Papers

Databasing the shopper's mind: Approaches to a 'mind genomics'

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Abstract Using conjoint analysis and self-profiling questionnaires, the authors created a 'mega' database to help understand the customer mind with respect to buying behaviour. The database comprises 30 different product categories and the studies comprise data from 3,500 respondents. The database reveals what phrases drive interest in a specific shopping experience and how respondents profile themselves. The combination of methods provides a unique way to create a database about the customer mind, allowing for analyses ranging from communication to store design to segmentation based upon cross-sectional response patterns to both external communications and self-descriptions.

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INTRODUCTION — DATABASING EXPERIENCES AND MIND SETS

An integral part of the total product experience is the experience while

shopping. Interest in what makes a good shopping experience, how customers react in stores and identifying the key drivers to successful merchandising

campaigns have generated significant information. For the most part, however, the information applies primarily at a *tactical* level, showing only what to do in a specific instance in order to improve the experience for the shopper. Tactical information fails to produce a real science of the shopper's mind.

By understanding shopping from a database about mind sets, managers can understand where and how to focus resources for situations not yet encountered. Databases about shopping situations allow managers to simulate 'what if' scenarios, to identify the features of a new shopping experience. Such a science of the shopper mind,¹ with its database, supports increasing recognition of retailing as a key factor in product success.

This study develops a knowledge base for shopping in a way that differs from most traditional 'single focus' studies. Shopping is examined using two approaches joined in one interview to craft a holistic picture of the shopper's mind. The first approach uses concepts, systematically varied by experimental design, which present vignettes about the shopping experience. Responses to those vignettes identify what stated factors are important to the shopper when presented with information. The second part, run with the same respondent, is self-profiling to identify in a more traditional fashion what the shopper considers to be important.

What makes this study especially relevant is the exceptional breadth of information derived from the shopping experiences from 30 product categories using conjoint analysis; the nature of the data (both self-profiling questionnaire and stimulus response-oriented conjoint analysis); and the use of the database to assess patterns and thus discover commonalities within and across categories.

RATIONALE FOR THE SHOPPING EXPERIENCE 'MEGA-DATABASE'

There is no experiment-derived, objective database available to understand how customers respond to different brand names, features of products, emotional aspects of products, or aspects of the buying situation. Most of the knowledge resides in unrelated sources, such as corporate offices, trade and academic journals, and the experience of development and marketing professionals. Creating a cross-sectional and longitudinal database to understand the 'algebra of the customer mind' could thus constitute a major contribution to product development, marketing and consumer sciences. The research methodology of conjoint analysis — ie experimentally designed concepts — helps because it combines the rigour of design, the specificity of concrete communications and the power of individual-level modelling for segmentation and optimisation. Furthermore, large-scale databases of the type presented here enable insight-developing comparisons across different shopping situations. Such comparisons invite both the identification of patterns across these situations and the development of working hypotheses rooted in empirical data.

One approach to creating such a database works from the 'bottom up', using responses to test concepts and deconstructing them to the contributions of their components. The concepts are developed using a specified architecture. The architecture comprises silos dealing with store design, merchandise selection, customer/shopper description and store name. Every silo has nine different options for each shopping situation, developed by the researcher. Mixing and matching elements from these silos, creating concepts, testing the concepts among respondents and getting ratings of

interest allows the researcher to create a model showing how the different elements drive the respondent's interest. Such an approach reveals the impact or utility of each concept element to the respondent at an intuitive response level, without forcing the respondent to intellectualise the process. Systematically creating this study for different products generates a database about the customer mind as it pertains to the shopping experience, much in the spirit of the genomics approach.

The studies reported here use a form of experimental design in which each concept element appears multiple times against different backgrounds, each respondent evaluates all elements in an individualised experimental design and all analyses are run at the individual respondent level. The coding is a dummy variable, with the presence of true 'zero conditions', meaning that the utilities from the study can be compared within a single study, across individuals, across studies and across times. When the study scope is expanded to 30 product areas, each with four silos or buckets of nine related elements, the database quickly becomes a unique resource for analysis. The 30 products $\times$ 36 elements generates a database of some 1,080 ideas, each of which has a utility value generated from 100+ respondents.

Of additional importance is that in the creation of such a database each concept element has a defined *raison d'être*, such as nature of product feature, emotional benefit, brand, usage etc. It is straightforward to compare the results of one shopping situation with the results of another, since the structure of the concept elements is parallel across the 30 studies. Each smaller study also has the same classification questionnaire, allowing for easier meta analyses across the different shopping situations.

So-called 'mega' or large-scale database

studies of the type presented here accomplish four objectives:

- 1 *Quantifying the impact or utility of individual elements in the shopping experience.* The conjoint analysis portion identifies the utility values for the different concept elements. *This utility value is the conditional probability that a respondent would be interested in the shopping experience if the specific element were to be introduced into the concept or shopping vignette.* The utility values are the coefficients of the regression modelling, done at the level of the individual respondent. The additive constant, also obtained from modelling, is a baseline or *conditional probability of interest in the shopping experience without any other information about the experience available to the respondent.*
- 2 *Comparison of similar elements across different studies.* Using the same or similar elements across the different studies reveals how the same type of element performs in different shopping venues and thus reveals the effect of the shopping task on specific features or communications such as emotional statement.
- 3 *Deeper understanding of other aspects through the self-profiling questionnaire.* By completing *virtually the same classification questionnaire* in each study, the respondents provide comparable self-profiles for different situations. These profiles can be compared easily in order to identify similarities and differences among the shopping situations (eg in terms of where respondents go shopping alone versus with someone).
- 4 *Emerging segments.* Attitudinal segmentation based upon different mind sets is now common. Individuals with similar utility patterns for a set of 36 elements fall into the same

segment, no matter how they describe themselves. The individuals behave similarly towards the vignettes ... individuals with different utility patterns fall into different segments. There are different points of view as to how the respondents should be segmented using the output of conjoint analysis,^{2,3} but these differences are not important. What is critical is the nature of these segments, and the specific phrasings that drive the segment's response. This second benefit, direct 'actionability' of the data, differs dramatically from what happens with conventional attitude segmentation, wherein after the segmentation is done there is still the necessary — albeit often absent — step of discovering what to say and do in light of the segmentation.

METHODOLOGY

The mega-study was developed, executed and analysed following nine steps.

Step 1 — Select 30 product categories from consumer hard-goods products to develop a broad database

Table 1 lists the 30 product categories.

Step 2 — Create a single, general structure for the shopping experience database applicable to each product

The underlying database structure comprised four silos of nine elements each. The same fundamental structure comprising four silos of nine elements was maintained across the 30 studies, but the elements were particularised where relevant to the individual shopping experience. Great care was taken to make the elements comparable across all

30 studies. Table 2 shows an extract of some of the silos and elements, and specific elements for one study — toasters.

Step 3 — Create a single, basic self-profile or classification questionnaire for each of the 30 studies

This classification questionnaire enabled the respondents to profile themselves on conventional geodemographics, as well as on attitudes towards shopping. Where possible, exactly the same question was used to enable direct comparisons to be made across the studies.

Step 4 — Create experimental design for the concept elements using principles of statistics

This step created a main effects design comprising the 36 independent variables embedded in 60 concepts or vignettes. The study was set up using a self-authored, internet-based, conjoint analysis system.⁴ Every concept comprised between two and four elements, specifically presenting only one or no element from each of the four silos depending upon the design, specification. Across the 60 concepts specified by the design each respondent evaluated the same element three times across three backgrounds. *The basic structure of the experimental design was fixed, but the specific combinations were changed for each individual experimental design by permuting the basic design so that the combinations varied, even though 'formally' the nature of the 60 combinations were the same across the different respondents.* For example, if the structure called for testing combinations A1 and B3, then the specific element corresponding to A1 and the specific element corresponding to B3 were changed for different respondents.

Table 1: 30 product categories for the Buy It! foundation study

Household items	Personal items	Big ticket items
Toaster	Bathing suits	Car
Blender	Sandals	Television
Dishes	Boots	Refrigerator
Towels	Business suit	Couch
Bed sheets	Ties	Lawnmower
Drinking glasses	Socks	Tyres
Tablecloths & napkins	Sunglasses	Washer/dryer
Candles	Pens	
Electric drills	Exercise equipment	
Decorative pillows	Writing paper	
Drapes & curtains	New baby gifts	
Lamps		

Table 2: Structure, rationale and selected concept elements for the 'toaster' database

Element rationale	Element text — toaster
Silo 1 — Store design/physical location	
E01 Features areas for ... everything you need for ...	We have catalogues that feature toasters, food processors, juice extractors and professional equipment ... page after page of toasters
E02 Lots of choices in the kind of ... you wear today ...	Online or in the store ... lots of choices in today's most popular styles or models
E03 A store with every kind of ... you can imagine ... plus places for kids to play while you make up your mind	Shop at our online store for every kind of toaster you can imagine ... plus all the accessories you could want
Silo 2 — Merchandise selection/pricing scheme	
E10 Lots of ... in your style ... it's easy to find what you want then try it right away ... it makes you feel good	The price is JUST RIGHT ... ALL OF THE TIME
E11 Designer ... with all the accessories	Self service... no one to get in your way or slow you down
E12 One stop shopping ... lots of choices and options ... brands, colours, sizes	Start anxious, leave happy ... spending that is well worth it
Silo 3 — Target customer, shopper/emotional	
E19 A ... store set up to be practical and useful ... just right for targeted shopping	A practical and useful store set up... just right for targeted shopping
E20 Lets you get your shopping done quickly	Lets you get your shopping done quickly
E21 Come in anxious ... leave happy, even though you may have spent a lot of money	One stop shopping ... lots of choices, options, brands, colours and sizes
Silo 4 — Hierarchy of brands/level of service/benefit	
E28 Hierarchy of store names	At a store such as Lowe's, Home Depot or Menard's
E29 Hierarchy of store names	At a store such as Wal-Mart, Kmart or Target
E30 Hierarchy of store names	At Sears

This permutation strategy preserves the statistical design, simply rotating the elements about in a systematised manner. *The permutation strategy ensured that the specific pairs of concept elements would not always appear together, by chance, as dictated by a single experimental design.* From time to time, some combinations may do unexpectedly well or unexpectedly

poorly by accident — perhaps due to the particular combination rather than to the elements.

Step 5 — Invite the respondents to participate by e-mail

An e-mail provider, Open Venue Ltd, sent 50,000 invitations, half to men and

half to women. The respondents were guided to a wall, which showed the 30 different studies. The respondent chose the study in which to participate based upon interest. The response rate for the full set of studies was approximately six per cent.

Step 6 — Computer interview on the internet

The respondent read an orientation page and then participated in the interview. The interview lasted 15 to 20 minutes. The respondent evaluated 60 unique combinations of the 36 elements, one vignette or concept at a time, assigning a rating to the vignette on a nine-point interest scale. Afterwards the respondent completed the self-profiling questionnaire.

Step 7 — Create the individual model

At the end of the interview the program had available the experimental design and the respondent's ratings. The design was set up for statistical analysis by dummy variable regression at the level of the individual respondent.⁵ The data analysis comprised individual-level regression models showing the relationship between the presence/absence of concept elements about shopping and the individual's rating of the vignette (interest in shopping for the particular product category as described by the vignette). Two sets of models were created, both using ordinary least squares regression analysis and both fitted at the level of the individual respondent.

- Model 1: the intensity of interest
Model 1 shows the relation between the rating and the presence/absence of concept elements. The model fitted to the data can be expressed by the

following equation, where the coefficients, $k_1 \dots k_{36}$, show the strength of interest in shopping for the particular product:

$$\text{Rating} = k_0 + k_1(\text{Element 1}) + k_2(\text{Element 2}) \dots k_{36}(\text{Element 36})$$

- Model 2: membership in the 'acceptor class.

The ratings were transformed to a binary scale. Ratings of 1–6 were transformed to the value 0. Ratings of 7–9 were transformed to the value 100; these were assumed to represent the response of an individual interested in the shopping situation. Ratings of 1–6 were assumed to represent the response of a disinterested individual. The transformation was done in the spirit of consumer research methods, which typically deal with membership in a class, eg with concept acceptors rather than with the more psychological aspect of intensity of feeling. This binary transformation changes the data to a 'membership-based' data set. The format of the equation is the same as in Model 1 but the interpretation of the coefficients differs. The coefficient for an element shows the conditional probability of a person being interested in the shopping situation if the element were to be inserted into the concept. The additive constant k_0 shows the estimated conditional probability of being interested if no elements are present and is a purely theoretical parameter which can, however, be useful as a baseline value.

Step 8 — Segment respondents based upon the pattern of their utilities

This segmentation works with the person's response to the shopping

concepts (Model 1), looking at the distance or dissimilarity between pairs of respondents based upon the correlation between their 36 utility values.

Segmentation is better done by looking at the pattern of intensity of feelings (Model 1) rather than the pattern of membership in the acceptor class (Model 2). Respondents whose utility values co-vary with each other fall into the same segment because they show similar patterns of intensity of feelings.

Respondents whose utility values do not co-vary, but rather show different patterns, fall into different segments.

Step 9 — Aggregate data from the respondents based upon specific criteria

All subsequent data beyond the segmentation was based upon Model 2, ie, membership in the 'acceptor class'. The coefficients from Model 2 were averaged across individuals who fall into specific subgroups, eg age, income, concept response segment (from Step 8) etc. The aggregate results for each subgroup comprise 37 means for that subgroup, corresponding to the additive constant and the 36 separate utilities (one per concept element in the particular study).

RESULTS

Each shopping study for a single product generates its own separate analysis. With 30 different shopping venues, the dataset becomes even more comprehensive because the same set of questions are asked for each, allowing meta analyses across products to reveal similarities and differences across the shopping situations. These analyses come from either the conjoint or the self-profiling classification. For example, Table 3 shows the attributes that respondents selected as being

important to them when shopping in a store. In the self-profiling classification, the respondent was given different aspects of the shopping experience — ranging from the shopping experience in the store to the price, to the product quality etc — and instructed to select the three most important aspects. It is clear even from these data that the average percentage selection differs from the selection for individual products.

Basic interest in shopping deduced from the additive constant of the utility model

A comparison of this baseline value across 30 different product categories reveals radical differences in basic interest. Much is written about the 'big ticket' items, such as cars, when in reality respondents appeared to find the smaller, more personal, items to be more basically interesting, based upon the value of the additive constant. As Table 4 shows, shopping for boots has a very high additive constant (46 — ie 46 per cent rating the basic idea 7–9), whereas shopping for cars has a very low additive constant (26).

How product category influences the response to the same concept element

Several elements appeared in all of the studies because they were appropriate for each study. These elements generated utility values for each respondent for each study. The utility values can be compared across the different shopping situations and further analysed by respondent gender. The two key elements presented for every product deal with service (*self service... no one to get in your way or slow you down*) and with price (*offering a GREAT DEAL on the suggested retail price*). Table 5 shows

Table 3: Percentage of respondents choosing various aspects as being relevant for the specific product being purchased.

	Average (%)	Exercise equipment (%)	Drapes (%)	Bathing suit (%)
Price	76	86	79	63
Appearance	62	15	90	82
Product quality	32	60	23	14
How I feel when shopping	10	7	6	15
Reviews	8	25	0	1
Coupons	8	20	3	0
Convenience	5	14	2	0
Brand	4	10	2	2
Service	4	7	2	1
Store location	2	2	2	1
Advertising	1	4	0	1
Package	1	2	1	0
Recommendations	1	1	1	1
Atmosphere in store	1	1	0	1

Table 4: Basic interest in shopping as shown by the additive constant

Personal items	Additive constant	Household items	Additive constant	Big ticket items	Additive constant
Boots	46	Candles	41	Tyres (a set)	37
New baby gift	46	Toaster	39	Washer/dryer	36
Bathing suit	38	Sheets for the bed	39	Refrigerator	35
Sandals	38	Decorative pillows	38	Couch	35
Pens	38	Blender	35	TV	33
Business suit	37	Dishes — a set	35	Lawnmower	33
Socks	37	Bathroom towels	35	Lamps	31
Ties	35	Drapes	34	Car	26
Sunglasses	35	Electric drill	33		
Writing paper	33	Drinking glasses	32		
Exercise equipment	30	Tablecloth and napkins	32		

the results by product for the whole panel and by gender. The same element performs quite differently, depending upon the shopping venue. For example, self service is a positive driver of interest for small items, such as socks, pens, sunglasses and candles but is either neutral or slightly negative (ie irrelevant) for larger items such as tyres and lawnmowers. Similarly, some shopping items become substantially more interesting (eg utility values > 10) when they are conjoined with price savings. These are sunglasses, bathing suits (both personal items), refrigerators and dishes, respectively. Other items, such as sandals, are less driven by price.

Gender differences emerge for the same concept element in some product categories but there is no simple pattern. For example, women want self service when they shop for household items (eg blenders, bed sheets and lamps) but not for bigger items such as tyres, lawnmowers and business suits. There are also clear gender differences with respect to low prices, which again make intuitive sense but which cannot be summarised by a single general rule. Women tend to be more swayed by price and show higher utilities for some items at low price, but not for all. The items to which women show lower responsiveness are sunglasses,

Table 5: How two elements perform when embedded in concepts about different products*

Element: Self service ... no one to get in your way or slow you down				Element: Offering a GREAT DEAL on the suggested retail price			
	Total	Men	Women		Total	Men	Women
Socks	9	7	10	Sunglasses	11	7	12
Pens	9	11	9	Bathing suit	11	3	11
Sunglasses	9	6	11	Dishes	10	-2	11
Candles	9	10	9	Refrigerator	10	12	10
Towels	9	4	9	Television	9	7	11
Writing paper	9	12	8	Blenders	9	0	11
Dishes	8	11	8	New baby gifts	9	-4	9
Drinking glasses	8	7	8	Towels	8	-2	9
New baby gifts	7	6	7	Washer/dryer	8	18	7
Ties	6	5	8	Socks	8	2	10
Decorative pillows	6	5	6	Exercise	8	5	9
Sandals	6	-5	7	Writing paper	8	4	8
Toaster	6	3	7	Drinking glasses	7	8	7
Tablecloths	6	11	5	Toaster	7	-7	10
Exercise equipment	5	5	5	Business suit	7	4	9
Boots	5	7	5	Lamps	7	1	8
Couch	5	19	4	Couch	6	3	7
Refrigerator	5	9	4	Tablecloths	6	2	6
Bathing suits	5	9	4	Car	6	4	7
Blenders	5	-3	7	Decorative pillows	5	-4	6
Drapes	4	0	5	Ties	5	4	6
Bed sheets	4	-2	5	Bed sheets	5	8	5
Car	4	7	1	Lawnmower	5	4	6
Television	4	6	3	Boots	5	4	5
Electric drill	4	3	5	Drapes	5	14	4
Lamps	3	-6	4	Pens	5	5	5
Washer/dryer	1	1	1	Tyres	4	1	9
Business suit	0	1	-1	Electric drills	4	4	4
Lawnmower	-1	2	-3	Candles	4	-8	4
Tyres	-3	0	-8	Sandals	3	2	3

*Numbers in the table are the utilities from the additive model (Model 2).

bathing suits, dishes, televisions and blenders.

DISCUSSION AND CONCLUSIONS

Implications for a new science of the customer's mind based on genomics models

A great deal of research involves attempts to understand the broad issues in a category. Market researchers and consultants often approach this problem through multi-phased studies, which can take a great deal of time, require resources and might not immediately lead to action. These large-scale category studies (eg to uncover the market structure) provide valuable information

and form the foundation of a great deal of corporate understanding of the marketplace. They are often positioned to management as being 'strategic' in nature and require follow-up studies to convert the strategic information to specific and measurable tactics.

The present authors propose an additional, possibly equally broad, level of learning about the category. More actionable understanding coming from this 'mega' study, could form the basis of a new science of the customer mind, developed in the spirit of genomics. There are seven clear reasons for this.

Scalability

The 'mega' studies can be scaled to create databases dealing with small

and/or large issues. Each individual study within the body of the 'mega' study is self-contained, and is easy to set up using a template. The individual studies can number in the tens, or even hundreds, so that the mega study can accommodate larger-scale categories as well as small ones.

Comparability and individuation

The mega studies can accommodate either the same set of elements, related elements, or even partially unrelated elements. The structure of the individual studies is sufficiently flexible to allow some parts of the database to be unique and others to be common across some or even all studies within the database.

Straightforward data analysis and presentation

The results can be immediately interpreted, especially the conjoint portion of the study, which comprises direct, declarative statements.

Segmentation

The segmentation can be done within a single study or across all of the studies simultaneously (on common elements) in order to identify segments, and the possibility of segments that apply more generally, beyond the limits of one product.

The self-authoring, internet-tool adds flexibility and power, providing a system for easy construction of the database

The system is self-authored, meaning that knowledge can be readily and directly obtained by those who need it. Although this freedom to acquire data and insight might be seen as detrimental if carried out by inexperienced individuals, the increasing sophistication of researchers, corporations' availability of conjoint technology and the ability to conduct these types of studies through

self-authoring will be important. The user is freed from the constraints of knowledge workers who, for one reason or another, may be wedded to old and not particularly effective systems.

Cost is low, speed is high

The system is relatively inexpensive to set up and run. Internet-based research is often far less expensive than face-to-face research and much faster than postal research. Of course the cost must be adjusted in light of the nature of the respondent. If the respondents are neurosurgeons, for example, instead of consumers, the field work and the implementation of the study will be longer and more expensive, despite the simple set-up. This is a field issue, not a technology issue.⁶

Databasing promotes a new science with specific archived knowledge, not just research-based solutions addressing specific, tactical problems

The system provides information that can be databased for ongoing analysis. A recent study on food cravings was carried out in 2001 and repeated in 2002. The results allow the comparison of similar elements in two separate years.⁷ For example, in the food study it became clear that in the period from August 2001 to August 2002, cravings for various foods increased, with a focus on more comfort food elements across the categories.

Implications for the world of the business corporation

Many new opportunities and much product development derives from professional insight, this insight can be formalised in a system that can be accessed by everyone, the corporation will flourish. Shopping research is in particular need of improved knowledge-based methods. Experts are,

of course, vital because they integrate all their field knowledge and can provide opinions that transcend the value of the data themselves. Experts are, however, people, not machines; they are not systems that can outlast the individual. The field of knowledge management, for instance, is built on the recognition that it is important to systematise knowledge so that information, insight and wisdom are available to everyone.

For the data collected in the 'mega' study shown here, results do not reside in the minds of experts. Certainly the expert can approach the data with a more informed point of view than the typical inexperienced researcher or marketer. Professionals with a great deal of experience operate based on their intuitive feelings, often not subject to rational answers, and thus not able to be shared or easily communicated. Experts discern the differences in the shopping experience for shoppers with different styles, but their operating criteria are not always public or even easy to establish. Thus the mega study might act as an intermediate step. It provides specific data that affords the corporation insight based upon systematised, formalised knowledge. In turn, the expert can use this database as a foundation on which to insert his/her own opinions and expertise. The result is a combination of public data and private insights that are made public by the interaction of the expert with the database. Conjoint analysis, or better experimental design of ideas, adds the discipline of specificity to the exercise because it presents data in a concrete format, not in less actionable, more general fashion.

Implications for the research professional

Traditionally, and in the eyes of senior corporate management, marketing

research is assigned the role of reporting what consumers want (consumer insight) or what consumers have done (tracking studies, *ad hoc* studies). The use of large-scale mega studies provides the research professional with a new tool to advance the corporate marketing effort by revealing patterns across different shopping situations and by showing precisely what to feature and what to communicate.

The paradigm presented here enhances the role of the researcher. The use of conjoint analysis to create mega studies is novel. Traditionally, conjoint measurement was a research tool used only for large-scale, customised, one-off studies. The mega study uses conjoint measurement as a way to understand the customer mind in a combination of cross-sectional and tracking research. The data is, at the same time strategic and actionable. The strategic aspect comes from the ability to look across many categories — something that is typically done only with purchase data. The mega study provides the same benefit but with attitudinal and communications data. The actionability comes from the fact that the stimuli are couched in words that can be immediately applied in the sales situation, rather than requiring yet another level of understanding, abstraction and then a new application of that knowledge to the action step, thus making the data more rapidly and easily applicable.

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