USING HIGH-LEVEL CONSUMER-RESEARCH METHODS TO CREATE A TOOL-DRIVEN GUIDEBOOK AND DATABASE FOR PRODUCT DEVELOPMENT AND MARKETING

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ABSTRACT

We present aspects and data for a tool-driven database for marketing and product development, which are publicly accessible. The objective is to create a method whereby knowledge of concepts and products can be archived using overviews of a specific product category. The first phase of the database comprises systematic analysis of product concepts, which contain elements dealing both with features and emotions. The concept phase provides an idea about responses to statements about product features, along with responses to emotional elements and brands. The second phase comprises an analysis of the competitive frame of products, even before systematic product development is initiated. This second phase identifies expected and thus reasonable ranges of product-sensory features, levels of acceptance of typical products, relations between liking and sensory attributes and segmentation of sensory preferences. Together, the two phases provide a guide to product developers new in a category, archive current knowledge and provide a sourcebook for marketers and developers alike, which is accessible using research tools. The two phases allow product development to become more scientific, more based on common experience rather than individual expertise and thus more efficient, without compromising corporate knowledge of specific ingredients, processes or business opportunities.

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INTRODUCTION

Today's product developers use consumer data to drive their development activities. A great deal of development begins first with trend watching to identify opportunities in the market, followed by ideation to create new concepts for a product, followed by concept tests and then product test and simulated test markets. To the degree that a developer uses consumer information to guide activities, there is a greater chance that the product will meet with consumer success. Consumer acceptance at the level of product concepts means that the developer is working on something that consumers say they find interesting. To the degree that the developer uses consumer data about product acceptance, there is a greater chance that the product will "taste" good, because product information is a scorecard about whether the product is accepted or rejected.

Much of the current business practice creates a set of concepts, presents these to consumers, e.g., in focus groups or in a so-called concept-screening test, identifies what concepts win and then proceeds to product development with the winner or at least with a concept that looks promising and is technically feasible. This current business practice may be a "hit or miss" proposition depending upon the nature of the concepts chosen. If the concepts are novel, well executed, fit a consumer need and are timely, then there is the chance that the product will achieve market success if the product lives up to the concept. All too often, however, the concept scores poorly, is not particularly different from other ideas on the market, i.e., a "me-too" entry and promises little in the way of market success. These poorly scoring concepts often drive product development nonetheless, because the marketer may have run out of time, money or ideas, and in distress proceeds with the nearest albeit suboptimal and even recognizably poor opportunity.

Today's product-development sequence is not much better. A lot of product development operates under time and budget constraints. Despite exhortations to be systematic, disciplined and thoughtful at all stages of development, a standard strategy in many companies is to run informal "bench top" screenings of prototypes, eliminating the clearly terrible performers, and then proceed with testing using low-budget test execution. With sufficient time and a little luck, the developer comes up with a few alternatives that are submitted for consumer evaluation. The evaluation may be run informally or formally, with few or many people, with a simple rating of like/dislike or an excruciatingly long list of attributes. The evaluations may be analyzed using simple statistics or submitted to state-of-the-art computer-driven statistical analyses that partial out every source of variability in the attempt to measure "true acceptance." Whatever the method, the objective is to narrow down a set of product prototypes to one, and ensure that that prototype is the best product to launch.

Improving the Approaches Using Experimental Design

Experimental design, a branch of statistics and mathematical modeling, comprises the orderly arrangement of test stimuli in a way that allows the researcher to assess the contribution of each element, and in some cases, the nature of the interactions between pairs of variables. The principles of experimental design have been laid down by a number of statisticians (Box, Hunter and Hunter 1978). Much of the statistical work began in agriculture and chemical engineering, where the cost of development is high, and where one must carefully plan one's research because the cost of failure can be very high.

Applying experimental design to food-product development has a long, 40-year history, but it is only in the past few years that we have seen experimental design come into its proper role. Forty years ago, Gordon (1965) talked about the application of experimental design in orange juice, and some years later at Pillsbury there were numerous applications of the method pioneered by Al May. Design of experiments (DOE) taught by chemists at DuPont (Unlimited Learning Resources 2004) helped spread the approach, bringing it into food-product development. One can scarcely read the *Journal of Food Science*, published by the Institute of Food Technologists in the U.S.A., without coming across several different articles in each issue that use experimental design.

DOE became far more popular when mainframe computing gave way to personal computing. With the bench chemist and product developer in possession of sophisticated yet easy-to-use programs, it was a very short time until experimental designs became popular. Product development benefited from experimental design, but over the past 30 years, concept research did so as well (Green and Srinivasan 1981; Cattin and Wittink 1982; Wittink and Cattin 1989), and it will be the use of experimental design in early-stage concept development that will be of concern in this article (Moskowitz and Martin 1993; Moskowitz *et al*. 2005).

Concept Screening and the Benefit of Concept Optimization

Concept screening, the first phase of development, has benefited enormously from experimental design. Concept development works with variables that need not be continuous as is often the case with physical-product variables. That is, in concept work the variables are different statements about the product itself, brand names, statements about emotional satisfaction etc. Rather than appearing at different physical levels in a concept, the concept elements either appear or do not in a particular concept as dictated by the experimental design. Each concept comprises a limited number of a potentially very big set of concept elements, arranged so that the concepts are themselves easy to read, comprising relatively few elements. Across the different concepts, the elements appear in a statistically independent fashion. This approach, known by its general category name "conjoint analysis," permits the researcher to test what appear to be simple concepts, comprised of a relatively small number of concepts, yet at the end of the study builds an equation showing the part-worth contribution of each of these concept elements to the consumer's response. By knowing what each concept comprises in terms of elements and the rating assigned to the concept, it becomes possible to identify the strong- and weak-performing elements, and actually calculate their part-worth contributions.

Conjoint analysis finds great use in food-product development, but it was used with reluctance only recently because of its high cost and consequent high visibility. The early uses of conjoint analysis were reserved for the so-called "big-ticket" items where the decisions had to be made about the features of a product such as a hotel (Wind *et al*. 1989) or consumer electronics (Rosenbaum 1987). With the advent of the Internet, however, and with the emergence of conjoint analysis as an easily affordable and widely available Internet tool, conjoint analysis has become more popular in the food industry (Moskowitz *et al*. 2005). This article will deal with the application of conjoint analysis to a broad range of ice cream concepts.

Conjoint analysis also makes another contribution – that of providing general background knowledge. Although the traditional applications of conjoint analysis have been in the realm of solving problems for specific product development or messaging (advertising), recent use of large-scale sets of conjoint analyses for arrays of foods and beverages have shown the potential for conjoint analysis to create a knowledge base of a more general use. That is, rather than setting up a study to solve a particular applied issue, Beckley and Moskowitz (2002) suggested that the conjoint-analysis approach be used to create foundations for knowledge, and have named their approach "foundational databases." The promise of these databases is that they can become public knowledge, available to all marketers and developers. The aspect of public availability allows concept research to enter the realm of science and archival knowledge, rather than remain a private–corporate domain where each truth has to be discovered and rediscovered anew, at great cost, and often with great error.

Assessing the Competitive Frame for Products and the Notion of a Product Model

When we move beyond concepts to products, the conventional approach is to test one or two "best guess" products using a so-called "selection test."

The selection test requires the respondent to evaluate the products on a number of attributes, including overall liking or some other similar evaluative criterion. Typically these products are not systematically varied, and may simply represent different alternatives that the product developer deems to be viable for the new product entry.

The aforementioned method of experimental design is often used prior to these selection tests by companies that develop products in a systematic way. Experimental design identifies the variables under the developer's control and prescribes a specific set of combinations. Most frequently, the developer's variables are continuous (e.g., level of an ingredient), and may show a consumer-acceptance peak in the middle range. Furthermore, two or more ingredients under the developer's control may interact, either to create a synergistic combination where the rating of acceptance is much higher than expected, or to create a suppressive combination where the rating of acceptance is much lower. In any case, the research develops an equation to relate the levels of the ingredients, their interactions and nonlinearities (e.g., optimum in the midlevel) to the ingredients and their interactions. The method of experimental design applied to products, often called response-surface analysis, does not provide the general knowledge needed to found a science of product development. Experimental design does not look for patterns as much as it looks for optimal combinations of independent, operationally controllable variables.

Another method, called category appraisal, may provide the basis for the science of product development, and holds promise for creating a body of publicly accessible knowledge. Category appraisal is used when the developer wants to discover what drives liking, but does not want to pursue experimental design. Perhaps the effort to create the combination of ingredients is deemed to be too great for the payout. In many instances, it is very time consuming and expensive to create the necessary 10–20 prototypes dictated by the experimental design. At the same time, however, the researcher wants to understand what features of the product, at least from a sensory level, drive overall liking. The researcher wants to discover the patterns, but not create the combinations. In these situations the researcher might then test a variety of in-market products, which are basically unrelated to each other except for the fact that they are representatives of the same type of product. However, through statistical methods such as principle components factor analysis followed by regression and optimization, it becomes possible to simulate an experimental design, and identify which particular sensory features of the product correspond to the optimally acceptable product. Category appraisal has been discussed in a number of books and articles (e.g., Moskowitz 1984; Munoz *et al.* 1996).

Anticipatory Databases from Multiple Concept Stimuli and Multiple Product Stimuli

The vast majority of research efforts for concept and product studies involve the solution of momentary problems. Indeed, it can be validly said of consumer research in product development that the research efforts are almost always directed towards practical applications of a momentary nature. Consequently, there is remarkably little in the way of database information about consumer responses to concepts and products that might be called a "science." Little appears in the published literature and very little of what is published can really be said to be oriented towards the development of a science of product development.

The preponderance of specific applications for concept and product research should not be surprising. For the most part, the research that companies support aims to solve practical, generally momentary issues. These issues revolve around what particular types of concepts perform well among consumers for a specific business opportunity, and in turn what types of products perform well among consumers as well as fitting the winning concept. There is no room in corporations to contribute to the science of consumer-product development because there is no thought that this development is anything but an activity that supports the corporation's business goals. Any contribution to a "science" of product development in the viewpoint of most corporations is accidental, and perhaps even inimical to corporate privacy and the search for corporate advantage in a highly competitive world.

Despite this potentially negative view by corporations about a public "science" of product development, the databasing methods discussed above for concept and product might well constitute the beginnings of such a science that in the end would benefit the corporations, which feel that they might lose some of their competitive advantage. Because two of the goals of science are to formalize knowledge and show relations among variables, we might consider these databases as providing some of this formalized knowledge in a less threatening way as follows.

Concept Databases Using Different Types of Elements. Databases about concepts show what types of concept elements drive consumer responses. If the concept elements are reasonably general for a specific food product, covering features, brands and emotions, then the database generated by the concept research becomes *de facto*, a scientific database with sufficient generality to drive insights rather than reveal secrets. Conjoint analysis, in turn, which shows the utility or driving power of each concept element, becomes therefore a very powerful technique in the creation of this database.

Product Elements Using Similar Types of Products. Databases about products reveal what sensory attributes "drive" acceptability. If the database comprises products that are not simply slight variations of each other because of changes in one ingredient, then the database becomes even more valuable because it may reveal more "general rules" that transcend effects because of changes in one simple ingredient. Such product databases become critical because they cumulate knowledge in a single repository.

Demonstration of the Databasing Approach – Ice Cream

We present the approach using concept and product data on ice cream. The concept data come from a set of studies called the It! foundation databases (Beckley and Moskowitz 2002). The goal of the foundation databases is to understand aspects of how people respond to concepts. More specifically, the databases try to formalize an understanding across products regarding the drivers of concept interest when concepts comprise systematically varied elements such as descriptions of product features, emotional benefits etc. The particular study presented here, for ice cream, is part of a larger scale set of studies for different foods, and represents our initial attempts to create this product-development science.

To complement the concept data, we also present a parallel database on sensory, acceptance and expert responses to ice creams, developed through the category appraisal method. Product data were originally used by product developers in order to understand the drivers of acceptance, based upon a broad cross section of in-market products. We feel that this type of data represents an appropriate example for the product half of the science of product development.

The product and the concept data were run at separate times, for different purposes in early 2001. It will become clear in the analyses that one need not combine the concept and product studies, as long as each study has the requisite variation in the stimulus set. We are looking for general patterns for perceptions of ice cream, and not the solution to a single problem. Thus the range of variation in the concepts and products provides the perfect type of information for a foundation database – not as general as to be useless for development direction, but not so specific as to be finely tuned to solve one particular problem. The goal of science is to provide generalities, knowledge, insight and principles, which will then guide solutions to problems. It is the body of organized knowledge, not the specific problem to be solved, that should be the focus.

MATERIALS AND METHODS

Part 1 – The Concept Database

The objective of the concept study was to develop a model showing how different concept elements drive consumer interest. To this end we developed a set of 36 elements, comprising 4 silos or categories comprising 9 features each. The silos were the following:

1. Product features
2. Situation or mood
3. Emotional benefit
4. Brand or other benefit (not emotional)

Because the overarching goal of the study was to create a database that could be used to guide product development for ice cream beyond a single project, the elements were selected to be fairly general rather than particular to a single ice cream. Although selecting more general elements does not answer a single particular problem that may arise for one manufacturer, the patterns emerging from the more general set of elements provide greater insight beyond that one single-focused problem. The patterns will reveal "what works and what does not," "drivers of interest" and concept-response segments. It is important to emphasize again that this more global approach differs from the focused problem–solution approach, and that it is more likely to be able to found a science with the global approach because of the greater applications later on. We see the concept elements listed in Table 1.

Concept Test Stimuli, Experimental Design, Field Execution and Analyses

The test stimuli comprised small, easy-to-read combinations of the concept elements. Each concept comprised 2–4 elements, at most 1 element from each of the 4 silos (see Fig. 1 for an example). The silos, therefore, act as bookkeeping devices as well. A single experimental-design structure created a set of 60 different combinations, ensuring that each element would appear 3 times in the 60 combinations, and would be statistically independent of the remaining 35 elements in the frequency of appearance across the concepts. Furthermore, the design was created so that in a number of concepts a category was entirely absent. Although most consumer researchers feel that a concept should comprise one element from each category or silo in order to be meaningful, this *a priori* requirement of "complete concepts" generates three severe interlinked statistical problems in the analytic phase, which the current approach avoids entirely.

TABLE 1.
THE 36 CONCEPT ELEMENTS SHOWN BY SILO AND THEIR UTILITIES

	Base size	322
	Constant	49
	Silo no. 1: Product features	
A1	Classic taste . . . the way you remember it	3
A2	A smooth, dense scoop of ice cream . . . any flavor you want	7
A3	Real ice cream made with ingredients like milk, cream, natural sugars and natural flavors	10
A4	Everything you want . . . all in one place . . . a mixture of tastes and textures	3
A5	Rich, creamy soft serve . . . have any flavor you want, maybe even two . . . swirled together or on top of each other	9
A6	Smooth, velvety ice cream . . . with a heavy texture, complex flavors and enticing appearance	7
A7	Exactly the way you always imagined it	2
A8	Ice cream that melts slowly to release delicate, intense flavor and has a rich, silky texture that just melts in your mouth . . . so sinful!	12
A9	Prepared just to your liking . . . add whatever your heart desires	4
	Silo no. 2: Situation or benefit (nonemotional)	
B1	Premium quality . . . the best ice cream in the whole world	6
B2	Available at a value price	–2
B3	With chunks of chocolate or nuts swirled in for added fun and flavor	5
B4	Over sliced bananas for the best banana split!	–5
B5	With no added sugar . . . so you can savor it without all the extra calories and carbohydrates	–8
B6	Layered with fresh water-ice made with your favorite fruit and a thick, creamy custard	–20
B7	Topped with thick sauce, chopped nuts, real whipped cream and a bright red cherry for the perfect ice cream sundae!	8
B8	With great tasting sprinkles, nuts, candy pieces or sauces like fudge and caramel . . . all your favorite toppings	5
B9	With your favorite beverage	–6
	Silo no. 3: Emotional benefit	
C1	So delicious, just thinking about it makes your mouth water	3
C2	When you think about it, you have to have it . . . and once you have it, you cannot stop eating it	1
C3	You would drive any distance . . . at any hour . . . to get it exactly the way you want it	–3
C4	Relaxes and refreshes you . . . inside and out	1
C5	A joy for your senses . . . seeing, smelling, tasting	1
C6	Eating it makes all the stress just melt away	1
C7	A quick snack for when you are on the run	–1
C8	To be enjoyed while surrounded by family and friends	–1
C9	A special treat . . . you will savor every bite	1
	Silo no. 4: Brand or benefit (nonemotional)	
D1	From Edy’s or Dreyer’s	–1
D2	From Breyers	1
D3	At Dairy Queen	1
D4	From Ben & Jerry’s	6
D5	At Baskin Robbins	2
D6	From Haagen Dazs	6
D7	Ready-to-eat, easy to find	0
D8	Certified to be natural and organic	–9
D9	Guaranteed to be safe for you to eat	–3

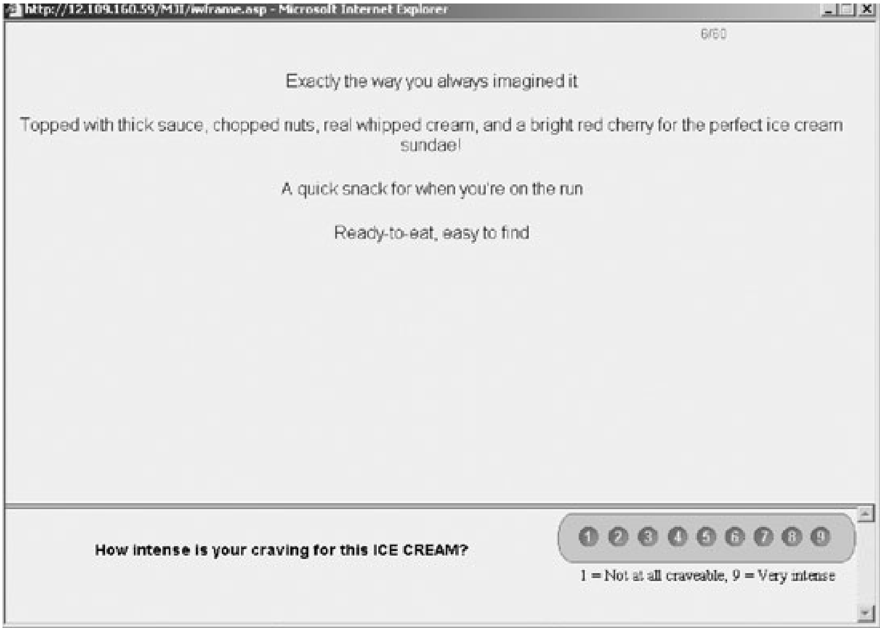

FIG. 1. EXAMPLE OF A CONCEPT FOR ICE CREAM, COMPRISING FOUR ELEMENTS
One element from each of the four silos.

Collinearity. By requiring complete concepts, it is impossible to estimate the true utility value of any concept element because of multicollinearity (i.e., knowledge of the presence/absence of any eight of nine elements in a category or silo automatically dictates knowledge of the presence/absence of the ninth, meaning that the elements in any category are not independent).

No True Estimate of the Basic Level of Interest. The statistical analyses of such complete concepts require a different type of regression analyses, known as the effects model, in which there is no estimate of the additive constant (the basic level of interest without any elements present), and the requirement that the utilities of the nine elements in a single category add up to zero.

No True Estimate of the Utility Value of the Individual Elements. The requirement of the constant sum equaling zero means that if a new element is introduced into the study, the utilities of the other elements must be readjusted. This readjustment means that one cannot use the results for databasing, and thus no science can be developed.

One of the key issues with concept testing in general and conjoint analysis in particular is the possibility that a concept will do unusually well or poorly because of the synergistic or suppressive combination of elements. This complaint, often voiced by advertising agencies and other professionals in the communications business, can be addressed in one of three ways.

1. Build in the combinations that might be synergistic or suppressive, in order to measure the degree of synergism if it actually exists. Building and assessing combinations is a common strategy for custom-research projects that have the luxury of testing many more elements in a conjoint task, or testing many specifically designed concepts in a concept-screening test. For the foundation study, this strategy is infeasible because there are 4 silos comprising 9 elements each, meaning that there are 6 pairs of silos, each pair having 81 possible combinations (i.e., 9 elements each from Silos A and B, generating 81 pairs). Thus, there is the total of 6×81 or 486 combinations. Which specific combinations should be created and tested? No one really knows, and to answer this question definitively would require an enormous expenditure with no promise of any results to emerge.
2. Systematically permute the combinations of elements so that each respondent tests a unique set of combinations. This strategy ensures that the spirit of the experimental design approach is maintained, even at the individual respondent level. Each respondent evaluates a unique set of 60 combinations created from the experimental design. The same experimental design is maintained, with its statistical rigor, allowing estimation of the utilities at the individual respondent level. However, the elements are permuted in such a way that the combinations differ from respondent to respondent. This design strategy ensures that no single combination of elements could possibly influence the utilities of the elements. The strategy here is to cancel out any such unexpected synergies or suppressions through the permutation process.
3. Develop a discovery system to identify synergisms. This approach has been done, but needs approximately 200 respondents or more (Marketo *et al*. 2004). The analysis of interactions suggests that about 10% of the pairs of elements will show some level of synergy or suppression, primarily suppression. The magnitude of the effect varies by the particular pair of elements, and becomes a topic unto itself.

Field Execution

The field execution of conjoint studies can be done very efficiently, especially when the studies are executed using the Internet. This study, like

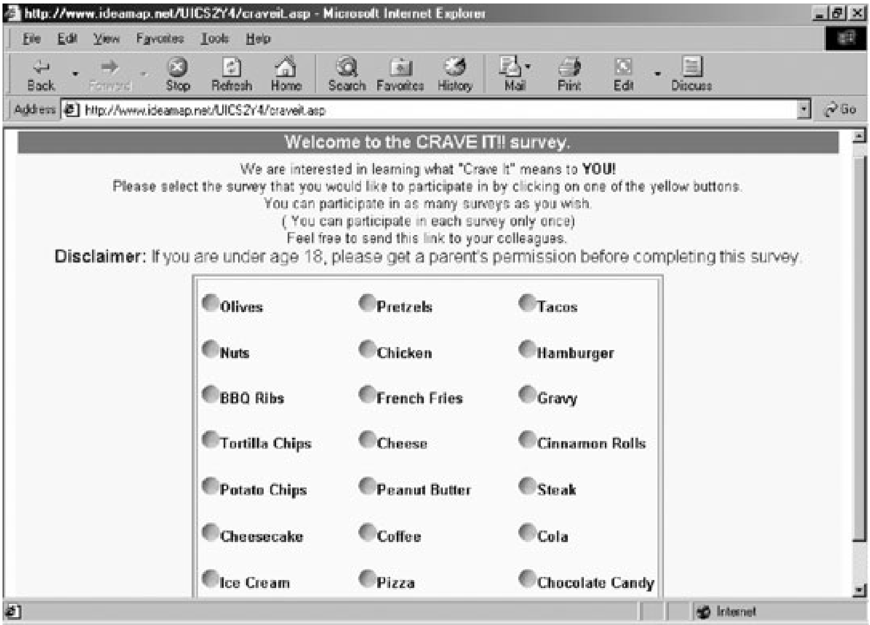

FIG. 2. EXAMPLE OF THE "WALL" WHICH PRESENTED THE RESPONDENTS WITH AVAILABLE STUDIES
Only respondents interested in the ice cream study participated.

other foundation studies designed to provide the database for product development, was executed following these steps:

1. Setup. The study was set up using a self-authoring Internet program (IdeaMap.Net), which allows the researcher to set up, edit, run and analyze studies automatically, with relatively little cost (Moskowitz *et al*. 2001). The tasks followed a structured sequence, guided by a protocol that forced the researcher to follow the steps before launching the study. These steps included typing in the welcome page, the concept elements, the rating questionnaire, the classification questionnaire and the goodbye page.
2. Email invitation. The respondents were invited to participate by an email invitation, which contained a link. All respondents were recruited by a service that specializes in email solutions to marketing problems. The link brought interested respondents to a "wall" presenting different studies from which the respondent could choose a study (see Fig. 2). The respondents who chose the ice cream study were led directly to the interview.
3. Concept order. The interview program was set up to present the respondents the different concepts in a unique randomized order, so that each

respondent received both a different set of combinations, and the particular combinations randomized in order.

4. Data acquisition. The respondent's ratings were captured for both the concepts and the classification. The typical interview length ranged from a short time of 10 min to a long time of approximately 20 min. The modal interview length was approximately 17 min. A total of 322 respondents participated.

The Foundation of the Concept Database – Utility Values for the Elements

The concepts themselves are only vehicles by which to embed the elements. The elements themselves are the real basis of the science, the real information whose utility is being sought after. The objective is to link together these elements or relatively simple ideas with utilities, so that in the development-knowledge database, one could find the idea (e.g., by a search engine), and then link that with a level of consumer interest. In this way, the foundational database goes beyond simply a compilation of ideas to the value of these ideas in the mind of the consumer.

Modeling the data is straightforward, and is done at the individual respondent level. Each individual evaluated the 36 elements embedded several times in the set of 60 combinations by means of experimental design. The design ensured that the elements would all be statistically independent of each other. Statistical independence, in turn, means that one can relate the presence/absence of the concept elements to the rating, by the following Eq. (1):

$$| \text{Rating} = k_0 + k_1(\text{Element A1}) + k_2(\text{Element A2}) \ldots k_{36}(\text{Element F6}) | \quad (1)$$

The equation is estimated by ordinary least squares (OLS), twice, using a simple transformation of the rating scale which generated a measure of "level of interest," and a second, binary transformation, which generated a measure of interest/disinterest.

The Persuasion Model. The first action transforms the rating from a 1 to 9 into a 0 to 100 scale in a very simple affine transform. The rating of "1" is transformed to 0, a rating of "3" is transformed to 25, a "5" is transformed to 50, a "7" transformed to 75, a "9" transformed to 100 etc. The intermediate scale values are likewise transformed in the same way. The result comprises a set of binary representations for the elements (0 if the element is absent from the concept; 1 if the element is present), a set of ratings (0–100), and 60 different combinations for a given individual. Through OLS, we estimate the parameters $k_1 - k_{36}$ for Eq. (1). The coefficient $k_1 \ldots k_{36}$ shows the number of rating points contributed by the particular element. The additive constant, k_0, shows the expected number of rating points to be assigned to the concept were no elements to be present. Clearly, this is impossible because all of the concepts comprised 2–4 elements, and thus the additive constant is merely a computed parameter. Nonetheless, however, the additive constant will be relevant as a baseline.

The Interest Model. Consumer researchers are accustomed to looking at data from the sociological viewpoint, which deals with the number or proportion of respondents who exhibit a certain behavior or fall into a certain classification. These researchers are not interested in the magnitude of interest in a concept, but rather in *whether or not* the respondent is interested in the concept. Creating a division in a category scale between interested and disinterested is an arbitrary decision. For these data, as for other data, the decision was made to call all ratings above 7 as representing an interested response (i.e., I like the concept, I would buy the product in the concept, I crave the product that is described). In contrast, ratings of 1–6 were assumed to represent disinterest in the concept. The ratings of 7–9, i.e., the interested ratings, were converted to 100. The disinterested ratings, i.e., 1–6, were converted to 0. Afterwards, the regression was run to relate the presence/absence of the concept element to interest/disinterest. The equations were run at the individual respondent level. By working at the individual level, it becomes possible to look at the models across different subgroups to identify product-development opportunities. At a practical level, the authors have observed that high-scoring elements in the persuasion model will remain the same in the interest model, and vice versa, although the interest model removes some of the detailed information.

RESULTS

Results – Total Panel

We see the basic data presented in Table 1, which shows the average utility from the interest model for all of the 322 respondents. The additive constant is 49, which means that without any elements present in the ice cream concept, approximately 49% of the respondents would say that they are interested in ice cream. This is a very high number, and suggests that to achieve high-concept acceptance, the elements have to do a moderate amount of work, not an exceptional amount of work. For example, in the case of credit cards, the additive concept is around 15 to 25, meaning that to achieve high-concept acceptance, the elements must do a great deal of work. The basic interest in credit cards is quite low.

How are these data used? Clearly, to found a science of product development, we are not interested in solving a single problem but rather should focus on developing principles on which product developers and marketers can rely on when they want to understand what to do for ice cream. Thus, we might foresee the following questions that could be answered from this database, simply with the data shown in Table 1:

1. What is the likelihood that a person will be interested in an ice cream product? Given that the additive constant is 49, it is likely that the consumers will be interested in the basic idea of an ice cream product.
2. What drives consumer interest? This is shown by the elements. We see that a lot of consumer interest is driven by the so-called "word pictures" or descriptions of products. Most of the winning elements come from the first category, which provides word pictures of products. Many of these word pictures are relatively "elaborate," comprising ice cream but with other features.
3. Do brands make a difference? The answer here is both yes and no, as it has been for many products. Although business runs on brand names, using these names in concepts may work for a few well-recognized brands (e.g., Ben & Jerry's; Haagen Dazs), but other brands do not perform well at all (e.g., Breyer's).

What Does the Work – the Basic Idea of Ice Cream or the Specific Elements?

The concept elements themselves span a relatively large range (see Table 1). The highest scoring elements present word pictures for the product developer. These are "Ice cream that melts slowly to release delicate, intense flavor and has a rich, silky texture that just melts in your mouth . . . so sinful!" (utility = 12) and "Real ice cream made with ingredients like milk, cream, natural sugars, and natural flavors" (utility = 10). Because the total utility of the concept is the sum of the additive constant and the utilities, a 4-element concept with 1 element from each of the 4 silos can achieve a utility of 78, of which virtually 62% comes from the basic interest. To the product developer, this strong performance of basic interest and a concept element suggests the ability to create strong-performing concepts by combining the proper elements.

The large base of 322 respondents can be divided into many different subgroups, based upon the self-profiling classification questionnaire administered after the evaluation, or concept-response segmentation, which divides respondents by the pattern of their utilities (Moskowitz 1996). Given the subgroups, one interesting question is whether the subgroups are alike in the degree to which a highly performing concept might be constructed. That is, what is doing most of the work – the additive constant which shows the predisposition to ice cream, or the specific elements, which work by communicating what the respondent wants to hear? The answer to this question comes by:

1. Identifying each relevant subgroup.
2. Estimating its additive constant from the regression model for interest.
3. Searching through the performance of its 36 elements to identify which is the highest scoring (the maximum).
4. Adding together the maximum and the additive constant to create a "sum."
5. Calculating what proportion of the sum is attributable to the additive constant, and what is for the best-scoring 4 elements, recognizing that a concept might comprise 2–4 elements.
6. From this analysis, the marketer and product developer get a sense of the difficulty of the job that awaits them. The first analysis looks at the highest level of the concept that can be achieved. If the highest level is very high, then the concept has a great deal of promise. If the highest level possible is not particularly high, then one might conclude that the task would be difficult because even by choosing the best elements, it appears difficult to get a strong-performing concept.
7. The second analysis looks at what contributes to the concept performance. If the majority of the concept performance score can be traced to the additive constant, then the task is relatively simple because the consumer respondents are interested in the product. However, the problem is that no matter what the marketer or developer does, the elements themselves will not make much of a contribution. In contrast, if the majority of the concept performance comes from the elements, then there is the distinct possibility that the product concept will score well because of the elements that are chosen. It is also possible that by choosing the incorrect elements, the concept will score poorly.

We see the results of this structural analysis in Table 2, which shows the following indices:

1. The base size or number of respondents participating in the study, and belonging to each subgroup.
2. The additive constant.
3. The maximum utility value for each of the four silos, independent of the specific concept to which that high utility corresponds.
4. The sum of these four maximum values.
5. The total, defined as the sum of the additive constant and the four maximum utility values.

TABLE 2.
OPTIMUM-CONCEPT SCORE FOR DIFFERENT SUBGROUPS AND THE CONTRIBUTION OF ELEMENTS AND ADDITIVE CONSTANT TO THIS OPTIMUM

Total sample	Base size	Constant	Max S1	Max S2	Max S3	Max S4	Sum max	Total	% Elem	% Const
	322	49	12	8	3	6	29	78	37	63
Self-reported hunger										
Extremely hungry	62	61	8	11	5	9	33	93	35	65
Moderately hungry	99	56	14	6	4	5	29	85	34	66
Slightly hungry	96	41	16	8	3	9	36	76	47	53
Not at all hungry	65	38	11	9	5	7	32	70	46	54
Eating frequency										
Once a day or more	36	60	14	6	5	8	33	92	36	64
4–6 times a week	80	51	14	10	3	8	35	86	41	59
2–3 times a week	104	46	15	10	5	9	39	84	46	54
Once a week	41	51	8	6	4	10	28	79	35	65
4–6 times a month	20	46	17	16	4	6	43	88	49	51
2–3 times a month	24	45	13	9	6	6	34	78	44	56
Once a month or less often	15	45	11	12	10	11	44	90	49	51
When eaten										
Midmorning	7	39	17	17	22	12	68	108	63	37
At lunchtime	22	48	16	15	11	8	48	99	48	52
Midafternoon	125	51	11	8	2	8	29	80	36	64
At dinnertime	18	54	8	9	7	5	29	83	35	65
Just after dinner	126	50	13	8	3	11	35	86	41	59
In the late evening, just before bedtime	198	50	13	9	4	6	30	82	37	63
When shopping	8	41	17	6	13	10	46	87	53	47
When watching TV	112	47	17	10	5	7	39	86	45	55
Gender										
Male	99	45	12	10	2	7	32	77	42	58
Female	223	50	13	7	4	6	29	80	36	64

Age										
18–30	22	39	17	18	2	11	47	86	55	45
31–40	71	45	13	14	6	5	36	82	44	56
41–50	102	45	13	13	3	10	39	83	47	53
51–60	83	58	11	4	2	9	26	84	31	69
61–75	41	57	15	2	5	7	28	85	33	67
My neighborhood										
Trendy urban neighborhood	16	33	18	17	7	6	47	80	59	41
Rural town or farm	51	46	14	15	4	6	39	85	46	54
Urban neighborhood in the heart of the city	37	54	16	7	5	12	41	95	43	57
Midsize suburban neighborhood outside of the city	67	46	11	12	3	8	34	80	43	58
Large suburban neighborhood within city limits	51	43	10	8	4	9	32	75	43	57
Small-town suburban neighborhood	88	53	16	8	6	9	39	92	42	58
Income										
Under $10,000	14	60	16	11	3	7	38	98	39	61
$10,000–19,999	35	46	21	16	9	12	58	104	56	44
$20,000–29,999	46	53	11	5	3	5	24	77	31	69
$30,000–39,999	46	55	10	9	5	7	31	86	36	64
$40,000–49,999	51	46	12	13	2	9	36	82	44	56
$50,000–74,999	50	51	17	10	2	9	38	89	43	57
$75,000–99,999	29	43	15	9	9	13	46	89	52	48
$100,000 and above	12	31	20	25	13	16	74	105	70	30
How I select and eat foods										
Only the basics . . . out of a box	57	46	17	16	5	8	45	92	49	51
Experimental	103	45	17	12	6	8	42	87	48	52
Full of flavor . . . lots of sauces or spices	89	49	15	11	6	8	41	89	46	54
Everything from scratch	67	50	11	7	7	8	34	83	41	59
Driven by variety and novelty	86	54	12	11	2	6	31	85	36	64
Classic cooking	152	56	13	6	3	3	25	80	31	69

TABLE 2.
CONTINUED

Total sample	Base size	Constant	Max S1	Max S2	Max S3	Max S4	Sum max	Total	% Elem	% Const
	322	49	12	8	3	6	29	78	37	63
My health concerns										
No red meat	16	35	17	13	16	27	73	108	68	32
High calorie, high fat (i.e., fast food)	44	45	18	18	5	7	48	93	52	48
Unplanned, whatever is available, I eat	157	48	14	11	4	6	35	83	42	58
Lots of fresh fruits and vegetables	122	48	14	11	4	7	35	84	42	58
Balanced carbohydrates, protein and fat	101	46	10	13	5	6	33	79	42	58
Low carbohydrate	18	61	10	12	11	9	42	103	41	59
Low cholesterol, low fat	61	47	15	7	3	7	31	78	40	60
Low sodium	40	53	14	9	0	11	33	86	38	62
Protein-rich meals and beverages	51	55	10	6	6	5	27	81	33	67
Diabetic or low in sugars	20	62	8	7	5	6	26	88	30	70
Low calorie	24	55	14	2	0	5	21	76	28	72
How I describe myself										
Traditional . . . straightforward . . . why mess with a good thing? (classic)	81	52	15	16	5	6	42	94	45	55
It is the total experience that matters most . . . the anticipation, the sharing . . . a good time with family and friends (imaginer)	191	46	12	6	5	6	29	75	39	61
Plain and simple can be so boring . . . add some excitement with variety, accessories . . . lots of stuff (elaborate)	50	55	10	6	3	9	29	84	35	65
How I respond to concepts										
Segment 1 of 3 (elaborate)	114	36	18	34	2	1	55	91	60	40
Segment 2 of 3 (classic)	106	54	12	8	6	19	44	98	45	55
Segment 3 of 3 (imaginer)	102	58	7	5	4	6	22	79	28	72

Max, maximum; Sum max, max 51 + max 52 + max 53 + max 54; % Elem, percent of the total that can be traced back to the four elements; % Const, percent of the total that can be traced back to the constant.

6. The percent of the total that can be traced back to the four elements (% Elem).
7. The percent of the total that can be traced back to the constant (% Const).

The results of the structural analysis suggest that:

1. For the total panel, 37% of the utility for the best-scoring concept will come from the elements, suggesting that it is the predisposition to ice cream, not the elements themselves, that does most of the work to drive concept performance. For the marketer and product developer, this suggests that they can achieve significant success, and that it will be relatively easy because there are winning-concept elements. However, the data also suggest that most of the concept performance is expected to come from the description of the product itself (Silo S1), rather than from brands or emotional statements. This is an important learning for the marketer because it suggests that brand value, by itself, or emotional benefits will not drive the written concept performance.
2. Self-reported hunger decreases response to the elements relative to the additive constant. Those respondents who rated themselves as being hungry when they evaluated the concepts appeared less responsive to the elements versus to the additive constant. Those respondents who reported themselves as not hungry or only slightly hungry paid relatively more attention to the elements. This would suggest to the developers two different strategies, depending upon when the product is consumed, and the respondent's state of hunger. For those times when the respondent eats the product in place of food (i.e., a snack), little attention need be directed to the elaboration of the product characteristics, because it is the additive constant or the predisposition to the product that is doing most of the work. In contrast, for those times when the respondent is satiated but is eating the ice cream, e.g., as dessert, more attention should be paid to elaborating the characteristics of the product.
3. Eating frequency does not have any effect on the relative sensitivity to elements, but does affect the highest level that a concept could achieve. That is, those who eat more frequently and those who eat less frequently show the same pattern of contribution to highest concept scores. However, the highest level a concept could achieve is substantially higher among the more frequent eaters than among the less frequent eaters.
4. Gender plays no role. The patterns are the same.
5. Age plays a major role. Older respondents generate higher-scoring optimal concepts than do younger respondents. Older respondents are less sensitive to the elements as drivers of interest in the concept.

6. Sociological differences play a role, primarily for those who live in self-defined trendy areas. They are more sensitive to the elements than those who say they live in less trendy areas.
7. Income plays a role, again for those respondents who earn much higher salaries ($100,000 or more). These high-income respondents are far more responsive to the contributions of the elements.
8. Self-defined cuisine and cooking style make a difference with those who say they are driven by either basics or “out of the box” (noncooking) interest in the elements, whereas those who are interested in novelty respond more to the elements, perhaps because they are not as much driven by the perception of specific ingredients as by something new.
9. Health concerns play a major role. Depending upon the specific health concern, the respondent can react strongly to the concept elements. These health descriptions vary from those who are concerned with red meat where elements play a major role, down to those who are concerned with calories where elements play a minor role. The dynamics are probably not traceable to the elements *per se*, but rather the degree to which the individual pays attention to specifics or ignores the product category and consumes ice cream infrequently. Those who said that they are concerned with calories also said they consumed ice cream less frequently (data not shown).
10. Consumers selected which one of three segments they felt most described their own personal style. The segments were Elaborate, Classic and Imaginer, and were based upon the 2001 Crave It! foundational database. Based upon the concept-response segmentation in that study, the respondents were divided into three groups. The segmentation was done across 30 products. From this early work we created a short descriptive sentence for each segment, and asked the respondents to choose which of the three statements most described them. The self-selected “Classic” respondent paid the most attention to the elements, whereas the self-selected “Elaborate” paid the least attention. This finding is counterintuitive, because we would have thought that Elaborates pay attention to the language of description. The data say something different, however, suggesting that the right elements for the “Classic” respondent can be far more powerful than the right description for the “Elaborate” respondent, even when it comes to the first silo, i.e., product description. This is an extremely important piece of knowledge for a product-development sourcebook, for it shows that a great deal of insight leading to proper product design and development can be obtained by understanding the mind-sets of the respondents, and what really makes a difference.
11. We segmented the respondents based upon the pattern of their utilities, using the method of K-Means clustering (Systat 1997). The respondents

fell into three groups to be discussed below. The dynamics of response to concepts shows startling and very critical differences across the three segments. We will deal with those differences in the next section.

Beyond Subgroups to Mind-set Segments and the Institutionalization of Segmentation

Our previous analyses of total panel and subgroups revealed that consumer subgroups differ from each other. Some of these differences may be random, others may be slight, but still others may be profound. A great deal of marketing effort is expended on segmenting the consumer market into groups of individuals who can be targeted with different products. Today's knowledge about consumer preferences is becoming more and more profound. Yet, there is no resource to which the marketer or product developer can turn to understand the mind-sets of a particular product area. There are general books in the popular domain, such as the *Nine American Lifestyles* (Mitchell 1983). These books on segmentation do not provide the product developer or marketer with direction; rather they simply hint at the possibilities of different mind-sets.

Market segmentation was recognized more than three decades ago (Wells 1975) and eagerly seized upon by marketers who recognized a major opportunity to differentiate products. However, most of the segmentation deals with general attitudes towards one's lifestyle. It is a very hard matter to translate these segment differences to product prescriptions. Even if one were to identify the segments more and more precisely, it is quite unlikely that the precision would translate to product development and marketing. Indeed, occasionally one might describe segmentation as the "metaphor that failed," or at least failed in the unspoken hopes of those who used it to gain competitive advantage.

A different approach to segmentation, called sensory segmentation, was presented in conjunction with product research. This approach looked at the relation between the sensory attributes and overall liking at the individual respondent level, and divided the respondents into different subgroups based upon the pattern of liking ratings and the sensory level at which the liking rating peaks (Moskowitz *et al*. 1985). The sensory segmentation method, perhaps the first or among the first methods of latent class segmentation now very popular in marketing circles, was applied to the world of concepts, using the same approach, and later a simpler approach that employed distance between two profiles. The approach was labeled "concept-response segmentation."

Applying the concept-response segmentation approach to these data generated three distinct segments, as shown in Table 3. We see in Table 3 the three segments. In segmentation, one can extract different numbers of segments, so beyond statistical consideration there are issues of interpretability. If the seg-

TABLE 3.
WINNING ELEMENTS FOR THE THREE CONCEPT-RESPONSE SEGMENTS

		Total	Seg1	Seg2	Seg3
			Elaborate	Classic	Imaginer
	Base size	322	114	102	78
	Constant	49	36	58	60
	Winners segment 1 (Elaborates)				
B7	Topped with thick sauce, chopped nuts, real whipped cream and a bright red cherry for the perfect ice cream sundae!	8	34	–21	8
B8	With great tasting sprinkles, nuts, candy pieces or sauces like fudge and caramel . . . all your favorite toppings	5	22	–9	2
B3	With chunks of chocolate or nuts swirled in for added fun and flavor	5	20	–11	5
A8	Ice cream that melts slowly to release delicate, intense flavor and has a rich, silky texture that just melts in your mouth . . . so sinful!	12	18	6	13
A5	Rich, creamy soft serve . . . have any flavor you want, maybe even two . . . swirled together or on top of each other	9	16	3	5
A3	Real ice cream made with ingredients like milk, cream, natural sugars and natural flavors	10	14	4	10
B4	Over sliced bananas for the best banana split!	–5	13	–27	–6
A6	Smooth, velvety ice cream . . . with a heavy texture, complex flavors and enticing appearance	7	12	3	6
B1	Premium quality . . . the best ice cream in the whole world	6	10	5	4
	Segment 2 (Classics?)				
A2	A smooth, dense scoop of ice cream . . . any flavor you want	7	8	7	6
A8	Ice cream that melts slowly to release delicate, intense flavor and has a rich, silky texture that just melts in your mouth . . . so sinful!	12	18	6	13
D3	At Dairy Queen	1	–2	6	0
	Segment 3 (Imaginers?)				
A8	Ice cream that melts slowly to release delicate, intense flavor and has a rich, silky texture that just melts in your mouth . . . so sinful!	12	18	6	13
D4	From Ben & Jerry’s	6	0	0	11
A3	Real ice cream made with ingredients like milk, cream, natural sugars and natural flavors	10	14	4	10
B7	Topped with thick sauce, chopped nuts, real whipped cream and a bright red cherry for the perfect ice cream sundae!	8	34	–21	8

TABLE 3.
CONTINUED

		Total	Seg1	Seg2	Seg3
			Elaborate	Classic	Imaginer
	Base size	322	114	102	78
	Constant	49	36	58	60
C1	So delicious, just thinking about it makes your mouth water	3	0	4	7
A6	Smooth, velvety ice cream . . . with a heavy texture, complex flavors and enticing appearance	7	12	3	6
A2	A smooth, dense scoop of ice cream . . . any flavor you want	7	8	7	6

Seg, segment.

ments cannot be named, then the marketer and developer really cannot deal with them, and the information does not add to the knowledge base. In contrast, if the segments can be named, then the information adds to the store of knowledge about ice cream in particular, and product development/ marketing in general.

We see the same radical differences among the segments when we look at the nature of the optimum concept, discussed above for the other subgroups (see the bottom of Table 2, which shows the results for the three concept-response segments). The optimal concept can achieve its highest level with Segments 1 (Elaborate) and 2 (Classic), but there are problems achieving a high score with Segment 3 respondents (Imaginer). Furthermore, the nature of the concept dynamics differs as well. For Elaborates, most of the work is done by the concept elements (60%) and less done by the additive constant (40%). The opposite is the case for the Imaginer, where the additive constant does most of the work (72%) and the elements do less work (28%).

Because we are attempting to lay the foundation of a database that transcends a specific product or period, it is instructive to use names for the segments that have been previously used, in order to create a coherent database. The three segments from the 2001 Crave It! foundational database were Elaborates, Classics and Imaginers. We have tried to use those same names. It is clear from these data that the Elaborates reemerge. One can plausibly assign the name "Imaginer" to the third segment because this segment strongly reacts to brand names and evocative images beyond the product experience. The second segment might be the "Classics," but this segment is so limited in what it likes that the "Classic" name is not necessarily the right one. Certainly, however, this third segment wants traditional things – Dairy Queen is the traditional soft-serve ice-cream outlet.

An Overview to the Concept Portion of the Database

If a product developer or marketer were to look for data about ice cream, then the information presented here about concepts for ice cream might well provide a good start. The concept-utility information is sufficiently general to provide a good start. The following types of information would emerge from this product-development database.

The Range of Element Acceptability. This type of information reveals how well or poorly the elements perform. Quite often those involved in early-stage development have no norms against which to check their guesses. There are no ready frames of reference. These results provide some needed norms, more in line with the general category than within a specific concept.

The Nature of Winning and Losing Elements. These data provide a sense of what does well, and thus act as a model for one's own development of other concept ideas.

Where Effort should be Placed – Finding the Right People Versus Finding the Right Message. All too often, those involved in concept research do not know where to begin – should they put their effort in ideation or in targeting? These results help to address that issue by identifying the dynamics of a winning concept.

What Types of Segments Emerge, and How to Address Them. Segmentation is critical. Knowledge of how the category operates in terms of mind-sets is quite critical for any developer who needs to go beyond simple information available in sales data. It is one thing to target consumers. It is quite another matter to know exactly how to develop for these consumers and what messaging to use.

The Composition of the Segments for Targeted Marketing. This information is not shown, but is contained in the classification portion of the study.

Part 2 – Product Knowledge from Category Appraisal

The second half of the database comes from a study of vanilla ice cream. It is important to stress that the two halves of the study need not be connected. Although linked studies are always to be desired because the same respondents can participate, practical considerations militate against this ideal situation. Rather than waiting for the perfect study to come alone, it is more profitable and more realistic to work with data that are available and deduce principles from it (Moskowitz 2001).

The study comprised 22 different variations of vanilla ice cream purchased commercially. The original objective of the study was to understand the drivers of liking for vanilla ice cream, which is a typical objective for category appraisal studies. By working with in-market products or with "rifle shot prototypes," i.e., prototypes that are not systematically varied, the researcher identifies general rules, although at the expense of not being able to easily tie these rules back to the ingredients. On the other hand, the category appraisal approach provides the preferred format of data for an archival guidebook or database for product development because the analysis extends *beyond* levels of ingredients and goes into perceptions. With ingredients as the main focus, the temptation, and indeed, a proper strategy, is to work only with the particular ingredients, not sensory perceptions. The strength of working with experimentally designed products actually limits the generalities to be obtained from the dataset, consequently reducing the nature of the learning to a formulation exercise.

Field Execution and Product Data

A sense of the type of product information can be obtained from Table 4, which shows the mean ratings of products 101 and 102 on attributes. The field execution of category appraisal studies varies from practitioner to practitioner, making any generalities hard to offer. The most important things to keep in mind about a category appraisal are:

1. The objective – to obtain measures of product performance, and to develop rules or generalities about variables that drive acceptance. When practitioners aver that consumers cannot evaluate the sensory characteristics of products, of which task must be left to the experts, they are losing a great deal of possible information, and reduce the usefulness of the database.
2. The field execution must be done so that the respondent can evaluate each product in a randomized order, profiling the product on attributes. Having the respondent compare two products to reveal a preference will simply not generate the needed data for subsequent pattern analysis.
3. The researcher may opt to acquire other forms of data, such as ratings by expert panelists using their own terminology as well as measures with instruments. This type of information becomes exceedingly valuable for the developer looking to create new products. The expert panelist provides a profile of sensory characteristics that a consumer could not provide, simply because the expert has been trained in a language that might be foreign to the consumer. The consumer can rate attributes meaningful to him, but will

TABLE 4.
AVERAGE RATINGS FOR TWO PRODUCTS ON DIFFERENT TYPES OF ATTRIBUTES

	Product	
	101	102
Liking and image		
Total	54	57
Segment 1	59	71
Segment 2	47	46
Attribute liking		
Appearance	64	55
Color	65	58
Aroma	61	50
Consumer sensory attributes		
Yellow	44	59
Creamy appearance	74	66
Icy appearance	30	48
Consumer image		
Rich	59	56
Fresh aroma	64	52
Fresh taste	59	59
Expert sensory attributes		
Icy	19	31
Hard	38	35
Dense	46	35

Partial data.

not be able to tap into a lexicon of attributes available to the expert panelist. To the degree that the protocols for training the expert panelist are included in the dataset, subsequent developers can access the profile of products in the category. Precious little of this type of information has been published, despite the more than 50 years during which expert panelists have been used to profile attributes. What is available in the scientific literature, published by academics, provides a valuable starting point.

4. Instrumental measures are a favorite of food scientists. With complete data and statistical-research capabilities more widely available, the sensory-instrumental relations can be made more useful to product development. Right now much of these published results are reported in terms of correlations, rather than in terms of actionable modeling (which will be discussed below).

What Should the Database Provide in Order to Make the Data Useful

The data in Table 4 present simply the beginning of information that could be used for the product developer's guidebook. The data will probably not be as valuable for the marketer because the information in Table 4 is limited to specific products. Nor will the data be useful if it is maintained in tabular form, even with data from all 22 ice creams. For specific projects, the developer will be understandably interested in the individual product-level data, but once the immediate business issue for the project goes away, the numerical data itself become irrelevant. It is either sensory range to identify norms or patterns relating pairs of variables or multivariate product models that will provide the necessary archival type of information for the science of product development. All of this information can be disguised because the products themselves never have to be identified.

If we were to develop the contents of this developmental guidebook for ice cream using the category appraisal, then we might begin with the two pieces of information.

Sensory Norms. What is the reasonable range of sensory attributes that we might expect from a random sample of products in the category? The developer might need to know this information because all too often, marketers ask for products that are physically impossible to achieve, or at least outside the boundaries of the typical products available in the market. Consider the range of consumer attributes shown in Table 5. By consulting this table, the marketer would learn that most of the ice-cream products on the market are acceptable, with the minimum level being 54 (on a 100-point scale) and the maximum being 100. Such information would tell the marketer and the developer that across all of the products tested in the market, there is a reasonable range within which the product attributes fall. This information would, in turn, reveal whether sensory objectives are reasonable and achievable, or whether they are so far outside the existing range that they are meaningless.

Is My Product Higher than the Median?

1. This is again very easy to answer if the researcher has tested a number of different products in order to generate a reasonable sensory range. There is rarely this type of normative information about products in a category. Indeed, for the most part every product developer working in a category tends to “fly blind,” working primarily with the ratings of liking which show whether the product achieves a certain level of acceptance. It is rare for a developer to be able to pinpoint the type of sensory region for a product based upon knowledge. It would be very beneficial for the developer to identify a sensory location where there are no products. This could only be done by knowing where the products lie, and therefore by analysis, where the holes in the category must be. The use of the sensory information to uncover holes in the market is worth further consideration.

TABLE 5.
RELEVANT STATISTICAL INDICES FOR THE VANILLA ICE CREAMS

Attribute	Min	Med	Max
Consumer liking and image			
Total	54	63	73
Purchase intent	37	46	61
Segment 1	55	62	73
Segment 2	46	59	74
Appearance	42	62	69
Color	40	63	71
Aroma	47	58	68
Texture	56	65	72
Consistency	55	63	66
Taste	54	61	71
Vanilla	50	56	68
Dairy	47	58	65
Sweet	52	59	63
Aftertaste	46	54	66
Consumer sensory			
Yellow	19	50	85
Creamy appearance	54	62	78
Icy appearance	29	40	50
Aroma	36	50	66
Crumbly	15	30	50
Sticky	31	45	65
Melt	46	59	72
Airy	30	45	60
Heavy	39	53	72
Sticky in mouth	27	40	53
Firm	37	57	78
Creamy	50	67	74
Smooth	56	70	75
Grainy	11	18	35
Icy	20	28	49
Thick	51	64	79
Taste	51	61	72
Vanilla	50	56	68
Dairy	45	57	67
Sweet	53	59	69
Aftertaste	46	54	63
Coating	39	47	54
Expert panel sensory			
Icy	16	28	36
Hard	32	38	44
Dense	31	41	52
Cohesive	23	37	48
Cooling	31	41	48
Particles	3	6	9
Astringent	10	12	18

TABLE 5.
CONTINUED

Attribute	Min	Med	Max
Melts quickly	30	40	49
Body	40	50	59
Mouth coating	29	36	47
Sweet	64	70	81
Sour	4	5	12
Bitter	2	3	9
Creamy	35	51	59
Consumer image			
Fresh aroma	50	60	67
Fresh taste	57	64	76
Natural	46	53	68
Expensive	45	52	70
Quality	51	58	73

The Min level achieved in the study representing the reasonably lowest level in the category, the Med level and the Max level.
Partial data only.
Min, minimum; Med, median; Max, maximum.

Beyond Statistics to Relations Between Variables (So-called "Drivers")

One of the more recent topics in product research is the notion of "drivers of liking," or the nature of sensory features that drive acceptance. It would be fair to say that most product developers cannot pick up a book or access a ready-to-use database which shows drivers of liking for a specific category that would allow the researchers to read about key sensory attributes. The result is repeated, painful experimentation whose results are often dictated as much by the expertise of the researcher as by the difficulty of the problem. There are at least five reasons for this lack of information:

1. Most data that are published deal with simply too few products to develop any meaningful database. Indeed, most of the product research deals with one or two products, generally in the form of preference tests (e.g., which of these two products do you prefer, for overall liking or for attributes etc.). It is impossible to develop any sort of relation between two variables with just one or two products, because there are simply no degrees of freedom on which to construct a pattern.
2. Statistical naïveté often holds or intrudes, compromising the best intentions and the noblest goals. When researchers do try to relate liking to sensory attributes, they often mistakenly do this on the raw data from one single product. The data appear to have variability – there is a range of liking (across the different respondents, albeit for the same product), and there is

a corresponding range of sensory-attribute level for a single attribute (albeit again against the same respondents). The analysis, terribly incorrect, correlates the liking ratings with the sensory ratings to show the "drivers of liking," not realizing that we are talking of one single product.

3. The data simply do not exist. There is a dearth of product data in the public literature for any single category wherein the liking and sensory ratings are published for the full dataset. If the data exist and have been published, the predilections of the analyst drive analysis to an incorrect simplicity that is easy-to-explain and to justify, even if wrong.
4. The incorrect, often misleading analyses are used because of one's intellectual heritage. Where there are attempts to develop the sensory-liking relation, the analyst generally uses linear correlations computed with the Pearson *r* statistic. The Pearson *r* or correlation statistic assumes a linear relation between liking and sensory-attribute level, whereas the true relation is probably more of a curve (Moskowitz 1981).
5. Occasionally all the factors come together to generate the right analysis with the right data by the right analyst. Only in a few rare cases do we see the sensory-liking curve plotted out, in the form of a scattergram, to show the nature of how overall liking or some other attribute covaries with a sensory attribute. These curves, such as those shown in Fig. 3, are developed by statistical plotting packages, that relate two set of attribute ratings by a quadratic function, and then smooth the data to simply reveal the nature of the function for the particular data without having to show the data points. The approach is a heuristic to reveal underlying patterns. The modal equation form is:

$$\text{Dependent variable} = k_0 + k_1(\text{Independent variable}) + k_2(\text{Independent variable})^2$$

Sensory Preference Segmentation Based upon Univariate Sensory Versus Liking Relations

One of the continuing findings in product research is the existence of subgroups of consumers who show different sensory preferences. This segmentation is most pronounced when we deal with products whose primary, distinguishing characteristics have to do with the chemical senses, especially taste. A great deal of sensory segmentation research reveals the existence of groups of people with radically opposing preferences – so what one individual likes, another hates. Methods for sensory-preference segmentation have been discussed in other articles (Moskowitz *et al*. 1985), so we only need summarize. The segments are defined by the sensory-liking patterns, and specifically

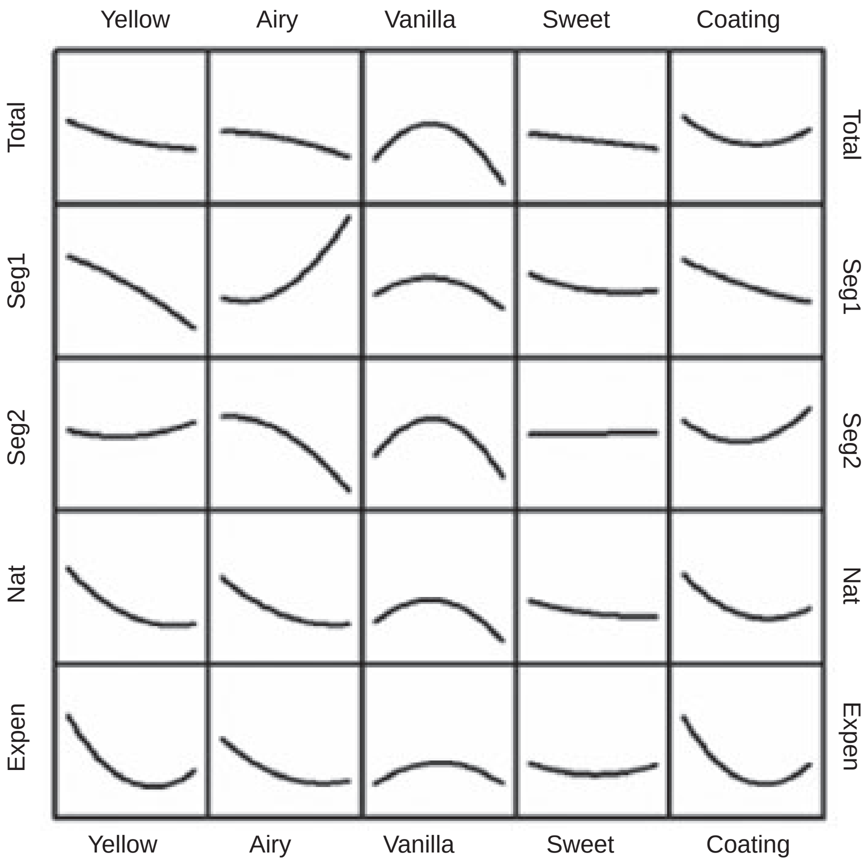

FIG. 3. SCHEMATIC RELATION BETWEEN THE SENSORY ATTRIBUTES OF VANILLA ICE CREAM AND BOTH LIKING (TOTAL PANEL, SEGMENTS), AND IMAGE CHARACTERISTICS (NATURAL, EXPENSIVE)
The curves are fit by a quadratic equation, and the points brought to the curve to show the overall expected relation.
Expen, expensive; Nat, natural; Seg, segment.

by the sensory level at which the sensory-liking pattern reaches it maximum. When the segmentation is done on a number of sensory-liking curves in tandem, so that each individual is defined by a profile of sensory optima, not just one, the results can be startling, especially when we plot the different sensory-liking curves. Figure 3 shows two segments (Segs) from the respondents, labeled Seg1 and Seg2. Segment 1 likes a vanilla ice cream with a light color, airy texture and is only modestly sensitive to departures from an optimal sensory level in the middle range of perceived vanilla flavor. In contrast, Segment 2 is indifferent to color, likes a dense ice cream and is very sensitive to departures from the optimal level of vanilla flavor. The segments distribute about equally in the consumer population based upon the results of the study.

Beyond Simple Univariate Models to Product Databases to Guide Understanding

We are accustomed to thinking about relations between pairs of variables. To a great degree, this mode of approaching scientific problems pervades marketing and product development, making itself known as the search for the "key driver" or "key factor" responsible for product acceptance. With an archival, guidebook-oriented database developed from many different and unrelated products, there is an opportunity to go beyond this two-variable thinking, into multivariate thinking.

One of the approaches commonly used by researchers is to plot the products in some type of geometrical space, perhaps with the property that the location in the space is a function of the sensory profile of the product. Although the plot is certainly interesting, we really do not know what to do with the plot other than look at it. It is hard to know what to do with this type of mapping data, a problem that pervades a great deal of mapping data from R&D product development. The data are shown visually, and the analysis is certainly multivariate so it goes beyond the two variables, but other than such visual representing, there is neither further insight nor a direct call to action. Figure 4 shows an example of this type of plot. Each point corresponds to one of the 22 ice creams. The axes are thickness, vanilla flavor and yellow color, reasons that will become clearer in a few paragraphs.

Let us look at how far we can go with this type of plotting, and what other refinements to the plotting approach we might make with a few new considerations. We begin with a very simple analysis of the different attributes to identify basic factors. This plot presents us with a snapshot of the market. The map shows a cluster of very thick, very yellow products, and some other products on the outskirts of the plot which are very thin and either white or yellow, depending upon the product. Looking at this type of plot is marginally instructive, for the plot tells the reader how the products fall. However, the key shortcoming is that the map is "inactionable." That is, the map is not particularly useful for product development other than as representing where the products are. However, we will use modeling to make the mapping more actionable, and provide a jumping-off point for product developers who consult this proposed database and product-development guidebook.

Identify a Set of Uncorrelated Sensory Attributes. This first step will prepare us for the modeling. Modeling requires relatively uncorrelated predic-

TABLE 6.
FACTOR STRUCTURE OF THE SENSORY ATTRIBUTES

	Factor		
	1	2	3
Factor 1: Thick and creamy			
Thick	0.94	–0.11	0.03
Heavy	0.93	–0.01	0.16
Airy	–0.91	0.17	0.08
Grainy	–0.86	–0.32	–0.09
Creamy	0.86	0.38	0.00
Icy	–0.82	–0.19	0.02
Sticky	0.80	–0.05	0.33
Sticky in the mouth	0.79	0.10	0.38
Dairy	0.74	0.36	0.08
Melts quickly	–0.72	0.38	0.33
Smooth	0.71	0.40	0.02
Crumbly	–0.65	–0.49	–0.11
Firm	0.64	–0.44	–0.32
Factor 2: Flavor			
Vanilla	0.11	0.90	–0.13
Taste	0.32	0.86	0.01
Time taken by vanilla flavor to appear	0.01	–0.82	–0.05
Aftertaste	0.07	0.80	0.40
Creamy appearance	0.33	0.79	–0.22
Sweet	0.05	0.79	0.19
Aroma	0.14	0.64	–0.12
Icy appearance	–0.49	–0.53	0.12
Factor 3: Color			
Yellow	0.13	–0.07	0.80
Coating	0.38	0.20	0.75
% of variance explained by the factors	41	25	8

The different consumer-rated sensory attributes were analyzed by principle-components factor analysis with the factors rotated by quartimax in order to create a simple solution. Numbers in the body of the table are simple correlations with the three factors.

course the data are expressed in terms of sensory characteristics rather than ingredients, which means to some purists the data will always beg the issue of ingredient level, and see how far we can get with the sensory versus liking data. As we saw demonstrated above in Figure 3, one of the deliverables of a category appraisal is the pattern of variables that drive liking. Figure 3 shows univariate or one-at-a-time relations, without giving the sensory characteristics a chance to interact with each other to drive acceptance.

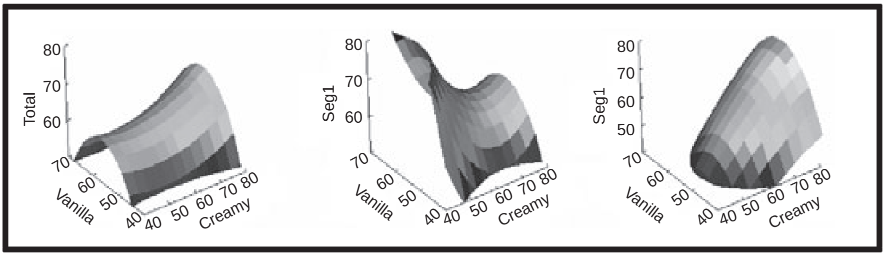

FIG. 5. THREE-DIMENSIONAL PLOTS OF THE RELATION BETWEEN VANILLA AND CREAMY AS INDEPENDENT SENSORY ATTRIBUTES AND LIKING AS THE DEPENDENT VARIABLE

The liking rating comes from the total panel, segment 1 or segment 2.

We can go beyond simple univariate models by incorporating several predictors into one equation, to see how these several predictors jointly drive the consumer response. A sense of what can be done by working with two predictors can be obtained by looking at Fig. 5, which shows two independent variables (creamy and vanilla) as drivers of overall liking. The curves were developed by using creamy and vanilla as the independent variable, and allowing them to jointly drive liking, using a quadratic model of the form:

$$\text{Liking} = k_0 + k_1(\text{Creamy}) + k_2(\text{Creaminess})^2 + k_3(\text{Vanilla}) + k_4(\text{Vanilla})^2$$

We fit the equation for three dependent variables – total panel, Segment 1 ("airy" and light-colored seekers) and Segment 2 ("dense" and darker seekers). Figure 5 is meant as a schematic, to show the nature of the relation among three variables, but is not necessarily useful when it comes to actually creating a product.

Extend the Model to Three Sensory Attributes which Are most Uncorrelated. A more productive approach to the modeling exercise, certainly one meaningful to product developers, builds an actual equation relating the independent variables of vanilla, creamy and yellow to attributes. By now the equation-fitting method is well accepted in the consumer-research and food-product development worlds, even if not necessarily practiced widely. We follow these steps to create the model, parts of which are shown in Table 7:

1. Identify the independent variables. These independent variables should be statistically independent of each other, so as not to cause statistical problems, such as multicollinearity where the independent variables are corre-

TABLE 7.
RESULTS FROM OPTIMIZING OVERALL LIKING FOR TOTAL AND SUBGROUPS AND FROM REVERSE ENGINEERING TO FIT AN IMAGE PROFILE

	Optimize a single liking attribute			Reverse engineering: Fresh taste, natural and rich at 65, expensive varies from 60–70			
	Total	Segment		Expensive			Range
		1	2	60	65	70	
Independent sensory variables							
Creamy	67	50	67	64	67	67	3
Vanilla	56	56	54	56	55	54	2
Yellow	19	34	19	27	21	19	8
Expected liking profile							
Total	69	59	69	67	69	69	2
Segment 1	65	79	63	67	64	64	3
Segment 2	72	41	72	66	71	72	6
Appearance	57	68	56	60	58	56	4
Color	56	69	55	61	58	56	5
Aroma	64	51	61	63	62	62	1
Texture	67	58	66	66	67	67	1
Consistency	64	55	64	62	64	64	2
Taste	69	55	69	66	68	69	3
Vanilla	66	50	66	62	65	66	4
Dairy	63	47	63	61	63	63	2
Sweetness	61	60	60	60	61	61	1
Aftertaste	64	48	63	60	61	61	1
Expected sensory profile							
Creamy appearance	61	59	60	61	61	60	1
Icy appearance	39	45	39	41	39	39	2
Aroma	56	38	53	54	54	54	0
Crumbly	28	54	27	32	28	27	5
Sticky	44	28	48	42	46	46	4
Melts	46	75	44	52	47	45	7
Airy	34	65	31	42	34	32	8
Heavy	58	35	59	52	58	59	7
Sticky in mouth	38	25	40	37	39	40	3
Firm	74	44	77	65	74	76	11
Smooth	69	58	68	67	69	68	1
Grainy	14	40	13	19	14	14	5
Icy	21	57	19	26	21	20	6
Thick	71	44	73	65	71	73	8
Taste	61	54	60	61	60	60	1
Time taken for vanilla to appear	40	40	41	39	40	40	1
Dairy	58	47	58	56	58	58	2
Sweet	55	61	53	56	54	54	2
Aftertaste	47	51	46	50	48	47	3
Coating	38	47	38	40	39	38	2

TABLE 7.
CONTINUED

	Optimize a single liking attribute			Reverse engineering: Fresh taste, natural and rich at 65, expensive varies from 60–70			
	Total	Segment		Expensive			Range
		1	2	60	65	70	
Consumer image							
Rich	64	51	64	60	63	64	4
Fresh aroma	67	58	64	65	65	65	0
Fresh taste	72	63	72	68	71	72	4
Natural	65	51	65	60	64	65	5
Expensive	67	49	66	60	65	67	7
Quality	70	54	70	65	69	70	5

lated with each other, making the regression modeling problematic. We have already identified our three candidate variables from the factor analysis. We know that they are reasonably uncorrelated.

2. The independent variables should span the space. That is, the independent variables should be selected so together they account for a lot of the variability in the sensory world. Our selection of creamy, vanilla and yellow covers the three major sensory inputs of texture, taste/aroma and appearance. Table 6 suggests that the three variables will account for more than 70% of the variability.
3. The regression model should use linear and quadratic terms, to ensure but not force a dependent variable such as liking to maximize in the middle range. A pure linear model, using only the linear and not the square terms, would never permit a curve to maximize anywhere but at the upper or lower extreme. In contrast, by incorporating a square term, the researcher allows, but does not force, the attribute to maximize in the middle level. We see such midlevel optima for liking in Fig. 5.
4. The equations can be expressed as simple mathematical functions, but to be best used, the model needs more than a mathematical expression. A sense of the type of equation that one might achieve appears in Fig. 6. The equation by itself is merely a description of the relation among variables. In order to move forward with the analysis, we have to operate with the equation, to optimize a product and to assess the sensitivity to changes in the sensory characteristics of the ice cream.

```
Dependent Variable -- SEG2
Squared Multiple R           = 0.635379
Adjusted Squared Multiple R  = 0.489531
Standard Error of Estimate   = 6.22448
Regression Equation:
CONSTANT          -334.792
CREAMY               5.60322
VANILLA              7.46153
YELLOW              -0.644221
CREAMY*CREAMY       -0.0350587
VANILLA*VANILLA     -0.0697529
YELLOW*YELLOW        0.00537666


Dependent Variable -- RICH
Squared Multiple R           = 0.778278
Adjusted Squared Multiple R  = 0.689589
Standard Error of Estimate   = 2.73878
Regression Equation:
CONSTANT           -15.0887
CREAMY              -0.547399
VANILLA              2.62568
YELLOW              -0.290741
CREAMY*CREAMY        0.0101108
VANILLA*VANILLA     -0.0230159
YELLOW*YELLOW        0.0026128
```

FIG. 6. TWO EQUATIONS FROM THE PRODUCT MODEL, RELATING LIKING FOR SEGMENT 2 AND ICE CREAM RICHNESS TO A QUADRATIC FUNCTION OF CREAMY, VANILLA FLAVOR AND YELLOW AND THEIR SQUARE TERMS

Using the Product Model to Optimize Acceptance for Total Panel and Segments. Optimization tries to discover the highest possible level of acceptance, using the equation as a guide, and as a way to test the expected performance of the specific combination of the independent variables. Of course the optimum does not tell us the formulation, but it does suggest the approximate type of sensory profile where liking would reach its highest level. Table 7 shows optimum "sensory profiles" generated for the total panel and for the two segments. With this type of information in a product-development guidebook, the developer would be led to the hypotheses about the type of product that he should develop for the segments. Because we are dealing with sensory attributes rather than formulations, the optimum product is a broad-stroke recommendation, more of a qualitative recommendation than an actual formulation. Nonetheless, by looking at the results in Table 7, one gets a sense of the different products for the segments. Going into the vanilla ice cream category with this type of data gives the developer a sense of the opportunities far more than going into the product category either with no data, or with results from limited product tests covering one or two products, most likely the category leader.

Reverse Engineering. Reverse engineering is the name given to a relatively intuitively simple approach using the product optimizer. Because the optimizer is constructed from a set of equations, knowing the level of the independent variables allows the developer to estimate the likely sensory and image profile of the remaining attributes, as we saw above for optimization shown on the left side of Table 7. That analysis moves "forward," from the independent variables to the dependent variables. What about the inverse case – where we specify a profile of dependent variables, e.g., an image profile, and look for the sensory profile that corresponds to this image profile? This type of directed development problem pervades each research stage, for often the product developer must produce a product that corresponds to a poorly defined "image profile." The image profile may come from the concept, as we saw in the first part of the article, or may come from a set of image attributes, such as natural, rich, expensive etc. In any case, the objective of reverse engineering is to discover the level of the independent variables that, in concert, produce a profile as close as possible to the objective or goal profile. Once this set of independent variables is discovered by mathematical means, the product model can be put to use estimating the likely level of all of the attributes. By having the model established across all of the competitor products, the developer can get a sense of which particular products possess the requisite level of the different sensory attributes that correspond to the goal profile.

We see a demonstration of reverse engineering on the right side of Table 7, which shows how a product developer might get guidance for a specific problem. We set the objectives as follows:

1. Set three attributes at a goal of 65 – rich, fresh taste and natural. These are image attributes, and part of the product model.
2. Run the reverse engineering procedure three times – with the image attribute "expensive" starting at low, midlevel and high level of 60, 65 and 70, respectively.
3. For each of the three goals, estimate the likely value of the three independent variables in the product model (creamy, vanilla, yellow).
4. Estimate the full profile, including liking attributes, sensory attributes and image attributes using the values of creamy, vanilla and yellow, respectively.
5. Use this type of analysis to identify what sensory attributes appear to covary with the image profile.

6. If a product developer were to consult this type of table, he would be able to get a sense of what are the key factors that correspond to these different image profiles, although it is clear from the foregoing discussion that the guidance would be qualitative.

Sensitivity Analysis. We conclude this treatment of product models by a discussion of sensitivity analysis. The product models reveal the relation between sensory attributes (creamy, vanilla, yellow) and all of the other attributes. We saw from Fig. 6 that the equation comprises several variables at once. In the simplest of cases the equation is linear, but the equations shown in Table 6 are more complicated, containing square terms. Even more complex equations can be developed with interaction or cross terms, e.g., vanilla × yellow.

It is not intuitively obvious from the equation how the attributes drive the ratings. It becomes more daunting when we realize that there are three or possibly more attributes driving each rating. The sensitivity analysis fills an important role. It shows how a single independent variable, e.g., creamy, drives the attribute ratings when the other variables are held constant. The sensitivity analysis works one variable at a time, but unlike the univariate relation between liking and a sensory attribute which we saw in Fig. 3, the sensitivity analysis uses the model. It simply holds the other variables constant and estimates the likely rating. We see a worked example of the sensitivity analysis in Table 8.

DISCUSSION

What a Database and Guide Book Contribute to the Product Development and Marketing Process

As noted in the introduction, companies have in their files an extraordinary amount of information about consumer responses to concepts and to food products. Most companies insist on interpreting their concept scores against a bank of "norms," so there is the perennial interest about "how did I do versus competition." The same type of curiosity holds for product performance as well, although usually the products are tested head to head against the market leader under the assumption that the market leader is "doing something right that we must know about."

Given this intense competitive nature of product development worldwide, we can ask about the specific contributions that such a database resource might provide. There are at least three:

TABLE 8.
SENSITIVITY ANALYSIS FOR SOME OF THE ATTRIBUTE RATINGS COMPUTED FROM THE PRODUCT MODEL

Creamy varies Vanilla = 56 Yellow = 19	50	53	56	59	61	64	67
Total	62	64	65	66	68	68	69
Segment 1	78	75	72	69	67	66	65
Segment 2	47	52	57	62	66	69	72
Rich	53	54	56	58	60	62	64
Fresh taste	68	68	69	70	70	71	72
Natural	57	58	60	61	62	64	65
Expensive	58	60	62	63	64	66	67
Vanilla varies	50	51	52	53	54	55	56
Creamy = 67, Yellow = 19							
Total	66	67	68	68	69	69	69
Segment 1	59	60	61	62	63	64	65
Segment 2	72	72	72	72	72	72	72
Rich	63	63	63	64	64	64	64
Fresh taste	70	71	71	72	72	72	72
Natural	63	64	64	65	65	65	65
Expensive	65	66	66	66	67	67	67
Yellow varies							
Creamy = 67, Vanilla = 56							
Total	19	24	29	35	40	45	50
Segment 1	69	68	67	66	66	65	64
Segment 2	65	65	65	65	65	65	65
Rich	72	70	68	67	65	64	64
Fresh taste	64	63	62	62	61	61	60
Natural	72	71	69	68	66	65	65
Expensive	65	63	61	59	57	56	55
Total	67	63	60	57	55	53	52

Two of three independent sensory attributes are held constant, the third sensory attribute is varied in small steps and the expected profile is calculated from the product model (i.e., the equations).

1. An "open source" foundation upon which to create concepts. Concepts are easy to develop, and remarkably easy to test with today's Internet-based evaluative systems. What happens, however, is that this very simplicity and rapidity of testing encourage bad habits. Rather than doing one's homework, the marketer feels that he simply needs to create a number of concepts, throw them out to test, see what works and then move forward with the winning ideas. There is little in the way of systematized learning. Not that the marketer is averse to learning about his product – that is never the case. No one is ever publicly against learning. Rather it is the easy testing

that leads to testing rather than understanding. Research becomes the enemy of knowledge, as inexpensive testing drives out expensive category understanding. A data resource about a category would thus serve as a guide to the category, helping the marketer to understand some of the dynamics of the category before moving on to focus groups and concept tests.

2. A *vade mecum* for the new product developer. A new product developer coming into a field does not have the knowledge of what works, what does not, what to look for and what to avoid. Certainly some of this information is present in the mind of the senior product developer, but with so much product development being outsourced, it is no wonder that in most cases the developer has to start from scratch and rediscover the rules of the game for himself. The guidebook becomes an informal mentor to the new product developer.
3. A tracking system for the popularity of ideas, open to all. Most companies are very secretive about the information that they possess. A lot of this information is already in the possession of the public, or can be easily created by a little bit of competitive intelligence. Dissective or deconstructive analysis to understand the competitive frame is already a well-recognized business practice, and a society, Society for Competitive Intelligence (SCIP), has been formed to link together professionals in the field. Given the availability of such knowledge worldwide, the ease of finding out what information competitors have access to through Internet-enabled search engines means that it is very unusual for most food and beverage companies to have a product idea that is so unique and a blockbuster that it cannot be copied. Those days are pretty much over. With the availability of open ideas for concepts and category knowledge, it remains for the company to spend its resources to capitalize on this knowledge, not just acquire it. The system will thus encourage better analytics, because the data, like so much other information, will be readily available.

A Vision of the Marketer/Developer Knowledge Base

What does this database for the marketer or developer look like? Given the information presented above for both product and concept, how can we imagine the database? One might think it is a book or set of books, or perhaps hyperlinked tables on the personal computer. This is one vision. An alternate vision is a “business tool kit” available on a subscription basis. We might consider the data to be resident on a central computer. The user would enter the category of interest, be taken to a set of automatically generated reports and to a system that automatically segments the data and reports the results.

The same type of business tool would be available for the product. Rather than providing merely a tool, the business model might be a subscription to data and the use of specific business tools to deal with that data. The tools could be systems for analyzing ranges of product scores, means by key subgroups, programs that plot sensory-liking curves and even programs that do product models and reverse engineering. None of the products would be labeled, however, because the goal of this business tool is to show relations between variables, holes in the category and opportunities expressed as sensory attribute levels.

What Type of Information Should Be Put into this Development Database?

The foregoing data presented primarily consumer-based language. There are multiple constituencies who would use this database, and therefore different requirements. Some of these information requirements may conflict with each other.

Concepts. In the concept area, what type of concept elements should be incorporated into the database? The foregoing set of concept elements for ice cream attempted to cover a wide range of elements, from product descriptions to brands to emotions. One might make an equally good case that the relevant information for this type of database ought to be limited to those that pertain directly to product elements, namely the elements contained within the first silo. Advertising agencies, brand-development specialists, merchandisers and the like could argue quite forcefully that the other types of material include, e.g., brand names, the appeal to emotion and even the concept response segmentation, should properly be eliminated from a product-development database because this type of information does not help the product developer. Indeed, many purists would argue that the only valid information for a development database should come from product features, not positioning. This polarized position might, in turn, be countered by the statement that any type of information, of a concrete descriptive nature or even of an evocative nature such as brand name or emotion, helps the product developer. The resolution of this disagreement remains to be seen.

Products. A whole school of researchers in “sensory analysis” has grown up feeling that the consumer is a poor judge of sensory characteristics. Faced with a database to help the product developer, these individuals would aver, quite vehemently, that the only product attributes from consumers should be acceptance, such as overall liking or attribute liking. Any sensory data about the existing in-market products should, in their minds, be limited to the types of information one obtains from the so-called expert or trained panel. At the opposite side of this viewpoint is the authors’ feeling that the database ought to include consumer data, with expert-panel data complementing the consumer data if these are available. There is more consumer data available than expert-panel data, and it is easier, faster and cheaper to acquire consumer data than it is to acquire expert-panel data. This second question will not be argued on its own merits but will collapse of its own weight when those involved in setting up the database and business tools recognize that relying on expert-panel data means not having very much information in the database at all.

Practical Considerations in Creating the Database System

A well-known cartoon from Pogo by Walt Kelly has the caption "We have met the enemy and they are us." Industry is exceptionally competitive, frightened and secretive. One of the practical considerations that must be dealt with is the overt hostility to information sharing. This hostility may be impossible to overcome, no matter what benefits ensue, requiring that other routes to creating a database might be needed that are not so dependent on corporate goodwill. Rather than having a company contribute information, which it deems to be its corporate lifeblood and its *ne plus ultra* for competitive advantage, we might foresee some collaborative situation mediated by a third party integrator:

1. The integrator would receive a substantial fee from each company to participate in this knowledge base. Companies that do not contribute do not have access to the knowledge base.
2. The integrator would do the studies, perhaps funding universities to gather the product data, and working with Internet specialists to do the concept work. The methods for doing the concept research already exist and are cost-effective.
3. The integrator might deal with government organizations for the larger scale databases that involve public policy and nutrition. Such involvement would be beneficial to all concerned because it would allow the government to fund actionable information that would be accessed by motivated companies.
4. The result would be a large-scale database, economically created, available to all supporters and sponsors, dealing with concepts and with products currently on the market.
5. To the degree that the product studies comprise questionnaires with rating attributes beyond sensory characteristics, e.g., healthful, appropriate for different occasions etc., the database would be even more valuable to understanding the sensory dynamics of "good for you" foods, and guide both large and small companies in their development efforts.

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