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Conjoint measurement is a new development in mathematical psychology that can be used to measure the joint effects of a set of independent variables on the ordering of a dependent variable. In this (primarily expository) article, the techniques are applied to illustrative problems in marketing. In addition, a number of possible areas of application to marketing research are discussed, as well as some of the methodology's limitations.

Conjoint Measurement for Quantifying Judgmental Data

The quantification of managerial or consumer judgment has long posed problems for marketing researchers, irrespective of their interest in normative or descriptive decision making. For example, most media selection models reflect some dependence on media planners' judgmental estimates [4, 5], which are often used in evaluating target populations in terms of households' or individuals' product usage or demographic and socioeconomic characteristics [6]. Moreover, subjective weights are frequently used in appraising vehicle appropriateness and advertising message perception.

Further, the study of consumer decision making requires ascertaining how buyers trade off conflicting criteria in making purchase decisions [8]. Finally, recent studies in public administration attest to a growing interest in the modeling of administrators' evaluations involving multiattribute alternatives in which the analyst must rely on judgmental estimates to a large extent [10].

The purpose of this article is to describe a new approach to quantifying judgmental data, conjoint measurement. Its procedures require only rank-ordered input, yet yield interval-scaled output.[1] The principles of conjoint measurement are discussed and synthetic data are used in solving some typical problems. The conclusion is a discussion of limitations of these techniques and potential areas of application to marketing planning and other types of choice behavior.

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CONJOINT MEASUREMENT

As the name suggests, conjoint measurement is concerned with the joint effect of two or more independent variables on the *ordering* of a dependent variable. For example, one's preference for various houses may depend on the joint influence of such variables as nearness to work, tax rates, quality of school system, anticipated resale value, and so on. Starting with the theoretical work of Luce and Tukey [14], mathematical psychologists have developed procedures for simultaneously measuring the joint effects of two or more variables at the level of interval scales (with common unit) from rank-ordered data alone.

An important special case of conjoint measurement is the *additive* model, which is analogous to the absence of interaction in the analysis of variance involving two (or more) levels of two (or more) factors in a completely crossed design [2]. In the latter procedure one tests whether or not original cell values can be portrayed as additive combinations of row and column effects. In additive conjoint measurement, however, one asks if the cell values can be monotonically transformed so that additivity can be achieved.[2]

Since the work of Luce and Tukey, mathematical psychologists have extended additive conjoint models to deal with nonadditivity, partially ordered data, and any polynomial type of function. Analogous to our discussion of the additive model, a data matrix satisfies the (more

[1] In the case of finite data, the scale is technically an ordered metric; as the number of input values increases, however, a unique representation at the interval scale level is approached.

[2] The typical handling of judgmental estimates in the media models examined here entails developing numerical estimates on a single-factor-at-a-time basis, i.e., *without* explicit consideration of interactions. In this regard the additivity assumption described here does not appear unwarranted.

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Table 1
RANK ORDER INPUT DATA FOR PROBLEM 1

Ads	Vehicles 1	2	3	4	5
1	1[a]	3	8.5	16.5	19.5
2	2	5	11	21	24.5
3	4	7	13	24.5	26
4	6	10	15	28	30
5	8.5	12	19.5	31.5	33
6	14	18	28	35	36
7	16.5	22.5	31.5	37	38
8	22.5	28	34	39	40

[a] Rank 1 indicates least effective ad-vehicle combination.

Table 2
"ORIGINAL" SCALE VALUES FOR PROBLEM 1

Ad impact values	Vehicle appropriateness values $b_1 = 2$	$b_2 = 6$	$b_3 = 13$	$b_4 = 22$	$b_5 = 24$
$a_1 = 1$	3	7	14	23	25
$a_2 = 4$	6	10	17	26	28
$a_3 = 6$	8	12	19	28	30
$a_4 = 9$	11	15	22	31	33
$a_5 = 12$	14	18	25	34	36
$a_6 = 18$	20	24	31	40	42
$a_7 = 21$	23	27	34	43	45
$a_8 = 25$	27	31	38	47	49

general) polynomial[3] model whenever it is possible to rescale each cell entry so that it is represented by a specified polynomial function of the row and column variables, and the representation preserves the rank order of the original cell entries as closely as possible [23, 26].

Without diminishing the importance of these extensions, the additive case seems to have proven quite useful in a variety of applications [3, 11, 18, 22]; thus in subsequent discussion we emphasize this special case.

Algorithms for Conjoint Measurement

The work of Luce and Tukey can be appropriately characterized as providing the conceptual foundations of conjoint measurement. One still requires algorithmic procedures for finding *numerical* representations that best satisfy the conditions described above. Recently a variety of algorithms have been developed by many of the same researchers [12, 13, 16, 24, 26] who have contributed to the (closely allied) field of nonmetric multidimensional scaling.

Kruskal's MONANOVA algorithm was used to illustrate the solution of Problems 1 and 2 (to follow) [12]. Problem 3 can be solved by a variety of nonmetric scaling algorithms. One such algorithm, Young and Torgerson's TORSCA [27] program, is employed illustratively here.

APPLYING CONJOINT MEASUREMENT PROCEDURES

Problem 1

> A media planner must select medical journals for promoting a new ethical drug. Specifically, he is interested in assigning importance values to 8 print advertisements (whose appeals vary) and 5 journals that represent possible vehicles for the candidate ads. He feels that he can rank the 40 ad-vehicle combinations in terms of overall effectiveness, but is not confident about assigning numerical (interval-scaled) weights to ad impact[4] or vehicle appropriateness, either on a one-variable-at-a-time basis or in combination. However, he would ultimately like to have numerical values (interval scaled and expressed in terms of a common unit) of *both* ad impact and vehicle appropriateness.

To make the discussion more transparent, the values in Table 1 are assumed to represent the media planner's ranking of the 40 ad-vehicle combinations in terms of overall effectiveness. In actuality the rank numbers of Table 1 were obtained by merely transforming the cell entries of Table 2, which *do* represent additive combinations of row and column effects, to integer ranks (including ties). If the procedure works, one would expect to "recover" the original row and column scales up to positive linear transformations (with common unit but arbitrary origins).

Kruskal's MONANOVA algorithm was applied to the ranked data of Table 1. The stress (badness of fit) was virtually zero (actually 0.002), as would be expected given the error-free data used in this example.

The upper panel of Figure 1 shows scatter plots of the main effects (estimated by the program) on the original row and column values, respectively, of Table 2. Also shown (in the lower panel of Figure 1) is the monotone function that relates the input data from Table 1 to the cell values that are estimated by the model. This function is also found by the program.

At this point, then, the media planner has developed:

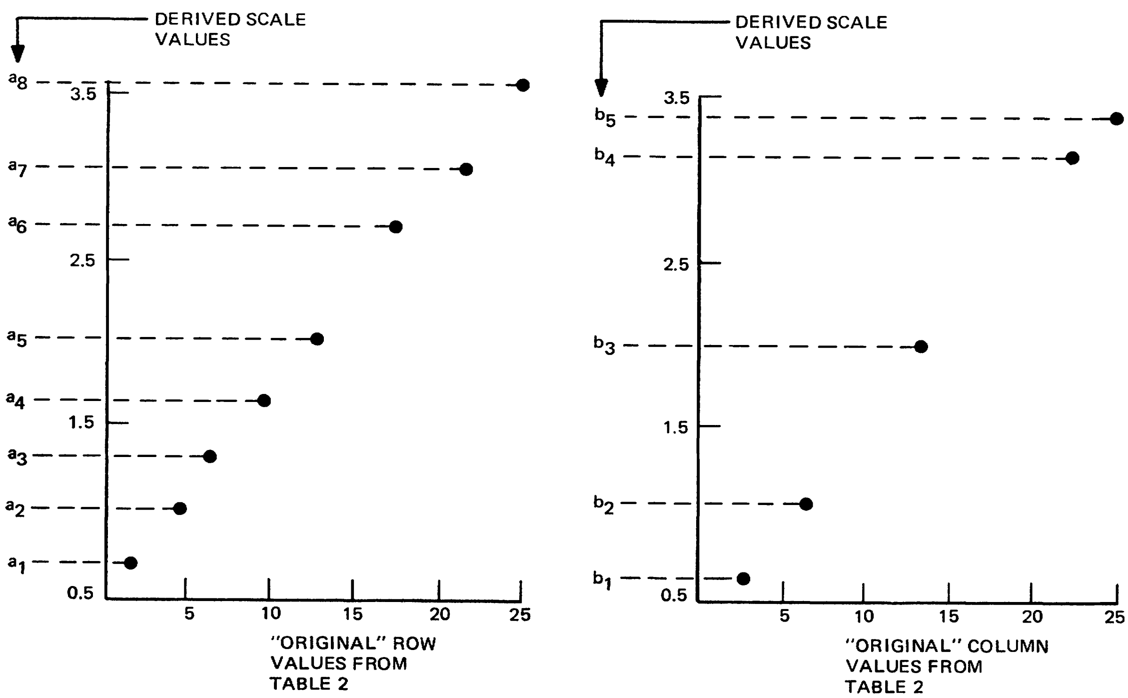
1. Separate interval scales for ad impact (the row values) and vehicle appropriateness (the column values), as shown by projections onto the vertical axes of the two scatter diagrams in Figure 1. Moreover, these scales are expressed in terms of a common unit.
2. Interval-scaled cell entries for each of the 40 ad-vehicle combinations. These represent the simple sum of the derived row and column scales whose values are shown on the vertical axes in the two scatter diagrams.

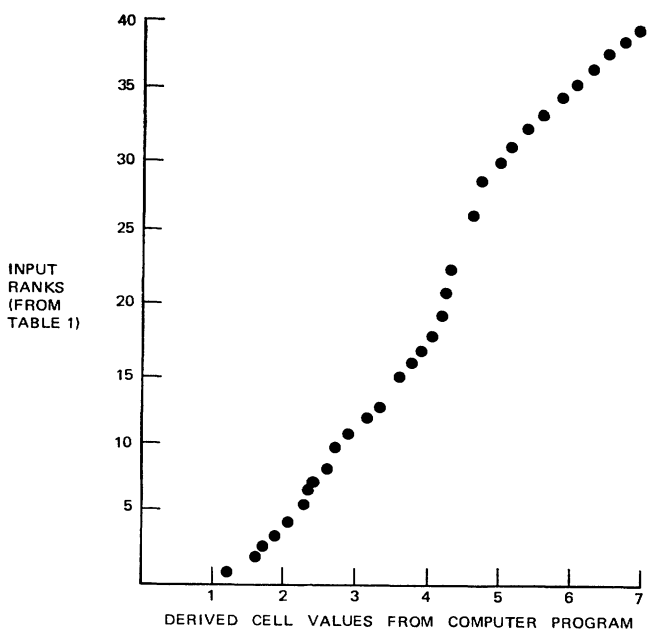
[3] A "polynomial" function involves a specific combination of sums, differences, and products of its arguments.

[4] Ad impact is defined as the relative value of an ad in prompting perception of the message. Presumably ad impact reflects the judger's evaluation of both its thematic and physical aspects [19].

Figure 1

SCATTER PLOTS OF DERIVED VS. ORIGINAL ROW AND COLUMN EFFECTS AND INPUT RANKS VS. DERIVED CELL VALUES





The above interval-scaled values can then be used as direct numerical judgments are used in various media selection models.

At this point it is useful to discuss the motivation and assumption structure underlying the application of additive conjoint measurement. First, we assume that the media planner would find direct numerical rating of the ads and vehicles too difficult; second, if he merely ranked ads and vehicles separately, he would *not* have enough information to derive interval scales. Ranking conjoint pairs (ad-vehicle combinations) provides sufficient information for finding separate *numerical* scales for each.

The additive conjoint measurement model entails the following assumptions:

1. The data matrix (Table 1) contains elements that can be at least weakly ordered (may contain ties).
2. Each derived cell value represents an additive combination of separate (real-valued) functions of the row and column elements.
3. Each numerical cell value in the derived solution comes as close as possible to maintaining the rank order of the input data.[5]

Thus the additive conjoint model is a monotone analogue of main-effects analysis of variance. In Problem 1 the arguments of the row and column functions are nominal variables, viz. the specific ads and vehicles.

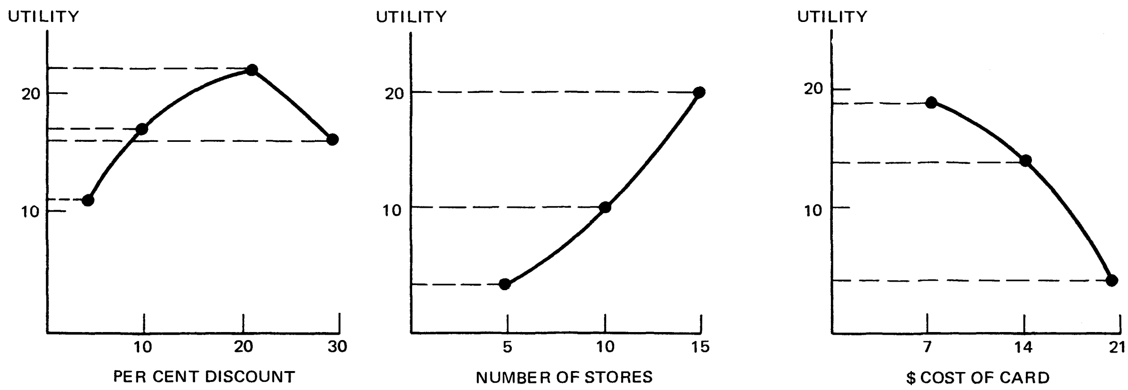
Problem 2

A marketing researcher is interested in finding component utilities (or part-worths) that housewives attribute to various characteristics of discount cards, e.g., size of discount, number of cooperating stores

[5] Necessary and sufficient conditions for the existence of such additive transforms can be found in [2]. The axiomatic structure for the more general polynomial model appears in [23].

Figure 2

GENERATION OF ORIGINAL VALUES FOR PROBLEM 2 AND CELL VALUES OBTAINED FROM COMPONENT UTILITIES



Size of discount	Cost of card								
	5 stores			*10 stores*			*15 stores*		
	$7	*$14*	*$21*	*$7*	*$14*	*$21*	*$7*	*$14*	*$21*
5%	34	29	19	40	35	25	50	45	35
10%	40	35	25	46	41	31	56	51	41
20%	45	40	30	51	46	36	61	56	46
30%	39	34	24	45	40	30	55	50	40

in the trading area, and initial cost of the card. Sample discount cards are prepared whose levels on each of the above characteristics are systematically varied on the basis of four levels for the first factor and three levels each for the second and third factors. A housewife is asked to rank the resulting 36 cards in terms of "best buy for the money." The researcher is interested in deriving the housewife's component utilities (positive or negative) for each of the three factors considered jointly.

This problem differs structurally from the previous one. First, it is represented by a three-way (4 × 3 × 3) rather than two-way design. Second, the arguments of the contributory factors—size of discount, number of cooperating stores, and initial cost of card—are ratio rather than nominal-scaled variables.

Table 3 illustrates the rank order data that could be gathered in this type of situation, and Figure 2 shows how these were actually generated. For each factor we assume that the housewife has an implicit component utility (or disutility) function, shown by the curved lines in Figure 2. While she cannot explicate these functions, her overall ranking of the discount cards reflects an additive combination of the values of each individual utility function for the discrete levels of each factor utilized in the experiment. For example, the first cell value of 34 in the lower panel of Figure 2 is the sum of 11, 4 and 19, the component utilities shown in the upper panels. The values of these functions are indicated by dotted lines. Note that the functions need not be linear or even monotone (as illustrated for the size-of-discount factor).

In this case we wished to find the selected values of each component utility function for selected levels of each factor. The ranked data of Table 3 were again processed [12] and the results are shown in Figure 3. The upper panel shows "recovered" component utilities. Note that the derived utilities match closely (up to a linear transformation with common unit) the original values shown in Figure 2. The lower panel of Figure 3 shows the appropriate monotone transform that links the derived cell values to the original ranked data of Table 3.

Problem 2 illustrates that additive conjoint measurement provides a potentially useful tool for estimating component utilities from preferences for a composite (complete) discount card profile.

Problem 3

A researcher in public administration is interested in developing an interval scale of law enforcement officers' opinions of the seriousness of various forms of drug abuse, e.g., marijuana, amphetamines, hashish, heroin, etc. Eight such drugs have been listed; for each pair of drugs the respondent is asked to state: (1) which drug of each pair is more serious (in terms of harm to the user) and (2) the intensity of difference in seriousness, expressed as a rank number on an ordered-category scale. From such ranked values the

Table 3

RANK ORDER INPUT DATA FOR PROBLEM 2

Size of discount	Cost of card								
	5 stores			10 stores			15 stores		
	$7	$14	$21	$7	$14	$21	$7	$14	$21
5%	9.5	5	1[a]	18	12	3.5	29.5	24	12
10%	18	12	3.5	27	21.5	8	34.5	31.5	21.5
20%	24	18	6.5	31.5	27	14	36	34.5	27
30%	15	9.5	2	24	18	6.5	33	29.5	18

[a] Rank 1 indicates worst buy for the money.

researcher would like to develop a unidimensional interval scale on which the eight drugs can be positioned in terms of perceived personal harm.

Problem 3 illustrates the more general (polynomial) form of conjoint measurement. Table 4 shows the law enforcement officer's set of responses of the intensity with which each pair of drugs is separated in terms of seriousness. For example, suppose he judged Drug 2 to be more serious than Drug 1. In addition, he assigned a rank of 1 on a 7-point intensity scale to reflect his feeling that the difference in seriousness is quite low in intensity. Thus the first cell shows the value of 1.

As before, Table 4 was derived from the synthetic data of Table 5, in which the (assumed) interdrug distances are shown. For example, the first cell value of 3 in Table 5 is the distance between Drug 1 and Drug 2 ($3 = 4–1$). Note that the ranked data of Table 4 do not tell us, per se, what the rank order of values (on a scale of seriousness) is, as derived from the respondent's paired comparisons. However, in the errorless case described here this rank order will be preserved.

The data matrix of Table 4 was then submitted to the TORSCA program to find a one-dimensional solution [27]. The stress value was 0.082, reflecting the large number of ties in the input data.

Despite the somewhat high stress value, recovery of the unidimensional scale—both in rank order and scale values—is excellent. The left-hand panel of Figure 4 shows a scatter plot of the derived scale values (from TORSCA) vs. the original scale values. The linearity between the two scales is quite evident. As a matter of interest, the product moment correlation between derived and original interpoint *distances* is 0.99. The right-hand panel shows a plot of input data ranks (shown originally in Table 4) on interpoint distances obtained from the scaling program, showing the specific monotone transform that links each set of values.

Problem 3, though viewed as a scaling-type problem, illustrates a more general combinatorial rule than the additive rule utilized in solving Problems 1 and 2. In this case the joint effect (as noted in Table 4) is in terms of a monotone transform function that is represented by the square root of the squared difference of each pair of scale values on a single dimension,[6] (the original scale of Table 5). In this sense nonmetric scaling, unidimensional or multidimensional, can be viewed as a special case of polynomial conjoint measurement.

LIMITATIONS OF THE TECHNIQUES

As might already have been surmised, the additive assumption used in solving Problems 1 and 2 may be unduly restrictive: bona fide interactions may be present. If so, more general polynomial models are called for.[7] However, we suspect that in many instances the simpler (additive) model represents a very good approximation of reality. That is, what are often called "interactions" in traditional ANOVA applications may be the result of our failure to measure the effects of independent variables on the correct scales in the first place [9].

However, as suggested by Problem 3, the respondent may not behave unidimensionally toward the prespecified criterion. This could be reflected in the failure of the paired comparisons to generate a complete rank order (necessitating the use of nearest adjoining order techniques [20]) or the failure of a one-dimensional scaling solution to accommodate the data. If such results occur, it seems to us that the researcher should recognize the multidimensional nature of the criterion and deal with it as such (e.g., as a linear combination of more basic dimensions). Some of our recent research suggests that multidimensional scaling results *can* occur in the context of so-called unidimensional constructs that are often used for rating scale purposes.

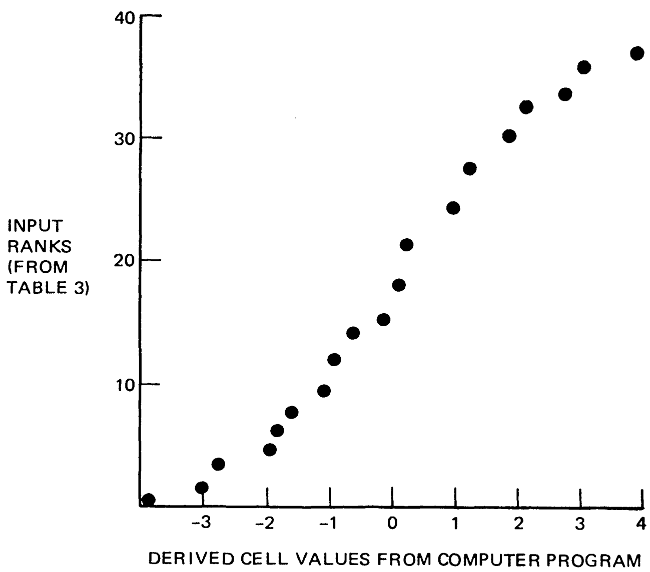
Third, in dealing with large-size problems (Problem 1 or Problem 2) the ranking task becomes formidable. Here we would favor the use of ordered categories, say, on a 9 or 11-point scale, in which each combination of ad-vehicles would receive a rating of favorableness. Moreover, some comparisons could be omitted, inasmuch as the programs tolerate missing data. However, relatively little is known about which (and how many) comparisons

[6] In the one-dimensional case all Minkowski metrics yield the same result.

[7] Recent developments [26] have provided appropriate algorithms for the more general case in which "genuine" interactions may exist.

Figure 3

DERIVED COMPONENT UTILITIES AND INPUT RANKS VS. DERIVED CELL VALUES



are the best ones to omit [8]. Finally, one could use various designs—fractional factorials—that reduce the number of combinations while still permitting the "estimation" of main effects.

Fourth, as in nonmetric scaling, conjoint solutions are susceptible to certain types of degeneracy; some of these cases are described by Kruskal [12].

Finally, it is still a moot point as to whether direct numerical estimation procedures would lead to results comparable to those arrived at through ranking followed by conjoint measurement. We have assumed throughout the exposition that it is easier for a judge to rank items than it is to provide direct numerical values. At this stage of methodological development it seems that cross-comparisons of procedures would be needed before one could make any definitive evaluation of the merits (or demerits) of conjoint measurement procedures vs. direct numerical estimation.

OTHER AREAS OF APPLICATION

Before commenting on other areas of potential application, it should be mentioned that the approach illustrated above can be generalized to deal with: (1) more than three independent variables and (2) more than a single assessor. An illustration of the first case is where the discount card profile is further characterized by: (1) nearness of stores to respondent's home and (2) type of cooperating store, e.g., specialty stores only vs. specialty and department stores. No new principles are involved; in this case a five-way (rather than three-way) matrix would be set up for evaluation. (The implied ranking task might be quite formidable, however, unless some type of fractional factorial design were used.)

If several assessors were involved one could: (1) develop each evaluator's scale values separately, (2) sum the rankings over assessors and do a group analysis, or (3) use a preliminary cluster analysis and develop a limited number of points of view with a separate set of scales for each. We favor the third procedure, particularly because of its value in linking between-group differences with other (background) characteristics of the evaluators.

It is not at all difficult to imagine other areas where conjoint measurement could be used in marketing research. The following list is meant to illustrate potential content areas and is included largely to stimulate the reader's curiosity about the applicability of the methodology to his own areas of interest. We emphasize the fact that the proposed applications are speculative—empirical research in conjoint measurement is just beginning.

Vendor Evaluations

In industrial marketing, conjoint measurement could be used in developing purchasing agents' ratings of (hypothetical) vendors on a variety of evaluative scales, such as delivery reliability, product quality, technical service back-up, and so on. For example, this could be done by setting up vendor profiles of, say, five factors, each at two levels of effectiveness, a total of 2^5 or 32 combinations [25]. By using a procedure similar to that in Problem 2, one could obtain component utilities for each level of each of the factors. These, in turn, could be utilized in developing effectiveness measures for real vendors.

Table 4

RANK ORDER INPUT DATA FOR PROBLEM 3

Drugs	Drugs 2	3	4	5	6	7	8
1	1[a]	2	4	4	6	7	7
2		1[a]	2	3	5	6	7
3			1[a]	3	5	6	7
4				1[a]	4	4	6
5					3	4	5
6						2	3
7							2

[a] Rank 1 stands for very little difference in seriousness between members of a pair of drugs.

Price-Value Relationships

A combination of additive conjoint measurement and intensity scaling could be used to measure consumers' evaluations of price-value [17]. First, intensity scaling (as applied in Problem 3) could be used to develop a unidimensional scale of quality for, say, a set of brands of electric dryers without any (explicit) price information about the brands. Then the respondent would be shown combinations of the brands and prices (e.g., all crossed combinations of 6 dryers and 6 price levels) and asked to rank the 36 brand-price combinations with regard to best value for the money. In this way one could obtain conjoint scales of price disutility and quality utility, as well as the psychophysical transforms that relate each, respectively, to objective price and the previously obtained quality scale.

Bayesian Prior Estimation

Intensity scaling could be used to develop Bayesian prior distributions by generalizing Smith's procedure to a higher-ordered metric [7, 15, 21]. The resulting interval scale would require some direct estimation to establish an origin in order to convert the interval-scaled values to a ratio scale. Moreover, by using more general conjoint measurement models (e.g., multiplicative), other types of probability assessment could be made as well (e.g., joint probabilities). Alternatively, log transformations could be used [23].

New Venture Appraisal

Conjoint measurement techniques could also be used to measure a decision maker's trade-offs between mean and variance of cash flow by showing him an array of cash flow distributions varying in mean and dispersion (or, if desired, additional moments of the distribution). The additive conjoint model could then be applied to assess the component utilities of each level of each moment of the probability distribution in overall preference.

In a variant of this procedure, the assessor would rank research project descriptions and cost outlay combinations in terms of likelihood of successful completion over a target planning period. Or his preference for alternative "futures" characterized by scenarios containing profile descriptions of company position and various environmental variables could be determined. This last application could have relevance for long-range planning studies.

Promotional Congruence Testing

Still another area of application concerns measurement of the joint effects of congruent characteristics—package design, copy theme, price, brand image—on the overall evaluation of a brand. The relationship among congruent (vs. discrepant) elements of the marketing mix could be assessed in terms of the component scale values derived from conjoint measurement models. In principle, advertising campaigns could be designed around those promotional elements that, in combination, produce the highest consumer evaluations for a specified target group and implementation cost.

Attitude Measurement

Many approaches to scaling attitudes toward objects assume a type of additive model in which total affect is represented by a linear combination of evaluative beliefs. For example, brands may be described in terms of a set of attributes and respondents asked to rate each brand: (1) with regard to the level of each attribute and (2) in terms of overall value. Multiple regression may then be used to solve for "importance weights" (the regression coefficients) for assigning to each attribute in order to maximize the correlation between overall worth and a linear combination of the attribute ratings.

This type of problem can be handled within the conjoint measurement framework by first using the scaling approach associated with Problem 3 to obtain attribute scale values. Then one can use the approach associated with Problem 2 to find part-worths for each evaluative belief, utilizing, for example, additive conjoint measurement. As such, the subject's overall evaluations need only be rank ordered, i.e., monotone regression would replace linear regression under this approach.

Functional vs. Symbolic Product Characteristics

One of the perennial problems in marketing concerns the relationship between functional vs. symbolic charac-

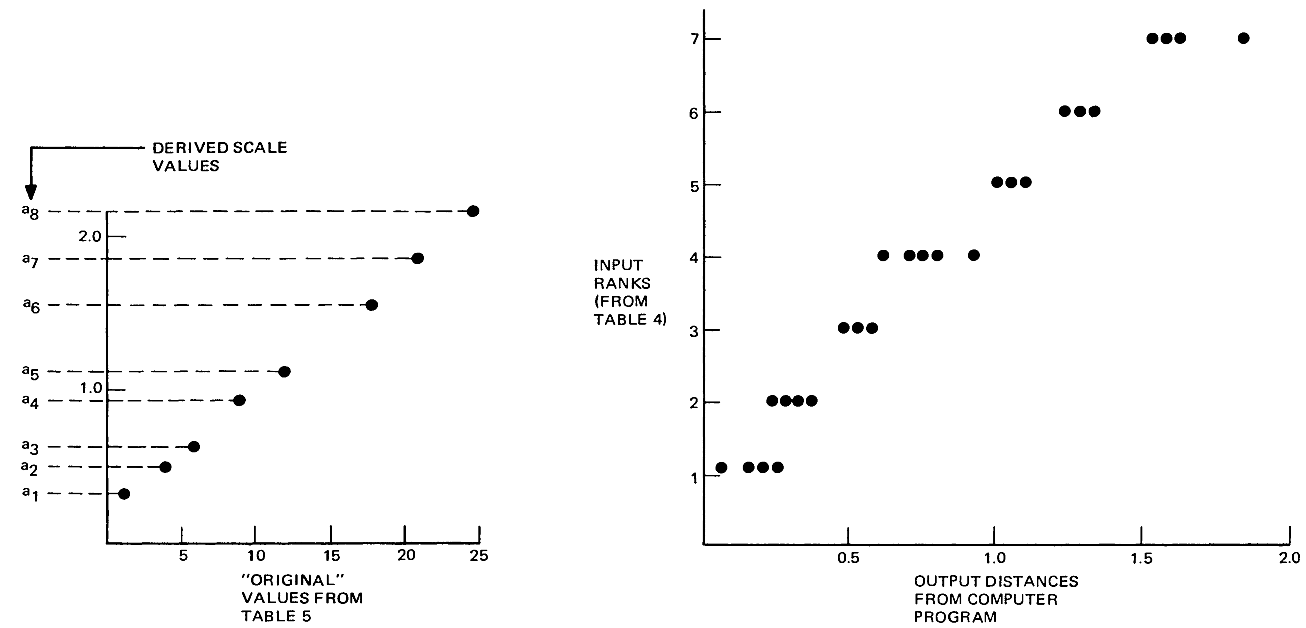
Table 5

"ORIGINAL" DISTANCE VALUES FOR PROBLEM 3

Scale value of drugs	Drugs d_2	d_3	d_4	d_5	d_6	d_7	d_8
$d_1 = 1$	3	5	8	11	17	20	24
$d_2 = 4$		2	5	8	14	17	21
$d_3 = 6$			3	6	12	15	19
$d_4 = 9$				3	9	12	16
$d_5 = 12$					6	9	13
$d_6 = 18$						3	7
$d_7 = 21$							4
$d_8 = 25$							0

Figure 4

SCATTER PLOTS OF DERIVED VS. ORIGINAL UNIDIMENSIONAL SCALE VALUES AND INPUT RANKS VS. OUTPUT DISTANCES



teristics of brands in consumer evaluation. In principle, this problem could be approached by first characterizing each (unidentified) brand in terms of a functional, or performance, profile. Brand "quality" scores could then be developed by obtaining consumer responses to various profile-price combinations according to a factorial design, similar to those already discussed.

Then, in a second phase of the experiment, the same subjects would be shown brand-price combinations and a new set of brand "quality" scores obtained for each (now identified) brand. Differences between each brand's score (identified and unidentified) may be taken as a rough approximation of "symbolic" quality. Moreover, each subject could be characterized in terms of the extent to which functional vs. symbolic characteristics are important to her overall evaluation. Finally, the approach might be extended across product classes in an attempt to develop indices of brand differentiation at the product class level.

Utility for Item Collections

Conjoint measurement could also be used as a complement to multidimensional scaling procedures in measuring the utility of collections of items. For example, multidimensional scaling may be used to scale separate sets of items, e.g., appetizers, entrees, and desserts. As might be surmised, the perceptual dimensions would probably differ across the three sets. Conjoint measurement could then be used to find utility scales for items of each set in the context of a complete menu of appetizer, entree, and dessert. These scales could then be related to the separate spaces obtained from the multidimensional scaling procedures.

If all items are from the same set, e.g., cereals, conjoint methods could still be used in conjunction with multidimensional scaling to develop utility scales in the context of collections of items—ideal assortments of cereals for combination packaging. It is possible that this approach may yield insight into such interesting problems as the utility for variety and the relationship of assortment values to component values when the latter are considered as alternative first choices (the usual assumption in the scaling of preference data).

Cost-Benefit Analysis

To us one of the most exciting areas of potential application is the use of conjoint measurement models in assessing trade-off relationships in the development of multiattribute effectiveness measures. As an illustration, suppose a number of alternative law enforcement plans were designed and characterized by such attributes as: (1) crime rate, by major category; (2) criminal arrest rate; (3) criminal rehabilitation rate; (4) cost, and so on. Again, in principle, one could develop public officials' trade-off relationships in terms of the implied component utilities developed from applying conjoint measurement models. One study has demonstrated the feasibility of this approach in education [1].

Analysis of Variance

The preceding areas have emphasized behavioral data, but additive conjoint measurement can also be used in analyzing factorial experiments, where the analysis is similar in spirit to ANOVA models. Perhaps the most useful procedure would be to apply the conjoint measurement model as a preliminary technique in order to see if a monotone transform is sufficient to make the cell entries additive combinations of row and column effects (in the two-way design). Since conjoint measurement algorithms include a display of the best fitting monotone transform, in discrete form, of course, this by-product is useful in the selection of a *specific* functional form—logarithmic, square root, etc.—prior to conducting a standard ANOVA test.

CONCLUSIONS

The primary purpose of this article has been to introduce marketing researchers to some of the concepts and potential applications of conjoint measurement. It seems to us that various types of marketing planning models and other procedures using judgmental estimates in a formal manner might benefit from the utilization of conjoint models—additive or, more generally, polynomial. Moreover, buyer preferences for multiattribute items may also be decomposed into part-worth evaluations in a similar manner.

Too little is known at this time about the relative advantages and disadvantages of these techniques compared to procedures using direct numerical estimation. Hopefully, some of the areas of application mentioned in this article will pique researchers' interests enough to prompt more thorough investigation of some of the research possibilities raised in this overview article.

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