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The authors suggest the use of D-efficient experimental designs for conjoint and discrete-choice studies, discussing orthogonal arrays, nonorthogonal designs, relative efficiency, and nonorthogonal design algorithms. They construct designs for a choice study with asymmetry and interactions and for a conjoint study with blocks and aggregate interactions.

Efficient Experimental Design with Marketing Research Applications

The design of experiments is a fundamental part of marketing research. Experimental designs are required in widely used techniques, such as preference-based conjoint analysis and discrete-choice studies (e.g., Carmone and Green 1981; Elrod, Louviere, and Davey 1992; Green and Wind 1975; Huber et al. 1993; Lazari and Anderson 1994; Louviere 1991; Louviere and Woodworth 1983; Wittink and Cattin 1989). Ideally, marketing researchers prefer *orthogonal* designs. When a linear model is fit with an orthogonal design, the parameter estimates are uncorrelated, which means each estimate is independent of the other terms in the model. More importantly, orthogonality usually implies that the coefficients will have minimum variance, though we discuss exceptions to this rule. For these reasons, orthogonal designs are usually quite good. However, for many practical problems, orthogonal designs are simply not available. In those situations, *nonorthogonal* designs must be used.

Orthogonal designs are available for only a relatively small number of very specific problems. They may not be available when some combinations of factor levels are infeasible, a nonstandard number of runs (factor level combinations or hypothetical products) is desired, or a nonstandard model is being used, such as a model with interaction or polynomial effects. Consider the problem of designing a discrete choice study in which there are alternative specific factors, different numbers of levels within each factor, and interactions within each alternative. Orthogonal designs are not readily available for this situation, particularly when the number of runs must be limited. When an orthogonal design is not available, an alternative must be chosen—the experiment can be modified to fit some known orthogonal design, which is undesirable for obvious reasons, or a known design can be modified to fit the experiment, which may be difficult and inefficient.

Our primary purpose is to explore a third alternative, the use of optimal (or nearly optimal) designs. Such designs are typically nonorthogonal; however, they are efficient in the sense that the variances and covariances of the parameter estimates are minimized. Furthermore, they are always available, even for nonstandard situations. Finding these designs usually requires the aid of a computer, but we want to emphasize that we are not advocating a black-box approach to designing experiments. Computerized design algorithms do not supplant traditional design-creation skills. Our examples show that our best designs were usually found when we used our human design skills to guide the computerized search.

First, we summarize our main points; next, we review some fundamentals of the design of experiments; then we discuss computer-generated designs, a discrete-choice example, and a conjoint analysis example.

Summary of Main Points

Our goal is to explain the benefits of using computer-generated designs in marketing research. Our main points follow:

1. The goodness of an experimental design (efficiency) can be quantified as a function of the variances and covariances of the parameter estimates. Efficiency increases as the variances decrease. Designs should not be thought of in terms of the dichotomy between orthogonal versus nonorthogonal but rather as varying along the continuous attribute of efficiency. Some orthogonal designs are less efficient than other (orthogonal and nonorthogonal) alternatives.
2. Orthogonality is not the primary goal in design creation. It is a secondary goal, associated with the primary goal of minimizing the variances of the parameter estimates. Degree of orthogonality is an important consideration, but other factors should not be ignored.

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3. For complex, nonstandard situations, computerized searches provide the only practical method of design generation for all but the most sophisticated of human designers. These situations do not have to be avoided just because it is extremely difficult to generate a good design manually.
4. The best approach to design creation is to use the computer as a tool along with traditional design skills, not as a substitute for thinking about the problem.

Background and Assumptions

We present an overview of the theory of efficient experimental design, developed for the general linear model. This topic is well known to specialists in statistical experimentation, though it is not typically taught in design classes. Then we suggest ways in which this theory can be applied to marketing research problems.

Certain assumptions must be made before applying ordinary general linear model theory to problems in marketing research. The usual goals in linear modeling are to estimate parameters and test hypotheses about those parameters. Typically, independence and normality are assumed. In conjoint analysis, each subject rates all products, and separate ordinary least squares analyses are run for each subject. This is not a standard general linear model; in particular, observations are not independent and normality cannot be assumed. Discrete choice models, which are nonlinear, are even further removed from the general linear model.

Marketing researchers have always made the critical assumption that designs that are good for general linear models are also good for conjoint analysis and discrete choice. We also make this assumption. Specifically, we assume the following:

1. Market share estimates computed from a conjoint analysis model using a more efficient design will be better than estimates using a less efficient design. That is, more efficient designs mean better estimates of the partworth utilities, which lead to better estimates of product utility and market share.
2. An efficient design for a linear model is a good design for the multinomial logit (MNL) model used in discrete choice studies.

Investigating these standard assumptions is beyond the scope of this article. However, they are supported by Carson and colleagues (1994), our experiences in consumer product goods, and limited simulation results. Much more research is needed on this topic, particularly in the area of discrete choice.

DESIGN OF EXPERIMENTS

Orthogonal Experimental Designs

An experimental design is a plan for running an experiment. The *factors* of an experimental design are variables that have two or more fixed values, or *levels*. Experiments are performed to study the effects of the factor levels on the dependent variable. In a conjoint or discrete-choice study, the factors are the attributes of the hypothetical products or services, and the response is preference or choice.

A simple experimental design is the *full-factorial design*, which consists of all possible combinations of the levels of the factors. For example, with five factors, two at two levels and three at three levels (denoted $2^2 3^3$), there are 108 possible combinations. In a full-factorial design, all main effects, two-way interactions, and higher-order interactions are estimable and uncorrelated. The problem with a full-factorial design is that, for most practical situations, it is too cost prohibitive and tedious to have subjects rate all possible combinations. For this reason, researchers often use *fractional-factorial designs*, which have fewer runs than full-factorial designs. The price of having fewer runs is that some effects become confounded. Two effects are *confounded* or *aliased* when they are not distinguishable from each other.

A special type of fractional-factorial design is the *orthogonal array*, in which all estimable effects are uncorrelated. Orthogonal arrays are categorized by their *resolution*. The resolution identifies which effects, possibly including interactions, are estimable. For example, for resolution III designs, all main effects are estimable free of each other, but some of them are confounded with two-factor interactions. For resolution V designs, all main effects and two-factor interactions are estimable free of each other. Higher resolutions require larger designs. Orthogonal arrays come in specific numbers of runs (e.g., 16, 18, 20, 24, 27, 28) for specific numbers of factors with specific numbers of levels.

Resolution III orthogonal arrays are frequently used in marketing research. The term "orthogonal array," as it is used in practice, is imprecise. It refers to designs that are both orthogonal and balanced, and hence optimal. It also refers to designs that are orthogonal but not balanced, and hence potentially nonoptimal. A design is *balanced* when each level occurs equally often within each factor, which means the intercept is orthogonal to each effect. Imbalance is a generalized form of nonorthogonality, which increases the variances of the parameter estimates.

Design Efficiency

Efficiencies are measures of design goodness. Common measures of the efficiency of an $N_D \times p$ design matrix $\mathbf{X}$ are based on the *information matrix* $\mathbf{X}'\mathbf{X}$. The variance-covariance matrix of the vector of parameter estimates $\hat{\beta}$ in a least squares analysis is proportional to $(\mathbf{X}'\mathbf{X})^{-1}$. An efficient design will have a "small" variance matrix, and the eigenvalues of $(\mathbf{X}'\mathbf{X})^{-1}$ provide measures of its "size." Two common efficiency measures are based on the idea of "average eigenvalue" or "average variance": *A-efficiency* is a function of the arithmetic mean of the eigenvalues, which is given by trace $(\mathbf{X}'\mathbf{X})^{-1}/p$, and *D-efficiency* is a function of the geometric mean of the eigenvalues, which is given by $|(\mathbf{X}'\mathbf{X})^{-1}|^{1/p}$. A third common efficiency measure, *G-efficiency*, is based on σ_M, the maximum standard error for prediction over the candidate set. All three of these criteria are convex functions of the eigenvalues of $(\mathbf{X}'\mathbf{X})^{-1}$ and hence are usually highly correlated.

For all three criteria, if a balanced and orthogonal design exists, then it has optimum efficiency; conversely, the more efficient a design is, the more it tends toward balance and orthogonality. A design is balanced and orthogonal when $(\mathbf{X}'\mathbf{X})^{-1}$ is diagonal (for a suitably coded $\mathbf{X}$). A design is orthogonal when the submatrix of $(\mathbf{X}'\mathbf{X})^{-1}$, excluding the row and column for the intercept, is diagonal; there may be off-diagonal nonzeros for the intercept. A design is balanced when all off-diagonal elements in the intercept row and column are zero.

These measures of efficiency can be scaled to range from 0 to 100 (for a suitably coded **X**):

$$\text{A-efficiency} = 100 \times \frac{1}{N_D \text{ trace } ((\mathbf{X'X})^{-1})/p}$$

$$\text{D-efficiency} = 100 \times \frac{1}{N_D \, |(\mathbf{X'X})^{-1}|^{1/p}}$$

$$\text{G-efficiency} = 100 \times \frac{\sqrt{p/N_D}}{\sigma_M}.$$

These efficiencies measure the goodness of the design relative to hypothetical orthogonal designs that may be far from possible, so they are not useful as absolute measures of design efficiency. Instead, they should be used relatively, to compare one design with another for the same situation. Efficiencies that are not near 100 may be perfectly satisfactory.

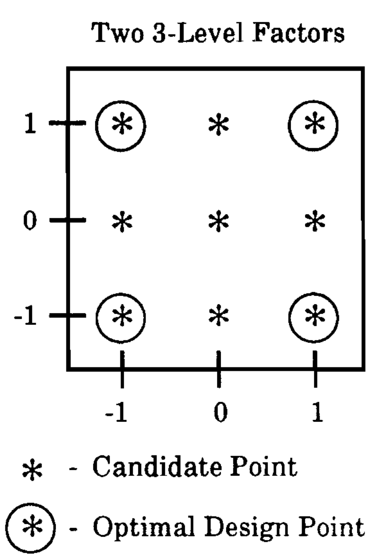
Figure 1 shows an optimal design in four runs for a simple example with two factors, using interval measure scales for both. There are three candidate levels for each factor. The full-factorial design is shown by the nine asterisks, with circles around the optimal four design points. As this example shows, efficiency tends to emphasize the corners of the design space. Interestingly, nine different sets of four points form orthogonal designs—every set of four that forms a rectangle or square. Only one of these orthogonal designs is optimal—the one in which the points are spread out as far as possible.

Computer-Generated Design Algorithms

When a suitable orthogonal design does not exist, computer-generated nonorthogonal designs can be used instead. Various algorithms exist for selecting a good set of *design points* from a set of *candidate points*. The candidate points consist of all of the factor-level combinations that can potentially be included in the design—for example, the nine points in Figure 1. The number of runs, N_D, is chosen by the researcher. Unlike orthogonal arrays, N_D can be any number as long as $N_D \geq p$. The algorithm searches the candidate points for a set of N_D design points that is optimal in terms of a given efficiency criterion.

Figure 1

CANDIDATE SET AND OPTIMAL DESIGN



It is usually not possible to list all N_D-run designs and choose *the* most efficient or optimal design, because run time is exponential in the number of candidates. For example, with $2^2 3^3$ in 18 runs, there are $108!/(18!(108 - 18)!) = 1.39 \times 10^{20}$ possible designs. Instead, nonexhaustive search algorithms are used to generate a small number of designs, and the most efficient one is chosen. The algorithms select points for possible inclusion or deletion, then compute rank-one or rank-two updates of some efficiency criterion. The points that most increase efficiency are added to the design. These algorithms invariably find efficient designs, but they may fail to find *the* optimal design, even for the given criterion. For this reason, we prefer to use terms like *information-efficient* and *D-efficiency* over the more common *optimal* and *D-optimal*.

There are many algorithms for generating information-efficient designs. We begin by describing some of the simpler approaches and then proceed to the more complicated (and more reliable) algorithms. Dykstra's (1971) sequential search method starts with an empty design and adds candidate points so that the chosen efficiency criterion is maximized at each step. This algorithm is fast, but it is not very reliable in finding a globally optimal design. Also, it always finds the same design (due to a lack of randomness).

The Mitchell and Miller (1970) simple exchange algorithm is a slower but more reliable method. It improves the initial design by adding a candidate point and then deleting one of the design points, stopping when the chosen criterion ceases to improve. The DETMAX algorithm of Mitchell (1974) generalizes the simple exchange method. Instead of following each addition of a point by a deletion, the algorithm makes excursions in which the size of the design may vary. These three algorithms add and delete points one at a time.

The next two algorithms add and delete points simultaneously and, for this reason, are usually more reliable for finding the truly optimal design; but because each step involves a search over all possible pairs of candidate and design points, they generally run much more slowly (by an order of magnitude). The Federov (1972) algorithm simultaneously adds one candidate point and deletes one design point. Cook and Nachtsheim (1980) define a modified Federov algorithm that finds the best candidate point to switch with each design point. The resulting procedure is generally as efficient as the simple Federov algorithm in finding the optimal design, but it is up to twice as fast.

Choice of Criterion and Algorithm

Typically, the choices of efficiency criterion and algorithm are less important than the choice between manual design creation and computerized search. All the information-efficient designs presented in this article were generated optimizing D-efficiency because it is faster to optimize than A-efficiency, and it is the standard approach. It is also possible to optimize A-efficiency, though the algorithms generally run much more slowly because the rank-one updates are more complicated with A-efficiency. G-efficiency is an interesting ancillary statistic; however, our experience suggests that attempts to maximize G-efficiency with standard algorithms do not work very well.

The algorithms, ordered from the fastest and least reliable to the slowest and most reliable, are sequential, simple exchange, DETMAX, and modified Federov. For small problems or fast computers, choose modified Federov. For certain extremely large problems, the sequential algorithm may be the only viable choice. We used the modified Federov algorithm in all our examples because it is the most reliable and it runs fast enough on our work stations.

It is certainly reasonable to try using other algorithms and/or criteria. For all but the most trivial of problems, only a tiny fraction of all possible designs will be examined. It is possible that alternative strategies will produce better designs. However, our experience suggests that they are unlikely to be much better. Techniques such as those outlined later in the "Strategies for Many Variables" and "Conjoint Analysis with Aggregate Interactions" sections are more likely to produce a more efficient design than changing the algorithm or criterion.

Nonlinear Models

The experimental design problem is relatively simple for linear models and much more complicated for nonlinear models. The usual goal when creating a design is to minimize some function of the variance matrix of the parameter estimates, such as the determinant. For linear models, the variance matrix is proportional to $(\mathbf{X}'\mathbf{X})^{-1}$, and so the design optimality problem is well posed. However, for nonlinear models, such as the multinomial logit model used with discrete-choice data, the variance matrix depends on the true values of the parameters themselves. Thus, in general, there may not exist a design for a discrete-choice experiment that is always optimal. However, Carson and colleagues (1994) and our experience suggest that D-efficient designs work well for discrete-choice models.

Lazari and Anderson (1994) provide a catalog of designs for discrete-choice models, which are good for certain specific problems. For those specific situations, they may be as good as or better than computer-generated designs. However, for many real problems, cataloged designs cannot be used without modification, and modification can reduce efficiency. We carry their work one step further by discussing a general computerized approach to design generation.

DESIGN COMPARISONS

Comparing Orthogonal Arrays

All orthogonal arrays are not perfectly or even equally efficient. In this section, we compare designs for $2^2 3^3$. Table 1 gives the information matrix $\mathbf{X}'\mathbf{X}$ for a full-factorial design using an orthogonal coding. The matrix is a diagonal matrix with the number of runs on the diagonal. The three efficiency criteria are printed after the information matrix. Because this is a full-factorial design, all three criteria show that the design is 100% efficient. The variance matrix (not shown) is $(1/108)\mathbf{I} = .0093\mathbf{I}$.

Table 2 shows the information matrix, efficiencies, and variance matrix for a classical 18-run orthogonal array for $2^2 3^3$, Chakravarti's (1956) L_{18}, for comparison with information-efficient designs with 18 runs. (The ADX menu system of SAS ®[1] software [1989] was used to generate the design. Tables A1 and A2 contain the factor levels and the orthogonal coding used in generating Table 2.) Note that although the factors are all orthogonal to each other, X1 is not balanced. Because of this, the main effect of X1 is estimated with a higher variance (.063) than X2 (.056).

The precision of the estimates of the parameters critically depends on the efficiency of the experimental design. The parameter estimates in a general linear model are always unbiased (in fact, best linear unbiased [BLUE]) no matter what design is chosen. However, all designs are not equally efficient. In fact, all orthogonal designs are not equally efficient even when they have the same factors and the same number of runs. Efficiency criteria can be used to help choose among orthogonal designs. For example, the orthogonal array in Tables 3 and A3 (from the Green and Wind 1975 carpet cleaner example) for $2^2 3^3$ is less D-efficient than the Chakravarti L_{18} (97.4166/98.6998 = .9870). The Green and Wind design can be created from a 3^5 balanced orthogonal array by collapsing two of the three-level factors into two-level factors. In contrast, the Chakravarti design is created from a $2^1 3^4$ balanced orthogonal array by collapsing only one of the three-level factors into a two-level factor. The extra imbalance makes the Green and Wind design less efficient. (Note that the off-diagonal 2 in the Green and Wind information matrix does not imply that X1 and X2 are correlated; it is an artifact of the coding scheme. The off-diagonal 0 in the variance matrix shows that X1 and X2 are uncorrelated.)

Orthogonal Versus Nonorthogonal Designs

Orthogonal designs are not always more efficient than nonorthogonal designs. Tables 4 and A4 show the results for an information-efficient, main-effects-only design in 18 runs. The OPTEX procedure of SAS software (1989) was used to generate the design, using the modified Federov algorithm. The information-efficient design is slightly better than the classical L_{18}, in terms of the three efficiency criteria. In particular, the ratio of the D-efficiencies for the classical and information-efficient designs is 99.8621/98.6998 = 1.0118. In contrast to the L_{18}, this design is balanced in all the factors, but X1 and X2 are slightly correlated, shown by the 2s off the diagonal. There is no known *completely* orthogonal (that is, both balanced and orthogonal) $2^2 3^3$ design in 18 runs. The nonorthogonality in Table 4 has a much smaller effect on the variances of X1 and X2 (1.2%) than the lack of balance in the orthogonal array in Table 2 has on the variance of X2 (12.5%). In optimizing efficiency, the search algorithms effectively optimize both balance and orthogonality. In contrast, in orthogonal arrays, balance and efficiency may be sacrificed to preserve orthogonality.

This example shows that nonorthogonal designs may be more efficient than an unbalanced orthogonal array. We have seen this phenomenon with other orthogonal arrays and in other situations as well. *Preserving orthogonality at all costs can lead to decreased efficiency.* Orthogonality was

[1]SAS is a registered trademark of SAS Institute Inc. in the USA and other countries. ® indicates USA registration.

extremely important in the days before general linear model software became widely available. Today, it is more important to consider efficiency when choosing a design. These comparisons are interesting because they illustrate, in a simple example, how lack of orthogonality and imbalance affect efficiency. Nonorthogonal designs will never be more efficient than balanced orthogonal designs, when they exist. However, nonorthogonal designs may well be more efficient than unbalanced orthogonal arrays. Although this point is interesting and important, what is most important is that good nonorthogonal designs exist in many situations in which no orthogonal designs exist.

DESIGN CONSIDERATIONS

Codings and Efficiency

The specific design matrix coding does not affect the relative D-efficiency of competing designs. Rank-preserving linear transformations are immaterial, whether they are from full-rank dummy variables to effects coding or to an orthogonal coding such as the one shown in Table A2. Any full-rank coding is equivalent to any other. The absolute D-efficiency values will change, but the ratio of two D-efficiencies for competing designs is constant. Similarly, scale for quantitative factors does not affect relative efficiency. The proof is simple. If design $\mathbf{X}_1$ is recoded to $\mathbf{X}_1\mathbf{A}$, then $|(\mathbf{X}_1\mathbf{A})'(\mathbf{X}_1\mathbf{A})| = |\mathbf{A}'\mathbf{X}_1'\mathbf{X}_1\mathbf{A}| = |\mathbf{A}\mathbf{A}'||\mathbf{X}_1'\mathbf{X}_1|$. The relative efficiency of design $\mathbf{X}_1$ compared with $\mathbf{X}_2$ is the same as $\mathbf{X}_1\mathbf{A}$ compared with $\mathbf{X}_2\mathbf{A}$, because the $|\mathbf{A}\mathbf{A}'|$ terms in efficiency ratios will cancel. We prefer the orthogonal coding because it yields "nicer" information matrices with the number of runs on the diagonal and efficiency values scaled so that 100 means perfect efficiency.

Quantitative Factors

The factors in an experimental design are usually qualitative (nominal), but quantitative factors such as price are also important. With quantitative factors, the choice of levels depends on the function of the original variable that is modeled. To illustrate, consider a pricing study in which price ranges from \$.99 to \$1.99. If a linear function of price is modeled, only two levels of price should be used—the end points (\$.99 and \$1.99). Using prices that are closer together is inefficient; the variances of the estimated coefficients will be larger. The efficiency of a given design is affected by the coding of quantitative factors, even though the relative efficiency of competing designs is unaffected by coding. Consider treating the second factor of the Chakravarti L_{18}, $2^2 3^3$, as linear. It is nearly three times more D-efficient to use \$.99 and \$1.99 as levels instead of \$1.49 and \$1.50 (58.6652 / 21.0832 = 2.7826). To visualize this, imagine supporting a yard stick (line) on your two index fingers (with two points). The effect on the slope of the yard stick of small vertical changes in finger locations is much greater when your fingers are closer together than when they are near the ends.

Of course there are other considerations besides the numerical measure of efficiency. It would not make sense to use prices of \$.01 and \$1,000,000 just because that is more efficient than using \$.99 and \$1.99. The model is almost certainly not linear over this range. To maximize efficiency, the range of experimentation for quantitative factors should be as large as possible, given that the model is plausible.

The number of levels also affects efficiency. Because two points define a line, it is inefficient to use more than two points to model a linear function. When a quadratic function is used (x and x^2 are included in the model), three points are needed—the two extremes and the midpoint. Similarly, four points are needed for a cubic function. More levels are needed when the functional form is unknown. Extra levels allow for the examination of complicated nonlinear functions, with a cost of decreased efficiency for the simpler functions. When the function is assumed to be linear, experimental points should not be spread throughout the range of experimentation. See Kuhfeld and Garratt (1992) for a discussion of nonlinear functions of quantitative factors in conjoint analysis.

Most of the discussion outside this section has concerned qualitative (nominal) factors, even if that was not always explicitly stated. Quantitative factors complicate general design characterizations. For example, we previously stated that "if a balanced and orthogonal design exists, then it has optimum efficiency." This statement must be qualified to be absolutely correct. The design would not be optimal if, for example, a three-level factor was treated as quantitative and linear.

Nonstandard Algorithms and Criteria

Other researchers have proposed other algorithms and criteria. Steckel, DeSarbo, and Mahajan (SDM) (1991) previously proposed using computer-generated experimental designs for conjoint analysis to exclude unacceptable combinations from the candidate set. They considered a nonstandard measure of design goodness based on the determinant of the correlation matrix ($|\mathbf{R}|$). Designs generated using nonstandard criteria will not generally be efficient in terms of standard criteria like A-efficiency and D-efficiency, so the parameter estimates will have larger variances. The SDM procedure could allow the use of both standard and nonstandard efficiency criteria through optional preprocessing of the data or user-created subroutines.

We generated a D-efficient design for SDM's example, treating the variables as all quantitative (as they did). The $|\mathbf{R}|$ for the SDM design is .9932, whereas the $|\mathbf{R}|$ for the information-efficient design is .9498. The SDM approach works quite well in maximizing $|\mathbf{R}|$; hence the SDM design is close to orthogonal. However, efficiency is not always maximized when orthogonality is maximized. The SDM design is approximately 75% as D-efficient as a design generated with standard criteria and algorithms (70.1182 / 93.3361 = .7512).

Choosing a Design

Computerized search algorithms generate many designs, from which the researcher must choose one. Often, several designs are tied or nearly tied for the best D, A, and G information efficiencies. A design should be chosen after examining the design matrix, its information matrix, and its variance matrix. *It is important to look at the results and not just routinely choose the design from the top of the list.*

Table 1
FULL-FACTORIAL DESIGN

Information Matrix									
	Int	X1	X2	X3	—	X4	—	X5	—
Int	108	0	0	0	0	0	0	0	0
X1	0	108	0	0	0	0	0	0	0
X2	0	0	108	0	0	0	0	0	0
X3	0	0	0	108	0	0	0	0	0
—	0	0	0	0	108	0	0	0	0
X4	0	0	0	0	0	108	0	0	0
—	0	0	0	0	0	0	108	0	0
X5	0	0	0	0	0	0	0	108	0
—	0	0	0	0	0	0	0	0	108

100.0000 D-efficiency
100.0000 A-efficiency
100.0000 G-efficiency

For studies involving human subjects, achieving at least nearly balanced designs is an important consideration. Consider, for example, a two-level factor in an 18-run design in which one level occurs 12 times and the other level occurs 6 times versus a design in which each level occurs 9 times. Subjects who see one level more often than the other may try to read something into the study and adjust their responses in some way. Alternatively, subjects who see one level most often may respond differently than those who see the second level most often. These are not concerns with nearly balanced designs. One design selection strategy is to choose the most balanced design from the top few.

Many other strategies can be used. Perhaps correlation and imprecision are tolerable in some variables but not in others. Perhaps imbalance is tolerable, but the correlations between the factors should be minimal. Goals will no doubt change from experiment to experiment. Choosing a suitable design can be part art and part science. Efficiency should always be considered when choosing between alternative designs, even manually created designs, but it is not the only consideration.

Adding Observations or Variables

These techniques can be extended to augment an existing design. A design with r runs can be created by augmenting m specified combinations (established brands or existing combinations) with r – m combinations chosen by the algorithm. Alternatively, combinations that must be used for certain variables can be specified, and then the algorithm picks the levels for the other variables (Cook and Nachtsheim 1989). This can be used to ensure that some factors are balanced or uncorrelated; another application is blocking factors. Using design algorithms, we are able to establish numbers of runs and blocking patterns that fit into practical fielding schedules.

Designs With Interactions

There is a growing interest in using both main effects and interactions in discrete-choice models, because interaction and cross-effect terms may improve aggregate models (Elrod, Louviere, and Davey 1992). The current standard for choice models is to have all main effects estimable both within and between alternatives. It is often necessary to estimate interactions within alternatives, such as in modeling separate price elasticities for product forms, sizes, or packages. For certain classes of designs, in which a brand ap-

Table 2
ORTHOGONAL ARRAY

Information Matrix									
	Int	X1	X2	X3	—	X4	—	X5	—
Int	18	6	0	0	0	0	0	0	0
X1	6	18	0	0	0	0	0	0	0
X2	0	0	18	0	0	0	0	0	0
X3	0	0	0	18	0	0	0	0	0
—	0	0	0	0	18	0	0	0	0
X4	0	0	0	0	0	18	0	0	0
—	0	0	0	0	0	0	18	0	0
X5	0	0	0	0	0	0	0	18	0
—	0	0	0	0	0	0	0	0	18

98.6998 D-efficiency
97.2973 A-efficiency
94.8683 G-efficiency

Variance Matrix									
	Int	X1	X2	X3	—	X4	—	X5	—
Int	63	–21	0	0	0	0	0	0	0
X1	–21	63	0	0	0	0	0	0	0
X2	0	0	56	0	0	0	0	0	0
X3	0	0	0	56	0	0	0	0	0
—	0	0	0	0	56	0	0	0	0
X4	0	0	0	0	0	56	0	0	0
—	0	0	0	0	0	0	56	0	0
X5	0	0	0	0	0	0	0	56	0
—	0	0	0	0	0	0	0	0	56

Note: multiply variance matrix values by .001.

Table 3
GREEN AND WIND ORTHOGONAL ARRAY

Information Matrix									
	Int	X1	X2	X3	—	X4	—	X5	—
Int	18	–6	–6	0	0	0	0	0	0
X1	–6	18	2	0	0	0	0	0	0
X2	–6	2	18	0	0	0	0	0	0
X3	0	0	0	18	0	0	0	0	0
—	0	0	0	0	18	0	0	0	0
X4	0	0	0	0	0	18	0	0	0
—	0	0	0	0	0	0	18	0	0
X5	0	0	0	0	0	0	0	18	0
—	0	0	0	0	0	0	0	0	18

97.4166 D-efficiency
94.7368 A-efficiency
90.4534 G-efficiency

Variance Matrix									
	Int	X1	X2	X3	—	X4	—	X5	—
Int	69	21	21	0	0	0	0	0	0
X1	21	63	0	0	0	0	0	0	0
X2	21	0	63	0	0	0	0	0	0
X3	0	0	0	56	0	0	0	0	0
—	0	0	0	0	56	0	0	0	0
X4	0	0	0	0	0	56	0	0	0
—	0	0	0	0	0	0	56	0	0
X5	0	0	0	0	0	0	0	56	0
—	0	0	0	0	0	0	0	0	56

Note: multiply variance matrix values by .001.

Table 4

MODIFIED FEDEROV ALGORITHM

Information Matrix

	Int	X1	X2	X3	—	X4	—	X5	—
Int	18	0	0	0	0	0	0	0	0
X1	0	18	2	0	0	0	0	0	0
X2	0	2	18	0	0	0	0	0	0
X3	0	0	0	18	0	0	0	0	0
—	0	0	0	0	18	0	0	0	0
X4	0	0	0	0	0	18	0	0	0
—	0	0	0	0	0	0	18	0	0
X5	0	0	0	0	0	0	0	18	0
—	0	0	0	0	0	0	0	0	18

99.8621 D-efficiency
99.7230 A-efficiency
98.6394 G-efficiency

Variance Matrix

	Int	X1	X2	X3	—	X4	—	X5	—
Int	56	0	0	0	0	0	0	0	0
X1	0	56	–6	0	0	0	0	0	0
X2	0	–6	56	0	0	0	0	0	0
X3	0	0	0	56	0	0	0	0	0
—	0	0	0	0	56	0	0	0	0
X4	0	0	0	0	0	56	0	0	0
—	0	0	0	0	0	0	56	0	0
X5	0	0	0	0	0	0	0	56	0
—	0	0	0	0	0	0	0	0	56

Notes: multiply variance matrix values by .001.
The diagonal entries for X1 and X2 are slightly larger at .0563 than the other diagonal entries of .0556.

Table 5

UNREALISTIC COMBINATIONS EXCLUDED

Information Matrix

	Int	X1	X2	X3	—	X4	—	X5	—
Int	18	0	0	0	0	0	0	0	0
X1	0	18	2	0	0	0	0	0	0
X2	0	2	18	0	0	0	0	0	0
X3	0	0	0	18	0	0	0	0	0
—	0	0	0	0	18	0	0	0	0
X4	0	0	0	0	0	18	0	–6	5
—	0	0	0	0	0	0	18	5	0
X5	0	0	0	0	0	–6	5	18	0
—	0	0	0	0	0	5	0	0	18

96.4182 D-efficiency
92.3190 A-efficiency
91.0765 G-efficiency

Variance Matrix

	Int	X1	X2	X3	—	X4	—	X5	—
Int	56	0	0	0	0	0	0	0	0
X1	0	56	–6	0	0	0	0	0	0
X2	0	–6	56	0	0	0	0	0	0
X3	0	0	0	56	0	0	0	0	0
—	0	0	0	0	56	0	0	0	0
X4	0	0	0	0	0	69	–7	25	–20
—	0	0	0	0	0	–7	61	–20	2
X5	0	0	0	0	0	25	–20	69	–7
—	0	0	0	0	0	–20	2	–7	61

Note: multiply variance matrix values by .001.

pears in only a subset of runs, it is often necessary to have estimable main effects, own-brand interactions, and cross-effects in the submatrix of the design in which that brand is present. One way to ensure estimability is to include in the model interactions between the alternative-specific variables of interest and the indicator variables that control for presence or absence of the brand in the choice set. Orthogonal designs that allow for estimation of interactions are usually very large, whereas efficient nonorthogonal designs can be generated for any linear model, including models with interactions, and for any (reasonable) number of runs.

Unrealistic Combinations

It is sometimes useful to exclude certain combinations from the candidate set. SDM (1991) have also considered this problem. Consider a discrete-choice model for several brands and their line extensions. It may not make sense to have a choice set in which the line extension is present and the "flagship" brand absent. Of course, as we eliminate combinations, we may introduce unavoidable correlation between the parameter estimates. In Tables 5 and A5, the 20 combinations in which (X1 = 1 and X2 = 1 and X3 = 1) or (X4 = 1 and X5 = 1) were excluded, and an 18-run design was generated with the modified Federov algorithm. With these restrictions, the efficiency criteria dropped (96.4182/99.8621 = .9655). This shows that the design with excluded combinations is almost 97% as efficient as the best (unrestricted) design. The information matrix shows that X1 and X2 are correlated, as are X4 and X5. This is the price paid for obtaining a design with only realistic combinations.

In the "Quantitative Factors" section, we state, "Because two points define a line, it is inefficient to use more than two points to model a linear function." When unrealistic combinations are excluded, this statement may no longer be true. For example, if minimum price with maximum size is excluded, an efficient design may involve the median price and size.

Choosing the Number of Runs

Deciding on a number of runs for the design is a complicated process; it requires balancing statistical concerns of estimability and precision with practical concerns like time and subject fatigue. Optimal design algorithms can generate designs for any number of runs greater than or equal to the number of parameters. The variances of the least squares estimates of the partworth utilities will be roughly inversely proportional to both the D-efficiency and the number of runs. In particular, for a given number of runs, a D-efficient design will give more accurate estimates than would be obtained with a less efficient design. A more precise value for the number of choices depends on the ratio of the inherent variability in subject ratings to the absolute size of utility that is considered important. Subject concerns probably outweigh the statistical concerns, and the best course is to provide as many products as are practical for the subjects to evaluate. In any case, the use of information-efficient designs provides more flexibility than manual methods.

Asymmetry in the Number of Levels of Variables

In many practical applications of discrete-choice modeling, there is asymmetry in the number of factor levels, and interaction and polynomial parameters must be estimated. One common method for generating choice model designs is to create a resolution III orthogonal array and modify it. The starting point is a $q^{\Sigma M_j}$ design, where q represents a fixed number of levels across all attributes and M_j represents the number of attributes for brand j. For example, in the consumer food product example in a subsequent section, with five brands with 1, 3, 1, 2, and 1 attributes and with each attribute having at most four levels, the starting point is a 4^8 orthogonal array. Availability cross-effect designs are created by letting one of the M_j variables function as an indicator for presence/absence of each brand or by allowing one level of a common variable (price) to operate as the indicator. These methods are fairly straightforward to implement in designs in which the factor levels are all the same, but they become quite difficult to set up when there are different numbers of levels for some factors or specific interactions must be estimable.

Asymmetry in the number of levels of factors may be handled either by using the "coding down" approach (Addelman 1962) or by expansion. In the coding down approach, designs are created using factors that have numbers of levels equal to the largest number required in the design. Factors that have fewer levels are created by recoding. For example, a five-level factor {1, 2, 3, 4, 5} can be recoded into a three-level factor by duplicating levels {1, 1, 2, 2, 3}. The variables will still be orthogonal because the dummy variables for the recoding are in a subspace of the original space. However, recoding introduces imbalance and inefficiency. The second method is to expand a factor at k-levels into several variables at some fraction of k-levels. For example, a four-level variable can be expanded into three orthogonal two-level variables. In many cases, both methods must be used to achieve the required design.

These approaches are difficult for a simple main-effect design of resolution III and extremely difficult when interactions between asymmetric factors must be considered. In practical applications, asymmetry is the norm. Consider, for example, the form of an analgesic product. One brand may have caplet and tablet varieties, and another may have tablet, liquid, and chewable forms. In a discrete-choice model, these two brand/forms must be modeled as asymmetric alternative-specific factors. If we furthermore anticipated that the direct price elasticity might vary, depending on the form, we would need to estimate the interaction of a quantitative price variable with the nominal-level form variable.

Computerized search methods are simpler to use by an order of magnitude. They provide asymmetric designs that are usually nearly balanced, as well as provide easy specification for interactions, polynomials, and continuous-by-class effects.

Strategies for Many Variables

Consider generating a 3^{15} design in 31 runs. There are 14,348,907 combinations in the full-factorial design, which is too many to use even for a candidate set. Two alternative candidate sets are an orthogonal resolution III design in 81 runs and an orthogonal resolution V design in 2187 runs. The resulting 31-run designs had D-efficiencies of 77.6502 and 80.3932, respectively. (Efficiencies tend to be larger with larger candidate sets, but run times are much slower.) Another alternative is to try a multistep process, beginning with a search for a small, good candidate set. We started with a 3^{12} orthogonal array in 36 runs, specified those 12 variables as fixed covariates, and used a search algorithm to create three additional variables, still in 36 runs. We then used that design as a candidate set. The resulting D-efficiency of 83.4952 was better than any previously found. Without computerized search algorithms, it is extremely difficult to find an efficient design for this situation. Just for comparison, we randomly generated one thousand 3^{15} designs in 31 runs. The best random design was only 57% as efficient as our most D-efficient design. For obvious reasons, we do not recommend using random designs.

EXAMPLES

Choice of Consumer Food Products

Consider the problem of using a discrete choice model to study the effect of introducing a retail food product. This may be useful, for example, to refine a marketing plan or optimize a product prior to test market. A typical brand team will have several concerns, such as knowing the potential market share for the product, examining the source of volume, and providing guidance for pricing and promotions. The brand team may also want to know what brand attributes have competitive clout and want to identify competitive attributes to which they are vulnerable.

To develop this further, assume our client wishes to introduce a line extension in the category of frozen entrees. The client has one nationally branded competitor, a regional competitor in each of three regions, and a profusion of private label products at the grocery chain level. The product comes in two different forms: stove-top or microwaveable. The client believes that the private labels are very likely to mimic this line extension and sell it at a lower price. The client suspects that this strategy on the part of private labels may work for the stove-top version but not for the microwaveable, for which they have the edge on perceived quality. They also want to test the effect of a shelf-talker that will draw attention to their product.

This problem can be set up as a discrete choice model in which a respondent's choice among brands, given choice set C_a of available brands, will correspond to the brand with the highest utility. For each brand i, the utility U_i is the sum of a systematic component V_i and a random component e_i. The probability of choosing brand i from choice set C_a is therefore

$$P(i|C_a) = P(U_i > \max(U_j)) = P(V_i + e_i > \max(V_j + e_j)) \;\forall\; (j \neq i) \in C_a.$$

Assuming that the e_i follow an extreme value type I distribution, the conditional probabilities $P(i|C_a)$ can be found using the MNL formulation of McFadden (1974)

$$P(i|C_a) = \exp(V_i)/\Sigma_{j \in C_a} \exp(V_j).$$

One of the consequences of the MNL formulation is the property of independence of irrelevant alternatives (IIA). Under the assumption of IIA, all cross-effects are assumed to be equal, so that if a brand gains in utility, it draws share from all other brands in proportion to their current shares. Departures from IIA exist when certain subsets of brands are in more direct competition and tend to draw a disproportionate amount of share from each other than from other members in the category. One way to capture departures from IIA is to use the mother logit formulation of McFadden (1974). In these models, the utility for brand i is a function of both the attributes of brand i and the attributes of other brands. The effect of one brand's attributes on another is termed a *cross-effect.* In the case of designs in which only subsets C_a of the full shelf set C appear, the effect of the presence or absence of one brand on the utility of another is termed an *availability cross-effect.*

In the frozen entree example, there are five alternatives: the client, the client's line extension, a national branded competitor, a regional brand, and a private label brand. Several regional and private labels can be tested in each market, then aggregated for the final model. Note that the line extension is treated as a separate alternative rather than as a "level" of the client brand. This enables us to model the source of volume for the new entry and quantify any cannibalization that occurs. Each brand is shown at either two or three price points. Additional price points are included so that quadratic models of price elasticity can be tested. The indicator for the presence or absence of a brand in the shelf set is coded using one level of the price variable. The layout of factors and levels is given in Table 6.

In addition to intercepts and main effects, we also require that all two-way interactions within alternatives be estimable: X2*X3, X2*X4, X3*X4 for the line extension and X6*X7 for private labels. This enables us to test for different price elasticities by form (stove-top versus microwaveable) and to see if the promotion works better combined with a low price or with different forms. Using a linear model for X1–X8, the total number of parameters including the intercept, all main effects, and two-way interactions with brand is 25. This assumes that price is treated as qualitative. The actual number of parameters in the choice model is larger than this because of the inclusion of cross-effects. Using indicator variables to code availability, the systematic component of utility for brand i can be expressed as

$$V_i = a_i + \Sigma_k(b_{ik} \times x_{ik}) + \Sigma_{j \neq i} z_j(d_{ij} + \Sigma_l(g_{ijl} \times x_{jl})),$$

where

a_i = intercept for brand i,
b_{ik} = effect of attribute k for brand i, where k = 1, ..., K_i
x_{ik} = level of attribute k for brand i,
d_{ij} = availability cross-effect of brand j on brand i,
$$z_j = \text{availability code} = \begin{cases} 1 \text{ if } j \in C_a, \\ 0 \text{ otherwise,} \end{cases}$$
g_{ijl} = cross-effect of attribute l for brand j on brand i, where l = 1, ..., L_j, and
x_{jl} = level of attribute l for brand j.

The x_{ik} and χ_{jl} might be expanded to include interaction and polynomial terms. In an availability cross-effects design, each brand is present in only a fraction of choice sets. The size of this fraction or subdesign is a function of the number of levels of the alternative-specific variable that is used to code availability (usually price). For example, if price has three valid levels and a fourth "zero" level to indicate absence, then the brand will appear in only three out of four runs. Following Lazari and Anderson (1994), the size of each subdesign determines how many model equations can be written for each brand in the discrete choice model. If $\mathbf{X}_i$ is the subdesign matrix corresponding to V_i, then each $\mathbf{X}_i$ must be full rank to ensure that the choice set design provides estimates for all parameters.

Table 6

ALTERNATIVE FACTOR LEVELS BRAND DESCRIPTION

Alternative	*Factor*	*Levels*	*Brand*	*Description*
1	X1	4	Client	3 prices + absent
2	X2	4	Client Line Extension	3 prices + absent
	X3	2		microwave/stove-top
	X4	2		shelf-talker yes/no
3	X5	3	Regional	2 prices + absent
4	X6	3	Private Label	2 prices + absent
	X7	2		microwave/stove-top
5	X8	3	Competitor	2 prices + absent

Table 7

PARAMETERS

Effect	*Client*	*Client Line Extension*	*Regional*	*Private Label*	*Competitor*
intercept	1	1	1	1	1
availability cross-effects	4	4	4	4	4
direct price effect	1 (2)	1 (2)	1	1	1
price cross-effects	4 (8)	4 (8)	4	4	4
stove versus microwave	—	1	—	1	—
stove/micro cross-effects	—	1	—	—	—
shelf-talker	—	1	—	—	—
price*stove/microwave	—	1 (2)	—	1	—
price*shelf-talker	—	1 (2)	—	—	—
stove/micro*shelf-talker	—	1	—	—	—
Total	10 (15)	16 (23)	10	12	10
Subdesign size					
22 runs	16	16	14	14	14
26 runs	19	19	17	17	17
32 runs	24	24	21	21	21

To create the design, a full candidate set is generated consisting of 3456 runs. It is then reduced to 2776 runs that contain between two and four brands so that the respondent is never required to compare more than four brands at a time. In the algorithm model specification, we designate all variables as classification variables and require that all main effects and two-way interactions within brands be estimable. The number of runs to use follows from a calculation of the number of parameters that we wish to estimate in the various submatrices $\mathbf{X}_i$ of $\mathbf{X}$. Assuming that there is a category "None" used as a reference cell, the numbers of parameters required for various alternatives are shown in Table 7 along with the size of submatrices (rounded down) for various numbers of runs. Parameters for quadratic price models are given in parentheses. Note that the effect of the private label being in a microwaveable or stove-top form (stove/micro cross-effect) is an explicit parameter under the client line extension.

The number of runs chosen was N = 26. This number provides adequate degrees of freedom for the linear price model and will also allow estimation of direct quadratic price effects. To estimate quadratic cross-effects for price would require 32 runs at the very least. Although the technique of using two-way interactions between nominal level variables will usually guarantee that all direct and cross-effects are estimable, it is sometimes necessary and a good practice to check the ranks of the submatrices for more complex models (Lazari and Anderson 1994). Creating designs for cross effects can be difficult, even with the aid of a computer.

It took approximately 18 minutes on an HP700 workstation to generate 200 designs. The code in Table A9 was used.[2] The final (unrandomized) design in 26 runs is in Table A6. The coded choice sets are presented in Table A7 and the level frequencies are presented in Table A8. Note that the runs have been ordered by the presence or absence of the shelf-talker. This ordering is done because it is unrealistic to think that once the respondent's attention has been drawn in by the promotion, it can simply be "undrawn." The two blocks that result can be shown to two groups of people or to the same people sequentially. It would be extremely difficult and time-consuming to generate a design for this problem without a computerized algorithm.

Conjoint Analysis with Aggregate Interactions

This example illustrates creating a design for a conjoint analysis study. The goal is to create a 3^6 design in 90 runs. The design consists of five blocks of 18 runs each, so each subject will only have to rate 18 products. Within each block, main effects must be estimable. In the aggregate, all main effects and two-way interactions must be estimable. (The utilities from the main-effects models will be used to cluster subjects, then in the aggregate analysis, clusters of subjects will be pooled across blocks and the blocking factor ignored.) Our goal is to create a design that is simultaneously efficient in six ways. Each of the five blocks should be an efficient design for a first-order (main-effects) model, and the aggregate design should be efficient for the second-order (main-effects and two-way interactions) model. The main-effects models for the five blocks have $5\ (1 + 6(3 - 1)) = 65$ parameters. In addition, there are $(6 \times 5/2)\ (3 - 1)\ (3 - 1) = 60$ parameters for interactions in the aggregate model. There are more parameters than runs, but not all parameters will be simultaneously estimated.

One approach to this problem is the Bayesian regression method of DuMouchel and Jones (1994). Instead of optimizing $|\mathbf{X'X}|$, we optimized $|\mathbf{X'X} + \mathbf{P}|$, where $\mathbf{P}$ is a diagonal matrix of prior precisions. This is analogous to ridge regression, in which a diagonal matrix is added to a rank-deficient $\mathbf{X'X}$ to create a full-rank problem. We specified a model with a blocking variable, main effects for the six factors, block-effect interactions for the six factors, and all two-way interactions. We constructed $\mathbf{P}$ to contain zeros for the blocking variable, main effects, and block-effect interactions, and 45s (the number of runs divided by 2) for the two-way interactions. Then we used the modified Federov algorithm to search for good designs.

[2]All the SAS code used in this article, for running the OPTEX, FACTEX, and other procedures, is available from the first author. E-mail requests are preferred at saswfk@unx.sas.com. Otherwise, write Warren F. Kuhfeld, Statistical R&D, R5227, SAS Institute Inc., Cary, NC 27513-2414.

With an appropriate coding for $\mathbf{X}$, the value of the prior precision for a parameter roughly reflects the number of runs worth of prior information available for that parameter. The larger the prior precision for a parameter, the less information about that parameter is in the final design. Specifying a nonzero prior precision for a parameter reduces the contribution of that parameter to the overall efficiency. For this problem, we wanted maximal efficiency for the within-subject main-effects models, so we gave a nonzero prior precision to the aggregated two-way interactions.

Our best design had a D-efficiency for the second-order model of 63.9281 (with a D-efficiency for the aggregate main-effects model of 99.4338) and D-efficiencies for the main-effects models within each block of 100.0000, 100.0000, 100.0000, 99.0981, and 98.0854. The design is completely balanced within all blocks. We could have specified other values in $\mathbf{P}$ and gotten better efficiency for the aggregate design but less efficiency for the blocks. Choice of $\mathbf{P}$ depends in part on the primary goals of the experiment. It may require some simulation work to determine a good choice of $\mathbf{P}$.

All the examples in this article so far have been straightforward applications of computerized design methodology. A set of factors, levels, and estimable effects was specified, and the computer looked for an efficient design for that specification. Simple problems, such as those discussed previously, require only a few minutes of computer time. This problem was much more difficult, so we let a work station generate designs for about 72 hours. (We could have found less efficient but still acceptable designs in much less time.) We were asking the computer to find a good design out of over 9.6×10^{116} possibilities. This is like looking for a needle in a haystack when the haystack is the size of the entire known universe. With such problems, we may do better if we use our intuition to give the computer "hints," forcing certain structure into the design. To illustrate, we tried this problem again, this time using a different approach.

We used the modified Federov algorithm to generate main-effects only 3^6 designs in 18 runs. We stopped when we had ten designs with 100% efficiency. We then wrote an ad hoc program that randomly selected five of the ten designs, randomly permuted columns within each block, and randomly permuted levels within each block. These operations do not affect the first-order efficiencies but do affect the overall efficiency for the aggregate design. When an operation increased efficiency, the new design was kept. We iterated over the entire design 20 times. We let the program run for about 16 hours, which generated 98 designs, and we found our best design in three hours. Our best design had a D-efficiency for the second-order model of 68.0565 (versus 63.9281 previously), and all first-order efficiencies of 100.

Many other variations on this approach could be tried. For example, columns and blocks could be chosen at random, instead of systematically. We performed excursions of up to eight permutations before we reverted to the previous design; this number could be varied. It seemed that permuting the levels helped more than permuting the columns, though this was not thoroughly investigated. Whatever is done, it is important to consider efficiency. For example, just randomly permuting levels can create very inefficient designs.

For this particular problem, the ad hoc algorithm generated better designs than the Bayesian method, and it required less computer time. In fact, 91 out of the 98 ad hoc designs were better than the best Bayesian design. However, the ad hoc method required much more programmer time. It is possible to create a design manually for this situation, but it would be extremely difficult and time-consuming to find an efficient design without a computerized algorithm for all but the most sophisticated of human designers. The best designs were found when we used both our human design skills and a computerized search. We have frequently found this to be the case.

CONCLUSION

Computer-generated experimental designs can provide both better and more general designs for discrete-choice and preference-based conjoint studies. Classical designs, obtained from books or computerized tables, can be good options when they exist, but they are not the only option. The time-consuming and potentially error-prone process of finding and manually modifying an existing design can be avoided. When the design is nonstandard and there are restrictions, a computer can generate a design, and it can be done quickly. In most situations, a good design can be generated in a few minutes or hours, though for certain difficult problems more time may be necessary. Furthermore, when the circumstances of the project change, a new design can again be generated quickly.

We do not argue that computerized searches for D-efficient designs are *uniformly* superior to manually generated designs. The human designer, using intuition, experience, and heuristics, can recognize structure that an optimization algorithm cannot. On the other hand, the computerized search usually does a good job, it is easy to use, and it can create a design faster than manual methods, especially for the nonexpert. Computerized search methods and the use of efficiency criteria can benefit expert designers as well. For example, the expert can manually generate a design and then use the computer to evaluate and perhaps improve its efficiency.

In nonstandard situations, simultaneous balance and orthogonality may be unobtainable. Often, the best that can be hoped for is optimal efficiency. Computerized algorithms help by searching for the most efficient designs from a potentially very large set of possible designs. Computerized search algorithms for D-efficient designs do not supplant traditional design-creation skills. Rather, they provide helpful tools for finding good, efficient experimental designs.

Table A1
CHAKRAVARTI'S L_{18} FACTOR LEVELS

X1	X2	X3	X4	X5
−1	−1	−1	−1	−1
−1	−1	0	0	1
−1	−1	1	1	0
−1	1	−1	1	0
−1	1	0	−1	−1
−1	1	1	0	1
1	−1	−1	0	0
1	−1	−1	1	1
1	−1	0	−1	0
1	−1	0	1	−1
1	−1	1	−1	1
1	−1	1	0	−1
1	1	−1	−1	1
1	1	−1	0	−1
1	1	0	0	0
1	1	0	1	1
1	1	1	−1	0
1	1	1	1	−1

Table A2
CHAKRAVARTI'S L_{18} ORTHOGONAL CODING

X1	X2	X3	—	X4	—	X5	—
−1	−1	−1.225	−.707	−1.225	−.707	−1.225	−.707
−1	−1	0.000	1.414	0.000	1.414	1.225	−.707
−1	−1	1.225	−.707	1.225	−.707	0.000	1.414
−1	1	−1.225	−.707	1.225	−.707	0.000	1.414
−1	1	0.000	1.414	−1.225	−.707	−1.225	−.707
−1	1	1.225	−.707	0.000	1.414	1.225	−.707
1	−1	−1.225	−.707	0.000	1.414	0.000	1.414
1	−1	−1.225	−.707	1.225	−.707	1.225	−.707
1	−1	0.000	1.414	−1.225	−.707	0.000	1.414
1	−1	0.000	1.414	1.225	−.707	−1.225	−.707
1	−1	1.225	−.707	−1.225	−.707	1.225	−.707
1	−1	1.225	−.707	0.000	1.414	−1.225	−.707
1	1	−1.225	−.707	−1.225	−.707	1.225	−.707
1	1	−1.225	−.707	0.000	1.414	−1.225	−.707
1	1	0.000	1.414	0.000	1.414	0.000	1.414
1	1	0.000	1.414	1.225	−.707	1.225	−.707
1	1	1.225	−.707	−1.225	−.707	0.000	1.414
1	1	1.225	−.707	1.225	−.707	−1.225	−.707

Table A3
GREEN AND WIND ORTHOGONAL ARRAY EXAMPLE

X1	X2	X3	X4	X5
−1	−1	−1	−1	−1
−1	−1	−1	1	0
−1	−1	0	−1	−1
−1	−1	0	0	1
−1	−1	0	1	−1
−1	−1	1	−1	0
−1	−1	1	0	1
−1	−1	1	1	0
−1	1	−1	1	1
−1	1	−1	−1	1
−1	1	0	0	0
−1	1	1	0	−1
1	−1	−1	0	−1
1	−1	−1	0	0
1	−1	0	1	1
1	−1	1	−1	1
1	1	1	1	−1
1	1	0	−1	0

Table A4
INFORMATION-EFFICIENT DESIGN, FACTOR LEVELS

X1	X2	X3	X4	X5
−1	−1	−1	0	−1
−1	−1	0	−1	0
−1	−1	0	1	−1
−1	−1	1	0	1
−1	−1	1	1	1
−1	1	−1	−1	0
−1	1	−1	0	−1
−1	1	0	−1	1
−1	1	1	1	0
1	−1	−1	−1	1
1	−1	−1	1	0
1	−1	0	0	0
1	−1	1	−1	−1
1	1	−1	1	1
1	1	0	0	1
1	1	0	1	−1
1	1	1	−1	−1
1	1	1	0	0

Table A5

INFORMATION-EFFICIENT DESIGN, UNREALISTIC COMBINATIONS EXCLUDED

X1	X2	X3	X4	X5
–1	–1	–1	1	0
–1	–1	–1	–1	1
–1	–1	–1	0	–1
–1	–1	0	–1	1
–1	–1	0	0	0
–1	1	1	1	0
–1	1	1	–1	–1
–1	1	1	0	1
–1	1	0	1	–1
1	–1	1	1	–1
1	–1	1	–1	0
1	–1	1	0	1
1	–1	0	1	–1
1	1	–1	1	0
1	1	–1	–1	–1
1	1	–1	0	1
1	1	0	–1	1
1	1	0	0	0

Table A6

CONSUMER FOOD PRODUCT (RAW) DESIGN

X1	X2	X3	X4	X5	X6	X7	X8
1	1	2	1	1	2	1	3
1	2	2	1	2	3	1	2
1	4	1	1	1	3	1	3
2	2	1	1	3	2	1	1
2	3	2	1	2	2	2	3
2	4	2	1	3	3	2	2
3	1	1	1	3	2	2	2
3	3	2	1	3	1	2	1
3	4	2	1	2	1	1	1
4	1	1	1	2	3	2	1
4	1	2	1	3	3	1	1
4	2	2	1	1	2	2	3
4	3	1	1	1	1	1	2
1	3	1	2	3	2	2	1
1	3	2	2	3	1	1	3
1	4	2	2	1	1	2	1
2	1	1	2	1	3	1	1
2	2	2	2	3	2	1	1
2	3	1	2	2	1	2	3
2	4	1	2	3	1	1	2
3	1	2	2	2	3	2	2
3	2	1	2	1	3	2	3
3	4	2	2	2	3	1	3
4	1	1	2	3	2	1	3
4	2	1	2	2	1	2	2
4	3	2	2	1	2	1	2

Table A7

CONSUMER FOOD PRODUCT CHOICE SET

Block 1: Shelf-Talker Absent For Client Line Extension

Choice Set	*Client Brand*	*Client Line Extension*	*Regional Brand*	*Private Label*	*National Competitor*
1	$1.29	$1.39/stove	$1.99	$2.29/micro	N/A
2	$1.29	$1.89/stove	$2.49	N/A	$2.39
3	$1.29	N/A	$1.99	N/A	N/A
4	$1.69	$1.89/micro	N/A	$2.29/micro	$1.99
5	$1.69	$2.39/stove	$2.49	$2.29/stove	N/A
6	$1.69	N/A	N/A	N/A	$2.39
7	$2.09	$1.39/micro	N/A	$2.29/stove	$2.39
8	$2.09	$2.39/stove	N/A	$1.49/stove	$1.99
9	$2.09	N/A	$2.49	$1.49/micro	$1.99
10	N/A	$1.39/micro	$2.49	N/A	$1.99
11	N/A	$1.39/stove	N/A	N/A	$1.99
12	N/A	$1.89/stove	$1.99	$2.29/stove	N/A
13	N/A	$2.39/micro	$1.99	$1.49/micro	$2.39

Block 2: Shelf-Talker Present For Client Line Extension

Choice Set	*Client Brand*	*Client Line Extension*	*Regional Brand*	*Private Label*	*National Competitor*
14	$1.29	$2.39/micro	N/A	$2.29/stove	$1.99
15	$1.29	$2.39/stove	N/A	$1.49/micro	N/A
16	$1.29	N/A	$1.99	$1.49/stove	$1.99
17	$1.69	$1.39/micro	$1.99	N/A	$1.99
18	$1.69	$1.89/stove	N/A	$2.29/micro	$1.99
19	$1.69	$2.39/micro	$2.49	$1.49/stove	N/A
20	$1.69	N/A	N/A	$1.49/micro	$2.39
21	$2.09	$1.39/stove	$2.49	N/A	$2.39
22	$2.09	$1.89/micro	$1.99	N/A	N/A
23	$2.09	N/A	$2.49	N/A	N/A
24	N/A	$1.39/micro	N/A	$2.29/micro	N/A
25	N/A	$1.89/micro	$2.49	$1.49/stove	$2.39
26	N/A	$2.39/stove	$1.99	$2.29/micro	$2.39

Table A8

CONSUMER FOOD PRODUCT DESIGN LEVEL FREQUENCIES

Level	X1	X2	X3	X4	X5	X6	X7	X8
1	6	7	12	13	8	8	14	9
2	7	6	14	13	8	9	12	8
3	6	7			10	9		9
4	7	6						

Table A9

CONSUMER FOOD PRODUCT DESIGN CREATION CODE

Construct the Design

```
proc plan ordered; * Create full-factorial design;
  factors x1=4 x2=4 x3=2 x4=2 x5=3 x6=3 x7=2 x8=3 / noprint;
  output out=full;
  quit;

proc optex data=full; * Create information-efficient design;
  * Last level will be N/A.  Count brands.  Exclude 0, 1, 5.;
  where (2 <= ((x1 < 4) + (x2 < 4) + (x5 < 3) +
              (x6 < 3) + (x8 < 3)) <= 4);

  class x1-x8;
  model x1-x8 x2*x3 x2*x4 x3*x4 x6*x7;
  generate n=26 iter=200 method=m_federov;
  examine information variance;
  output out=sub1;
  quit;
```

Print the Design

```
proc format;
  value f1_ 1 = '$1.29' 2 = '$1.69' 3 = '$2.09' 4 = 'N/A';
  value f2_ 1 = '$1.39' 2 = '$1.89' 3 = '$2.39' 4 = 'N/A';
  value f3_ 1 = 'micro' 2 = 'stove';
  value f5_ 1 = '$1.99' 2 = '$2.49' 3 = 'N/A';
  value f6_ 1 = '$1.49' 2 = '$2.29' 3 = 'N/A';
  value f8_ 1 = '$1.99' 2 = '$2.39' 3 = 'N/A';
  run;

data sub1f;
  length b1-b5 $ 12;
  set sub1;
  b1 = put(x1,f1_.);
  b2 = put(x2,f2_.);
  if b2 ne 'N/A' then b2 = trim(b2)||'/'||put(x3,f3_.);
  b3 = put(x5,f5_.);
  b4 = put(x6,f6_.);
  if b4 ne 'N/A' then b4 = trim(b4)||'/'||put(x7,f3_.);
  b5 = put(x8,f8_.);
  label b1 = 'Client Brand'
        b2 = 'Client Line Extension'
        b3 = 'Regional Brand'
        b4 = 'Private Label'
        b5 = 'National Competitor';

  run;

proc sort; by x4 b:; run;

proc print label; var b:; run;
```

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