297

Working Paper

AVERAGING AS A GENERAL PRINCIPLE OF
INFORMATION INTEGRATION

By

Ramadhar Singh

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Ramadhar Singh
Organizational Behavior Area
Indian Institute of Management, Ahmedabad

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Virtually all situations require a judgment on the basis of several pieces of information. Grading a term paper, evaluating a job applicant, selecting a leader, ingratiating the boss, or simply watching a cricket match, all involve integration of several separate pieces of information. To say then that judgments depend upon information integration is to stress the obvious.

Because of its pervasiveness, integration process has been a subject of great interest in recent years. Much of the work on this topic has been stimulated by Norman H. Anderson's theory of information integration (1974a). According to the theory, information integration obeys simple algebraic rules. Adding, subtracting, multiplying, dividing, and averaging are all employed in making judgments, and these rules are detectable with experimental methods.

An important virtue of the integration rule is that it can serve as the base and frame for scaling stimuli as well as responses (Anderson, 1970, 1976). In this <u>functional measurement</u> approach, psychological measurement is woven in the fabric and structure of the integration rule itself. This approach, it should be noted, is exactly opposite to the customary approach (e.g., Stevens, 1971; Thurstone, 1959) in which measurement is viewed as a methodological preliminary to any substantive inquiry.

Over the past several years, I have been studying integration processes, using the methods of information integration theory and functional measurement. A number of judgmental tasks have been considered -- likableness of persons, perception of groups, favorableness of leadership situations, and prediction of performance, to mention a few. Depending upon the nature of the stimuli and dimension of judgment, college students, young children, supervisors, computer programers, and bus users have all been used as subjects. The present report presents an overview of the experiments completed so far, and argues that the weighted average rule may be considered as a general principle of information integration.

AVERAGING MODEL

Basic Ideas

Within integration theory, each piece of information is described by two parameters: a scale value, $\underline{s}$, and a weight, $\underline{w}$. The $\underline{s}$ refers to the location of the stimuli along the dimension of judgment. For example, low pay and high pay will have different satisfaction scale values. Similarly, coming late to duty, disobeying one's supervisor, and slapping him will have different values along the scale of punishment.

The *w* reflects the psychological importance of the information. When several pieces of information are available about a person, they all may not be equally important determinants of our opinion of him. Some may be more useful and informative than others. The extent to which a particular piece of information is used in judgment is reflective of its weight. Two stimuli may have the same scale value, but they can differ in their weight. Weight of a particular piece of information thus denotes how important it is to the judge in relation to the other pieces of information entering into the judgmental task.

Once stimuli are processed with respects to their *s* and *w*, they are integrated according to an averaging rule. That is,

$$J = \sum_{i=o}^{n} \underline{s}i\ \underline{w}i \;/\; \underline{w}i\ , \qquad (1)$$

where J is judgment, *wi* and *si* are weight and scale value of a particular piece of information, *n* is the number of pieces of information, and *o* is an organismic variable. This *o* includes many characteristics of the individual subject such as his past experiences, response dispositions, motivational and other momentary states, and it is represented in the numerator as having scale value of $\underline{s}_o$ and weight of $\underline{w}_o$. The denominator in Equation 1 is just the sum of weights of all relevant inputs for judgment. As weights reflect the relative importance of the various inputs for judgement, they sum to unity, the condition for the averaging model.

It should be noted that inclusion of the organismic variable within the averaging model is important. It recognizes the role of individual variable in judgment. It also allows quantitative account for the set-size effect (Anderson, 1965, 1967; Singh, 1976; Singh, Byrne, Gupta, & Clouser, 1974; Sloan & Ostrom, 1974) within the averaging framework. As the set-size controversy has been examined earlier (Singh, 1977), it will be ignored here. For simplicity in presentation, the role of organismic variable will also be ignored.

Methodological Aspects

Some key features of experimental method that is often employed in integration-theoretical analysis deserve brief mention. They are considered below.

Response Scale. The scale to measure judgment should be continuous. It does not matter whether the response measure is a 7-point graphic scale (Singh, 1975a) or a 31-point graphic scale (Dalal, 1978; Dalal & Singh, Note 2); whether it is a set of squares (Gupta, 1979; Singh, Sidana, & Srivastava, 1978) or a set of human faces (Anderson & Cuneo, 1978; Singh, Note 5). As long as a continuous scale is used, it is fine. The advantage with a continuous scale is that it allows a direct conversion of the response into numerical value.

In general, however, a longer scale having 20-30 points is preferable to a short scale having 7-10 points. It permits finest discriminations among stimuli. However, it requires that the subjects be enabled to use the entire scale through practice and other experimental procedures (Anderson, Note 1).

Factorial Design. It is convenient to construct stimuli according to a factorial design. This kind of design pairs all the factors in a systematic manner; hence, it provides the necessary conditions to test the averaging model in a simple way. Among many advantages, one is that analysis of variance can directly be used to diagnose the operative integration rule.

Within-Subject Design. Stimuli constructed from a factorial design may be distributed among groups of subjects using a between-subjects design, or they all may be given to just one group of subjects. When repeated measurements are taken on one group of subjects, the design becomes within-subject.

The within-subject design is more suitable than the between-subjects design for studying integration rule. Statistically, a repeated measurement design is more powerful than a nonrepeated measurement design (Winer, 1971). Use of a within- subject design is more justified even psychologically. As the purpose is to see how a person coordinates the various pieces of information, it is more meaningful to run the same person across all the treatment conditions than to use separate groups of subjects.

Another important virtue of the within-subject design is that it allows analysis of data at the level of individual subject. If all the stimuli of the factorial design are rated more than once, then analysis of variance can be performed for each subject separately, and generality of the operative rule can be ascertained more rigorously. Individual analyses are important to check that the group averages are not hiding alternative integration strategies by different subjects. Usefulness of such analyses is well documented in two recent doctoral dissertations submitted to the Indian Institute of Technology, Kanpur (Dalal, 1978; Gupta, 1979).

Two Predictions

For judgment of stimuli prepared from a factorial design, the averaging model makes two specific predictions. Depending upon the pattern of weights of the different factors, parallelism or nonparallelism can be obtained in the factorial plot of data.

Parallelism Pattern. Consider a Row x Column design, for example. If the two stimuli do not interact, and the respective weights of the two stimuli remain invariant over rows (or across columns) of the design, then the averaging model predicts a family of parallel lines in the factorial plot of the data. The logic for this parallelism prediction can be understood by looking at the structure of the theoretical responses to nine cells of a 3 x 3 design in Table 1.

Table 1

Theoretical Structure of Nine Pairs of Stimuli Constructed from a 3 x 3, Row x Column Design

Levels of Row Factor	Levels of Column Factor		
	C_1	C_2	C_3
R_3	$R_3W_1 + C_1(1-W_1)$	$R_3W_1 + C_2(1-W_1)$	$R_3W_1 + C_3(1-W_1)$
R_2	$R_2W_1 + C_1(1-W_1)$	$R_2W_1 + C_2(1-W_1)$	$R_2W_1 + C_3(1-W_1)$
R_1	$R_1W_1 + C_1(1-W_1)$	$R_1W_1 + C_2(1-W_1)$	$R_1W_1 + C_3(1-W_1)$

Note. R and C represent scale value of the row and column stimuli, respectively.

Consider any pair of rows in Table 1. The difference between two rows is the same across all the three columns. Because of this constant algebraic difference between rows across columns, the factorial plot will display exact parallelism.

To show parallelism, it is only necessary to plot the cell means. No a priori knowledge of scale value or weight of any factor is needed. In addition, parallelism holds with any number of levels of the row and column factors as well as with any number of factors in the design. A simple graphic plot of the data thus provides a reasonably good test for the averaging model.

Because of response variability, however, the graphic test of parallelism cannot be always perfect. An objective, statistical test of parallelism will generally be essential. Parallelism is equivalent to a zero interaction in analysis of variance. A non-significant Row x Column interaction can, therefore, be taken as support for parallelism pattern.

One technical aspect of parallelism deserves mention. Success of parallelism prediction establishes not only that the averaging model is correct but also that response scale is a linear or equal-interval scale. Furthermore, the row means of the design are valid interval scale estimates of the psychological values of the row stimuli, as are the column means for the column stimuli (see Anderson, 1976).

Nonparallelism Pattern. When weights of the row and column factors vary in accordance with their own scale value, systematic deviations from parallelism are to be expected. For instance, if the weight of the column factor decreases with its own increasing scale value, then the factorial plot produces a set of diverging lines, known as linear fan shape (Anderson, 1976). A direct relalationship between scale value and weight of the stimuli, in contrast, results in a converging set of curves.

Let us look at the numerical examples of Table 2. They are made to give an idea of the conditions under which diverging and converging patterns are obtained. In Example 1, the column weight decreases with its own increasing scale value. So, the difference between predicted responses to any pair of rows, given at the bottom of Table 2, widens across the three columns. In Example 2, on the contrary, the column weight increases with its increasing scale value. Therefore, the difference between predicted responses to any pair of rows diminishes across the three columns.

Table 2

Examples of Diverging and Converging Types of Nonparallelism

Scale Value of Row Factor		Scale Value and Weight of Column Factor					
		Example 1			Example 2		
	s	2	4	6	2	4	6
	w	.8	.6	.4	.4	.6	.8
$R_3 = 6$		2.8	4.8	6.0	4.4	4.8	6.0
$R_2 = 4$		2.4	4.0	4.8	3.2	4.0	5.6
$R_1 = 2$		2.0	3.2	3.6	2.0	3.2	5.2
$R_3 - R_2$		0.4	0.8	1.2	1.2	0.8	0.4
$R_3 - R_1$		0.8	1.6	2.4	2.4	1.6	0.8
$R_2 - R_1$		0.4	0.8	1.2	1.2	0.8	0.4

Note. The predicted response of 2.8 for $R_3C_1 = (6 \times .2) + (2 \times .8)$ in Example 1. The weight for the row factor was always 1 − weight for column factor.

Both converging and diverging types of nonparallelism imply that the row by column interaction is nonzero. In analysis of variance, therefore, the Row x Column effect will be statistically significant. More importantly, the entire interaction would reside in just the Linear x Linear trend (Anderson & Butzin, 1974; Graesser & Anderson, 1974; Singh, Note 6). When this statistical requirement is satisfied, the row and column marginal means can readily be treated as interval estimates of the row and column stimuli, respectively. In fact, it has been noticed that spacing of the levels of column factor on the abscissa of graph according to their marginal means results in excellent set of straight lines (Dalal, 1978; Singh, Note 6).

ALTERNATIVE RULES

The parallelism and nonparallelism patterns in factorial plot are not restricted to the operation of averaging rule alone. They can be engendered by other rules as well. For example, an adding operation would also produce a family of parallel lines. Similarly, a multiplying rule predicts a linear fan shape. It is, therefore, proper to examine these alternative rules here.

Averaging versus Adding

Numerical Example. To see that both the adding and averaging rules predict parallelism, look at the numerical examples of Table 3. The first set of nine values, on the left side, are simple sum of the value of the row and column factors. The other set of nine values, on the right side, are simple average of the value of the row and column factors. Graphic plots of both sets of predicted values will produce perfect parallelism. Parallelism pattern thus supports adding as well as averaging rule, but does not discriminate them.

Table 3

Numerical Examples of Predicted Responses by Adding and Averaging Rules

	Scale Value of Column Factor					
	Adding Rule			Averaging Rule		
Row Value	2	4	6	2	4	6
6	8	10	12	4	5	6
4	6	8	10	3	4	5
2	4	6	8	2	3	4

Note. The adding rule predicts that Response = Row Value + Column Value. The averaging rule predicts that Response = (Row Value + Column Value)/2. The entries in the table have been prepared accordingly.

Distinguishing Tests. Can adding be discriminated from averaging? Anderson (1965) has suggested a simple method: Ask subjects to judge a stimulus on the basis of a highly polar information, and also on the basis of a highly polar and a mildly polar information. If the adding model is correct, then adding a mildly polar information to a highly polar information would increase the overall rating of the stimulus. On the other hand, if the averaging model is correct, then adding a mildly polar information to a highly polar information would decrease the overall rating (see Anderson, 1974a, p. 254). The reason for this decrease is simple. The average value of a mildly polar and a highly polar information is less than the average of a highly polar information alone.

To understand this distinguishing test between adding and averaging, let us examine the findings of a study by Singh, Sidana, Saluja (1978a). Subjects were told about groups of two or four children, of varied goodness and badness, and judged now much he/she would like to play with the group on a 9-point scale. The design can be understood most readily by referring to Table 4. B and G stand for very bad and very good children, respectively, so that BB and GG represent groups of two very bad and two very good members. B^- and G^- stand for slightly bad and slightly good children, respectively, so that BBB^-B^- represents a group of two very bad and two slightly bad members, and GGG^-G^- represents a group of two very good and two slightly good members.

Table 4

Mean Attractiveness of Playgroups as a Function of Group Size and Composition

Group	Attractiveness
GG	7.88
GGG^-G^-	6.71
BB	2.17
BBB^-B^-	4.33

Note. G, G^-, B, and B^- denote group members who are good, slightly good, bad, and slightly bad, respectively. Data after Singh, Sidana, and Saluja, 1978a; Experiment 2. Reproduced with the permission from the Academic Press, Inc.

The results presented in Table 4 clearly support the averaging rule. The GG group with two very good members was more attractive than the $GGG^{-}G^{-}$ group with two very good members and two slightly good members. Comparison of groups having bad members also favors the averaging rule. The $BBB^{-}B^{-}$ group was more attractive than the BB group. This is consistent with the averaging rule, but is completely opposite to what the adding model predicts. These results suggest that it is possible to discriminate between operations of adding and averaging rules.

The averaging test can be done in a slightly different manner also. In addition to stimuli prepared from the Row x Column design, stimuli based on just the column factor can also be employed. If the adding rule is correct, then the curve based on only the column factor will be one of the parallel curves in the factorial plot of the data. The averaging operation, in contrast, will make the curve based on column factor alone cross over at least one row curve (Anderson, 1974b; Lampel & Anderson, 1968).

The logic for these two predictions can be understood by referring back to Table 3. With adding rule, responses to the three levels of column factor are 2, 4, and 8, just the values given at the top. Hence, a curve based on these values would be parallel to other three curves. With averaging rule, however, the same curve would clearly cross over the middle row curve.

Differential-Weight Averaging versus Multiplying

Numerical Example. Table 2 gave two numerical examples for s systematic nonparallelism predicted by the differential-weight averaging model. The linear fan type nonparallelism follows from a multiplying rule also. If the row and column values, given in Table 2, are simply multiplied and a curve is plotted, an exact linear fan shape will emerge. A linear fan shape is, therefore, supportive of both the multiplying and differential-weight averaging rules.

Distinguishing Test. The distinguishing test used to discriminate adding from averaging can also be employed to distinguish differential-weight averaging from multiplying. According to the multiplying rule, the curve based on column factor alone should plot as the lowest curve in a family of diverging straight lines, for the multiplier, row value, is absent. Even if the judges impute some value for the missing row information, the curve based on column factor alone would still form part of a linear fan (Singh, Note 6; Singh, Gupta & Dalal, 1979). The differential-weight averaging rule, on the contrary, predicts that the curve for column factor alone should cross over at least one of the curves forming the linear fan shape. The rationale for this prediction is similar to the cross over prediction mentioned earlier.

EXPERIMENTAL ILLUSTRATIONS

Affective Judgments

During early years of my career, I did three experimental studies of interpersonal attraction within Donn Byrne's attraction paradigm (1971). Bogus strangers were prepared according to a 2 x 2 (Attitude Similarity x Personality Similarity) design (Singh, 1973a), a 2 x 2 x 2 (Subject's Evaluations by Stranger x Attitude Similarity x Personality Similarity) design (Singh, 1973b), or a 2 x 2 (Subject's Evaluations by Stranger x Attitude Similarity) design (Singh, 1975b), and subjects indicated their attraction toward those strangers. In all the three studies, only the main effects were present; the interaction effects were statistically nonsignificant. Results thus conformed well to the parallelism pattern.

The third study had taken measures of subjects' mood also. The ratings of mood obeyed the parallelism pattern as did the ratings of attraction. That affective judgments follow such a simple process has further been confirmed by a study of happiness in children (Singh, Sidana, & Saluja, 1978b).

The studies just mentioned were not designed to discriminate adding from averaging. Results from some other studies, however, suggest that it is possible to interpret parallelism in affective judgment as constant-weight averaging. In the study by Singh (1973a), for example, subjected had also rated attractiveness of 2 strangers on the basis of personality similarity alone (see also Singh, Note 4). A curve drawn on the basis of these two strangers had slope sleeper than the other two curves, as required by the averaging rule. Similar trends are evident in the data reported by Byrne and Rhamey (1965) and by Clore and Baldridge (1970). Averaging rule can, therefore, account for the results obtained in most of the attraction studies (see also Kaplan & Anderson, 1973; Byrne, Clore, Griffitt, Lamberth, & Mitchell, 1973).

It should be added here that the averaging model predicts a crossover interaction between weight and scale value. This prediction has indeed been confirmed with both attraction and feelings measures (Singh, 1974).

Disciplinary Judgments

Figure 1 plots results from an experiment on disciplinary judgment. Thirty-six students evaluated complaint cases against 12 hypothetical employees according to (a) how serious was the offense, and (b) how much punishment they would recommend. Both judgments were made along a 10-point scale. The 4 x 3 design had rule-infraction and performance record as the row and column factors. So, mean disciplinary judgments are plotted in Figure 1 as a function of rule-infraction by the employee (curve parameter) and his performance record (listed on horizontal axis). The first set of curves on left side are based on pooled ratings of severity of offense and punishment.

Figure 1 exhibits a pattern of parallelism in all three sets of curves. Although minor discrepancies from parallelism are visible, they were not statistically significant. This indicates that the basic property of the data is indeed parallelism. It can, therefore, be said that information about rule-infraction and performance record were averaged in disciplinary judgments. This result is open to an adding interpretation also, for distinguishing test between adding and averaging was not employed.

Judgements of Groups

Does overall attractiveness of a playgroup result from an averaging of information about the various attributes of the group? To get answer to this question, look at Figure 2 which plots mean attraction toward playgroups as a function of the number of toys in the group (curve parameter) and the ratio of good to bad members in the group (listed on horizontal axis). Subjects of this experiment were 20 boys and 20 girls enrolled in Standard II at Guru Nanak School, Kanpur. Ages ranged from 6 to 7 years, with a mean of 6 years, 6 months for boys, 6 years, 7 months for girls.

Under the constant-weighting condition, the averaging model predicts that the four toy curves should be parallel. This appears

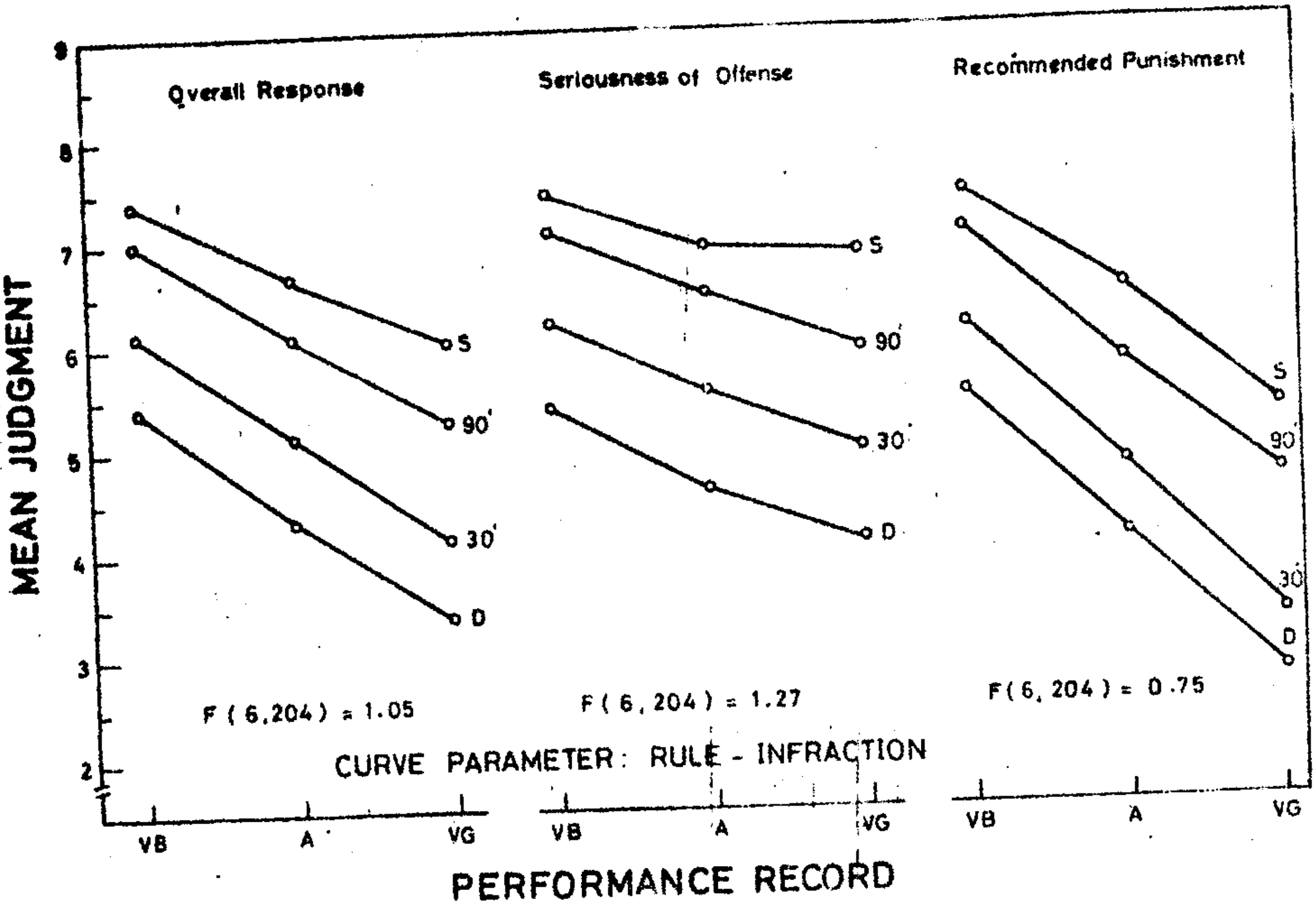

Figure 1. Mean judgments as a function of rule-infraction and performance record of the offender. Data from Singh, 1978; Figure 1. (Letters S and D denote slapping and disobeying the supervisor, and 30' and 90' indicate late comers by the indicated minutes. Listed *F* ratios are for Rule-infraction x Performance Record effect. VB, A, and VG refer to very bad, average, and very good performance, respectively). (Reprinted with the permission from the Journal Press.)

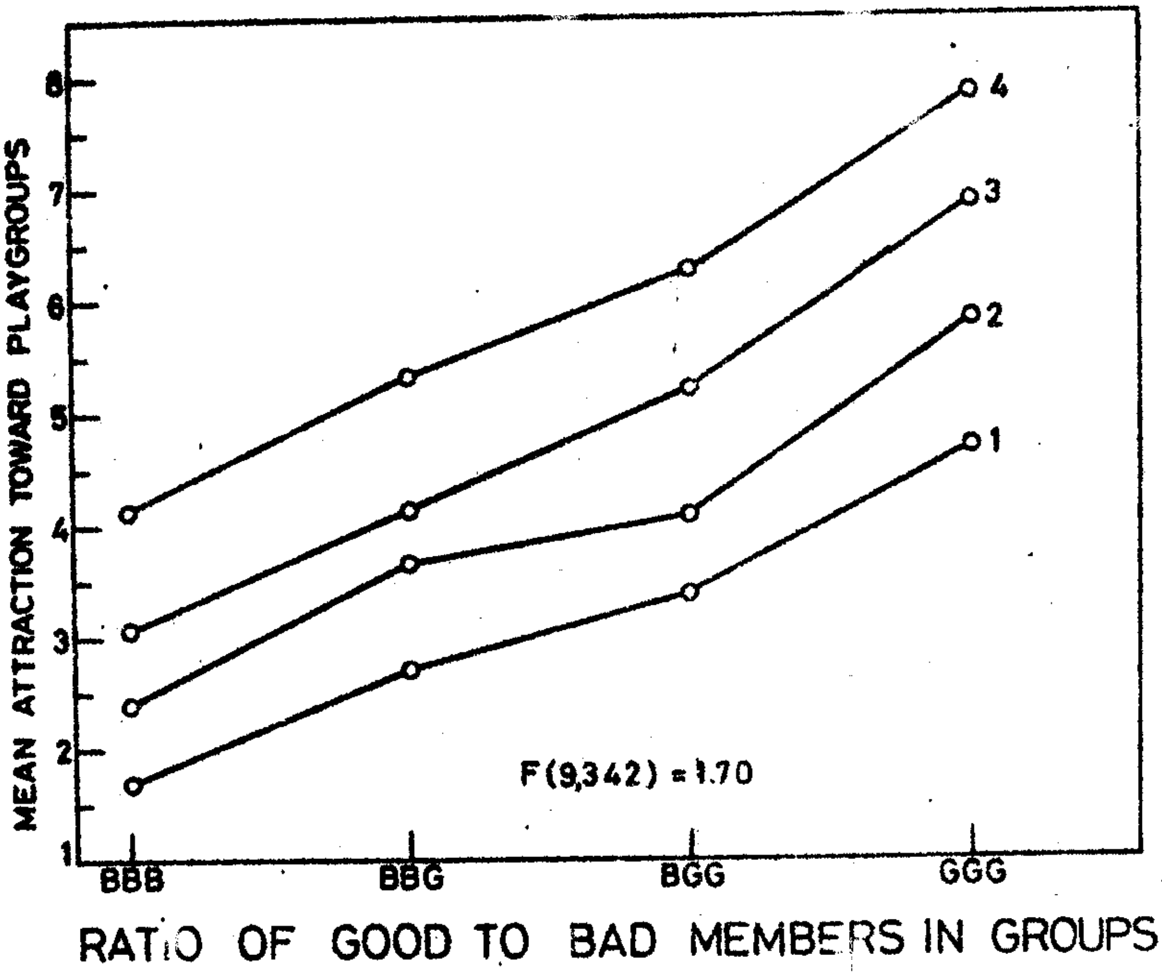

Figure 2. Mean attractiveness of three-person playgroups as a function of the number of good (G) to bad (B) members (listed on the horizontal axis) and the number of toys available to the group (curve parameter). Data from Singh, Sidana, and Saluja 1978a; Figure 1, Experiment 1. (Reprinted with the permission from the Academic Press, Inc.)

to hold quite well in Figure 2. Statistical test of the Toy x Nature of Group Members effect was nonsignificant which supports parallelism. The three-way interaction including sex of subject was also nonsignificant. This indicates that boys and girls followed the same constant-weight averaging rule in judgments of playgroup attractiveness.

Critical tests between adding and averaging ruled out the former, ruled in the latter. Results related to these tests were discussed earlier under the alternative rules section.

That group perception obeys an averaging rule has been demonstrated in a different study also (Singh et al, 1978). Children of 6-7 years of age judged happiness of a child member on the basis of the nature of two adult members (i.e., his mother and father) of a family group. The data supported the averaging model, although with some evidence for unequal weighting. Four distinguishing tests between averaging and other alternative rules were also made. All four tests clearly confirmed the operation of averaging rule in perception of family groups.

These two studies have some clear implications for the study of cognitive processes in children. In Piagetian theory, it is assumed that preoperational children (approximately upto 6-7 years), in general, center attention on a single aspect of the stimulus (Flavell, 1963; Ginsberg & Opper, 1969). They pay attention to only the most silent aspect of the stimulus and ignore the other aspects. This tendency to center on just one aspect of the stimulus is known as _centration_. As age increases, children tend to divide their attention to several aspects, and so show _decentration_. Results from the present sets of studies (Singh et al, 1978, 1978a, 1978b) argue against centration: Children not only pay attention to two aspects of stimuli but also integrate them in accord with the averaging rule. This point has been elaborated well by Gupta (1979).

Favorableness of Leadership Situations

The contingency model of leadership effectiveness (Fiedler, 1967, 1971) conceptualizes situational favorableness as "the degree to which the situation provides the leader with potential power and influence over the group's behavior" (1971, p. 129). The model further assumes that _group atmosphere_ (the degree to which the group accepts and respects it leader), _task structure_ (the degree to which the task of the group is clear and well defined), and _position power_ (the degree to which the leader has direct power to control the actions of the group) contribute to situational favorableness according to an _adding_ rule (Nebeker, 1975).

Singh, Bohra, and Dalal (1979) conducted a series of four judgmental experiments to determine whether situational favorableness really obeys an adding rule. They constructed descriptions of leadership situations from a 3 x 3 x 3 (Group Atmosphere x Task Structure x Position Power) factorial design, and asked subjects to judge how favorable those situations were to their respective leaders. Nine situations were defined by just one level of a single variable. In Experiments 3-4, subjects also judged 27 situations defined by the three two-variable designs.

This study had 18 separate tests for parallelism and 18 tests for averaging versus adding rules. Of the 18 tests of parallelism, 15 tests supported parallelism; three tests yielded relatively small deviations. These deviations were inconsistent, nonreplicable across the four experiments. Quantitative evidence for the parallelism prediction from adding and averaging models was, therefore, strong.

Figure 3 presents results from Experiment 2 to show how clear was the support for the parallelism pattern. The solid curves are infact parallel.

The dashed curve of each of the three panels in Figure 3 are important for distinguishing adding and averaging rules. They represent judgments based on information about just one component listed on the horizontal axis. The adding model requires the dashed curve to be parallel to the solid curves; the averaging model, as mentioned earlier also, predicts that the dashed curve would cross over at least one row curve. The three tests of

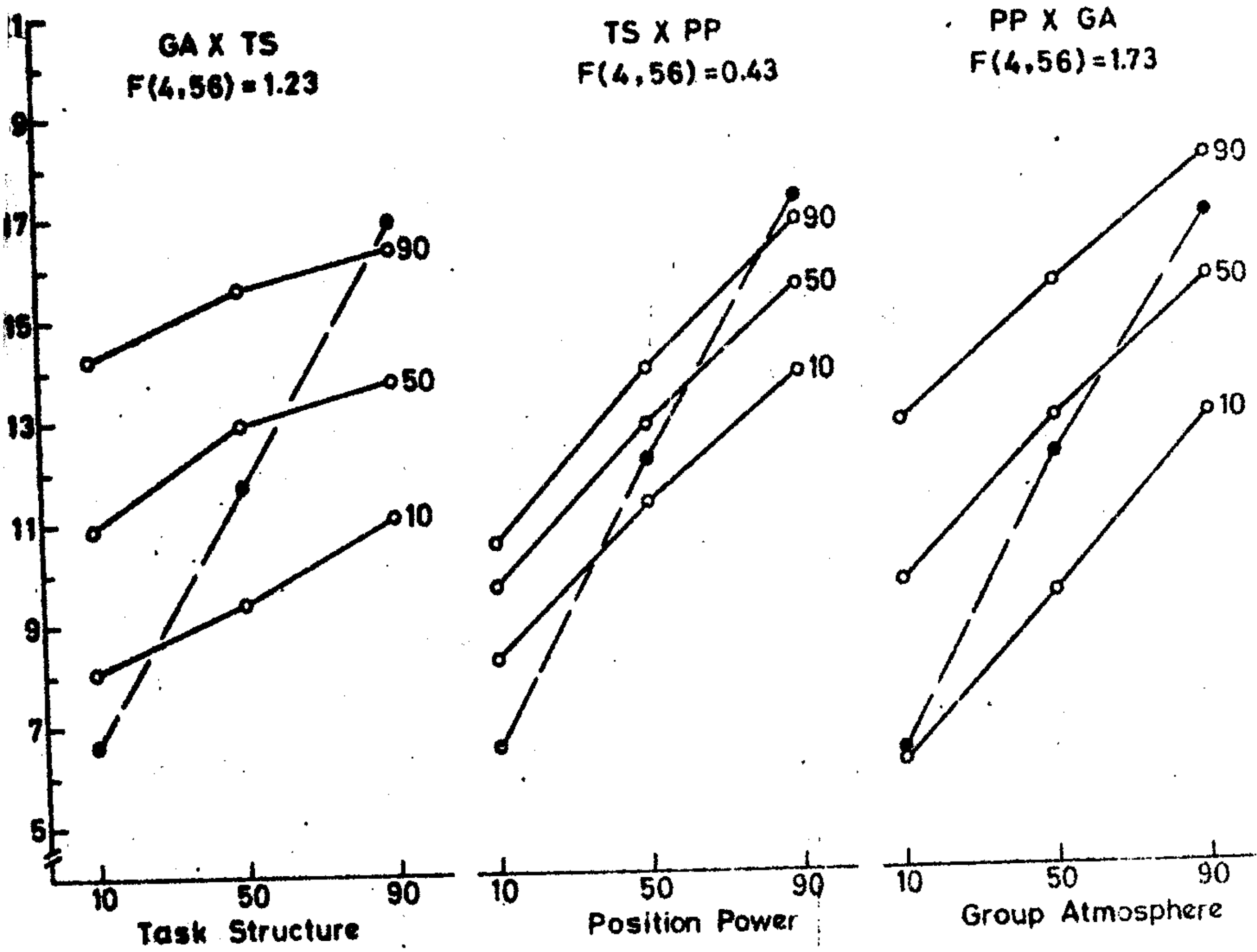

Figure 3. Mean situational favorableness as a function of group atmosphere (GA), task structure (TS), and position power (PP) of the leader. Data after Singh, Bohra, and Dalal, 1979; Figure 2, Experiment 2. (Only the profiles of 2-way interactions from the 3 x 3 x 3, GA x TS x PP, design are plotted. Listed F ratios pertain to the respective interaction effect. The dashed curves are based on only the factor listed on the horizontal axis). (Reprinted with the permission from the John Wiley & Sons, Ltd.)

Figure 3 support the averaging rule, and eliminate the adding one (Nebeker, 1975). The other 15 tests also confirmed the averaging prediction.

Success of the averaging rule in this judgmental task is very important in at least three ways. First, stimuli were described by numbers, not verbal labels as in other studies. Second, the averaging rule was supported, although the theory had predicted an adding rule. Third, and perhaps the most important, the spacing of Fiedler's octants, generated by two extreme levels of the three components, on the horizontal axis according to their functional measurement values, generated a considerably better bow-shaped curve for correlation between leadership style and effectiveness than was obtained with original octant scale (Nebeker, 1975). The judgmental data thus provide a markedly superior quantification of leadership situations than does Fiedler's octant scale.

Job Attractiveness and Satisfaction

In organizational psychology, integration rules have been of concern to those who study job satisfaction. Much of this work has related to the two-factor theory (Herzberg, Mausner, & Snyderman, 1959), which divides job factors into <u>context</u> (salary, working conditions) and <u>content</u> (achievement, work itself) categories. Factors in these two categories are assumed to have qualitatively different effects on job satisfaction. Graen (1966) stated that Herzberg et al (1959) postulate different nonlinear relationships between each of these factor categories and job satisfaction.

Figure 4 presents results from a study of expected job attractiveness and satisfaction (Singh, 1975a). Engineering students rated job descriptions according to (a) how much they would like to accept the job and (b) how satisfied they would feel with that job. Job descriptions were constructed from a 2 x 2 design, with bad and good levels of context and content factor. The mean ratings for liking (job acceptance), satisfaction, and the combined scores are thus plotted in Figure 4 as a function of context (curve parameter) and content (on horizontal axis) factors. The curves clearly exhibit parallelism contrary to the prediction from two-factor theory. It seems that the context and content factors were integrated in accord with a linear rule (i.e., constant-weight averaging).

Dalal and Singh (Note 2) extended this work further by employing more than two levels of each factor, using distinguishing tests between adding and averaging, and taking procedural precautions required by information integration theory. Graphic plots of the Context x Content effect showed a good deal of parallelism, though a small nonadditive element was also present in analysis of variance.

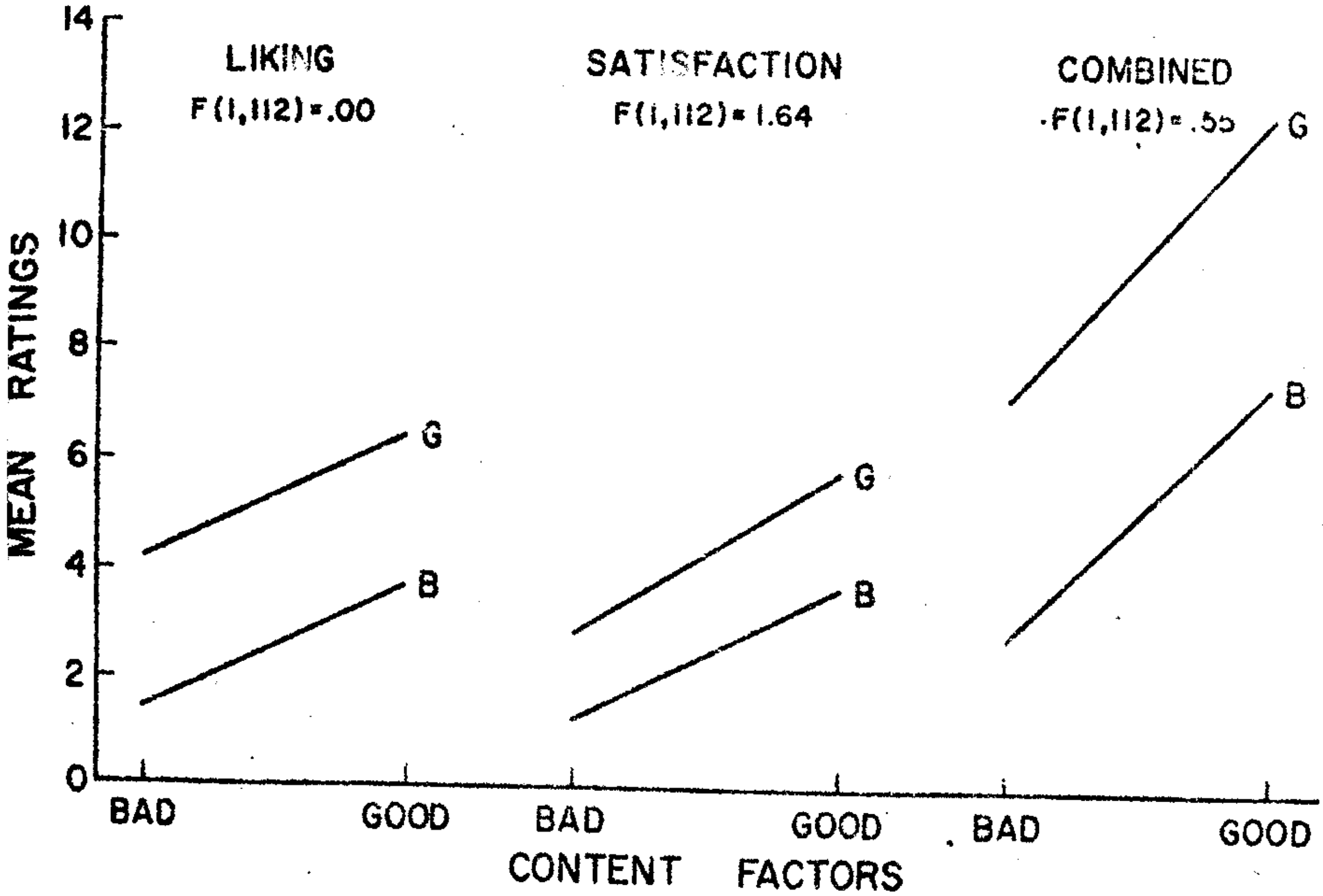

Figure 4. Mean ratings as a function of context (curve parameter) and content factor information (listed on the horizontal axis). Data from Singh, 1975a; Figure 1. (Letters B and G denote bad and good context factors. Listed F ratios are for Context x Content interaction). (Reprinted with the permission from the American Psychological Association, Inc.)

More importantly, statistical analyses of the group and individual subject data indicated applicability of the averaging rule. The averaging rule was able to account for both the parallelism and nonparallelism patterns in judgments of expected job attractiveness and satisfaction.

Attribution of Performance

How do people integrate information about motivation and ability when they predict performance? As motivation is an energizer of ability, a multiplying rule (Heider, 1958) should naturally operate. Studies of Anderson and Butzin (1974) and of Kun, Parsons, and Ruble (1974), in fact, obtained a linear fan shape as if subjects followed a multiplicative rule.

Singh, Gupta, and Dalal (1979) argued that the linear fan pattern is not unique to the multiplying rule. This pattern also follows from the differential-weight averaging rule. If lower values of motivation and/or ability had greater weight, then the averaging model would produce an approximate linear fan.

To test the plausibility of a differential-weight averaging interpretation for the multiplying-type result obtained by Anderson and Butzin (1974) and by Kun et al (1974), Singh, Gupta, and Dalal (1979) conducted a series of three experiments. Each experiment included a distinguishing test between multiplying and differential-weight averaging which was not used in the American studies.

Figure 5 plots mean judgment of performance as a function of interest in studies (curve parameter) and IQ. The IQ levels are spaced on the horizontal axis according to the marginal means of the factorial design. This spacing allows the linear fan pattern to appear. If the two pieces of information were integrated in accord with the multiplying rule, then the four solid curves would form a diverging fan of straight lines.

It is clear that the pattern of the data is contrary to the multiplying rule. There is not any evidence for divergence at all. Instead, the four solid curves display parallelism. The dashed curve, which is based on IQ information alone, further indicates that the parallelism was due to the constant-weight averaging.

This failure to replicate a linear fan pattern was unpleasant, but certainly not a methodological error. Similar results emerged in Experiments 2-3. Figure 6 lists 3 two-way interactions from a 3 x 3 x 3 (Past Performance x Laboriousness x IQ) design. The solid curves are approximately parallel in each panel. The dashed curve, which represents judgments based on just the single cue listed on the horizontal axis, also crosses over the lowest solid curve in each panel. These results suggest that attribution of performance obeys an averaging rule in India.

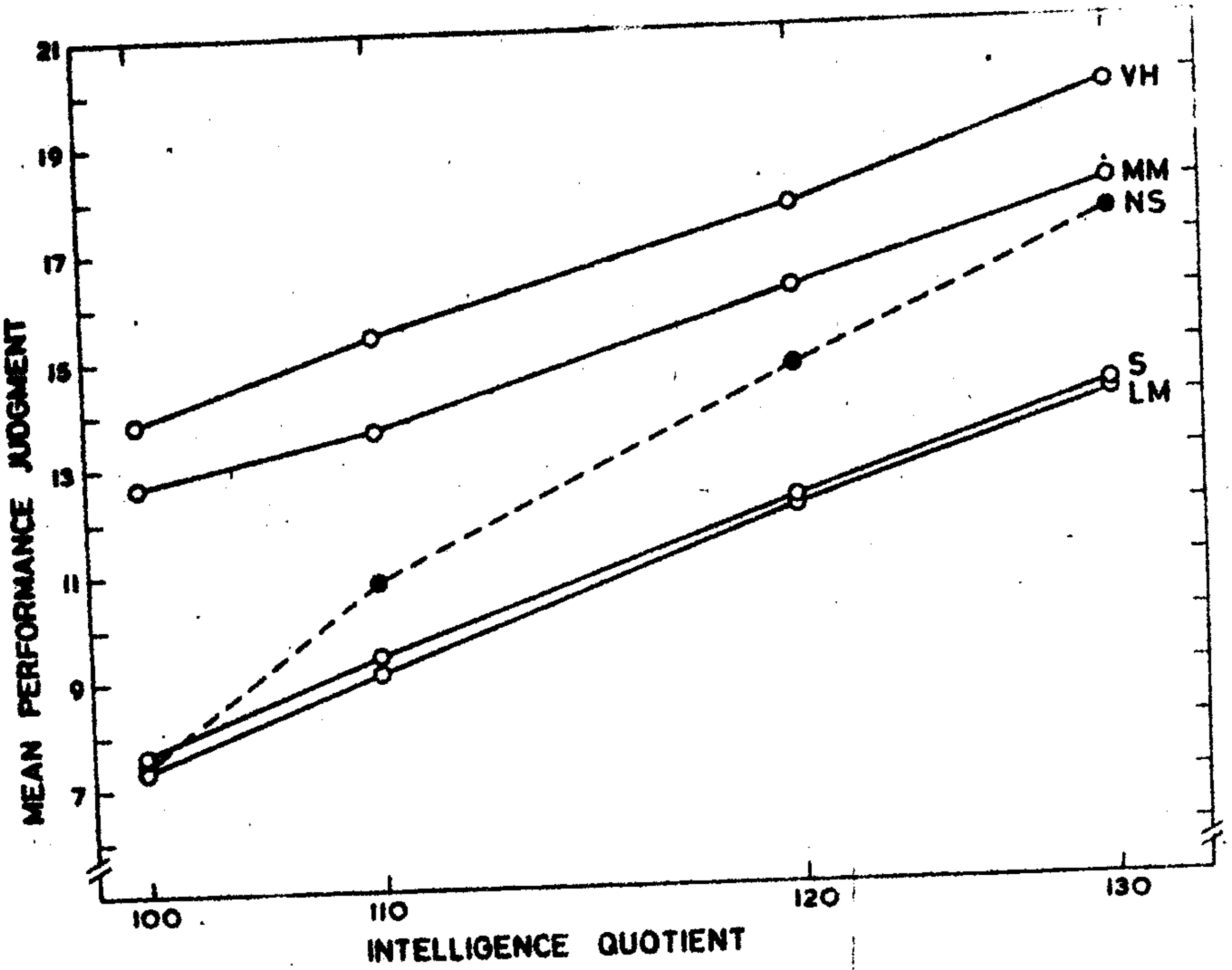

Figure 5. Mean judgment of performance as a function of interest in studies (curve parameter) and IQ (listed on the horizontal axis). Data from Singh, Gupta, and Dalal, 1979; Figure 1, Experiment 1. (VH, MM, LM, and S denote very high, more than most, less than most, and slight interest in studies, respectively. The dashed curve is based on IQ information only; interest in studies was not specified, NS). (Reprinted with the permission from the American Psychological Association, Inc.)

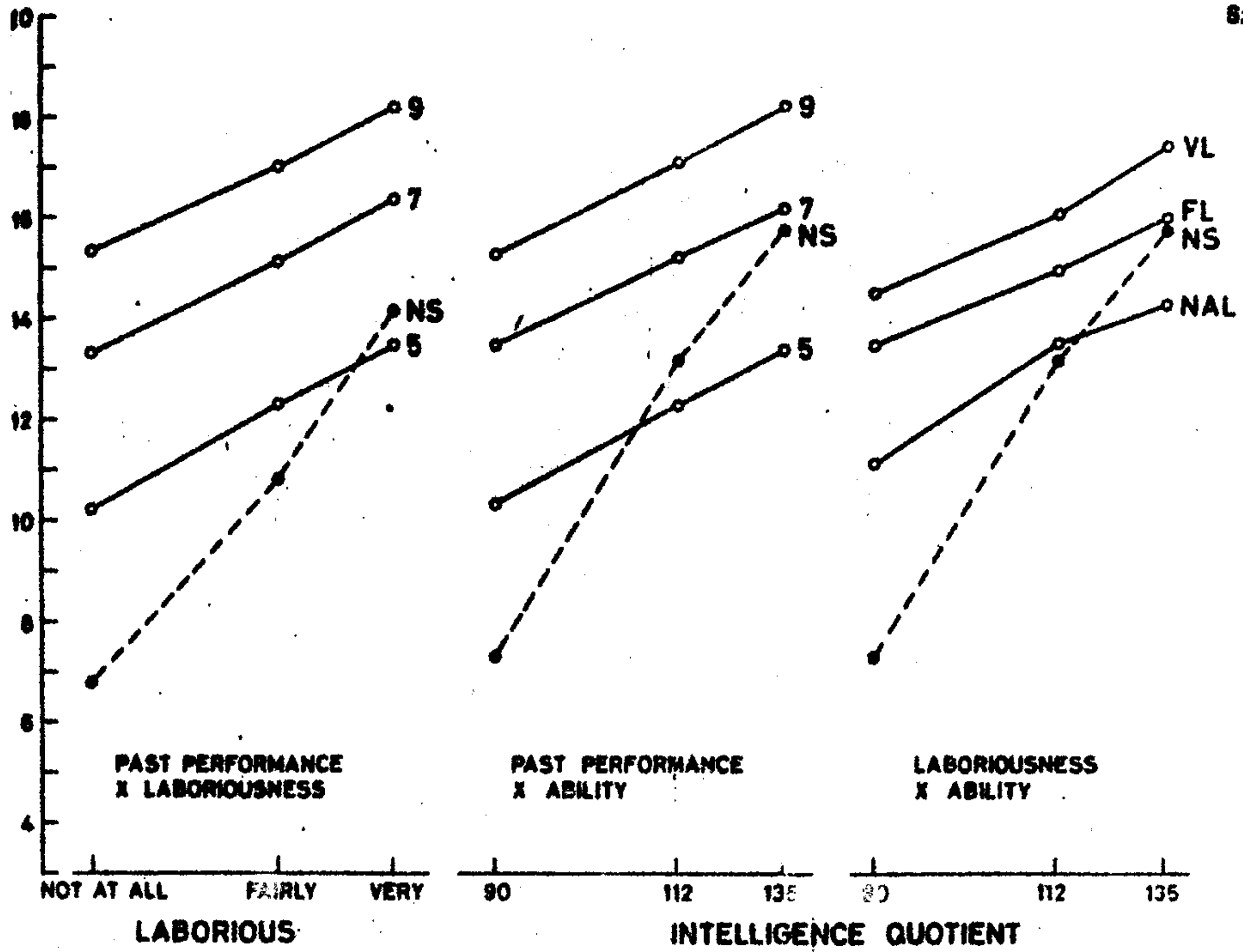

Figure 6. Two-way factorial plots of Past Performance x Laboriousness, Past Performance x Ability, Laboriousness x Ability effects on performance from the 3 x 3 x 3, Past Performance x Laboriousness x Ability design. Data from Singh, Gupta, and Dalal, 1979; Figure 3, Experiment 3. (The dashed curve of each panel is based on just the single factor listed on the horizontal axis. Digits 5, 7, and 9 represent levels of past performance; NAL, FL, and VL represent <u>not at all laborious</u>, <u>fairly laborious</u>, and <u>very laborious</u>, respectively. NS means that the row information was not specified.) (Reprinted with the permission from the American Psychological Association, Inc.)

In a developmental study, Gupta (1979) followed the logic and methods used by Singh, Gupta, and Dalal (1979). Although subjects varied in age from 6-19, her results basically corroborated the averaging rule for attribution of scholastic performance. Analyses of the data of individual child showed that information portaining to past performance, ability, and motivation were averaged in prediction of scholastic performance. This result further illustrates the power of integration-theoretical analysis of children's social perception and cognition.

Attribution of Gift Size

Although attribution of performance from information about motivation and ability was not made according to a multiplying-type rule, attribution of gift size from income (capability factor) and generosity (energizing factor) information, a conceptually very similar task, yielded a linear fan shape. Look at Figure 7 which plots mean judgment of gift size on the basis of income and generosity of the donors. The four solid curves display real divergence as was obtained in two experiments by Graesser and Anderson (1974).

However, the dashed curve, which is based on just the generosity information, does not form part of the linear fan shape as is required by the multiplying rule. According to the averaging rule, the dashed curve should cross over at least one of the solid curves.

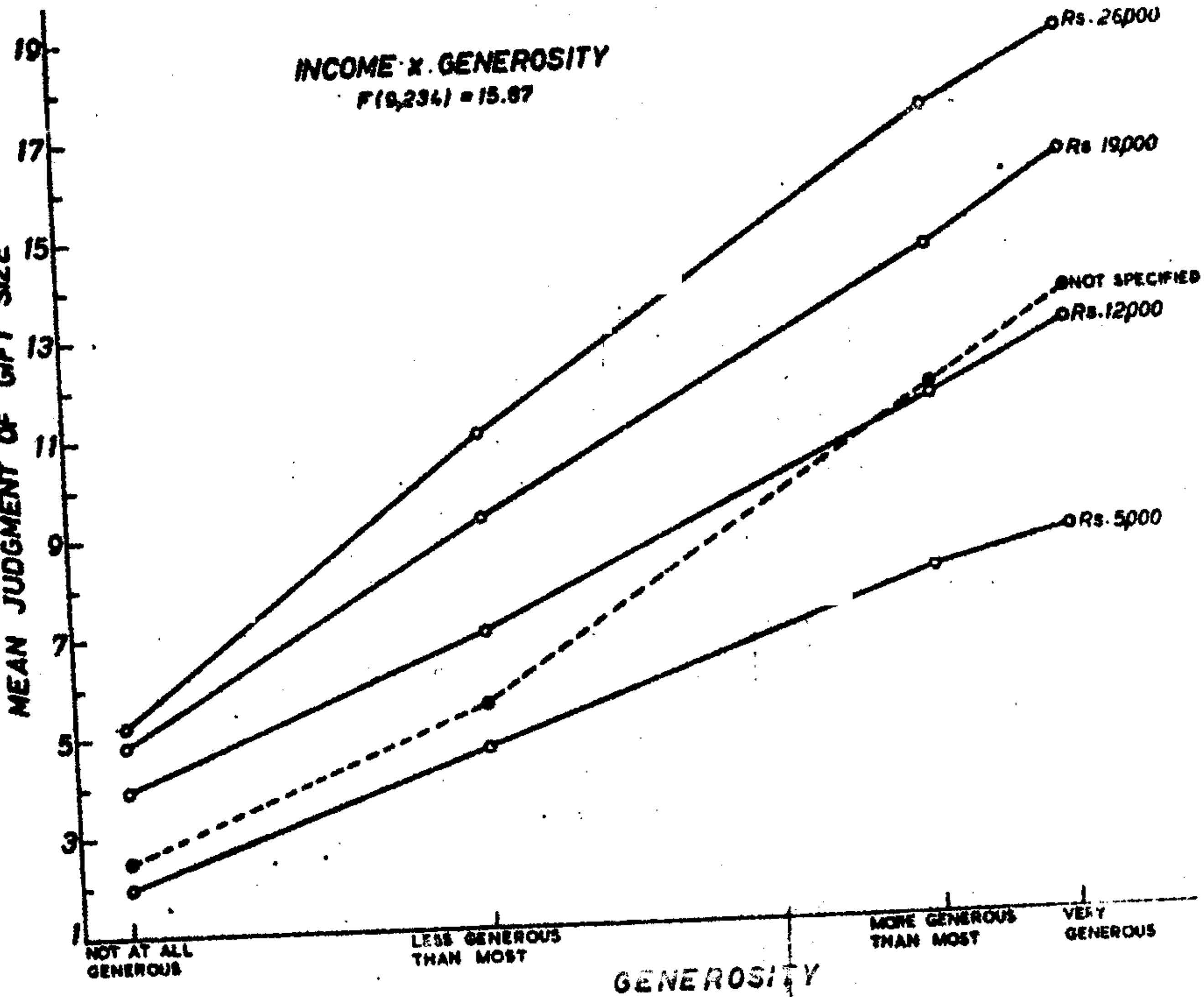

Figure 7. Mean judgment of gift size as a function of income (curve parameter) and generosity (listed on the horizontal axis) information. Data from Singh, Note 6; Figure 1, Experiment 1. (The listed *F* ratio is for Income x Generosity effect. The dashed curve is based on just the generosity information.) (Copyright © 1980 Ramadhar Singh.)

This is indeed borne out by the data. It is striking that what has been considered as multiplying (Graessor & Anderson, 1974) really turns out to be a differential-weight averaging.

Two more experiments were conducted to test the plausibility of a differential-weight averaging interpretation for the multiplying-type result in attribution of gift size. In these two experiments, information about income was varied along with two separate cues of generosity, for example, two previous actions of donations, or opinions of two fast friends. In general, results were supportive of the differential-weight averaging.

To get an idea of the results from these 3-factor experiments, examine Figure 8. It plots mean judgment of gift size as a function of income (curve parameter) and generosity (on horizontal axis) information. The generosity levels are products of two previous actions of donations constructed from a 3 x 3 design, but they are spaced on the horizontal axis according to their functional values (i.e., marginal means).

The four solid curves in Figure 8 illustrate excellent linear fan shape. The dashed curve rules out the multiplying interpretation for the linear fan pattern, however.

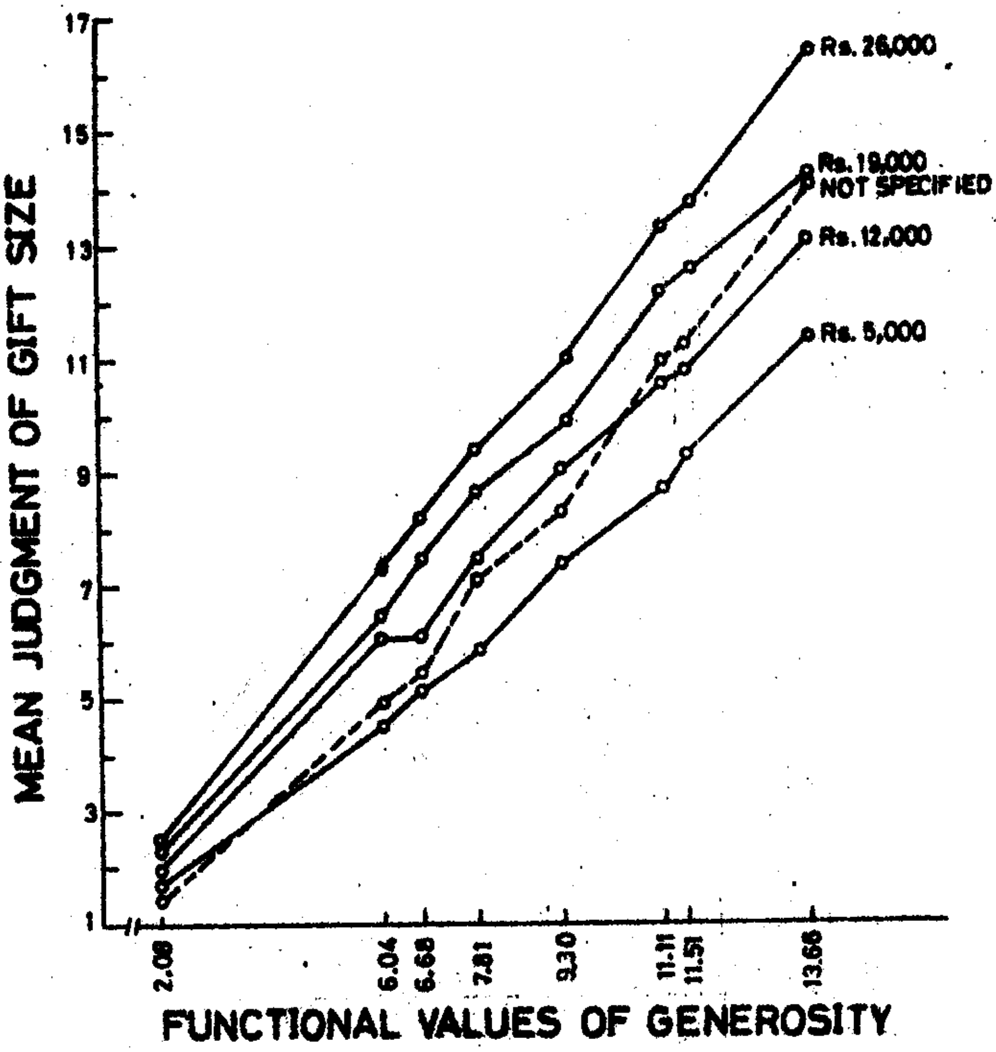

Figure 8. Mean judgment of gift size as a function of income (curve parameter) and functional values of generosity (listed on the horizontal axis). The dashed curve is based on only the generosity information. Data from Singh, Note 6; Figure 4, Experiment 3. (Copyright © 1980 Ramadhar Singh.)

Life Satisfaction

Would satisfaction of a person with his life be an average of his satisfaction with family and job? A group of sixteen supervisors from an industry made judgments of life satisfaction of some hypothetical workers prepared from a 4 x 4 (Family Satisfaction x Job Satisfaction) design. In addition, four workers were described by one of the four levels of just the job satisfaction factor. The relevant results are presented in Figure 9. The three panels plot data for all sixteen supervisors, for eleven additive supervisors, and for five nonadditive supervisors, respectively. Classification of supervisors into additive and nonadditive groups was based on single subject analyses of the 4 x 4 (Family Satisfaction x Job Satisfaction) design.

The four solid curves of Figure 9 exhibit near-parallelism. The Family Satisfaction x Job Satisfaction effect was statistically nonsignificant, which supports the visiual impression of parallelism. Also notable is the result that all supervisors followed averaging rule.

This experimental task was used with a group of sixteen students also. Students judged life satisfaction as did the supervisors. This result is important. It suggests that the often heard complaint against the generality of results obtained from

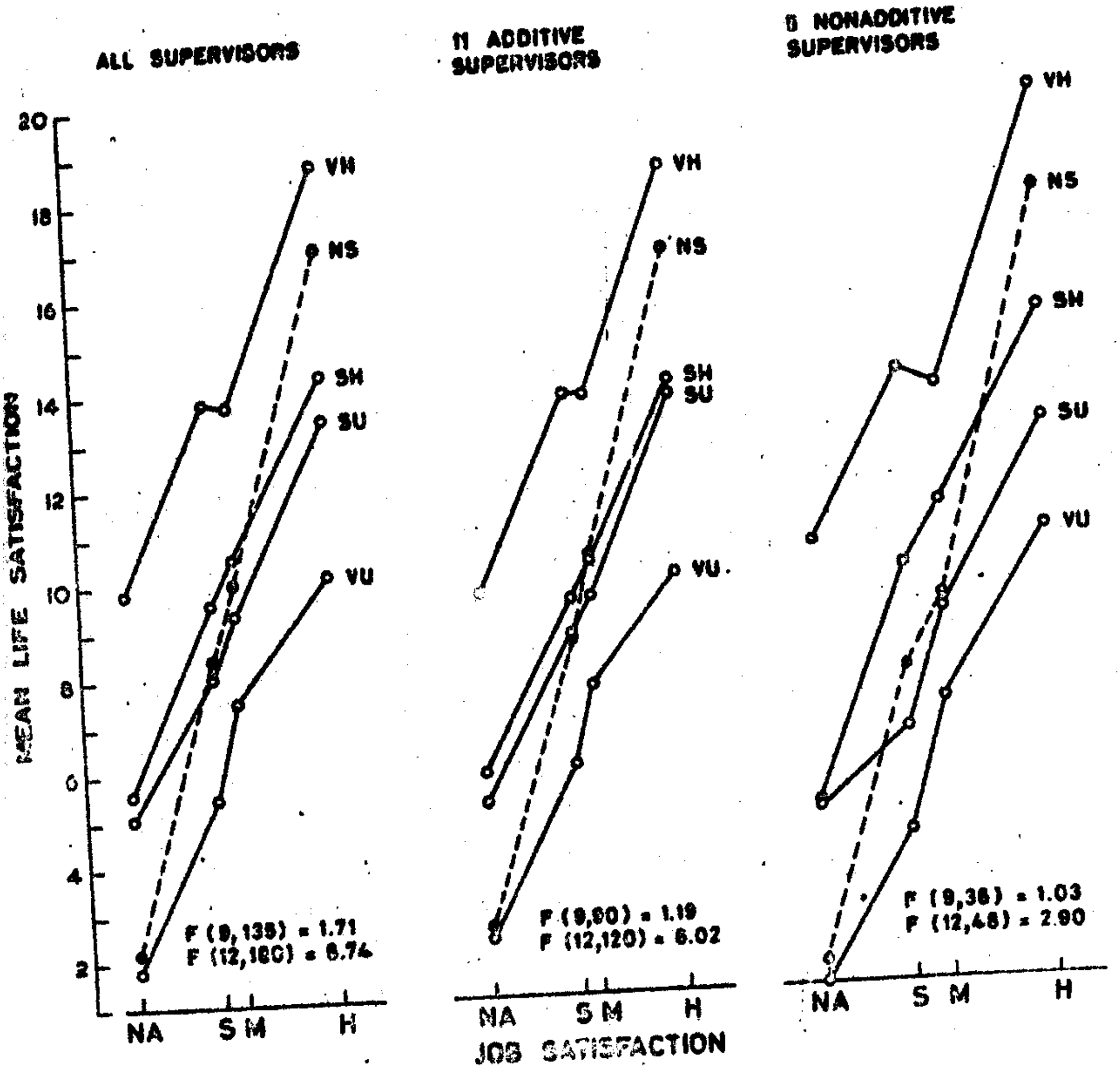

Figure 9. Mean judgment of life satisfaction as a function of family satisfaction (curve parameter) and job satisfaction (listed on the horizontal axis). The dashed curve is based on only the job satisfaction information. The three sets of curves are for all sixteen supervisors, eleven additive, and five nonadditive supervisors, respectively. The listed *F* ratios of each panel are from the 4 x 4 and 5 x 4 analyses of variance. The nonsignificance of the top *F* ratio supports parallelism of the four solid curves; the significance of the bottom *F* ratio supports crossover by the dashed curve. Data from Singh, Bohra, and Kapoor, Note 7. (VU, SU, SH, and VH refer to very unhappy, slightly unhappy, slightly happy, and very happy family life, respectively. NS means that family information was not specified. NA, S, M, and H denote not at all, slight, moderate, and high job satisfaction, respectively.) (Copyright (C) 1979 Ramadhar Singh.)

student subjects is not as serious as it is assumed to be. The averaging process is fairly general and robust.

Other Judgments

At Indian Institute of Technology, Kanpur, two engineering students applied information integration theory to the problems of transportation and computer programs. Pradhan (Note 3) asked bus users to rate attractiveness of bus systems, and obtained results supportive of the averaging rule. Chaudhary (1979) varied size, control structure, data structure, and computation structure of computer programs and obtained judgments of program complexity from computer programers. As in other studies, Chaudhary found clear support for the averaging rule in the evaluation of program complexity.

AVERAGING AS A GENERAL RULE

Results presented in the preceding section clearly show the generality of the weighted average model. Although the experiments varied widely with respects to the nature of stimuli, background of subjects, and dimensions of judgments, the findings conformed rather well to the averaging formulation. Therefore, it is appropriate to conclude that averaging is a general rule of information integration.

Most of the experiments indicated that judgments follow the simple constant-weight averaging. Evidence for the differential-weight averaging rule was limited (Dalal & Singh, Note 2; Singh, Note 6; Singh et al, 1978). Perhaps the differential-weight averaging rule is used less frequently than the constant-weight averaging rule. It does not, however, mean that it is less important. In fact, it is the differential-weight averaging that provides validation for the weight parameter of the averaging model. Furthermore, it suggests that the scale value alone is not sufficient to characterize a piece of information; weight parameter is also necessary and by no means less important.

From the vantage of the weighted average model, parallelism and nonparallelism patterns reflect the same basic averaging operation. They are obtained because of different weighting strategies, not because of different integration strategies. Results from the distinguishing tests really supported this interpretation. This power of the averaging model to unify a wide variety of seemingly different trends in human judgments is indeed commendable.

The position that averaging rule underlies much of human judgments is not new at all. The congruity model of Osgood and Tennenbaum (1955) is a weighted average model, so is Byrne's (1971) law of attraction (see Kaplan & Anderson, 1973). Manis, Gleason and Dawes (1966) have also argued for an averaging model. The problem with these models, however, is that they are not as clearly spelled out as is Anderson's model. Also, they have less solid experimental base than has the Anderson model. Because Anderson's model has passed many demanding experimental tests, qualitative as well as quantitative, its portrayal of human organism as "an analog computer of stimulus averages" (Anderson, 1968, p. 731) seems to have merit. In fact, the weighted average model has received unambiguous support in so many different stimulus situations and with so many subject populations, including young children, that it can be regarded as a general principle of human judgment and decision.

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