A + R_B)$$

$$R_{AD} = C_2\ (R_A + R_D)$$

$$R_{ABC} = C_1\ (R_A + R_B + R_C)$$

$$R_{ADG} = C_2\ (R_A + R_D + R_G)$$

II. Simple Averaging Models

The simple averaging models to be tested in this study are based on equation (4)

$$R_{AV} = \frac{1}{n} \sum_{T=1}^{n} S_T$$

which predicts that the liking judgment for a set of traits will equal the mean of the ratings of the single traits in the set.

In terms of the ANOVA, these models predict that there will be no set size effect. The coincidence of the trait vectors should not affect the judgments. No predictions are made concerning valence, time, order of instructions or any interactions containing these variables.

As in the case of the adding models, three versions of the simple averaging model have been developed. The second and third version include multiplicative estimated parameters, for the reasons cited above.

<u>The 0-parameter simple averaging model</u>. Applying equation 4 to all trait sets,

$$R_{AB} = 1/2\ (R_A + R_B)$$

$$R_{AD} = 1/2\ (R_A + R_D)$$

$$R_{ABC} = 1/3\ (R_A + R_B + R_C)$$

$$R_{ADG} = 1/3\ (R_A + R_D + R_G)$$

<u>The 1-parameter simple averaging model</u>. This model simply includes a single multiplicative parameter:

$$R_{AB} = \frac{C_1}{2} (R_A + R_B)$$

$$R_{AD} = \frac{C_1}{2} (R_A + R_D)$$

$$R_{ABC} = \frac{C_1}{3} (R_A + R_B + R_C)$$

$$R_{ADG} = \frac{C_1}{3} (R_A + R_D + R_G)$$

<u>The 2-parameter simple averaging model</u>. This model includes a separate multiplicative parameter for coincident and for noncoincident trait sets. A comparison between the two parameters, as for the 2-parameter adding model, will provide a measure of the effect of trait coincidence.

$$R_{AB} = \frac{C_1}{2} (R_A + R_B)$$

$$R_{AD} = \frac{C_2}{2} (R_A + R_D)$$

$$R_{ABC} = \frac{C_1}{3} (R_A + R_B + R_C)$$

$$R_{ADG} = \frac{C_2}{3} (R_A + R_D + R_G)$$

III. The Congruity Model

The congruity model predicts that the liking judgment for a set of traits will equal the weighted average of the judgments for the single traits, where the weights are based on the polarity of these single trait judgments. In its general form, the congruity model may be represented by the following equation:

$$R_{CG} = \frac{\sum_{T=1}^{n} |S_T| S_T}{\sum_{T=1}^{n} |S_T|} \tag{35}$$

In terms of the ANOVA, the congruity model predicts a small set size effect: the judgment for a two-trait set will be closer to the more polarized of the two single-trait ratings. This set-size effect should be very small, relative to the ratings for the single traits. No effects for coincidence, valence, order of instructions, time or any of their interactions would be predicted.

Since the process implied by congruity theory's model of trait integration is essentially an averaging process, versions of this model which include estimated parameters were not tested.

The application of equation 35 to the two- and three-trait sets is given below:

$$R_{AB} = \frac{|R_A|R_A + |R_B|R_B}{|R_A| + |R_B|}$$

$$R_{AD} = \frac{|R_A|R_A + |R_D|R_D}{|R_A| + |R_D|}$$

$$R_{ABC} = \frac{|R_A|R_A + |R_B|R_B + |R_C|R_C}{|R_A| + |R_B| + |R_C|}$$

$$R_{ADG} = \frac{|R_A|R_A + |R_D|R_D + |R_G|R_G}{|R_A| + |R_D| + |R_G|}$$

IV. The Dual-Process Models

These models are not designed to represent a theoretical process of attribute integration. Instead they are intended to examine the conception that some linear combination of the adding and simple averaging predictions may serve as a good predictor of subjects' responses. These models are based on the following general formula:

$$R_{DP} = \alpha(R_{AV}) + (1-\alpha)\ (R_{ADD}) \qquad (36)$$

where α is a parameter to be estimated from the data.

This model predicts that the magnitude of the set size effect will be an inverse function of α. The greater the dependence on the adding formulation in predicting a subject's responses, the greater the magnitude of the set size effect. The set size effect, whatever its magnitude, is expected to be highly linear. No effects of valence, trait coincidence, time, or order of instructions or any of their interactions are predicted.

The 1-parameter dual process model. This model is obtained directly from equation 36.

$$R_{AB} = \alpha_1\left(\frac{R_A + R_B}{2}\right) + (1-\alpha_1)\ (R_A + R_B)$$

$$R_{AD} = \alpha_1\left(\frac{R_A + R_D}{2}\right) + (1-\alpha_1)\ (R_A + R_D)$$

$$R_{ABC} = \alpha_1\left(\frac{R_A + R_B + R_C}{3}\right) + (1-\alpha_1)\ (R_A + R_B + R_C)$$

$$R_{ADG} = \alpha_1\left(\frac{R_A + R_D + R_G}{3}\right) + (1-\alpha_1)\ (R_A + R_D + R_G)$$

The 2-parameter dual-process model. This model examines the possibility that a different linear combination of adding and averaging may be required to account for predictions within coincident trait sets than that required within noncoincident trait sets. Once again, comparison of the two parameters provides for an assessment of the effect of trait coincidence.

$$R_{AB} = \alpha_1\left(\frac{R_A + R_B}{2}\right) + (1-\alpha_1)\ (R_A + R_B)$$

$$R_{AD} = \alpha_2\left(\frac{R_A + R_D}{2}\right) + (1-\alpha_2)\ (R_A + R_B)$$

$$R_{ABC} = \alpha_1\left(\frac{R_A + R_B + R_C}{3}\right) + (1-\alpha_1)\ (R_A + R_B + R_C)$$

$$R_{ADG} = \alpha_2\left(\frac{R_A + R_D + R_G}{3}\right) + (1-\alpha_2)\ (R_A + R_D + R_G)$$

V. The Anderson Equal-Weighting Model

The Anderson equal-weighting model is an averaging model which includes an initial impression parameter in the averaging process. This model is based on equation 7,

$$R_{AEW} = \frac{w_1 \sum_{i=1}^{n} S_i + w_0 I_0}{nw_1 + w_0}$$

In the application of this model to attribute integration predictions, S_i, the "real" scale value of trait T, is not known, since the I_0 parameter is included in the formula for the response to the single trait:

$$R_T = \frac{w_1 S_T + w_0 I_0}{w_1 + w_0} \tag{37}$$

However, solving for S_A in equation 37 results in

$$S_T = \frac{R_T\ (1 + w') - I_0}{w'} \tag{38}$$

where $w' = \frac{w_1}{w_0}$.

Application of equation 7 to two- and three-trait sets results in the following equations:

$$R_{AB} = \frac{w_1 (S_A + S_B) + w_0 I_0}{2w_1 + w_0} \tag{39}$$

$$R_{AD} = \frac{w_1(S_A + S_D) + w_0I_0}{2w_1 + w_0} \tag{40}$$

$$R_{ABC} = \frac{w_1(S_A + S_B + S_C) + w_0I_0}{3w_1 + w_0} \tag{41}$$

$$R_{ADG} = \frac{w_1(S_A + S_D + S_G) + w_0I_0}{3w_1 + w_0} \tag{42}$$

Substitution of equation 38 into equations 39 through 42 results in the following equations predicting responses to sets of size two and three from single-trait responses:

$$R_{AB} = \frac{(1 + w')(R_A + R_B) - I_0}{1 + 2w'}$$

$$R_{AD} = \frac{(1 + w')(R_A + R_D) - I_0}{1 + 2w'}$$

$$R_{ABC} = \frac{(1 + w')(R_A + R_B + R_C) - 2I_0}{1 + 3w'}$$

$$R_{ADG} = \frac{(1 + w')(R_A + R_D + R_G) - 2I_0}{1 + 3w'}$$

In this model, w' and I_0 are each parameters to be estimated from the data. Least squares estimates for these parameters were obtained using a least squares regression procedure in an extension of the method used by Wyer (1969).

In terms of the ANOVA, Anderson's equal-weighting model predicts a set size effect, as long as the estimate of I_0 is less polarized than the liking responses to the single traits. This effect is predicted to be a negatively accelerated--nonlinear--function of set size. A significant nonlinear component for the set size effect would be expected. No effects due to trait coincidence, time, order of instructions, or their interactions are predicted.

VI. The Wyer Redundancy Models

The 0-parameter Wyer redundancy model. Wyer's redundancy models are based on equation 9.

$$R_{WRM(A,B)} = \left(1 - \frac{P_{A/B}}{2}\right) R_A + \left(1 - \frac{P_{B/A}}{2}\right) R_B$$

where $P_{A/B}$ is the conditional probability that A applies, given B. $P_{A/B}$ is estimated from independently obtained trait usage data by dividing the proportion of times a stimulus person was described by both A and B in combination by the proportion of times the person was described by B. An identical equation is used for the noncoincident two-trait sets:

$$R_{AD} = \left(1 - \frac{P_{A/D}}{2}\right) R_A + \left(1 - \frac{P_{D/A}}{2}\right) R_D$$

For purposes of this study, in which three-trait sets were used, Wyer's formulation was extended, as follows:

$$R_{ABC} = 1 - \left(\frac{P_{A/B} + P_{A/C} - P_{A/BC}}{3}\right) R_A + \left(1 - \frac{P_{B/A} + P_{B/C} - P_{B/AC}}{3}\right) R_B + \left(1 - \frac{P_{C/A} + P_{C/B} - P_{C/AB}}{3}\right) R_C \tag{43}$$

This extension follows from Wyer's set-theoretic definition of redundancy. An equation identical to R_{ABC} applies for the prediction of R_{ADG}.

The 1-parameter Wyer redundancy model. The single-parameter version of Wyer's model simply includes a multiplicative parameter estimated from the data, based on the rationale described in the discussion of the adding models. This model may be represented by the following equations:

$$R'_{AB} = C_1 R_{AB}$$

$$R'_{AD} = C_1 R_{AD}$$

$$R'_{ABC} = C_1 R_{ABC}$$

$$R'_{ADG} = C_1 R_{ADG}$$

where $R_{T_1T_2T_3}$ represents the prediction of the nonparameterized version of the Wyer model.

In terms of the ANOVA, the Wyer models predict a set size effect which is a function of the degree of trait redundancy. The lower the level of redundancy of the traits in a set, the greater the predicted set size effect. Assuming that for set sizes 2 and 3 the level of redundancy is independent of set size, a relatively linear set size effect would be expected.

Since the CCT conception of the development of attribute structure treats this structure as derived from experience, Wyer's redundancy measure would be expected to be highly related to trait coincidence. In terms of the measures of trait coincidence used to select traits for each subject in this study, coincident traits should be those which are used together as descriptors of persons. Thus there is every reason to expect that Wyer's model would predict a greater set size effect for noncoincident than for coincident trait sets in this study. No effects of valence, time or order of instructions or their interactions is predicted.

VII. CCT Multidimensional Models

There are three basic sets of CCT models which will be considered in this paper. The first, which involves substitution of equation 15 into equation 13, is simply a multidimensional version of Anderson's model. As long as the dimensional I_0 parameters are either estimated directly from the data or are scaled by use of an estimated multiplicative parameter, the process of predicting trait set judgments from single trait judgments is identical for the two models. Thus the formulas and predictions listed in Section V for the Anderson model apply to this simple multidimensional I_0 model.

The second set of CCT models is based on the nonexplicit projection formulation (equations 26, 27, and 29). These models fall into two categories: (1) those which assume that $E(e_{ik})$--the expected value of the projection of person i on dimension k in the absence of any information--is equal to zero, and (2) those which assume that $E(e_{ik})$ is equal to I_{0k}.

A. The CCT Nonexplicit Zero-expected-value Models (CCT Model A)

This model predicts a strict averaging effect for coincident traits and a strict adding effect for noncoincident traits. The hypothesized effect of instructions on these predictions is discussed at the end of Chapter I. In terms of the ANOVA, under the internal instruction condition no set size effect is expected for the coincident traits, while a strictly linear set size effect is expected for noncoincident traits. Under the external instruction condition, some set size effect (based on increased certainty) may occur for coincident traits, with a greater set size effect for noncoincident traits. This instruction effect should be represented by an interaction between set size, coincidence, time, and order of instructions. No valence effect is predicted.

The 0-parameter version of CCT Model A. The equations for coincident and noncoincident trait sets differ in this model:

$$R_{AB} = 1/2\ (R_A + R_B)$$

$$R_{AD} = R_A + R_D$$

$$R_{ABC} = 1/3\ (R_A + R_B + R_C)$$

$$R_{ADG} = R_A + R_D + R_G$$

The two-parameter version of CCT Model A. This version of the above model examines the improvement in the model resulting from the inclusion of a separate multiplicative parameter for the coincident and noncoincident traits:

$$R_{AB} = \frac{C_1}{2}\ (R_A + R_B)$$

$$R_{AD} = C_2\ (R_A + R_D)$$

$$R_{ABC} = \frac{C_1}{3} (R_A + R_B + R_C)$$

$$R_{ADG} = C_2 (R_A + R_D + R_G)$$

Comparison of the two parameters will provide an indicator of the relative efficacy of the model in predicting responses for coincident versus noncoincident sets.

B. The CCT Nonexplicit I_0 Model (CCT Model B)

This model is based upon the assumption in the second type of nonexplicit projection model that $E(e_{ik}) = I_{0k}$. According to this assumption judgments for coincident trait sets are once again predicted to be equivalent to the average of the single-trait judgments. For noncoincident trait sets, a function of the weighted sum of the I_0 parameters is subtracted from the sum of ratings for the single traits. This model essentially corrects for scale origin in the case of noncoincident traits. This model makes general predictions which are essentially the same as those made for CCT Model A.

The formulas for CCT Model B may be stated as follows:

$$R_{AB} = 1/2 (R_A + R_B)$$

$$R_{AD} = R_A + R_D - C_1(\lambda_1 e_{s1} I_{01} + \lambda_2 e_{s2} I_{02} + \lambda_3 e_{s3} I_{03})$$

$$R_{ABC} = 1/3 (R_A + R_B + R_C)$$

$$R_{ADG} = R_A + R_D + R_G - 2C_1(\lambda\ e_{s1} I_{01} + \lambda_2 e_{s2} I_{02} + \lambda_3 e_{s3} I_{03})$$

The C_1 parameter for this model is estimated from the data using a least-squares procedure. The parameters λ_k, e_{sk} and I_{0k} are estimated from independent data: λ_e is estimated from the percent of variance accounted for by dimension k in the factor analysis of trait usage; e_{sk} and I_{0k} are estimated from the rating of the self and "the average other person" on the semantic differential scales loading on dimension k. Since these variables were measured on scales differing from that used in the impression formation task in this study, a scaling parameter, C_1, was necessary. The magnitude of this parameter will provide information concerning the utility of this model in predicting attribute integration.

C. The CCT Distance-weighting Models

The CCT distance-weighting models are each based upon equation 31:

$$r_{si}/T=1.....n = \sum_{k=1}^{m} \lambda_k e_{Sk} \left[\frac{\sum_{T=1}^{n} W_{Tk} T_k}{\sum_{T=1}^{n} W_{Tk}} \right]$$

where W_{Tk} represents the cosine of the angle between the vector representing T and dimension k; and where T_k represents the projection of trait T on dimension k. In terms of the ANOVA, this model predicts a greater set size effect for noncoincident than for coincident trait sets. For traits which are perfectly coincident, the model predicts strict averaging. For trait sets in which each trait is perfectly coincident with a different attribute dimension, the model predicts strict adding. The degree of departure from these predictions is assumed to be due to less than perfect coincidence and noncoincidence--in the above sense--among the trait vectors chosen as stimuli. The general CCT predictions concerning the effects of instructions on the trait judgments, outlined above for CCT Model A, hold for this model as well.

In terms of predicting judgments for multiple-trait sets from single-trait judgments, equation 31 fails to yield appropriate predictor equations, without either estimating a large number of parameters or making simplifying assumptions. The problem stems from the fact that T_k, like S_i in the Anderson model, cannot be directly measured. The rating for a single trait in this study is represented by the following formula:

$$r_{si/A} = \lambda_1 e_{S1} T_{A1} + \lambda_2 e_{S2} T_{A2} + \lambda_3 e_{S3} T_{A3} \tag{44}$$

Unfortunately, the inclusion of the three values, T_{A1}, T_{A2} and T_{A3}, make simple substitution into the equations for two- and three-trait sets impossible. These values could be estimated from the data. Unfortunately, however, the estimation procedures would be extremely complex, and the predictions involving the estimation of such a large number of parameters would not be comparable to predictions from other models. In this study, two solutions have been adopted to allow for the test of this model.

The first solution involves the assumption that the trait sets are perfectly coincident or noncoincident, in the sense described above. Under this assumption, the distance weighting model becomes equivalent to CCT Model A. The parameters estimated in the multiplicative version of this model provide a potential measure of the adequacy of this assumption for each subject.

The second solution involves the adoption of a different mathematical formula involving the distance weights which has a number of the characteristics of the function implied by equation 31. This model should be regarded as an approximation to rather than a derivation from the general CCT formulation.

The 0-parameter CCT approximation model. (CCT Model C). This model takes the following form for the three-dimensional case:

Define $S_{T=1.....n}$ such that

$$S_{T=1.....n} = 1 - \frac{1}{n} \sum_{k=1}^{m} \prod_{T=1}^{n} W_{Tk} \tag{45}$$

Then for the three-dimensional case, define

$$R_A = (A_1 + A_2 + A_3) \tag{46}$$

$$R_{AB} = S_{AB} [(A_1 + B_1) + (A_2 + B_2) + (A_3 + B_3)] \tag{47}$$

$$\begin{aligned} R_{ABC} = {} & S_{AB} [(A_1 + B_1) + (A_2 + B_2) + (A_3 + B_3)] + \\ & S_{AC} [(A_1 + C_1) + (A_2 + C_2) + (A_3 + C_3)] + \\ & S_{BC} [(B_1 + C_1) + (B_2 + C_2) + (B_3 + C_3)] - \\ & S_{ABC} [(A_1 + B_1 + C_1) + (A_2 + B_2 + C_2) + (A_3 + B_3 + C_3)] \end{aligned} \tag{48}$$

By substitution, it may be shown that

$$R_{AB} = S_{AB} (R_A + R_B) \qquad \text{and} \tag{49}$$

$$R_{ABC} = S_{AB} (R_A + R_B) + S_{AC} (R_A + R_C) + S_{BC} (R_B + R_C) - S_{ABC} (R_A + R_B + R_C).^* \tag{50}$$

This model is, in essence, a complex adding model with a subtracted factor. This factor is a function of the polarity of the single-trait responses multiplied by the sum, across dimensions, of the product of the cosines of the angles between the trait vector and each dimension. Thus the more highly coincident and the more highly polarized the traits, the larger the quantity subtracted from the sum of the polarity of the single trait ratings in arriving at the prediction of the polarity of the response to the set. It may easily be shown that if the trait vectors are perfectly coincident or perfectly noncoincident in the sense defined above, this model is equivalent to the CCT Model A. For traits of intermediate closeness, a value between the adding and averaging model predictions is expected. This model allows for the use of the factor loadings (treated as the cosine between the trait vector and the dimension) to modify the predictions made under the assumptions of perfect coincidence and noncoincidence. It is in this way that this model approximates the predictions resulting from equation 31. The general predictions derived from this model are identical to those resulting

*The formulas for R_{AD} and R_{ADG} are identical to those above.

from equation 31, outlined above. Once again, the general instruction effect predicted in the discussion of model A would be predicted.

The 1-parameter CCT approximation model. This model is equivalent to the model described above, with the inclusion of a single multiplicative parameter to be estimated from the data. That is,

$$R_{AB'} = C_1 R_{AB}$$

$$R_{AG'} = C_1 R_{AG}$$

$$R_{ABC'} = C_1 R_{ABC}$$

$$R_{ADG'} = C_1 R_{ADG}$$

where $R_{T1\ T2\ T3}$ represents the prediction made by the zero parameter approximation model. The general predictions made by this model are, of course, identical to those made for the model above.

D. The CCT Single-Trait Predictions

As was noted above, equation 31 cannot be applied directly to the problem of predicting multiple-trait judgments from single trait ratings because T_k cannot be measured directly. The general form of this model, as well as that of the nonexplicit projection models, however, allows for a test of the theory which is beyond the scope of the predictions made by the other models in this paper: The CCT models suggest that the single-trait ratings may themselves be predicted from independent data. That is, equation 13--the basic equation of CCT--may be used to predict the liking judgment for person i, given the stimulus "Person i is friendly," based upon information concerning the subject's attribute structure.

Let us begin by assuming that each piece of trait information results in the identification of a point which is equally distant from the origin. That is, we will assume that all trait stimuli result in the placement of the point for person i at positions which are equally polarized along those trait vectors. This is equivalent to the assumption that all trait points are equally distant from the origin of the attribute space. As was noted earlier, the projection of a trait on a dimension is equal to the polarization of that trait along its vector times the cosine between the vector and the dimension. That is

$$T_k = \cos_{Tk} \cdot F_T.$$

If we assume $F_T = F$ for all traits, then $T_k = \cos_{Tk} \cdot F$. In this case, equation 44, which predicts the rating of the single trait T, may be rewritten,

$$r_{si/A} = F\ (\lambda_1 e_{S1} \cos_{T1} + \lambda_2 e_{S2} \cos_{T2} + \lambda_3 e_{S3} \cos_{T3})$$

or adopting the notation in which $w_{T1} = \cos_{T1}$,

$$r_{si/A} = F\ (\lambda_1 e_{S1} w_{T1} + \lambda_2 e_{S2} w_{T1} + \lambda_3 e_{S3} w_{T3}) \qquad (51)$$

Equation 51 suggests that if the equal polarity assumption is adopted, the liking judgment made to a single trait statement should be a linear function of the sum, across the three dimensions, of the product of (1) the weight of the trait dimension (the proportion of variance accounted for by that factor in the rotated factor solution); (2) the rating of the self on that trait dimension (equal) to the weighted average of the self-rating on the three scales loading on that dimension, where the weights are the factor-loadings of those scales on that dimension); and (3) the cosine between the dimension and the trait vector (equal to the factor loading of the trait on the dimension).

Thus equation 51 provides a test for the CCT conceptualization by examining the ratings made on the basis of the single-trait stimuli. It predicts that these ratings will be a function of the relative importance of the three dimensions, the position of the self on these dimensions, and the spatial relationship between the trait vectors and the dimensions. While the test of this prediction is not the test of a specific model of the <u>integration</u> of attribute information, it does provide an important test of the basic underlying assumptions of the theory.

CHAPTER III

DATA COLLECTION AND RESULTS

I. Subjects and General Procedure

A. Subjects

The subjects participating in the study were 27 undergraduate students at Michigan State University who enrolled in a two-term upper-division course titled The Psychology of Yourself. The students ranged in age from 18 to 40 and were primarily juniors and seniors. Twelve of them were psychology majors, with the majority of the remainder majoring in areas outside the College of Social Science. Most of the students were members of the Honors College.

The course itself was designed to provide an examination of topics in experimental personality and personality theory through the use of self-related experimental results. During the first term of the course, students spent 2-3 hours per week responding to a number of personality and social-psychological instruments. The class met as a whole for one hour per week during this term for purposes of providing instructions, discussing test schedules, and receiving feedback from students on the testing procedures. The students were aware of the fact that their test responses were being recorded individually and that these responses would be made available to them on an individual basis, with interpretation, during the second term of the course. The students were assured that their specific responses would be made available only to themselves and to the course instructor.

The psychological instruments taken by the students included a number of traditional personality measures, as well as the measures of attribute use and the impression formation tasks that are the focus of the study. The students received minimal feedback on the purpose of specific tests when all tests of that type had been completed. However, the tasks were not fully explained until all the data collection had been completed. Despite the minimal feedback and the amount of time (20-30 hours) required to complete the tests during this first term, 27 of the 28 students enrolled for the course completed the required work. While most of the students found specific tasks to be somewhat tedious, they reported that they were able to maintain their interest and that they felt they had completed each task carefully and honestly.

During the second term of the course, the class met in a three hour seminar once a week to discuss the concepts underlying the various categories of measures and the interpretation of test results. In addition, the students participated in six two-hour labs over the course of the term in which they met in small groups to receive test results and discuss these results in more detail. In these discussions and in their papers the students reported having adopted a highly self-disclosing set while taking the instruments. A number of the students indicated that they specifically had resisted trying to "psych the tests" and had made an effort to answer questions independently and honestly. These reports are supported by the low social desirability scores received by this group on the Crowne and Marlowe (1964) Social Desirability Scale, relative to national norms, and by the failure of this test among these subjects to correlate with self-esteem in the manner generally reported (Wylie, 1974).

B. General Procedure

Test Administration

The majority of the psychological instruments taken by the subjects were presented by means of computer terminals interfaced with an HP 2000 mini computer. The subjects received a list of instruments to be taken each week and signed up to use the computer terminals for one-hour periods at their convenience during the week. At each session, subjects signed in and then typed the name of the instrument to be taken. Instrument directions were presented on the terminal, followed by the questions to be answered, presented one at a time. The subject then typed in a response to each question. Responses were collected in each student's response file and were recorded weekly on tapes for transfer to the CDC 6500 for analysis.

Overview of Experimental Procedures

The instruments included in this study fall into three categories: (1) instruments designed to determine patterns of attribute usage, used to select stimuli for individual subjects for the impression formation task; (2) the impression formation experiment itself; and (3) instruments designed to obtain independent estimates of parameters used in various models of the impression formation process. The methodology and results for the first category of instruments will be presented in Section II of this chapter, while the instruments in the latter two categories will be discussed in detail in Section IV. However, the entire set of procedures may be summarized briefly to provide an overview of the study as a whole.

First, data were obtained for each subject on patterns of trait usage in order to select stimuli on an individual basis for the impression formation task. The purpose of this section of the study was to obtain a representation of the dimensional attribute structure for each subject. This representation was obtained using two procedures. During the fourth week of the term, each subject rated each of 40 acquaintances on a set of semantic differential scales. The results of these ratings were factor-analyzed for each subject, using orthogonal rotation procedures, to obtain dimensions of trait usage in person-ratings. During the third week of the term, each subject made a series of judgments of difference or distance in meaning between pairs of traits. These distance judgments were subjected to multidimensional scaling procedures. This multidimensional scaling was done for each subject's protocol separately, and dimensions of overall trait meaning were obtained.

On the basis of these dimensional representations, stimuli were chosen for each subject for the impression formation task. A three-dimensional model of attribute structure was used in this study. On the basis of the data from the factor analysis and the multidimensional scaling, three attribute dimensions were chosen for each subject--dimensions which were defined by particular trait scales in both the factor analysis of trait usage and the multidimensional scaling of trait meanings. From each of the three dimensions selected for each subject, three bipolar trait scales loading highly on the dimension were then chosen. This resulted in the selection of eighteen trait words for each subject--three traits associated with each pole of each dimension.

In the impression formation task the subjects were asked to estimate their liking for hypothetical persons described by each of the single trait adjectives chosen as described above. They were also asked to make liking judgments for hypothetical persons described by sets of two or three of the above traits. These sets were chosen so as to consist of either all positive or all negative traits, with half the sets composed of coincident traits (traits loading on the same dimension) and half of entirely noncoincident traits (in which none of the traits in the set loaded on the same dimension).

The impression formation task was given under two sets of instructions. The external instructions directed subjects to consider the trait descriptions as statements made by an acquaintance about a third person. In the internal instructions, subjects were directed to think of the descriptions as judgments they themselves had made about the person. Each subject completed the task once under each set of instructions, with the order of instructions being randomly determined. The task was performed for the first time during the seventh week of the first term of the course and for the second time during the first week of the second term of the course.

A number of models predicting judgments in the double- and triple-adjective sets from judgments made for the single adjectives were tested. These models were of three types: (1) those using only the single adjective judgments in making the prediction; (2) those using parameters estimated from the impression formation data; and (3) those using parameters estimated through independent experimental procedures. The measures used to estimate parameters for the last category of models were presented to the subjects following the other experimental procedures, during the last week of the first term of the course. These tasks included (1) rating of the self and "the average other person" on the semantic differential scales used in the acquaintance ratings, and (2) Wyer's (1969) measure of the redundancy of the attribution of traits.

II. Measurement of Attribute Structure: Method

In this study trait stimuli for use in the impression formation task were chosen individually for each student on the basis of patterns of trait usage in two tasks: (1) ratings of 40 acquaintances on a semantic differential instrument; and (2) direct distance judgments of trait meaning similarity in a paired comparisons task.

A. The Semantic Differential Measure

At the first class meeting the subjects were presented with a questionnaire asking them to provide stimulus materials for use in later measures. The first two pages of this questionnaire elicited the names of 40 stimulus persons to serve as concepts in the semantic differential measure of trait usage. On the first page each subject was asked to list 20 people (by name, initials or other identification) whom he or she knew well. The directions specified that this list should include both liked and disliked people. On the second page the directions requested a list of 20 people who were known only slightly, again specifying that liked and disliked people be included. Names were not required--a student could list "the person who sits next to me in physics." The subjects were simply asked to provide enough information to identify the person when the stimulus was presented subsequently.* They completed this list during the first week and turned it in at the second class meeting.

A semantic differential instrument was prepared for each subject by associating each of the 40 stimulus person identifications with a set of 40 semantic differential scales in a modified semantic differential format. The complete set of instructions for the instrument is included in Appendix A.

Sets of bipolar adjectives for use in the semantic differential instrument were chosen from a number of sources. Primary emphasis was placed on scales which were clearly evaluative in nature. Eight scales were selected from those classed as evaluative in the development of the semantic differential instrument by Osgood, Suci, and Tannenbaum (1957). Additional scales were then created by choosing adjectives used in studies involving the multidimensional scaling of

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*The instructions for this task are included in Appendix A.

traits (Rosenberg, Nelson and Vivekananthan, 1968; Rosenberg and Sedlak, 1972; and Rosenberg and Jones, 1972) and from an earlier investigation of patterns of trait synonymity (Phillips, Thompson, and Gard, note 4). These scales were chosen so as to represent the major clusters of synonymity found in the Phillips et al. study as well as the major trait dimensions found in previous investigations of attribute structure. Of the 35 scales selected as evaluative scales, the positive poles of 22 are listed among the most positive 150 of Anderson's (1968b) 555 trait words. The negative poles of 15 of the evaluative scales are listed among the most negative 150 traits on this list. Only one evaluative trait used in this study (unhappy) is included among the more moderately evaluated traits on Anderson's list. Thus in terms of these normative ratings, the majority of the evaluative scales represent normatively "extreme" traits in terms of their degree of likableness.

In addition to the 35 evaluative scales, 5 predominantly nonevaluative scales were included in the instrument. Three of these scales were chosen primarily as potency scales (hard-soft, strong-weak, dominant-submissive) and two as activity-related scales (active-passive, and persistent-wavering). With the exception of active, rated as an extreme positive trait on Anderson's list, the traits from these scales included in this list received moderate likability ratings. The complete list of scales used in the instrument is included in Appendix B.*

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*Earlier unpublished research had indicated a decrease in the complexity of the factor structure of semantic differential responses upon repetition of this instrument. Since such a change

The individualized acquaintance-rating instruments were separated into four sets of ten concept-persons each, so that it could be completed at several different sittings. The entire instrument, rating 40 concept-persons on each of the 40 scales, required 2-3 hours to complete. Each subject completed the instrument within one week.

B. Trait Distance Judgments

The second task used to measure patterns of trait usage required the subjects to make direct judgments of trait meaning similarity in a paired comparisons task. In this measure, subjects were presented with pairs of evaluative trait words on the computer terminals and were asked, for each pair, to judge the distance in meaning between the two words in the pair.

The evaluative traits used in this task were the 70 trait words from both poles of the 35 evaluative semantic differential scales used in the acquaintances ratings. Because of the length of the task, it was not possible to obtain ratings for all possible pairs of the 70 trait words. Instead, two paired comparison instruments were prepared, each using 35 traits from one end of each of the bipolar scales. The traits for the first instrument were selected by choosing one trait at random from each evaluative bipolar pair. The second instrument contained the 35 traits not used in the first.

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could be accounted for by a decreased error rate due to familiarity with the scales and the instructions, a prior task using the semantic differential was administered prior to the acquaintance ratings. In this task, given the first week of the term, the subjects rated a set of occupations on the same semantic differential scales.

Each instrument thus contained 595 pairs of trait adjectives. Because of time limitations, these pairs were divided into eight groups for administration, with the first seven groups containing 80 pairs and the last group containing 35 pairs. Within each group, the trait pairs were presented to the subjects in a random order.

Subjects were instructed to rate each pair of traits on a scale of distance in meaning which ranged from 0 to 100. They were instructed to use 0 to indicate no distance in meaning between the words in a trait pair--that is, to indicate that the words were as similar in meaning as possible. A rating of 100 was to be used to indicate that the traits were as distant or opposite in meaning as possible. Traits which were unrelated to each other in meaning were to be given a mid-range rating. The traits used in each instrument are presented in Appendix B, and the rating instructions are presented in Appendix A.

Subjects could complete as many of the 16 groups of pairs at a single sitting as time permitted. The entire task took approximately 2 1/2 to 3 hours. Each of the subjects completed the task within one week.

III. Measurement of Attribute Structure: Results

The ratings made by each subject for the 40 acquaintances on the 35 evaluative semantic differential scales formed a pattern matrix which was examined for intrinsic dimensionality by factor-analytic procedures. The principal axis solution for each subject was obtained. A varimax rotation was then performed using the number of factors required to account for 75% of the variance in the principal axis solution. For the 27 subjects, the number of factors rotated ranged from 4 to 9. Thus for each subject the number of dimensions needed to account for the data exceeded the three dimensions required for the test of the dimensional model in the impression formation task.

There were substantial individual differences between subjects in both the number of factors in the solution and in the specific traits loading on each factor. For most subjects, the social good-bad/intellectual good-bad distinctions found in prior studies of attribute structure based on group data were maintained. However, many subjects had multiple factors which could be placed in these two broad categories.

The trait distance judgments made by each subject in the paired comparison tasks were analyzed by means of multidimensional scaling techniques. The two 35 x 35 dissimilarity matrices obtained for each subject (one for each subset of the 70 evaluative traits) were used as input to an MDSCAL analysis (Kruskal, 1964). Two- through six-dimensional solutions were obtained for each analysis for each subject. The maximum slope of the stress values was used as the criterion to determine the best estimate of intrinsic dimensionality. According to this criterion, dimensionality across subjects ranged from 3 to 6 dimensions.

The factor loadings of the 35 evaluative semantic differential scales on each of the 4-9 factors for each subject provided the initial basis for the grouping of the scales. The bipolar traits from the scales were grouped together based on high loadings on the same factor and near-zero loadings on other factors. This procedure generated a set of clusters of bipolar scales for each subject. These clusters were then compared with the results of the multidimensional scaling. Those scales from a cluster which were associated with the same dimension on one or the other or both of the multidimensional scaling solutions were considered to be coincident. This comparison with the MDS solutions typically reduced the number of clusters. If, after this reduction, more than three clusters remained, those three clusters whose factor loading pattern gave the best approximation to Thurstone's (1947) criterion of simple structure were retained. If fewer than three clusters survived the MDS reduction, those original clusters for which at least three traits were common to the factor loading and MDS criteria were selected. In a very few cases, this dual selection process could not be made to yield three clusters. In these cases, the factor loading criterion alone was used, with the selected clusters being those best exhibiting simple structure.

Thus, three clusters of three scales each were chosen for each of the 27 subjects as stimuli for the impression formation task, resulting in 81 clusters. While there are 39,270 possible three-trait clusters from the 35 scales, only 31 of the clusters selected are unique; 50 of the clusters were chosen for two or more of the subjects. Of the 31 unique clusters, 20 contain two traits in common with one of the multiply-chosen clusters. The clusters used and the number of subjects for which each was chosen are listed in Table 1. It is clear from this table that the data showed both general consensus

Table 1.--Sets of Coincident Three-Trait Clusters Selected as Stimuli in the Impression Formation Task.

Trait Cluster	Number of Subjects For Whom the Cluster Was Selected
warm (cold); friendly (unfriendly); kind (cruel)	10
warm (cold); friendly (unfriendly); good-humored (ill-humored)	3
warm (cold); friendly (unfriendly); happy (unhappy)	1
warm (cold); friendly (unfriendly); tolerant (intolerant)	1
warm (cold); friendly (unfriendly); attractive (unattractive)	1
warm (cold); friendly (unfriendly); polite (impolite)	1
warm (cold); friendly (unfriendly); cheerful (cheerless)	1
warm (cold); kind (cruel); trustworthy (untrustworthy)	1
warm (cold); kind (cruel); tolerant (intolerant)	1
warm (cold); cheerful (cheerless); sincere (insincere)	1
warm (cold); deep (superficial); broadminded (narrow-minded)	1
friendly (unfriendly); tolerant (intolerant); courteous (rude)	1
smart (stupid); intelligent (unintelligent); rational (irrational)	6
smart (stupid); intelligent (unintelligent); educated (uneducated)	6
smart (stupid); intelligent (unintelligent); competent (incompetent)	2
smart (stupid); intelligent (unintelligent); wise (foolish)	1
smart (stupid); intelligent (unintelligent); broadminded (narrow-minded)	1
smart (stupid); educated (uneducated); wise (foolish)	1
educated (uneducated); rational (irrational); intelligent (unintelligent)	2

Table 1.--Continued.

Trait Cluster	Number of Subjects For Whom the Cluster Was Selected
ambitious (unambitious); successful (unsuccessful); motivated (aimless)	3
ambitious (unambitious); successful (unsuccessful); effective (ineffective)	1
ambitious (unambitious); successful (unsuccessful); smart (stupid)	1
ambitious (unambitious); motivated (aimless); dependable (undependable)	1
ambitious (unambitious); motivated (aimless); intelligent (unintelligent)	1
ambitious (unambitious); efficient (inefficient); intelligent (unintelligent)	1
ambitious (unambitious); efficient (inefficient); competent (incompetent)	1
successful (unsuccessful); competent (incompetent); wise (foolish)	1
reliable (unreliable); responsible (irresponsible); dependable (undependable)	5
reliable (unreliable); responsible (irresponsible); trustworthy (untrustworthy)	3
reliable (unreliable); responsible (irresponsible); wise (foolish)	1
reliable (unreliable); responsible (irresponsible); competent (incompetent)	1
responsible (irresponsible); dependable (undependable); respectful (disrespectful)	1
responsible (irresponsible); dependable (undependable); efficient (inefficient)	1
reliable (unreliable); dependable (undependable); trustworthy (untrustworthy)	1
truthful (untruthful); trustworthy (untrustworthy); sincere (insincere)	2
truthful (untruthful); trustworthy (untrustworthy); honest (dishonest)	1
truthful (untruthful); trustworthy (untrustworthy); competent (incompetent)	1
truthful (untruthful); honest (dishonest); reliable (unreliable)	1
polite (impolite); respectful (disrespectful); courteous (rude)	3
good (bad); kind (cruel); attractive (unattractive)	1
tolerant (intolerant); broadminded (narrow-minded); courteous (rude)	1
trustworthy (untrustworthy); reliable (unreliable); friendly (unfriendly)	1
respectful (disrespectful); truthful (untruthful); broadminded (narrow-minded)	1

patterns of trait grouping and the existence of individual differences in trait association.

IV. The Impression Formation Experiment: Method

A. The Impression Formation Task

The stimuli for the impression formation task were chosen individually for each subject based upon the three representations of attribute structure discussed in Section III. Three evaluative trait dimensions were selected for each subject, and three bipolar scales loading highly on each of the dimensions were then chosen. This resulted in the selection of 18 trait stimuli for each subject--three traits associated with each pole of each of the three dimensions. There were thus three positive and three negative groups of adjectives, each containing three coincident traits.

One hundred and sixty-two experimental stimuli were generated for each subject from these six three-trait groups. Each trait or set of traits was presented in the form of a sentence, "He (she) is trait" for single traits or "He (she) is trait. He (she) is trait . . ." for multiple-trait sets. Male subjects received the "he" descriptions, female subjects, the "she" descriptions. Eighteen single trait stimuli were presented, one for each of the selected traits. Coincident sets of size two were created by pairing each trait with each of the other traits in its group. Coincident triples were created by presenting together the three traits from a group. All possible orders of the coincident doubles and triples were presented, resulting in 36 coincident doubles and 36 coincident triples. Noncoincident doubles and triples were prepared by presenting each trait from a group with one of the traits from each of the other groups of the same valence. Once again, each pair and each triple was presented in all possible orders, resulting in 36 noncoincident pairs and 36 noncoincident triples. A table presenting the composition of the 162 stimuli is included in Appendix B.

Two sets of instructions for the impression formation task were prepared. In the first set of instructions--the external instructions--subjects were told that they would receive statements of the form, "He (she) is trait" and were directed to think of this statement as a description of someone unknown to them whom they would be meeting in the near future. The subjects were instructed to think of the description as one given to them by a personal acquaintance who knows the person being described very well. They were then asked to predict how well they believed they would like the person being described when they met this person.

The second set of instructions--the internal instructions--directed the subjects to regard the trait descriptions as judgments they themselves had made about the person, on the basis of knowing and interacting with him or her. The subjects were asked to indicate how much they would like a person whom they themselves thought of as possessing that particular set of traits.

In both sets of instructions, subjects were told that the stimuli would include statements consisting of one-, two-, and three-trait descriptions. They were asked to make their likability judgments on a 21-point scale ranging from -10 (dislike very much) to 10 (like very much). The subjects were told that the trait words were chosen individually for each subject on the basis of their semantic differential ratings of acquaintances and their trait distance judgments. They were instructed to take their time in completing the task, to read each description carefully, and to try to "visualize" a hypothetical person fitting each description before making the ratings.

Each subject completed the impression formation task twice, once with each set of instructions. The subjects were divided randomly into two groups: One received the internal instructions first; the second, the external instructions first. The two randomly-divided groups of subjects were directed to separate rooms during the one-hour class period, and the instructions were presented verbally to each group. Both groups were directed not to discuss the instructions they had received with other class members.

The impression formation instruments were presented to the subjects on CRT computer terminals. Each subject called up his or her own instrument, identified by student number. An abbreviated set of instructions was presented, reminding the subjects of the scale points for the likability judgments.* The trait stimuli were then presented in a different random order for each subject. The screen was cleared after each stimulus presentation so that subjects were unable to refer back to earlier ratings in making their judgments. The 162 stimuli were divided into 2 sets of 81 statements each, because of limitations in the storage of responses, but subjects were requested

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*Both the full and abbreviated instructions are included in Appendix A.

to complete the instrument at one sitting if possible and otherwise to complete the two sets on successive days, without any intervening measures.

B. Tasks Providing Independent Parameter Estimates

Several of the impression formation models being investigated require the independent measurement of one or more parameters. Two tasks were presented in order to obtain these measures: (1) rating of the self and the average other person on a semantic differential instrument, and (2) Wyer's measure of trait redundancy.

The semantic differential instrument used to rate the self and the average other person contained the same 40 scales as were used for the acquaintance ratings. This instrument was presented on the computer terminal during the eighth week of the term. Subjects received the standard semantic differential instructions and were presented first with "self" and secondly with "the average other person" as concepts to rate on the scales. For each subject a dimension score for self and a dimension score for other were obtained for each of the three selected dimensions by averaging the ratings of the concept across the three scales chosen as loading on that dimension. Thus the self rating on dimension 1 for a subject whose three scales for that dimension were "warm-cold," "friendly-unfriendly," and "kind-cruel" would consist of the mean of the self-ratings on those three scales.

The Wyer redundancy measure was given in booklet form during the ninth week of the term. A set of 40 stimulus persons were selected who would be assumed to vary in likableness and to be familiar to the subjects. Some of the stimulus persons were specific (e.g., Gerald Ford, Fidel Castro, etc.), while others were more generally described ("your high school English teacher," "a person you have met recently that you would least like to know better," etc.).* Each stimulus person was listed at the top of a page, followed by a list of the 70 traits from both poles of the 35 evaluative semantic differential scales. The stimulus persons were presented in the same random order to all subjects. The subjects were asked to go through the booklet and indicate with a check which of the 70 adjectives they would use in describing each person.

From the relative frequencies with which each adjective was assigned to the 40 stimulus persons, it was possible to calculate redundancy scores for each subject. The data were used to estimate the probability that any traits or set of traits were used to describe a person, and also the conditional probability that a person described by a specified trait or set of traits was also described by each of the other traits. The amount of redundancy of one adjective (B) with a second (A) was defined as the conditional probability of B given A, as estimated from the division of the relative frequency of joint occurrence of A and B by the relative frequency of the use of A (Wyer, 1974). Similarly the conditional probability of C given A and B was estimated from the relative frequency of the joint occurrence of all three traits divided by the joint occurrence of A and B.

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*The list of stimulus persons is presented in Appendix B.

V. Qualitative Analyses: Results and Preliminary Discussion

A. Results

In order to assess the effects of attribute coincidence, set size, valence, order of instructions, and first or second administration of the instrument on likability judgments, an analysis of variance was performed on the impression formation data. Of the 27 students serving as subjects in the study, the data for both administrations of the impression formation instrument was complete only for 23. Two subjects did not take the instrument the second time. For two other subjects, problems with data storage and retrieval made one set of data unusable. Thus for the purposes of the analysis of variance, the data for 23 subjects were available. The data for one of these subjects, selected randomly, was dropped, in order to obtain equal cell size for the between-subjects (order of instructions) factor.

The dependent variable in the analysis of variance was the average polarity of liking for all stimulus persons at the same level of set size/attribute coincidence (5), valence (2), and time of administration (2). Thus, for each subject, 20 separate values of the dependent variable were computed. For both positive and negative traits and both first and second administration these were: set size of one (mean of 9 values), coincident set size of two (mean of 18 values), coincident set size of three (mean of 18 values), noncoincident set size of two (mean of 18 values), and noncoincident set size of three (mean of 18 values).

Sets of size one, containing only a single trait, cannot be classified either as coincident or noncoincident, since they are not presented in juxtaposition with other traits. In order to assess the effects of coincidence of the traits and also to include set size one in the analysis, coincidence and set size were collapsed into a single factor with five levels--set size one, coincident set size two, coincident set size three, noncoincident set size two, and noncoincident set size three. Tests for the effects of set size and trait coincidence could then be made by planned comparisons between means.

An omnibus ANOVA was performed with set size/coincidence, valence, and first or second administration (time) as within-subjects factors and with order of instructions as a between-subjects factor. The main effects for set size/coincidence and valence were both significant, as were the following interactions: set size/coincidence by valence, set size/coincidence by order of instructions, and set size/coincidence by time. A summary of the ANOVA is presented in Table 2.

The valence main effect indicates that positive traits resulted in more polarized liking judgments than negative traits. Simple effects tests of the set size/coincidence by valence interaction showed that this valence effect holds for set size one and for both coincident and noncoincident set size two. At set size three, for both coincident and noncoincident traits, the differences between means for positive and negative traits is not significant. A greater set size effect was thus found for negative than for positive traits (see Figure 2).

Table 2.--Summary of ANOVA for Instrument Order, Coincidence/Set Size, Time, and Valence.

Source	df	MS	F
Instrument Order	1	14.40	.30
Error	20	48.37	
Coincidence/Set Size	4	78.32	159.17**
Instrument Order x Coincidence/Set Size	4	2.84	5.78**
Error	80	.49	
Time	1	13.33	1.60
Instrument Order x Time	1	19.33	2.32
Error	20	8.32	
Valence	1	18.84	5.74*
Instrument Order x Valence	1	.49	.15
Error	20	3.28	
Coincidence/Set Size x Time	4	.93	2.97*
Instrument Order x Coincidence/Set Size x Time	4	.17	.55
Error	80	.31	
Coincidence/Set Size x Valence	4	1.32	6.84**
Instrument Order x Coincidence/Set Size x Valence	4	.08	.41
Error	80	.19	
Time x Valence	1	1.78	1.43
Instrument Order x Time x Valence	1	.70	.57
Error	20	1.24	
Coincidence/Set Size x Time x Valence	4	.08	.78
Instrument Order x Coincidence/Set Size x Time x Valence	4	.13	1.32
Error	80	.10	

* $p < .05$.

**$p < .001$.

Ten Scheffe' comparisons were performed to test all possible differences in the means involved in the set size/coincidence main effect. These comparisons indicated that set size three differed from set size two, averaged over coincidence; and that noncoincident traits differed from coincident traits, averaged over levels two and three of set size. In addition, each of the five means differed from each of the other means. Results of these tests indicate that sets of size two resulted in significantly more polarized judgments than sets of size one and that sets of size three resulted in significantly more polarized judgments than sets of size two. At both set size two and set size three, noncoincident traits resulted in significantly more polarized judgments than coincident traits. A comparison of the sum of squares representing linearity across set size with that representing nonlinear effects demonstrated that, for both coincident and noncoincident traits, the linear component accounts for more than 99% of the variance. The set size/coincidence effect is illustrated in Figure 1.

When the same Scheffe' comparisons were performed separately for each level of valence, once again all comparisons were found to be significant, with one exception: For negative traits, coincident trait judgments did not differ from noncoincident trait judgments at set size two. Comparisons between sums of squares indicated that when valence is controlled, the effects of set size are once again almost completely linear (see Figure 2).

Simple effects tests and Scheffe' tests were also performed in order to examine the significant set size/coincidence by time

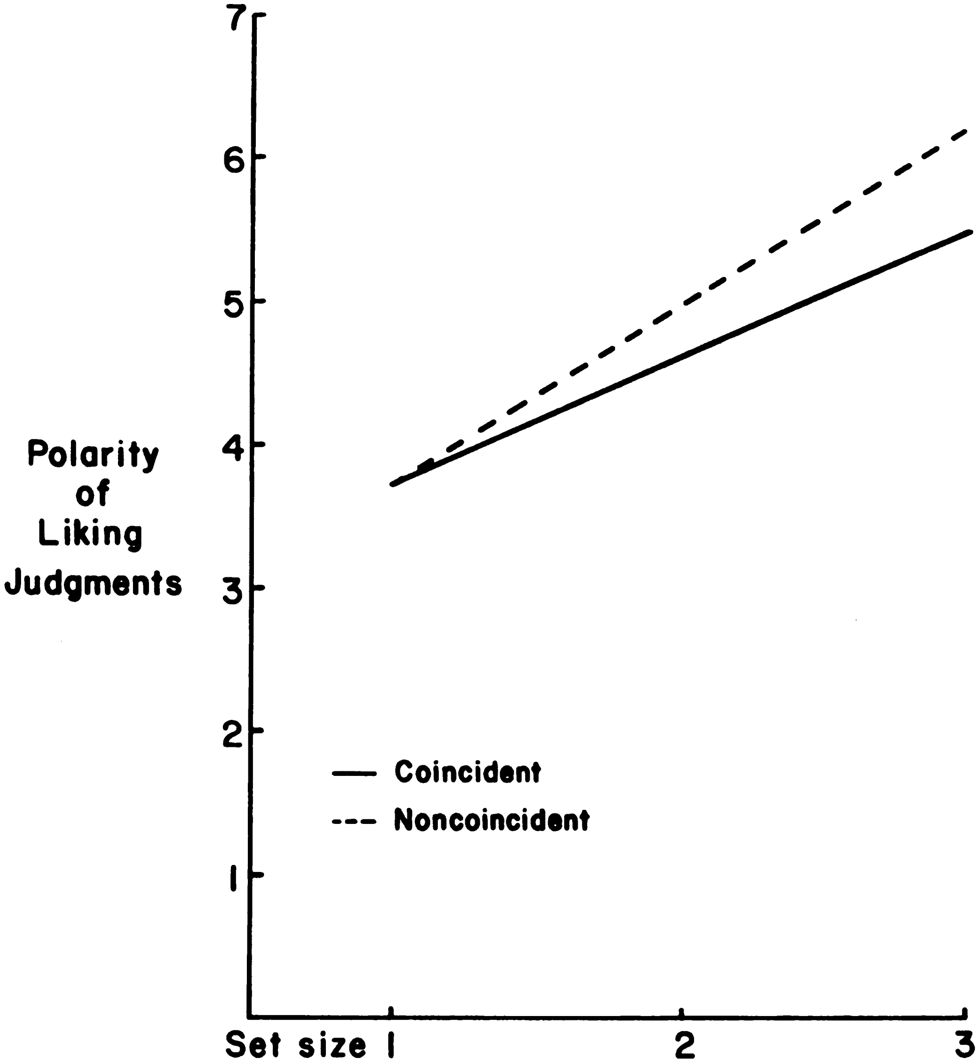

Figure 1. Mean Polarity of Liking as a Function of Trait Coincidence, and Set Size

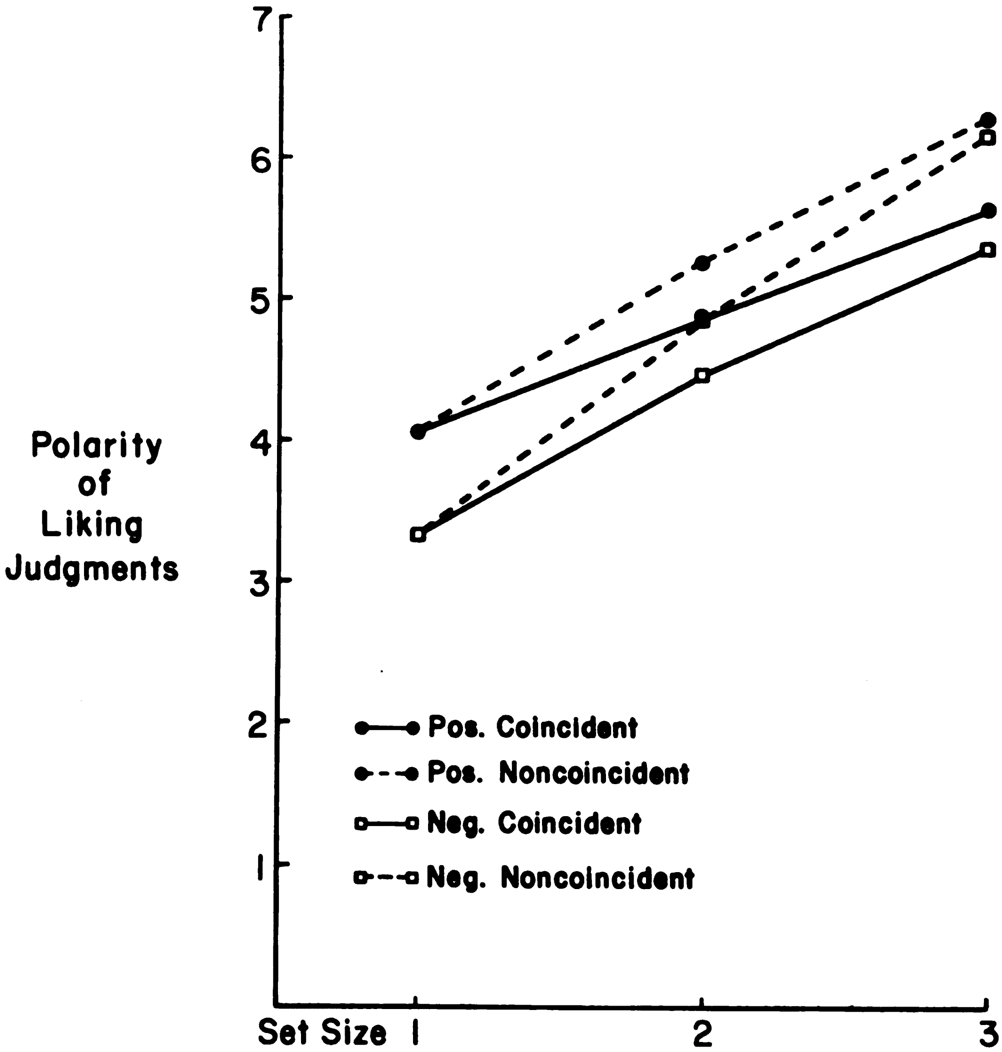

Figure 2. Mean Polarity of Liking as a Function of Trait Coincidence, Set Size, and Valence.

interaction (see Figure 3). Simple effects tests examining the effects of time within levels of set size/coincidence indicated that judgments made during the first test administration differed from those made during the second only at set size one: Subjects made significantly less polarized judgments for single traits during the second administration of the instrument. Scheffe' comparisons across levels of set size/coincidence within the two levels of time indicated once again that all comparisons were significant with one exception: During the first administration of the instrument, judgments for coincident traits did not differ from those for noncoincident traits at set size two.

Examination of the significant set size/coincidence by order of instructions interaction (see Figure 4) was carried out using the same procedures for planned comparisons. Simple effects tests examining the effect of order of instructions within levels of set size/coincidence indicated no significant differences between means. However, the ten Scheffe' comparisons made at each of the levels of instruction order indicated an effect of order of instruction on the difference between coincident and noncoincident trait judgments. For subjects receiving external instructions first, all Scheffe' comparisons indicated significant differences. However, for subjects receiving internal instructions first, coincident trait judgments did not differ from noncoincident trait judgments averaged over set sizes two and three, nor did they differ within set size two or within set size three. Thus receiving the internal instructions first

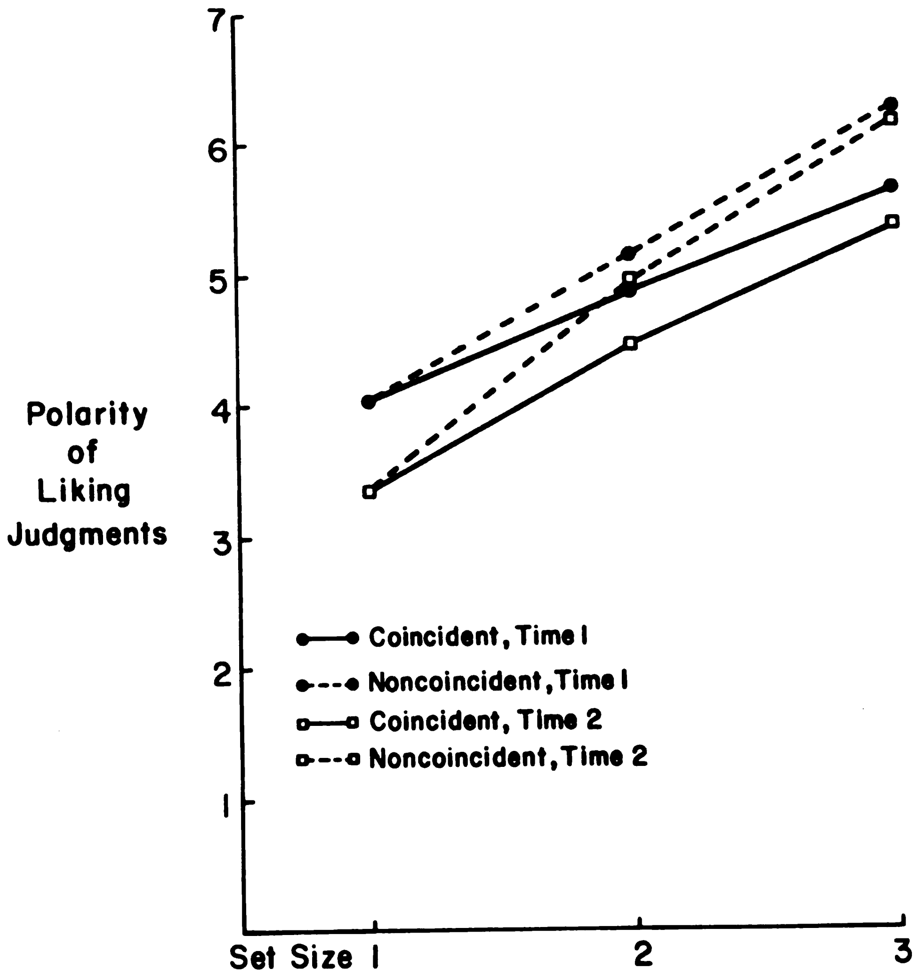

Figure 3. Mean Polarity of Liking as a Function of Trait Coincidence, Set Size, and Time of Administration.

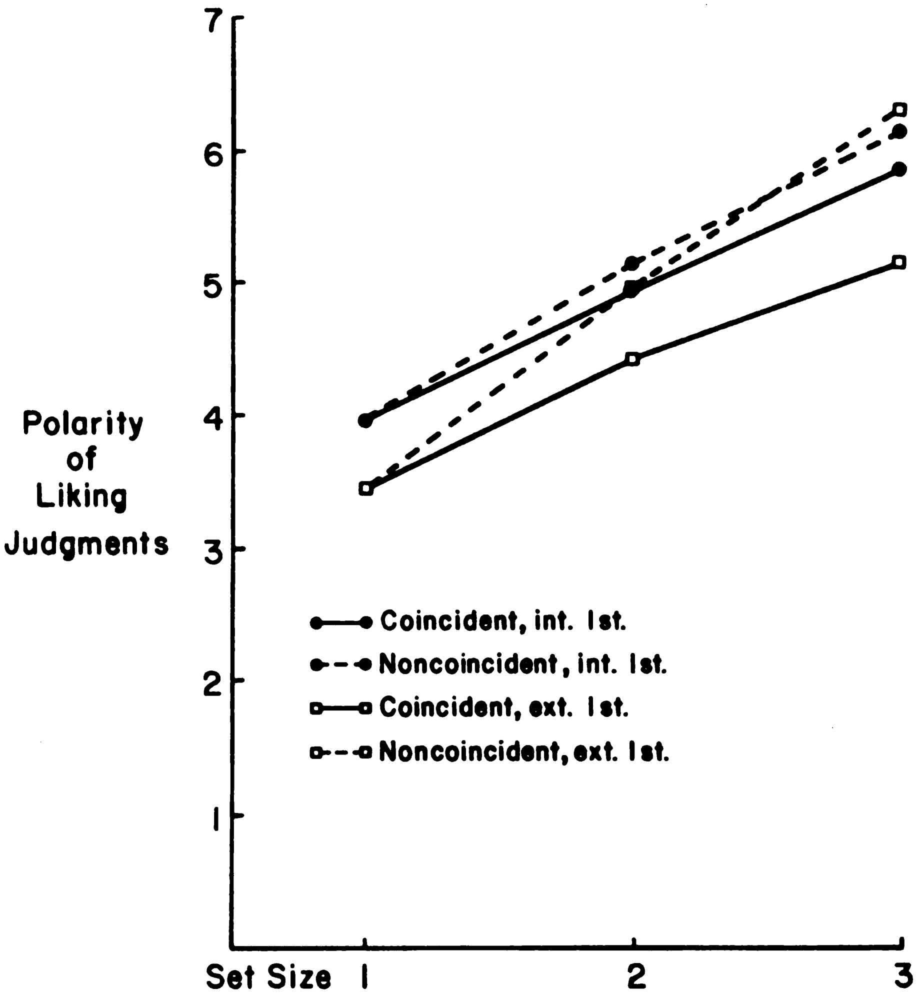

Figure 4. Mean Polarity of Liking as a Function of Trait Coincidence, Set Size, and Order of Instructions.

appeared to moderate the effect of trait coincidence upon likability judgments.

It should be noted that differences created by type of instructions would have been indicated by a significant time by order of instructions interaction. This interaction was not significant, nor did it play a role in any higher-order interactions. Thus it appears that while order of instructions affected likability judgments, the nature of the instructions themselves did not.

B. Preliminary Discussion

Since the interpretation of the ANOVA results depend upon the results of the rather complex set of comparisons of means, it seems appropriate to summarize the implications of these results and to present a preliminary discussion in this section. A more complete discussion of the theoretical implications of these findings will follow the summary of the results of the tests of the models, since these data add substantial information relevant to the discussion of the theoretical issues involved.

The results of the analysis of variance indicate once again the reliability of two of the major phenomena in the impression formation literature. First, the set size effect was clearly demonstrated in all conditions. The polarity of judgments of likability for three-trait sets was significantly greater than that for two-trait sets overall, as well as when trait coincidence, valence, order of instructions, and time were controlled. Correspondingly, the polarity of judgments for two-trait sets was significantly greater than that for single traits under all conditions. Moreover, this effect was linear in all cases.

The second impression-formation phenomenon receiving further support in this study concerns trait coincidence. In this experiment, in which "redundancy" of traits was manipulated for subjects on an individual basis in terms of coincidence of trait vectors with dimensions in the subject's attribute space, a substantially greater set size effect was found for noncoincident (nonredundant) than for coincident (redundant) traits. This effect mirrors that found when trait redundancy has been defined on the basis of normative measures of trait co-occurrence (Dustin and Baldwin, 1966; Kaplan, 1971; and Wyer, 1968, 1969, 1970) or normative measures of synonymity of meaning (Phillips et al., note 4), thus suggesting that this distinction must be taken into account in the comparison of models. In the current study, the polarity of liking judgments for noncoincident trait sets averaged over set size two and three significantly exceeded that for coincident trait sets overall, as well as when valence and time were controlled. The greater polarity of noncoincident trait judgments fell below the level of significance only when instruction order was controlled, in the case in which internal instructions were received first.

It is clear from these results that even when coincident and noncoincident traits are chosen on an individual basis--in contrast to the more normative selection techniques of prior studies--a set size effect does occur in the case of coincident traits. Thus the hypothesis developed from CCT Model A that subjects would adopt a strict averaging model in the case of highly coincident traits, showing no set size effect, was not supported. The issues concerning the process underlying the judgments made for sets of coincident traits will be discussed in detail following presentation of the data from the model predictions. It is clear, however, that while a set size effect, and thus some form of "adding" did occur in the case of coincident traits, the set size effect on the whole was substantially greater for noncoincident sets. Moreover, comparing the results of the planned comparisons between means in this study with comparisons in an earlier study using the same design (Phillips et al., note 4) indicates that controlling "redundancy" on an idiographic basis through individual selection of traits as coincident or non-coincident produced clearer effects than those resulting from selection of traits for all subjects on the basis of normative synonymity judgments. While the pattern of results in this earlier experiment was similar to that obtained in the current study, the results of the Scheffe' tests indicated somewhat weaker effects for redundancy in the case in which normative data was used.

The set size/coincidence by time interaction appears to be accounted for primarily by the significantly less polarized judgments made for single traits under the second administration of the instrument. This may well be a "practice effect," leading subjects to make less extreme judgments to single traits in order to "leave room" on the scale for more extreme responses to multiple-trait sets. The substantial set size effect found in this study indicates that subjects almost uniformly choose to give more polarized responses to multiple-trait sets. If their responses to single trait stimuli encountered in the task have been extreme, there is little room for making more polarized judgments to two- and three-trait sets. On their second encounter with the task, the subjects may choose to use a greater range of the scale, dropping the polarity of single-trait judgments. This explanation is supported by the improved fit of adding models on the second administration, as will be discussed subsequently.

The significant set size/coincidence by order of instructions interaction is difficult to interpret. The nature of the instructions themselves did not affect the judgments in the ways predicted, as is demonstrated by the absence of a set size/coincidence by time by order of instructions interaction. In terms of the CCT model predictions, it was expected that subjects receiving internal instructions would show a smaller set size effect for coincident traits than those receiving external instructions. In the case in which information is received from an external source, it was hypothesized that the ambiguity of the trait information would be decreased by additional trait items, resulting in a set size effect in the case of coincident traits. For trait descriptions representing internal judgments, coincident trait descriptions were expected to be entirely redundant, producing no set size effect. These predictions were not supported: The set size effect occurred reliably in all cases, and the predicted set size/coincidence by time by order of instructions interaction was not significant.

In discussing the impression formation study in class, the subjects indicated that in the case of external instructions they assumed that the acquaintance was someone who used attributes similarly to their own usage and that they assumed their own judgments would be similar to the acquaintances'. Thus it appears that more detailed instructions specifying the relationship between the subject and the acquaintance would be required to examine the effects of ambiguity of trait communication on impression formation judgments. However, the hypothesis that for this set of instructions, subjects simply treated external information as though it were internal fails to explain the set size/coincidence by order of instructions interaction. Receiving internal instructions first somehow obscured the differences found in every comparison between coincident and noncoincident traits. Given the failure to find any differences due simply to type of instructions, there appears to be little basis for explanation of this effect. While subjects were randomly assigned to the two groups, this effect may in fact be accounted for by a difference between the groups. Given that the "source" of the traits presented has typically not been specified in prior studies, the question of the effects of these instructions on likability judgments remains unclear and warrants further study.

VI. Quantitative Analyses: Procedures, Results, and Preliminary Discussion

A. Procedure

Assessment of the goodness of fit of the models described in Chapter II was performed on an individual-subject basis. The rating judgments made by each subject to the 18 single-trait statements were used as values in the equations for each model in order to obtain predictions for each subject's responses to the multi-trait stimuli. These predicted judgments were compared with the actual responses made by each subject across the trait sets. Thus measures of goodness of fit were obtained for each subject for each model. These measures of goodness of fit were then aggregated across subjects to provide an overall assessment of the adequacy of each model.

Each subject made 162 likability judgments--18 judgments for the single-trait sets and 144 judgments for the multiple-trait sets. Since order effects were not of concern in this study, responses to sets containing the same trait stimuli in different orders were combined. Thus each obtained value for a pair is the mean of the two ratings for that pair in the two orders. Correspondingly, each obtained value for a triple is the mean of six ratings. This combining of the multiple orders within a trait set resulted in 48 data points for each subject. The fit of each model was assessed by comparing these 48 observed values with the 48 trait-set ratings predicted for that subject by the model's equations.

All parameters in the models tested were also obtained separately for each subject. For those parameters estimated from independent measures, scores were obtained for each subject from the appropriate instrument. For those parameters estimated from the data, least squares estimation procedures were used to find the best-fitting parameter value for each subject.

Of the 27 subjects, three were excluded from the first-administration analysis--one because of failure to complete one of the independent parameter estimation tasks and two because of problems in the recording of the data. Twenty-four students took the instrument on the second administration. All are included in the analysis.

A number of measures of goodness of fit of the models are reported in this study. Warr and Smith (1970) have pointed out that there is no single statistical test which provides a rationale for accepting or rejecting a model by comparing its predictions with observed data. In general, studies of impression formation models have relied solely on correlation coefficients between predicted and observed values. However, when correlation is used as the only criterion, all that is being examined is the extent of a linear relation between predicted and observed values, rather than their equivalence. In order to examine the predictive accuracy of the models, measures of deviation between predicted and observed values are necessary. As Warr and Smith have suggested, the use of multiple criteria of goodness of fit is particularly valuable when these tests generate information about <u>why</u> particular models are less satisfactory than others.

Five measures of goodness of fit were calculated for each subject. These include, first, the Pearson product-moment correlation (r) between predicted and observed values; second, the absolute deviation of predicted from observed values; and third, the standard error of estimate of the model, computed by summing the squares of deviations of predicted from observed ratings and dividing by the appropriate degrees of freedom for the model (48 minus the number of parameters estimated from the data). This standard error of estimate is used to obtain the fourth test statistic, the proportion of variance accounted for by the model. This measure is equal to 1 minus the ratio of the standard error of the estimate to the variance of the observed scores, that is, $1 - (\sigma_e^2/\sigma_v^2)$ (Wyer, 1969). This measure has the advantage of being independent of scale size, allowing for comparison between the results obtained in this study and those obtained in other experiments which use a different scaling of the liking judgments. The fifth measure of goodness of fit included in this study is the intercept of the regression curve of predicted on observed values. This statistic was included to examine, overall, the assumption of a zero origin in the testing of the models and to assess any differences in accuracy of the models relating to this assumption.

B. Results

The measures of goodness of fit for each of the models tested in this study are presented in Table 3. Examination of the median correlation between predicted and observed values across subjects for each of the models indicates that, for all the models tested, some linear function of the predicted values fits the observed data very well. The median correlation exceeded .94 for each of the models tested. The uniformity of these correlations suggests that the predictions of the various models were themselves highly intercorrelated. This was, in fact, the case. The correlations between the predictions

Table 3.--Measures of Goodness of Fit for Attribute Integration Models.

	0-Parameter Models					
	Adding	Simple Averaging	Congruity	Wyer Redundancy	CCT Model A	CCT Approximation Model
First Administration (n=24)						
Measures of goodness of fit						
Mean standard error	9.44	5.08	4.37	7.54	7.01	6.43
Mean proportion of variance accounted for	68.30	79.64	82.95	73.65	75.14	78.51
Mean absolute deviation	2.40	1.63	1.39	2.01	1.94	1.82
Median r	.9726	.9608	.9700	.9671	.9441	.9649
Mean intercept	-.18	-.26	-.11	-.17	-.15	-.15
Second Administration (n=24)						
Measures of goodness of fit						
Mean standard error	5.38	4.72	3.18	4.19	4.40	3.86
Mean proportion of variance accounted for	77.63	80.89	86.44	83.35	81.39	84.90
Mean absolute deviation	1.84	1.76	1.40	1.59	1.65	1.52
Median r	.9769	.9607	.9722	.9664	.9422	.9691
Mean intercept	-.34	-.37	-.18	-.30	-.30	-.35

Table 3.--Continued.

	1-Parameter Models					
	1-P Adding	1-P Simple Averaging	1-P Dual Process	1-P Wyer	CCT Model B (Io)	1-P CCT Approximation Model
First Administration (n=24)						
Measures of goodness of fit						
Mean standard error	3.27	3.18	3.08	2.93	6.76	3.03
Mean proportion of variance accounted for	84.73	84.64	86.14	85.17	76.38	85.86
Mean absolute deviation	1.25	1.19	1.08	1.13	1.88	1.16
Median r	.9726	.9608	.9729	.9671	.9434	.9649
Mean intercept	-.18	-.26	-.21	-.17	-.06	-.20
Second Administration (n=24)						
Measure of goodness of fit						
Mean standard error	2.37	2.47	1.98	2.22	4.22	2.31
Mean proportion of variance accounted for	90.11	89.19	90.94	90.29	82.80	89.80
Mean absolute deviation	1.16	1.17	1.01	1.10	1.60	1.12
Median r	.9769	.9607	.9782	.9664	.9433	.9691
Mean intercept	-.34	-.37	-.37	-.30	-.20	-.35

Table 3.--Continued.

	2-Parameter Models				
	2-P Adding	2-P Simple Averaging	2-P Dual Process Model	Anderson e.w. Model	2-P CCT Model A
First Administration (n=24)					
Measures of goodness of fit					
Mean standard error	2.74	3.16	3.23	5.81	3.18
Mean proportion of variance accounted for	86.20	84.72	85.95	82.22	85.47
Mean absolute deviation	1.05	1.17	1.16	1.46	1.19
Median r	.9729	.9631	.9730	.9668	.9659
Mean intercept	-.18	-.26	-.21	.00	-.20
Second Administration (n=24)					
Measures of goodness of fit					
Mean standard error	1.94	2.34	1.95	2.97	2.20
Mean proportion of variance accounted for	91.44	89.77	91.25	88.09	90.60
Mean absolute deviation	1.00	1.13	.97	1.29	1.09
Median r	.9773	.9713	.9796	.9653	.9763
Mean intercept	-.34	-.37	-.37	-.16	-.35

made by the various models were computed for each subject. These correlations ranged from .81 to 1.00, with the great majority exceeding .95. This finding, which will be examined further in the discussion, indicates that when the stimuli to be combined in attribute integration models range over a broad portion of the rating scale, correlational measures of goodness of fit fail to serve as an adequate basis for distinguishing between the models. The use of correlation as the prime measure of goodness of fit is more justified in cases in which the stimuli being tested are all similar in scale value.

Examination of the tests dependent on measures of deviation between predicted and observed values--the absolute deviation, standard error of estimate, and proportion of variance accounted for--indicates more clearly the precise predictive accuracy of the models. A general comparison of the values presented in Table 3 indicates that the measures of deviation between predicted and observed values are highly sensitive to the number of parameters estimated from the data. Estimation of a single parameter--especially a multiplicative one--provides a substantial improvement in fit for most of the models, while the estimation of two parameters increases the predictive accuracy somewhat further. Comparisons between models, then, must clearly take into account the number of parameters estimated. It is also clear from Table 3 that the fit of the models--particularly those models assuming some sort of summative process--was more accurate for the second than for the first administration of the task. It should be noted that a portion of this improvement in fit is accounted for by the data of one subject whose data fit none of the model predictions on the first administration but corresponded to the predicted values on the second.

In terms of measures of deviation between predicted and observed scores, the strict adding model provides the poorest fit to the data. This model accounts for only 68% and 78% of the variance for the first and second administrations respectively. Relative to the other models, the adding predictions are more inaccurate for the first than for the second administration. Among the single-parameter models, however, the 1-parameter adding model is equivalent in accuracy to the other models. The basis for this improvement in the predictive accuracy of the model resulting from the inclusion of the multiplicative parameter can be demonstrated by examining the mean value (across subjects) of this parameter, presented in Table 4. The closer the multiplicative parameter is to 1, the more accurate the unparameterized version of the model is in predicting observed scores. The value of this parameter is .56 for the first administration and .63 for the second. It is thus clear that the adding model predicts scores which are much more extreme than the ratings obtained. Reduction of these predicted scores by approximately 2/5 results in relatively accurate predictions.

The simple averaging model does a more adequate job than most of the other 0-parameter models in predicting accurately the observed scores. It accounts for 80% and 81% of the variance for the first and second administrations respectively. Inclusion of a single multiplicative parameter in this model does not provide as great an improvement in fit as that resulting from parameterization of most of the other

Table 4.--Estimated Parameter Values for Attribute Integration Models.

Model	Type of Parameter	Mean Parameter Value, First Administration (n=24)	Mean Parameter Value, Second Administration (n=24)
One-Parameter Models			
1-p. Adding	Multiplicative	.56	.63
1-p. Averaging	Multiplicative	1.28	1.43
1-p. Dual Process	Multiplicative	.66	.52
1-p. Wyer Model	Multiplicative	.75	.81
CCT Model B (I_o model)	Additive	.09	.04
CCT Approximation Model	Multiplicative	.81	.90
Two-Parameter Models			
2-p. Adding			
a. Coincident sets	Multiplicative	.63	.69
b. Noncoincident sets	Multiplicative	.65	.71
2-p. Averaging			
a. Coincident sets	Multiplicative	1.24	1.34
b. Noncoincident sets	Multiplicative	1.34	1.53
2-p. Dual Process			
a. Coincident sets	Multiplicative	.70	.59
b. Noncoincident sets	Multiplicative	.57	.47
Anderson equal-weighting model			
a. I_o	Combination	.63	.49
b. $\hat{w}$	Combination	3.45	1.54
2-p. CCT Model A			
a. Coincident sets	Multiplicative	1.24	1.34
b. Noncoincident sets	Multiplicative	.65	.71

0-parameter models. The value of the single multiplicative parameter for the averaging model--1.28 for the first administration and 1.43 for the second--indicates that the responses predicted by simple averaging are too low in polarity.

CCT Model A predicted that the ratings of coincident traits would be averaged while those of noncoincident traits would be added. This model lies between the strict adding and simple averaging models in predictive accuracy, accounting for 75% and 82% of the variance in the first and second task administrations. The failure of this model to improve on both the adding and averaging models indicates that the predictive inaccuracy in the adding model does not only occur for coincident traits, nor is the averaging model inaccurate only in predicting responses for noncoincident traits. Further implications of the tests of the models for the coincident/noncoincident trait set distinction will be examined in looking at the results for the 2-parameter models in which parameters were estimated separately for each type of trait set.

In terms of single-parameter models, inclusion of the additive parameter in the CCT B model provided little additional predictive power over the CCT Model A. CCT Model B was based upon the assumption that the addition of trait information to a set may "replace" the expected position of the person on the dimension--the I_{0k} value. This model allowed for the inclusion of an additive parameter in the prediction of noncoincident trait ratings, essentially permitting adjustment of the scale origin. This provided little improvement in accuracy, and the value of the estimated parameter--.09 and .04 for first and second administrations--indicates its lack of predictive power.*

The Wyer redundancy model and the CCT approximation model each provided a moderately accurate fit to the data--74% and 83% of the variance was accounted for by the Wyer model for the first and second administrations, while the CCT approximation model accounted for 79% and 84% of the variance. Inclusion of a single multiplicative parameter provided a substantial improvement in fit for both models, to 85% and 90% of the variance for the Wyer model and 86% and 90% for the CCT approximation model. In both cases, the inclusion of the single multiplicative parameter increased the fit to exceed that of both the 1-parameter adding and 1-parameter simple averaging model. Examination of the parameter values for the Wyer and CCT approximation models (.75 and .81 for the Wyer model, first and second administration; .81 and .90 for the CCT approximation model) indicates that the unparameterized versions of both models predicted scores which were too extreme. Both models are based on the assumption of the summation of single-trait ratings, with a value subtracted from the polarity of the resulting scores based on redundancy or coincidence of the traits. While this subtractive function improved the accuracy of these models relative to a strict adding model, the resulting predictions were still more extreme than the observed values. The CCT approximation model does provide a somewhat better

*The mean of this parameter across subjects might not indicate its utility if the valence of the parameter were positive for half the subjects and negative for the other half. However, the absolute value of the parameter exceeded .10 in only 3 cases for the first administration and 2 cases for the second.

fit to the data than the Wyer model, with the Wyer model requiring a somewhat smaller multiplicative constant.

Among the 0-parameter models, the congruity model clearly provides the most accurate fit to the data. This model predicts responses which are more polarized than those predicted by simple averaging but which are less extreme than the responses predicted by models presuming a summation process. The proportion of variance accounted for by the congruity model--.83 for the first administration and .86 for the second--is in the range of that accounted for by the 1-parameter models tested in this study.

The remaining 1-parameter model--the dual process model--was developed in order to examine the fit which could be obtained from the optimal linear combination of adding and averaging predictions. As Table 3 indicates, this model provided the best fit of any 1-parameter model tested, accounting for 86% and 91% of the variance in the first and second administrations respectively. The dual process model takes the form

$$R_{DP} = \alpha\ (R_{AV}) + (1 - \alpha)\ R_{ADD}.$$

The mean best estimate of α is .66 for the first administration and .52 for the second. This model indicates, as do the 1-parameter adding and averaging models, that a value intermediate between the adding and averaging prediction is a good predictor of the obtained responses.

Among the two-parameter models tested in this study, Anderson's equal-weighting model is of primary theoretical importance.

The two parameters--w' and I_0--estimated in this model each include both a multiplicative and an additive component. Even with the estimation of these two parameters, the Anderson model did not provide a particularly accurate fit to the data. The proportion of variance accounted for--82% in the first administration, 88% in the second--was less than that for the other two-parameter models tested. Since tests of CCT Model B indicated little predictive power resulting from inclusion of an additive parameter, the Anderson model might more fairly be compared with the models estimating 1 multiplicative parameter. Even in this comparison, however, the Anderson model predicts less accurately than the models with which it is compared. Examination of the mean estimated parameter values indicates that they are within the range expected by the Anderson's theoretical formulation: The I_0 parameter is relatively neutral* and the ratio of the weight of stimulus scale values to the weight of I_0 in the integration process is greater than 1.

The remaining two-parameter models tested in this study were designed to compare the processing of coincident trait sets to that of noncoincident trait sets. In each case, two multiplicative parameters were estimated--one for each type of trait set. For the adding, averaging, and dual process models, the estimation of the two parameters did not provide a substantial improvement in the fit of the models over that provided by the use of a single multiplicative

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*This was generally true for individual subjects as well as in terms of the mean value. The absolute value of I_0 was less than 3 for two thirds of the subjects in the first administration and for all the subjects in the second.

parameter. Examination of the parameter estimate values, however, shows that the best estimate of the multiplicative parameters does differ somewhat for coincident and noncoincident trait sets in each case. The values of these parameters, for all three models, indicate that the best fitting predictions for noncoincident traits are a more extreme function of the single-trait ratings than are the predictions for coincident traits.

The use of a separate multiplicative parameter for coincident and noncoincident trait set predictions in CCT Model A clearly improves the fit of this model over the 0-parameter version. The value of the two parameters indicates that the assumption of simple averaging underestimates the rating polarity for coincident traits, while the assumption of strict adding overestimates response polarity for noncoincident trait sets.

C. Test of the CCT Single-Trait Predictions

The last set of equations discussed in Chapter II differ in their focus from the other models examined in this study. These equations deal with the general predictions from Configurational Consistency Theory, which tie the liking judgment made in response to any single trait stimulus to (1) the relative importance of the three dimensions; (2) the rating of the self on these dimensions; and (3) the position of the trait vector relative to these dimensions in the attribute space. Making the simplifying assumption that all trait stimuli are represented by points which are equally distant along their vector from the origin of the attribute space resulted in equation 55,

$$r_{Si/T} = F\ (\lambda_1 e_{S1} w_{T1} + \lambda_2 e_{S2} w_{T2} + \lambda_3 e_{S3} w_{T3}).$$

This predictive equation was tested for each subject by examining the correlation between the liking ratings for the 18 single traits and the value,

$$(\lambda_1 e_{S1} w_{T1} + \lambda_2 e_{S2} w_{T2} + \lambda_3 e_{S3} w_{T3})$$

where e_{Sk} was obtained from the ratings of the self on the semantic differential and λ_k and w_{Tk} were obtained from the rotated factor solution of the semantic differential ratings of acquaintances. The test of equation 55 was thus based on the correlation, for each subject, between 18 observed values (the single-trait ratings) and 18 predicted values.

It should be emphasized that this test, unlike the other tests of the specific models, did not involve the prediction of 48 data points in one task based on information obtained from 18 separate data points in the same task. Instead, it involved the prediction of 18 data points in the impression formation task based on entirely independent data concerning the subject's attribute system. Correlational methods were required here, since these independent measures involved ratings using scales which differed from that used in the impression formation task.

The results of this test indicated an extremely strong relationship between the trait ratings and the predicted values. For the first administration of the impression formation task, the median correlation across subjects between the predicted and observed values was .90; for the second administration, the median correlation was .83. For the first administration this correlation was significant with $p < .02$ for all but one subject. For the second administration, the correlation was significant at this level for all subjects.

CHAPTER IV

DISCUSSION AND CONCLUSIONS

In this dissertation, several theories of attribute structure and a number of models of attribute integration have been examined. The data obtained from the present study have provided two types of criteria which should be used in making comparisons between the models and between the underlying theoretical conceptions. First, the models must be examined in terms of their ability to account for the qualitative features of the data, summarized in the ANOVA results. Secondly, the models must be evaluated in terms of their accuracy in predicting the quantitative aspects of the data--the actual numerical values of the responses.

In this final chapter, the major conclusions to be drawn from this study will be discussed. These conclusions may be summarized briefly as follows:

1. Although the simple averaging model and congruity model provide a good fit to the quantitative features of the data, they do not appear to reflect adequately the process of trait integration.
2. The stable effects of trait coincidence (and trait redundancy in prior studies) call into question all attribute integration

models which are based on the single evaluative dimensional conception of attribute structure.

3. The Anderson equal-weighting model, considered the major theoretical model of trait integration, is not adequate to explain the qualitative features of this data--the linearity of the set size function and the effect of trait coincidence--nor does it provide an accurate quantitative fit to the data.
4. The adding models with a subtractive function--the Wyer redundancy model and the CCT approximation model--provide the best overall account for the current data, both in terms of its quantitative and qualitative features.
5. The ability of the CCT formulation to predict the ratings for the single-trait stimuli based upon the properties of the subject's attribute structure provides support for the utility of this theoretical conception in the investigation of attribute organization and processing.
6. The failure to find effects due to the use of internal versus external instructions calls into question the CCT hypotheses resulting from a focus on the ambiguity of the communication of trait information. This issue requires further investigation.
7. The use of a highly idiographic methodology--including individual stimulus selection and parameter estimation--allows for substantial predictive accuracy when models are tested in terms of fit to individual responses. This accuracy exceeds that found in previous studies using normative

selection and estimation procedures which attempted to predict individual responses.

The results of the ANOVA indicated an extremely clear set size effect, with the responses to the three set sizes differing significantly overall, as well as when any other variable was controlled. This set size effect was linear across the three set sizes. The existence of a set size effect as great as that found in this study, together with the ubiquity of the set size phenomenon in the impression formation literature, argues strongly against the assumptions of the simple averaging model. The effect and its linearity do provide support for models based on the assumption of an underlying additive process--the strict adding model, the Wyer redundancy model and the CCT approximation model. The results of the tests of accuracy of fit for the 0-parameter simple averaging and adding models are at variance with these models' set size predictions. The simple averaging model provides a reasonably accurate fit for the data, while the adding model does not. If all single traits received the average single-trait rating of 3.71, the adding model would predict a rating of 7.42 for two-trait sets and 10 (the extreme point of the scale) for three-trait sets. Such predictions are clearly in excess of the observed mean ratings of 4.86 and 5.88 for two- and three-trait sets respectively; and the deviations of the observed ratings from the adding model's predicted values are greater than the deviations from the simple average of 3.71. Thus a model which failed to account for a clear qualitative effect in the data showed greater predictive accuracy than the model which overestimated the magnitude of the effect which did occur. The inclusion of a parameter in the adding model which directly reduced the extremity of the predicted ratings of the two- and three-trait sets did provide for a reasonably accurate fit to the data.

The two models which assume a basically additive process, with a value dependent on trait redundancy being subtracted from the absolute value of the summative prediction, do a reasonably adequate job of accounting for the set size effect and predicting the responses with some accuracy. The 0-parameter Wyer and the CCT approximation models accounted for an average of 78% and 82% of the variance in the responses respectively. The estimation of multiplicative parameters for these models indicated, however, that even with the subtractive function, both models made predictions for set sizes two and three which were more extreme than the observed values.

The relationship between the observed set size function and the general predictions of the Anderson and congruity models in this study is somewhat unclear. The Anderson model clearly predicts a set size effect but predicts an effect which is less linear than that observed. Only when $I_0 = S_i$ or w' is very small or very large does the Anderson model approach linearity, and under these circumstances the set size effect would be very small. The congruity formulation can predict a substantial set size effect for the paradigm used in this study with certain restrictions on the single trait values. If the ratings of most of the single traits are relatively neutral while a portion of the traits have quite extreme ratings and if these traits are properly distributed among sets, a major set size effect could be predicted. This condition was not characteristic of the present data. It remains the case, however, that the congruity model is capable of predicting a set size effect, and this model did provide an accurate fit to the observed data in this study.

The second qualitative feature of the data which must be accounted for by a predictive model is the effect of trait coincidence on set size. The choice of trait stimuli for each subject on the basis of the dimensional analysis of trait usage resulted in a clearly defined effect of trait coincidence in this study. A significantly greater set size effect was found for noncoincident than for coincident traits. The significance of this finding is supported by similar results in studies using other measures of trait redundancy. The failure of the adding, simple averaging, congruity, or Anderson equal-weighting models to distinguish between predictions for coincident and noncoincident trait sets constitutes a significant failure of these models and of the underlying single-evaluative-dimension model of attribute organization. It is clear from the significance of this effect that aspects of meaning other than unidimensional evaluative favorability must be taken into account in predicting liking judgments. It is theoretically insufficient to attempt to account for this effect by manipulating the weights associated with scale values, as has been attempted with the Anderson model. If the aspects of "denotative meaning" considered in determining trait informativeness are nonevaluative, they should not affect a basically evaluative judgment.

The differing parameter estimates obtained for the two-parameter adding, averaging, and dual-process models provide further substantiation of the effect of trait coincidence on likability judgments. It is clear, however, that CCT Model A predicts a greater difference in the effect of coincident and noncoincident traits on set size than that obtained in this data. It clearly was not the case that coincident trait ratings were averaged and noncoincident trait ratings were summed. The 2-parameter dual-process model indicates, however, that averaging receives a substantially greater weight in the case of coincident traits than in the case of noncoincident traits. Thus while the version of CCT which made the assumption that all coincident traits were perfectly coincident and all noncoincident traits loaded perfectly on distinct dimensions did not provide an extremely accurate fit to the data, the assumed underlying process received support.

The two models which both account for the qualitative aspects of the differences between coincident and noncoincident traits and provide a relatively accurate numerical fit to the data are the Wyer redundancy model and the CCT approximation model. Both models predict that the polarity of the judgment for a set of ratings will equal the absolute value of the sum of the ratings for the individual traits minus a value which is a function of the trait redundancy or coincidence. Both models predict strict summation in the case of complete nonredundancy (Wyer) or perfect loadings on distinct dimensions (CCT approximation), and both models predict an averaging effect in the case of perfect redundancy or perfect trait coincidence. To the extent that trait sets approach perfect redundancy or perfect coincidence, the averaging effect predominates; to the extent that they approach perfect nonredundancy or perfect noncoincidence (as defined above), the adding effect predominates.

While the models are similar in form, they stem from two different theoretical conceptions. Wyer's model is concerned with the degree of overlap of attributes as categories. The CCT approximation model is a function which attempts to approximate the predictions stemming from the CCT distance-weighting model (equation 31). This model is concerned with the information carried by trait adjectives in terms of their use in locating the person described in a multidimensional evaluative attribute space. It is clearly not possible to use the current study as a basis for choosing one of these models over the other. The CCT approximation model accounted for a slightly higher proportion of the variance than did the Wyer model, and the multiplicative parameter in the single-parameter version of the CCT approximation model was somewhat closer to 1 than the value of the multiplicative parameter for the Wyer model. However, both the independent measures of trait interrelations and the form of the predictive equations for the two models differed, and it is not possible to examine the effects of these two sources of variation separately.

It is the case that Configurational Consistency Theory would regard the Wyer task as an appropriate measure of trait interrelationship when it is administered and scored on an individual basis, as it was in this study. Adopting the multidimensional evaluative organization of attributes as a framework, one would expect that traits which are coincident or near-coincident in the attribute space for a given domain would be used together in descriptions of elements in that domain. Correspondingly, traits which load on different dimensions would be expected to be used independently. Methodologically, CCT would argue with the Wyer redundancy task on two minor issues--the loss of information resulting from using the traits in a binary fashion rather than as rating scales; and the possibility that the range of person-objects in the Wyer measure is less likely to represent a unitary domain of elements in the subject's cognitive space than is a task which uses that subject's own acquaintances to obtain measures of trait interrelations.

In previous tests of the Wyer model, Wyer's trait description task has been used to obtain normative trait redundancy ratings. The measure has not been used on an individual basis. Using the normative values, Wyer (1969) assessed the fit of the Wyer model both for aggregated data and separately for each subject. He found the mean standard error of the estimate across subjects to be substantially higher than the standard error of the estimate for the aggregate judgments. The proportion of variance accounted for by the Wyer model in the aggregate test was 83%, with the best linear transformation of the predictions accounting for 88% of the variance. The substantially higher standard error scores for the tests of the model on an individual basis suggest that the model would account for a smaller proportion of the variance when tested at an individual level. In the current study, however, the idiographic test of the model accounted for a mean of 79% of the variance for the unparameterized version and

88% for the single-parameter version. This would suggest that it may be the case that for individual-based tests of the model, individualized measures of trait redundancy are appropriate.* Wyer's position on the role of individual differences in his theory of attribute organization is not clear. Methodologically, however, Wyer uses aggregate measures of trait interrelationships very heavily.

It is interesting to note that the Anderson equal-weighting model also showed a substantially higher standard error of estimate in the Wyer study when applied to individual as opposed to aggregated data. Moreover, while the Anderson model clearly resulted in more accurate predictions than the Wyer model for Wyer's grouped data, the differences between the means of the standard error of estimate for the individual model tests were not significant. This was the case even with estimation of the I_0 and w' parameters performed separately for each subject. With the aggregate data, Wyer found Anderson's model to account for 92% of the variance. This clearly is substantially higher than the mean proportion of variance accounted for by the Anderson model in the current study. This finding may be due to the fact that the Anderson model is generally more accurate when applied to aggregate data. It is also the case, however, that in his experiment Wyer attempted to predict only the judgments for two-trait sets. In the current study, the Anderson parameters were chosen so as to maximize the fit of the model for both two- and three-trait sets. Since the ANOVA results showed the set size effect to be highly linear,

*Due to the use of different trait adjectives for each subject in the current study, a comparison of the fit of the model using normative as opposed to individualized redundancy measures was not performed.

while the Anderson model predicts a negatively accelerated function, the inclusion of the three-trait sets may be at least partially responsible for the poorer fit of the Anderson model in the current study.

One additional discrepancy between Wyer's test of the Anderson model and that in the present experiment should be noted. As was discussed in Chapter I, while Wyer found that the Anderson model fit the data extremely well, the I_0 parameter estimate obtained by Wyer was discrepant from the value required by Anderson's theory. Rather than being relatively neutral, the best-fitting estimate of I_0 in Wyer's test was extremely positive--more positive than the rating of the most positive single trait. In the current study, while Anderson's model provided a less accurate fit to the data, the I_0 parameter estimate was relatively neutral for most of the subjects.

Wyer's 1969 experiment also tested the fit of the congruity, simple averaging, and adding models. Contrary to the present findings, Wyer found the congruity model to be relatively low in predictive accuracy, accounting for only 67% of the variance. The adding and averaging models each showed even a poorer fit to the data. Unfortunately, Wyer does not report tests of these three models on an individual basis. Wyer does state, as was found in the current study, that a linear transformation of the adding model provided an excellent fit to the data. Based on existing information, it is not possible to answer the question of whether the unusually good fit of the congruity model in the current study might be due to the application of the model to individualized data. The previous results reported in

Chapter I which failed to support the congruity position were all based upon aggregated data.

In attending to qualitative features of the data and the capacity of various models to account for them, the obtained interactions between set size/coincidence and valence, time, and order of instructions must be noted. The overall reliability of impression formation judgments involving no instruction manipulation has not been studied systematically. It has often been Anderson's practice, in his use of the paradigm, to provide practice trials prior to recording the experimental judgments. Other investigators have used this procedure infrequently. The set size/coincidence by time interaction suggests that such practice trials may have the effect of lowering single-trait judgments and accentuating the set size effect. None of the models or theories examined in this paper predict such effects. The reliability of their occurrence requires further investigation.

The overall instructions effect suggested by the CCT analysis of the ambiguity of trait information did not occur. As was noted earlier, the subjects reported screening out such ambiguity by assuming the communicator meant the same thing they did by the trait descriptions, suggesting that testing of the instructional manipulation requires further clarification of the instructions. The interaction between order of instructions and set size/coincidence is certainly not predicted by any of the theoretical conceptualizations examined, and it must remain unexplained.

The set size/coincidence by valence interaction is of some theoretical significance with regard to the Anderson model. Studies of a number of phenomena in the impression formation literature (examined in some detail in Phillips et al., note 4) have indicated that negative traits are weighted more heavily than positive traits when traits of both valence are presented in combination. The use of greater weights for negative than for positive traits in equation 7, together with the assumption of a near-neutral I_0 parameter, would result in the prediction of less polarized judgments for single positive traits, together with a greater set size effect for positive traits. The results in the current study showed the reverse effect--a lower single-trait polarity and greater set size effect were found for negative traits. Such a finding is compatible with the Anderson model and the assumption of greater weights for negative traits if a somewhat polarized positive value for I_0 is assumed. In any case, the Anderson model requires that the initially (for set size 1) less polarized traits show the greater set size effect, and this prediction was confirmed in this study. Prior evidence (Phillips et al., note 4) has not uniformly supported this finding. The interaction between trait valence and coincidence/set size is not dealt with by the other models tested in this study.

The discussion to this point has reviewed the competing models of trait integration in terms of both their ability to account for the qualitative features of the data and their ability to predict accurately, on an individual basis, the judgments for multiple trait stimuli based on single-trait ratings. Before considering the conclusions to be drawn, in terms of the specific models and their underlying theories of attribute organization, there are two minor issues which should be addressed. These two issues concern (1) the adequacy of the ratio scale assumption in this study, and (2) the high correlations among the predictions of the various models.

Except for those models requiring them in the predictive formulas, additive parameters were not estimated for the models tested in this study. As was stated in Chapter II, the assumption was made that both in the semantic differential ratings and in the impression formation judgments, a meaningful zero point was defined. Therefore, ratio scale measurement was assumed. In general, this assumption proved warranted. Estimates of the intercept of the regression of predicted on observed values were close to zero for most subjects. Inclusion of an additive parameter in those models requiring it on a theoretical basis provided little overall improvement in fit. Very little power would appear to be gained in predicting these data with the estimation of an additive parameter.

The extremely high correlations between the sets of predicted values calculated from the various models in this study made correlational tests of the adequacy of the models relatively meaningless. It is clear that these high correlations are a function of the wide range of judgments made to single-trait stimuli in this study. For a collection of identically-valued stimuli, the adding and averaging predictions concerning ratings of trait sets, for instance, would be completely uncorrelated. However, when the stimuli included in the prediction equations range from moderately negative to moderately positive, the predictions of these models--even confined to sets of same-valence traits--will be related. Both the adding and the averaging models predict a higher rating for a set consisting of two quite positive traits than for a set containing a positive and a moderate trait. Correspondingly, both models predict lower ratings for sets containing only relatively neutral traits, etc.

This fact suggests caution in evaluating impression formation models on strictly correlational criteria. The finding of high inter-model correlations is not confined to this study. Warr and Smith (1970) report extremely high correlations between predicted and observed values for each of the models tested in their experiment, clearly implying high inter-model correlations. If a broad range of stimulus values is used, it would appear that almost any reasonable model of the impression formation process will show a high correlation with the data. This suggests that caution be used in treating this measure of goodness of fit as a sufficient criterion for a model's predictive accuracy. Moreover, it suggests that future comparative tests of the models would benefit from choosing some range of trait stimuli for which the models make clearly competing qualitative predictions and examining closely the fit of the models over this restricted range of values. It is clear that models of trait integration have reached the point where procedures used to test these models must focus attention on the differential predictions resulting from the differences in the processes hypothesized. As Warr and Smith (1970) have pointed out, the statistical operations used to examine competing models should provide information concerning why, as well to what extent, these models fail in their predictions.

Based on the dual criteria that an acceptable model of the attribute integration process must account for the major qualitative features of the data and must also predict the observed responses with some degree of accuracy, the two models receiving the most support in this study are the Wyer redundancy model and the CCT approximation model. Both models account for the observed set size effect and predict its linear form,* and both models provide a theoretical basis for the observed effects of trait coincidence. In addition, while the two models predict judgments for trait sets which are somewhat too extreme, their predictive equations each account for a substantial proportion of the variance in the current experiment. Both compare favorably to the major competing model of impression formation processes--the Anderson model.

It was noted earlier that Configurational Consistency Theory would predict that Wyer's measure of trait redundancy would be sensitive to the degree of trait coincidence in the multidimensional conception. The reverse is probably also true. While Wyer rejects the dimensional analysis of trait usage, he would no doubt expect such analysis--based either on correlation of trait usage patterns or on interpoint distance measures of meaning--to isolate overlapping trait clusters. We are thus faced with two formulations which are similar in mathematical form, whose predictions are both empirically and theoretically interrelated but which are based on very different

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*Both models predict a linear set size effect as long as redundancy or coincidence is held constant. As trait sets become quite large, the probability of redundancy or coincidence would necessarily increase, resulting in nonlinearity.

theoretical representations of cognitive processing. It is certainly not appropriate here to attempt to make any kind of case against Wyer's theoretical formulation. It is important, however, to examine the extent to which the current data justifies the continued development and testing of models based upon the Configurational Consistency Theory framework.

The basic CCT formulation received extremely strong support from the findings concerning the predictions of the single-trait judgments. The theoretical basis of CCT depends on the proposed correspondence between the cognitive representation of relationships between elements and the evaluative attributions made concerning those elements. The theory states as one of its basic postulates that individuals will attempt to maintain consistency by evaluating objects on multiple evaluative dimensions in such a way that these evaluations can explain or account for the ways in which these objects interrelate. This correspondence between evaluation and the observed pattern of interelement relationships is postulated to assume a specific mathematical form: in order for a cognitive structure to be attributionally consistent, the vectors representing the dimensions of the evaluative attribute space must correspond to the eigenvectors of the matrix of interelement relationships. As was shown in Chapter I, it is this assumption which forms the basis for equation 13

$$r_{Si} = \sum_{k=1}^{m} \lambda_k e_{Sk} e_{ik}.$$

By making a series of simplifying assumptions about the ways in which a person may process trait stimulus information in order to arrive at e_{ik}, equation 51 was derived, to predict single trait judgments assuming a three-dimensional attribute structure:

$$r_{Si/A} = F\ (\lambda_1 e_{S1} w_{T1} + \lambda_2 e_{S2} w_{T2} + \lambda_3 e_{S3} w_{T3}).$$

The correlational analysis showed this equation to be an extremely good predictor of liking judgments for person i, given the information that person i possesses trait A. This equation clearly is strongly tied to the basic postulates of the theory. CCT is the only theory dealing with attribute integration which attempts to predict the liking judgments for single-trait stimuli based on information about the subject's attribute structure. CCT predicts that these judgments will be a function of the interaction between the importance of the dimensions in accounting for interelement relations, the rating of the self on the dimensions, and the spatial relationship between the vector representing the trait stimulus and the dimensions. Specifically, this formulation suggests that trait words which load highly on important dimensions will result in more extreme liking responses than those which load highly on less important dimensions. This conceptualization also suggests a similarity effect--subjects will tend to like individuals who are rated highly on dimensions on which they rate themselves highly. Additional research on these specific predictions resulting from equation 13, within the impression formation paradigm, is clearly essential to further investigation of the theory. The support obtained for the overall predictive effectiveness of equation 51 in this study is clearly impressive, and is certainly sufficient to justify further investigation of the theory at this level.

The support for the CCT based models of the integration of attribute information is less impressive. The model based on the simplifying assumption of perfect coincidence among coincident trait sets and perfect noncoincidence among noncoincident trait sets did not provide an accurate account of the data. While a clear difference in set size effect was found between coincident and noncoincident sets, the difference was certainly not as extreme as that predicted by CCT Model A. One source of the failure of this model was its limitation in this study to three attribute dimensions. Based on prior research in the area of implicit personality theory, it appeared that three dimensions would be likely to provide a reasonable representation of the attribute space for most subjects. In fact, there was initial concern that three dimensions might be over-sufficient, based on the stability of the two evaluative dimensions, social good/badness and intellectual good/badness, across prior multidimensional analyses of trait meaning. In this study, however, the modal number of factors across subjects required to account for 75% of the variance in the factor analysis of trait usage was 5, and more than half the subjects required more than 5 factors. It is unclear to what extent this high dimensionality was due to (1) the idiographic basis of the dimensional analysis, (2) the use of individually-generated stimuli for the rating task, and/or (3) a high level of cognitive complexity on the part of these Honors College undergraduates, at least in the domain of "people I know."

In any case, it is clear that stimuli chosen on the basis of a high degree of coincidence or noncoincidence in the three dimensional space selected for each subject would be likely to be less purely coincident or noncoincident in the 6-, 7- or 8-dimensional space which forms the best representation of that subject's structure of trait attributions. The subjects themselves expressed this concern in discussing the issue of synonymity among the coincident trait sets, following the current set of experiments. Few subjects felt that the traits chosen for them as coincident were truly synonymous in meaning. In fact, most made distinctions among the traits in a set on the basis of dimensions not used for them in the study--saying something like, "'Smart' and 'intelligent' mean the same thing in terms of their relationships with warmth traits or responsibility traits, but to me 'smart' implies a focus on practical details that isn't implied by 'intelligent' and so 'smart' is more likely to imply 'effective' and 'competent' than intelligent is." In fact, many of the highly complex subjects expressed the feeling of not having enough trait words in their vocabularies to represent adequately their attributions, and stated that they deliberately attached differential meanings to trait words in order to place objects in the attribute space. Essentially, for a 9-dimensional subject, there may be no truly coincident traits. Thus for highly dimensional subjects the limitation in finding stimuli which meet the criteria of coincidence and noncoincidence required to provide an accurate test of CCT Model A may not be due to

inaccuracies in the methodology used to define the intrinsic dimensionality of the attribute space but rather to linguistic limitations in trait availability.

While this study used idiographic procedures to select stimuli for the subjects, the use, across subjects, of an experimental design which required the selection of three dimensions for each subject clearly compromises the idiographic approach demanded by CCT. The decision to adopt this uniform design was made for two reasons. First, a comparison of the results of this study with prior studies based on normative, aggregated data demanded the use of a constant experimental design. Secondly, the statistical problems in examining the qualitative features of an individual subject's data through analysis-of-variance-type techniques remain problematic, due to the autocorrelation problem. It would certainly be of interest to examine, for instance, the linearity of the set size effect for a highly-dimensional subject, with noncoincident stimuli selected across the large numbers of dimensions. Such an approach to the problem--a more idiographic one than that adopted in this study--deserves further examination.

The CCT approximation model was an attempt to define a mathematical formulation which would allow the use of the available information about spatial relationships within the attribute structure in predicting trait integration processes. This model serves the function of making the appropriate qualitative predictions required by the CCT distance-weighting conception. That is, the model predicts averaging in the case of perfect coincidence, adding in the case of perfect noncoincidence, and a process falling between strict adding and averaging for moderately related traits which is dependent upon the degree of trait coincidence. As such, it provided a reasonably accurate fit for the data. The model is certainly not an elegant one. It is not derivable directly from the theoretical formulation, nor is it elegant mathematically in its application to sets with a relatively large number of traits. Its success in the current study, however, suggests that further work in refining and testing the CCT distance-weighting formulation is justified.

The data from the current study indicate that a multidimensional conception of attribute organization which adopts the position that attribute structure will differ across individuals is capable of providing a basis for the study of processes of trait attribution. When stimuli were chosen on an idiographic basis, from the results of individual multidimensional analyses of patterns of trait usage, these stimuli were processed by those individuals in ways consistent with the multidimensional representations. Using idiographic bases for stimulus selection and parameter estimation as well as for the testing of models resulted in explanatory power for both the Wyer and CCT approximation models which equalled or surpassed the power of models in previous studies to predict _aggregate_ data. As was noted above, Wyer (1969) found both the Anderson and Wyer models to show substantially less accuracy of prediction when applied to individual data than when they were applied to grouped data. However, in the current study use of idiographic procedures throughout the various experiments resulted in high predictive power at the individual level.

It is clearly a bias of Configurational Consistency Theory that any model of cognitive processing must apply at the individual level of analysis rather than simply to the analysis of aggregate data. A question may be raised as to whether the current study has done more than simply develop a complex set of idiographic research procedures which substantiate existing knowledge with some greater degree of precision. In fact, the results of these experiments have indicated that Configurational Consistency Theory in general and the distance-weighting model of CCT in particular are of some value in accounting for patterns of trait attribution. The findings of the current study together with the impressive support for multidimensional evaluative models in studies of implicit personality, indicate that unidimensional evaluative models of attribute organization fail to account for patterns of attribute processing. It is clear that multidimensional evaluative models and category models of attribute structure will remain the major competing conceptualizations. More refined research techniques must be developed to attempt to distinguish between the implications of these two theoretical positions. In the meantime, Configurational Consistency Theory has demonstrated a potential for generating models of information processing from within the framework of a multidimensional conception of evaluative attribution.

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APPENDIX A

TASK INSTRUCTIONS

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TASK INSTRUCTIONS

Instructions - Acquaintance List

Questionnaire 1 - Concept Lists

The purpose of this questionnaire is to obtain lists of concepts--things, people, and ideas--that are meaningful to you. These concepts will then be entered into some of the questionnaires you'll be taking, so that you can make judgments about them, etc.

1. First, we'd like a list of friends and acquaintances--people you know and think about. You may identify these people by their first names or their initials or any other way that will let you identify them again when you see them listed--for example, "the guy I sit next to in physics." Try to list some people you like and others you don't like so much.

First, list 20 people whom you feel you know quite well. Then, list 20 people whom you know only slightly--whom you would consider as being "acquaintances." Remember, you don't have to know their names--you may identify them in some other way.

Complete Instructions - Semantic Differential

The purpose of the semantic differential scales is to assess your feelings about a number of concepts--things, places, people, ideas, etc. You will be asked to rate each concept on each of the scales in order.

First you will be presented with the concept and then with a series of scales to use in rating the concept. Each scale consists of 2 opposite adjectives with 7 spaces between them. Each scale will look like this:

Famous /.1./.2./.3./.4./.5./.6./.7./ Obscure

You are to respond with the number that best represents where you feel the concept fits on the rating scale.

If you feel the concept is very closely related to one end of the scale, you should choose 1 if you would rate the concept as very famous or 7 if you feel the best concept rating is very obscure.

If you feel the concept is closely related to one or the other end of the scale (but not extremely), then you should choose 2 or 6. If the concept seems to you to be slightly related to one side as opposed to the other (but is not really neutral), then you should choose 3 or 5 as the rating. The number you choose, of course, depends upon which of the two ends of the scale seem most characteristic of the concept you are rating.

If you consider the concept to be neutral on the scale, or if it seems equally related to both of the scale adjectives, or if the scale is completely irrelevant to the concept, then you should choose 4, the middle number on the scale.

Do not try to remember how you rated earlier items. Make each scale a separate and independent judgment. Do not puzzle over individual judgments. Give your first impressions.

Brief Instructions - Semantic Differential
(presented at each administration of a semantic differential task)

The purpose of the following scales is to assess your feelings or opinions about each of a number of concepts which will be listed. First, you will be presented with a concept and then with a series of scales to use in rating the concept. Each scale will look like this:

Famous /.1./.2./.3./.4./.5./.6./.7./ Obscure

Consisting of two opposite adjectives, with seven spaces between them. You are to respond with the number that best represents where you feel the given concept fits on the rating scale. You should consider how close to each of the opposite adjectives you think the concept is and then choose the best number. For more complete instructions, check the mimeographed semantic differential instructions.

Trait Pair Judgment Instructions

The purpose of this task is to obtain judgments about pairs of traits--adjectives used to describe a person's personality and behavior. You will be presented with a series of pairs of trait words--for example, suspicious - boastful. For each pair, you will give a response to indicate how dissimilar you feel the two trait words in the pair are, how distant the meanings of the 2 words are from each other. You may use any number between 0 and 100. You would use 0 to indicate the two words have no distance in meaning between them--they mean exactly the same thing. You would use 100 to indicate that the 2 traits are as distant in meaning--as opposite--as they could possibly be. You may use numbers in between 0 and 100 to represent intermediate distances in meaning. Remember, small numbers mean the words are close in meaning. Large numbers indicate large differences in meaning.

Impression Formation Instructions - External Condition

In this task you will receive a series of statements which read, "He (or she) is trait word" or "He (or she) is trait word 1. He (or she) is trait word 2" or "He (or she) is trait word 1. He (or she) is trait word 2. He (or she) is trait word 3." In other words, you will be reading trait descriptions about a set of hypothetical people, and each of these descriptions will contain either 1, 2, or 3 personality trait words.

Treat each of these statements as though it represents traits which you know are true of the person. That is, think of each of the statements as though you know the person and this is a statement you would make to describe the person. Then make a judgment about how much you would like a person whom you would describe as having this trait or set of traits.

You will indicate your judgment of how much you think you would like each of the hypothetical people described on a scale from -10 to 10. Use -10 to indicate that you would dislike the person extremely. Use 10 to indicate that you think you would like the person extremely. Use 0 to indicate that you think your feelings for the person would be neutral--that you could neither like nor dislike the person. You may use any number between -10 and 10, using negative numbers to indicate disliking and positive numbers to indicate liking.

Take your time to make these judgments. Treat each set of statements as though it describes a separate person. Try to visualize a person who actually fits the description and then make your liking judgment. Don't try to remember the judgments you made for earlier statements--treat each description independently.

Impression Formation Instructions - Internal Condition

These instructions were identical to those above, with the exception of the * paragraph, which was replaced by the following:

Treat each of these statements as though it is a description of someone you don't know but will be meeting in the future. Imagine that the description is given to you by an acquaintance of yours who knows this person. Then make a judgment about how much you think you would _like_ a person who is described to you as having this trait or set of traits.

Brief Impression Formation Instructions
(presented on the computer with the impression formation instrument)

In this task you will be presented with descriptions of hypothetical people, as you were instructed earlier. You are to make liking judgments about each of the people described, considering each description independently. Make these liking judgments on a scale from -10 (strong disliking) to 10 (strong liking).

APPENDIX B

STIMULUS MATERIALS

APPENDIX B

STIMULUS MATERIALS

List of Semantic Differential Scales

1. educated - uneducated
2. trustworthy - untrustworthy
3. sincere - insincere
4. dominant - submissive
5. reliable - unreliable
6. complex - simple
7. competent - incompetent
8. active - passive
9. good - bad
10. kind - cruel
11. successful - unsuccessful
12. responsible - irresponsible
13. wise - foolish
14. beautiful - ugly
15. strong - weak
16. ambitious - unambitious
17. efficient - inefficient
18. warm - cold
19. motivated - aimless
20. friendly - unfriendly
21. smart - stupid
22. polite - impolite
23. deep - superficial
24. tolerant - intolerant
25. respectful - disrespectful
26. truthful - untruthful
27. dependable - undependable
28. attractive - unattractive
29. effective - ineffective
30. happy - unhappy
31. cheerful - cheerless
32. courteous - rude
33. intelligent - unintelligent
34. persistent - wavering
35. broad-minded - narrow-minded
36. valuable - worthless
37. hard - soft
38. honest - dishonest
39. rational - irrational
40. good-humored - ill-humored

List of Traits Used in the Trait Difference

Judgment Task

Traits used in Instrument 1:

1. educated
2. untrustworthy
3. sincere
4. unreliable
5. complex
6. competent
7. good
8. kind
9. successful
10. irresponsible
11. wise
12. beautiful
13. ambitious
14. inefficient
15. warm
16. aimless
17. friendly
18. smart
19. polite
20. deep
21. intolerant
22. disrespectful

Traits used in Instrument 2:

1. uneducated
2. trustworthy
3. insincere
4. reliable
5. simple
6. incompetent
7. bad
8. cruel
9. unsuccessful
10. responsible
11. foolish
12. ugly
13. unambitious
14. efficient
15. cold
16. motivated
17. unfriendly
18. stupid
19. impolite
20. superficial
21. tolerant
22. respectful

23. untruthful	23. truthful
24. undependable	24. dependable
25. unattractive	25. attractive
26. effective	26. ineffective
27. happy	27. unhappy
28. cheerless	28. cheerful
29. rude	29. courteous
30. unintelligent	30. intelligent
31. narrow-minded	31. broad-minded
32. valuable	32. worthless
33. dishonest	33. honest
34. irrational	34. rational
35. ill-humored	35. good-humored

Composition of 162 Impression Formation Stimuli

Stimulus Number	Trait Words Used	Stimulus Number	Trait Words Used
1.	1	25.	4-5
2.	2	26.	5-4
3.	3	27.	4-6
4.	4	28.	6-4
5.	5	29.	5-6
6.	6	30.	6-5
7.	7	31.	7-8
8.	8	32.	8-7
9.	9	33.	7-9
10.	10	34.	9-7
11.	11	35.	8-9
12.	12	36.	9-8
13.	13	37.	10-11
14.	14	38.	11-10
15.	15	39.	10-12
16.	16	40.	12-10
17.	17	41.	11-12
18.	18	42.	12-11
19.	1-2	43.	13-14
20.	2-1	44.	14-13
21.	1-3	45.	13-15
22.	3-1	46.	15-13
23.	2-3	47.	14-15
24.	3-2	48.	15-14

Stimulus Number	Trait Words Used	Stimulus Number	Trait Words Used
49.	16-17	73.	10-13
50.	17-16	74.	13-10
51.	16-18	75.	10-16
52.	18-16	76.	16-10
53.	17-18	77.	13-16
54.	18-17	78.	16-13
55.	1-4	79.	11-14
56.	4-1	80.	14-11
57.	1-7	81.	11-17
58.	7-1	82.	17-11
59.	4-7	83.	14-17
60.	7-4	84.	17-14
61.	2-5	85.	12-15
62.	5-2	86.	15-12
63.	2-8	87.	12-18
64.	8-2	88.	18-12
65.	5-8	89.	15-18
66.	8-5	90.	18-15
67.	3-6	91.	1-2-3
68.	6-3	92.	1-3-2
69.	3-9	93.	2-1-3
70.	9-3	94.	2-3-1
71.	6-9	95.	3-1-2
72.	9-6	96.	3-2-1

Stimulus Number	Trait Words Used	Stimulus Number	Trait Words Used
97.	4-5-6	121.	16-17-18
98.	4-6-5	122.	16-18-17
99.	5-4-6	123.	17-16-18
100.	5-6-4	124.	17-18-16
101.	6-4-5	125.	18-16-17
102.	6-5-4	126.	18-17-16
103.	7-8-9	127.	1-4-7
104.	7-9-8	128.	1-7-4
105.	8-7-9	129.	4-1-7
106.	8-9-7	130.	4-7-1
107.	9-7-8	131.	7-1-4
108.	9-8-7	132.	7-4-1
109.	10-11-12	133.	2-5-8
110.	10-12-11	134.	2-8-5
111.	11-10-12	135.	5-2-8
112.	11-12-10	136.	5-8-2
113.	12-10-11	137.	8-2-5
114.	12-11-10	138.	8-5-2
115.	13-14-15	139.	3-6-9
116.	13-15-14	140.	3-9-6
117.	14-13-15	141.	6-3-9
118.	14-15-13	142.	6-9-3
119.	15-13-14	143.	9-3-6
120.	15-14-13	144.	9-6-3

Stimulus Number	Trait Words Used	Stimulus Number	Trait Words Used
145.	10-13-16	155.	17-11-14
146.	10-16-13	156.	17-14-11
147.	13-10-16	157.	12-15-18
148.	13-16-10	158.	12-18-15
149.	16-10-13	159.	15-12-18
150.	16-13-10	160.	15-18-12
151.	11-14-17	161.	18-12-15
152.	11-17-14	162.	18-15-12
153.	14-11-17		
154.	14-17-11		

<u>Stimulus Persons - Wyer Task</u>

Your mother

Your favorite professor

Fidel Castro

Ted Kennedy

Ronald Reagan

Charles Manson

John Mitchell

Hugh Hefner

Your least favorite entertainer

Betty Ford

Your favorite character in a book

Barbara Walters

Your high school principal

Fred Harris

George Wallace

Julie Nixon Eisenhower

Billie Jean King

Henry Kissinger

President Clifton Wharton

Your favorite entertainer

Gloria Steinem

Your best friend

Your least favorite professor

Patricia Hearst

Your least favorite character in a book

Your least preferred co-worker (or co-student)

Morris Udall

Adolf Hitler

Joseph Stalin

Jimmy Carter

Birch Bayh

Your most preferred co-worker (or co-student)

Your worst enemy

The person you've met recently whom you would least like to know

A particular sales clerk who has waited on you

Your high school English teacher

Your father

Richard Nixon

President Gerald Ford

Governor Milliken