The International Center for Research on the Management of Technology

Premarket Forecasting of Really New Products

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May 1994 **WP # 104-94**

Sloan WP# 3689

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ABSTRACT

We explore some of the challenges in forecasting customer acceptance of products that revolutionize product categories or define new categories. Specifically we address future conditioning, full information, user experience, user control, and active search. We describe a new method based on multimedia computing technology that allows us to accelerate information to consumers so that they can react to a really-new product in a full-information setting. We describe the application of this technology to forecasting the sales of electric vehicles and illustrate what has and what has not yet been accomplished. After reporting on the managerial implications for the electric vehicle we discuss other applications and initial data on external validity. We close with research challenges including expected advances in the technology.

New product development has been and will continue to be important to corporate profit and social welfare. For firms, and even countries, to stay competitive they must maintain a stream of profitable new products. Some of these new products are new variants -- new flavors of cereals, the next generation laser printers, or the next model-year minivan. Other products are new brands in existing markets -- a new brand of cereal, a combined laser-based printer-scanner-facsimile-copier, or a new brand (say Lexus) of luxury automobile. In general we can forecast well the potential sales of new variants and new brands.

However, some products revolutionize product categories or define new categories. Hewlett-Packard's Laserjet printers, Apple (then IBM) personal computers, Sony's Walkman, beta-blockers (hypertension medicine), Visicalc (then Lotus, Quattro, and Excel) spreadsheets, Black & Decker's Dustbuster, Swatch (watch-as-fashion), and cellular telephones are really-new products. Really-new products shift market structures, represent new technologies, require consumer learning, and induce behavior changes. Forecasts must consider the diffusion of information, the evolution of the technology, the discovery of new uses, the reduction in price from high initial levels, the growth of an infrastructure, and the entry of competition. Forecasts can be made and are made, often with a judgmental consideration of the challenges imposed by the really-new nature of the products.

In this paper we address some of the challenges of forecasting for really-new products. We begin with a brief review of existing methods and discuss specific forecasting challenges: future conditioning, information availability, user experience, active-user information search, and flexibility to incorporate existing methods. We focus on one method, a multimedia computer-technology called information acceleration (IA), and describe how IA addresses each challenge for one really-new product -- electric vehicles. We describe our experience with other applications and report data from some initial attempts at validation. IA is not a panacea, but it does show potential in understanding and forecasting response to really-new products.. We close by highlighting some of the many remaining research challenges and suggest how new approaches might overcome these challenges. Although we present IA within the context of electric vehicles, we believe that IA has broad applicability.

Existing Premarket Forecasting Methods

Concept evaluation, perhaps one of the oldest methods, is still in common use. With concept evaluation potential customers are presented with descriptions of new products, usually written, and asked to express their intentions to purchase the new product. The usage situation is described and intentions for the new product are compared to existing products for which sales are known. Concept evaluations have proven accurate for new product variants and for new brands that can be described well with a written description. See Blattberg and Neslin (1990), Jamieson and Bass (1989), Mahajan and Wind (1988), Pessemier, et. al. (1971), Shocker and Srinivasan (1979), Tauber (1977), Urban and Hauser (1993), Wind (1982).

A more sophisticated form of concept evaluation, known as pretest markets, is based on simulated purchasing behavior. For example, packaged-good manufacturers routinely use methods where potential consumers are shown advertising for the new products and competitive products and allowed to shop in a simulated store. Call-backs measure repeat usage and questionnaires measure preference within a competitive set. Pretest market models have proven accurate to within two percentage points of market share two-thirds of the time. They work best when the competitive set is well-defined and when advertising is a sufficient stimulus to induce trial. See Blattberg and Golanty (1978), Charlton, et. al. (1972), Claycamp and Liddy (1969), Eskin (1973), Fourt and Woodlock (1960), Mason (1990), Parfitt and Collins (1968), Pringle, et. al. (1982), Robinson (1981), Silk and Urban (1978), Urban and Katz (1983), Wind, Mahajan, and Cardozo (1981).

For consumer durable goods prelaunch models replace pretest markets. In prelaunch models a set of potential consumers are shown advertising, simulated magazine articles, and word-of-mouth videotapes and are allowed to try a prototype. Intentions are measured. Another set of potential consumers are shown similar stimuli, but for a product whose sales are known. This product acts as a control allowing managers to "calibrate" the measured intentions for the (test) new product. Prelaunch models are appropriate when a close analogy exists in today's market, when a working prototype is available, and when the environment in which the new product will be sold is not too different from the environment in which it is tested. See Urban, Hauser, and Roberts (1990) and Urban, Hulland, and Weinberg (1993).

Managers recognize that information takes time to diffuse, that new generations of products are developed, that costs decline, and that usage by innovators encourages imitators. When initial sales can be observed diffusion equations model these phenomena and project lifecycle sales. Related concepts, called decision-flow models, prove useful to forecast lifecycle sales from data obtained in pretest markets or prelaunch clinics. Decision-flow models track consumers as they receive information from various sources including advertising, word-or-mouth, visits to retailers, and magazines or newspapers. The models enable managers to make forecasts that vary depending upon the marketing plan that is implemented. Such models consider the flow of information to consumers, but do not model active search on the part of consumers. Nonetheless, when the category is well-defined, working prototypes are available, and the environment of the forecast is not too different from the environment of the test, diffusion/decision-flow models have a reasonable track record. See Bass (1969, 1980), Dodson and Muller (1978), Dolan and Jeuland (1981), Gatignon, Eliashberg, and Robertson (1989), Hauser and Wisniewski (1982). Hirokazu and Jain (1991), Horsky (1990), Jain, Mahajan and Muller (1991), Lenk and Rao (1990), Mahajan and Muller (1979), Mahajan, Muller, and Bass (1990), Mahajan and Wind (1988), Roberts and Urban (1988), Robinson and Lakhani (1975), Schmittlein and Mahajan (1982).

When new products are based on new levels of features, say a faster math co-processor or a redesigned "courtyard" hotel, forecasts are often made with one of many forms of conjoint analysis. The stimuli vary from written descriptions to actual prototypes; the data collection varies from self-stated importance measures to choice from an experimental design; and data is obtained from personal interviews, telephone interviews, computer-based interviews, and even mail; and the analysis varies from analysis-of-variance to complex quantal-choice maximum-likelihood estimates. Many hybrids are in common use customizing techniques to match the forecasting task. Conjoint is appropriate when new levels of features are being introduced or new features can be described well to potential customers. See Cattin and Wittink (1982), Cattin, Hermet, and Pioche (1982), Green (1984), Green, Krieger, Agarwal and Johnson (1991), Green and Srinivasan (1978, 1990), Louviere and Woodworth (1983), Srinivasan and Wyner (1988), Wind, Green, Shifflet and Scarbrough (1989), Wittink and Cattin (1989).

In summary, both managers and academic researchers have invested considerable energies to develop tools for new-product forecasting. Any new models must build upon this heritage. However, the majority of the applications (and the majority of new products) are not "really-new." The models have the best track record for new variants, new brands introduced to existing markets, new products where a close analogy is now on the market, or new products based on new levels of features. In this paper we present some ideas to improve the capability of these models to handle really-new products.

New Challenges

Really-new products present difficult challenges. To some extent each of these challenges is addressed with existing methods. For really-new products it is a matter of degree. Addressing these challenges better enhances accuracy; sometimes quite a bit. Among these challenges are the following.

Future Conditioning

Without a world of sophisticated, easy-to-use spreadsheet, word-processing, graphics, and communications software and without experiencing the benefits these tools provide, it was hard for initial personal computer purchasers to evaluate how they would use the hardware. By the same token, many of the advantages of today's software, particularly operating systems, was hard to evaluate without the corresponding hardware and applications software. Many of the advantages of multimedia will not come until the fiber-optic information highway is pervasive. Electric vehicles will depend upon an infrastructure to support them not unlike the infrastructure of gas stations and repair shops that supports internal combustion vehicles. The more new a really-new product is, the more forecasts will depend upon future scenarios. This means that a forecasting system for really-new products must bring the future to the customer so that the customer understands and can react to how the product would fit into such an environment.

Full Information

The success of a fashion item such as a Swatch watch depends upon whether or not other consumers consider it fashion. A television advertisement and a chance to handle a Swatch watch would not have been sufficient. The consumer would have to "experience" a world where Swatches are acceptable in the board room (as they are in Europe), where it is acceptable to wear two watches, and where it is socially acceptable to have a watch as a fashion statement. This means they have to "talk" to other consumers, read simulated fashion magazines, and "see" a social situation where cultural icons are wearing fashion watches. Electric vehicles (cars, vans, and trucks) are complex products. They are more attractive to a customer if regulations favor electric vehicles (tax breaks), if consumer magazines (*Consumer Reports*) report that they are reliable, if environmental imperatives are more severe, and, most importantly, if the consumer gets a chance to drive a vehicle. Advertising and concept descriptions would not be sufficient to provide the consumer with enough information with which to make a choice. Really-new products require that more information be available to the consumer.

User Experience

Really-new products are usually experience goods. Getting concert-hall sound while jogging from super-light earphones attached to a consumer's belt becomes real when the consumer tries a prototype Sports Walkman. The advantages and disadvantages of a graphical user interface (GUI) and what-you-see-is-what-you-get (WYSIWYG) technology in a word-processor becomes real after composing a research paper while using one. In some cases the consumer must learn new patterns of usage to take advantage of the really-new product. (For both of these examples consider the world when these products were really-new. Today they are just upgrades to existing products.) Electric vehicles accelerate well and are very quiet, but the energy demands usually imply a small vehicle. Driving an electric vehicle on a prototypical course helps the potential user to image using such a vehicle for commuting. However, if a full prototype or an initial production car were available, most of the capital investment that is at risk for the really-new product would have been committed. The challenge of a forecasting system is to give the user a surrogate for experience. Such experience might include a prototype, but often it might depend upon only a partial prototype or a computer simulation.

User Control and Active Search

Some of us read computer magazines, software magazines, seek out user groups, talk to the head of information services, and otherwise search for information on the latest word processing products. But not all adopters do so. Car buffs go to rallies, read magazines, have test-driven all kinds of vehicles, and have a complete vocabulary to describe how a car handles. But not everyone in the target market for an electric vehicle is a car buff. To forecast for a really-new product such as an electric vehicle, some "expert" consumers will have good information on future technology. But we can not assume that everyone will seek out this information. Our forecasts must be take account of consumers who will seek out information and must take account of how much they will obtain. This suggests we give the user control of the search process and observe how the consumer reacts.

Existing methods, e.g., Urban, Hauser, and Roberts (1990) and Urban, Hulland, and Weinberg (1993), give different consumers different sources of information, record consumer response, and then use mathematical models to project a distribution of sources that consumers will receive. But this assumes passive consumers. Recent evidence (Hauser, Urban and Weinberg 1993) suggests that consumers optimize their own searches. If the consumer is not given a chance to do this reallocation, any forecast may be conditioned on the wrong assumptions. Furthermore, because active learning is often more effective than passive learning, future conditioning, full information, and surrogates for user experience are more likely to be internalized by the customer if the consumer searches for this information actively.

Information Acceleration

Because of the strategic importance of really-new products, firms are experimenting with new methods. One of these methods is "Information Acceleration" (IA). The basic idea behind IA is to place the consumer in a virtual buying environment that includes *future conditioning*. For example, if done correctly in 1991, the electric vehicle customer will imagine him or herself in 1995 at the time of the new product launch. *Full information* is attained by using a virtual buying environment with a broad spectrum of information sources available. *User experience* depends upon a combination of real and virtual prototypes. The customer decides which information sources to visit, when, and for how long. This achieves *user control and active search.*

While IA might evolve to include full virtual reality methods such as "goggles with tiny TV screens that show computer simulations, headphones that present corresponding three-dimensional sound, and gloves with sensors that relay hand movements back to the computer" (Sheridan and Zeltzer 1993, p. 22), current systems rely primarily on multimedia computers. In this paper we illustrate how IA can work by describing a multimedia-computer IA for an electric vehicle. The basic technology is a MacIntosh II computer, with a Mitsubishi Multisync 14" video monitor, a Truvision New Vista video card, and a Pioneer 4200 laser videodisc. The software was written in Macromind Director. (A videotape illustrating the computer laboratory is available from the authors.) By accessing the videodisc, the computer displays television advertising and videotapes of consumer word-of-mouth. The software enables the word-of-mouth to be interactive. State-of-the-art surrogate travel technology enables consumers to interact with virtual prototypes. When combined with drivable partial prototypes, the IA provides user experience.

We begin the application by reviewing the managerial problem. As we describe the IA application we attempt to interpret how well today's technology meets the new challenges. We hope the reader joins us in a critical evaluation of the adequacy of this technology. Later sections describe other applications, initial validations, and research challenges.

Application to Electric Vehicles

In many ways electric vehicles (EVs) are really-new products. They employ new technologies including new composite materials, propulsion control systems, high-pressure low-friction tires, and deep-discharge batteries. A new dimension of utility is created as consumers fulfill their environmental responsibility (and advertise this to their peers) by driving a car with no on-road emissions. New attributes such as recharging time (4-8 hours), limited driving range on a charge (150-300 miles), potential stranding (with the batteries discharged the car is stranded), and shock hazard (from very high amperages) become important. There are new levels of existing attributes such as noise (the engine is <u>very</u> quiet), smooth acceleration (0 to 60 mph in 10 seconds and no need to rely on shifting gears), and size (usually quite small). Acceptance depends upon new scenarios (tax breaks, greater environmental awareness, government mandates) and infrastructure (charging stations at work, "tow" services replacing battery packs) and could vary with new technologies (lithium polymer or nickel cadmium batteries replacing lead-acid batteries as the technology with greater range or lower cost).

Furthermore, EVs are of major management interest. Regulation in California and 15 other states mandates that by 1998 two percent of all new cars sold by the "top-7" manufacturers be zero-emission vehicles. This percentage is to increase to five percent in 2001 and ten percent by 2003. If consumers purchase this number of EVs then this could become a $10-20 billion market in the USA and almost $1-2 billion in california. Indeed competition is keen with many US, European, and Japanese manufacturers experimenting with either all-electric or electric-hybrid vehicles in various body styles. (A hybrid vehicle uses both electric and internal-combustion power and this propulsion system could be made available in sedan, two-seat, or van configurations. Even Swatch has entered the market for an environmentally sound city car. Choi and Studer 1994.)

In this IA application a major automobile manufacturer developed an initial two-seated electric vehicle concept called Apex. They had available the concept description and minimum customer requirements (range, recharge time, safety) from qualitative group research and "voice of the customer" interviews. Preliminary engineering specifications included a fiber-glass body and interior. An existing 1992 model-year vehicle was retrofitted with an electric power train to enable the customer to experience driving an electric vehicle. If the program was to be continued it would require a commitment of several hundred million dollars. The goal of the IA was to make a go/no go decision based on the ability of the Apex to meet the legal California regulations and the firm's financial return on the investment.

Specific managerial questions included:

- Will the EV concept meet the sales level mandated by the California law?
- If the two-seater strategy is not sufficient, how much would the availability of a van or sedan increase the sales penetration.
- How vulnerable is the two-seat auto sales level to the entry of another competitive two-seat car?

Sample and Design

The study was performed in Los Angles in the fall of 1991 within an Information Acceleration context. The sample was drawn randomly from consumers who would consider spending more than $15,000 the next time they bought a car, would consider purchasing a car for commuting or driving around town, whose average round trip commute was less than or equal to 80 miles, and who did not reject the idea of an electric vehicle. Respondents were given a $50 incentive for participation. Of the 606 respondents who agreed to participate 587 were interviewed.

We selected an experimental design that would enable us to measure some of the potential biases induced by the IA. For example, we selected a popular internal-combustion-engine (ICE) car, a 1992 Toyota Celica, to serve as a control. The price of the Celica was roughly the target price of the Apex in 1991 dollars. The respondents who experienced the IA for the Celica received and IA conditioning corresponding to the 1991-1992 environment. By comparing the forecasts from the IA to actual Celica sales, we could estimate the bias introduced by the IA laboratory.

We were also concerned that the future conditioning might include an "environmental hype" in which respondents overstated their willingness to purchase an environmentally sound car. Thus, some respondents experienced the IA for a high-mileage ICE car that had a reputation for being environmentally sound, the high-mileage version of the 1992 Geo Metro. To provide further insight, roughly half of the Geo Metro respondents received the same future conditioning as the Apex respondents while the other half of the Geo Metro respondents received an IA conditioning corresponding to the 1991 environment. (For this last cell of the experiment, the measures confound some heightened awareness of environmental concerns with the state of the world represented by the IA. We will need expert judgment to untangle these effects.)

Of these 587 respondents interviewed, 284 experienced an IA for the Apex, 101 experienced the IA for a popular ICE car, and 200 experienced the IA for a high-mileage internal combustion engine (ICE) car. Of the 200 who experienced the high-mileage ICE car, 99 received the same future conditioning as did the Apex respondents and 101 received conditioning that corresponded to the 1991 environment.

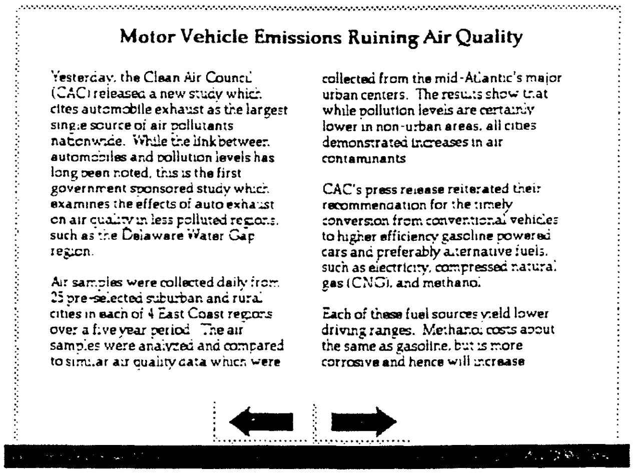
All of the 284 Apex respondents were exposed to an additional IA for a second environmental vehicle. 204 were asked to indicate if they preferred a van or sedan style and then were given a complete IA for an all electric vehicle in that body style. The remaining 80 respondents were exposed to two additional vehicles. One vehicle was a competitive two-seat EV (competitors chosen randomly) and the second vehicle was the respondent's choice of alternative-fuel vehicles (high ICE, methanol, hybrid, and compressed natural gas). In all cases the exposure and the measures were placed after all measures on the Apex were completed. This allowed us to compare the Apex respondents to the Celica and the Geo respondents. While the sponsor recognized that some biases might be introduced by question-order effects and respondent fatigue, they felt that the additional information could be used with suitable caveats.

Future Conditioning

Although the study was conducted in September 1991, the target time frame was the 1995 model year. The respondent was moved forward in time with the future-conditioning stimuli. Some of these stimuli were specific to the environment in which the car would be evaluated; other stimuli provided a background to encourage the respondent to image himself/herself in the future. Specifically:

- Time frame text told the respondent about the 1992 presidential election and the 1994 Winter Olympics. The stimuli attempted to evoke images of these events without being too specific.

- Two newspaper articles described concerns about pollution levels and the availability of infrastructure. They were displayed on the multimedia computer so that the respondents could read them at their own speed. See figure 1 for an example.


Motor Vehicle Emissions Ruining Air Quality

Yesterday, the Clean Air Council (CAC) released a new study which cites automobile exhaust as the largest single source of air pollutants nationwide. While the link between automobiles and pollution levels has long been noted, this is the first government sponsored study which examines the effects of auto exhaust on air quality in less polluted regions, such as the Delaware Water Gap region.

Air samples were collected daily from 25 pre-selected suburban and rural cities in each of 4 East Coast regions over a five year period. The air samples were analyzed and compared to similar air quality data which were collected from the mid-Atlantic's major urban centers. The results show that while pollution levels are certainly lower in non-urban areas, all cities demonstrated increases in air contaminants.

CAC's press release reiterated their recommendation for the timely conversion from conventional vehicles to higher efficiency gasoline powered cars and preferably alternative fuels, such as electricity, compressed natural gas (CNG), and methanol.

Each of these fuel sources yield lower driving ranges. Methanol costs about the same as gasoline, but is more corrosive and hence will increase

Figure 1. Example of Future Conditioning

In this study the manufacturer wanted a forecast for the most likely scenario. In other studies, following the tenets of robust design (Taguchi and Clausing 1990), IA might be used to provide a variety of scenarios such that the product could be evaluated in a range of scenarios. If alternative designs or marketing strategies were being evaluated, forecasts for multiple scenarios would enable the product team to choose the design and marketing strategy that did well in the most and/or the most likely scenarios.

Full Information

Based on qualitative consumer interviews, manufacturer and dealer experience, and prior research (Furse, Punj and Stewart 1984, Hauser, Urban, and Weinberg 1993; Kiel and Layton 1981, Newman and Staelin 1972, Punj and Staelin 1983, and Westbrook and Fornell 1979) we chose showroom visits, advertising (television, magazine, and newspaper), magazine articles, newspaper articles, brochures, and word-of-mouth as representative of the types of information that consumers access in their search for information about automobiles. These information sources were implemented as follows.

- **Showroom visits**. We used surrogate travel (figure 2a) on a computer monitor. By clicking on the appropriate arrows the consumer could walk around the car, get in and examine the interior, look in the engine compartment and trunk, and talk to a salesperson. The salesperson was neutral and informative in this study; the consumer could select from a range of questions and observe (video and sound) the salesperson's response.

- **Advertising**. By clicking on an icon, the consumers could watch a potential television advertisement (produced from stock footage). Another icon used "beauty shots" of the electric vehicle with the tag line "The Apex for those who feel personally responsible for the environment." See figure 2b. A third icon gave newspaper advertising (figure 2c) which provided information on price and availability. In each case the advertising appeared real to the consumers in the same form that the respondent is used to seeing. (We have removed the manufacturer's name and modified the vehicle in figure 2 to protect confidentiality.)

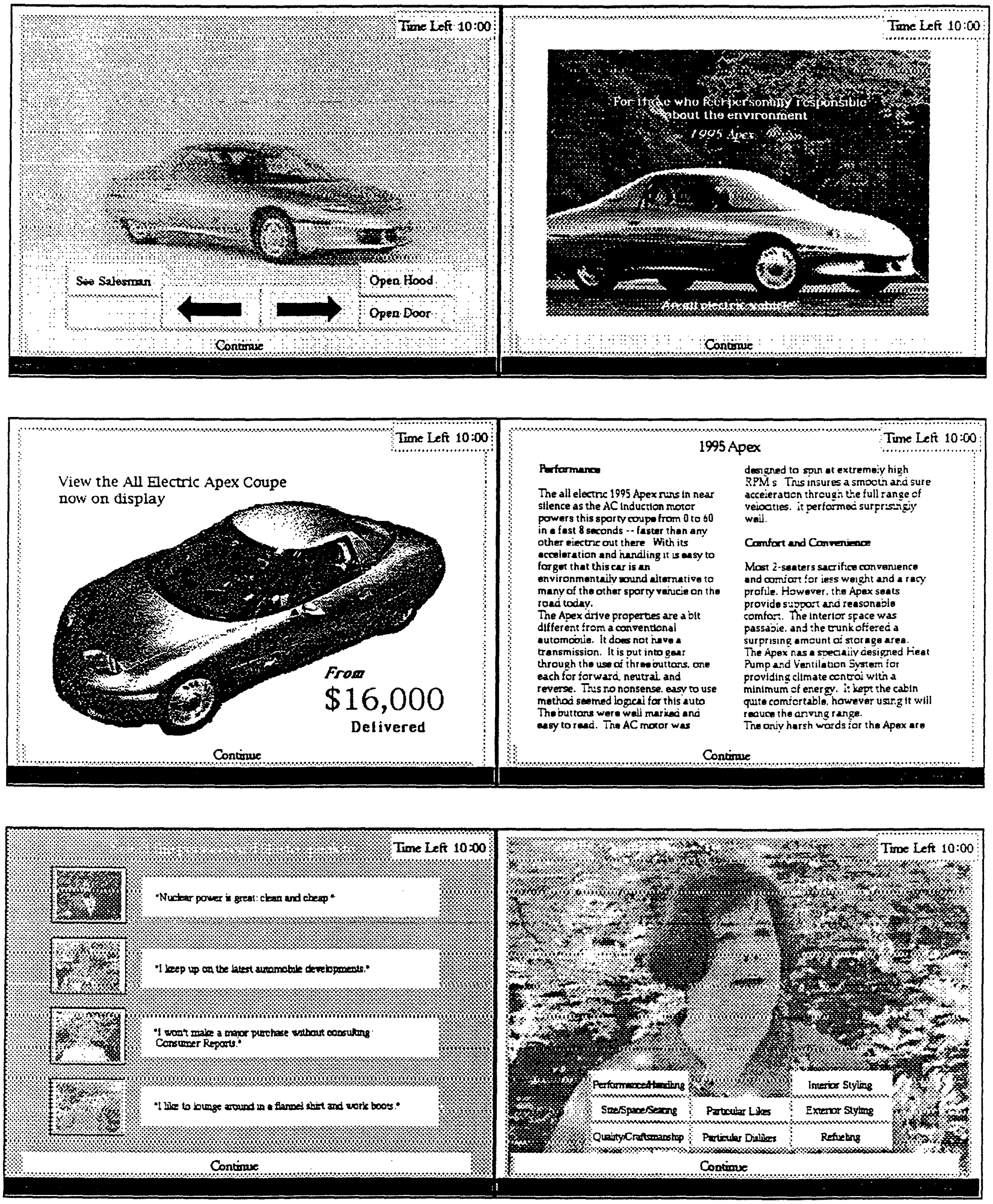


Figure 2. Screen Shots from the Apex Information Accelerator. (a) Surrogate Travel, (b) Magazine Advertising, (c) Newspaper Advertisement, (d) Consumer Magazine Article, (e) Selection of Word-of-Mouth Videos, (f) Example Word-of-Mouth Video.

- **Articles**. The consumers could view, at their own pace, simulated auto magazine report about the Apex (figure 2d). These articles provided information on construction, value, appearance, safety, performance, comfort, cargo space, and environment -- the attributes that consumers indicated were important in earlier, qualitative interviews.

- **Word-of-mouth**. Professional improvisational actors took on the characters of five representative consumers. The five consumer profiles were chosen based on a psychographic segmentation study and voice-of-the-customer interviews conducted by the automobile manufacturer. The respondent sees a menu of video clips where each menu item is represented by a still shot of the word-of-mouth consumer and a short quote from that consumer (figure 2e). After clicking on the icon, the respondent sees a full screen image of the respondent and a set of topics. The respondent can choose video clips on any or all of the topics (figure 2f).

We do not know whether the word-of-mouth in 1994-1995 will be positive or negative. Thus, we created two experimental treatments for the EV -- a positive and a negative treatment. Half of the Apex test sample was exposed to each treatment. To decide which treatment (or which combination of treatments) to use in the forecast, we asked respondents, at the end of the entire measurement and test drive, how positive or negative their word-of-mouth communication would be to others. We also assessed the probability that they would visit an actual dealer.

User Experience

An electric powertrain drives differently than internal-combustion vehicles. After respondents exited the virtual dealer visit described above, they were allowed to test drive a 1992 GEO Storm that was retrofitted with an electric powertrain. This enabled the respondent to experience the shifting (just push a button), acceleration (0 to 60 mph in less than 10 seconds), handling, and the silence of electric-vehicle driving. We instructed respondents to evaluate the drive vehicle with respect to its drive characteristics only, that is acceleration, braking, etc.

Full information and user experience could induce a demand effect. By comparing the Apex respondents to the Celica respondents we estimate the laboratory bias and correct our forecasts accordingly.

User Control and Active Search

The respondents could select any information source in any order and "visit" the source for as long as they chose. They could visit as many or as few sources as they chose and could visit any source as often as they wanted. The computer recorded the time in each source (or subsource). For more discussion on the impact of active search see Hauser, Urban, and Weinberg 1993.

Table 1 reports the decisions that respondents made with respect to which source to visit and when. The showroom was visited first most often and most often overall. This is generally consistent with results reported in Hauser, Urban, and Weinberg (1993) for the Buick Reatta[1]. Respondents were asked to estimate the probability that they would visit an actual showroom to search for the EV. The average judged probability was 0.69. However, this could be biased due to the laboratory measurement. To correct for this bias we compare intentions to actual behavior for cars already on the market which are respondents considered. The adjusted estimate is reduced to 0.30.

Table 1. Sources Searched

	First Source	Percent Visited
Showroom	44.0%	99.6%
Advertising	27.8%	64.4%
Magazines	19.4%	66.9%
Word-of-mouth	8.8%	69.0%

Measurement and Modeling

After putting respondents in the virtual future buying environment measures are taken of their likelihood of purchase, perceptions and preferences. These measures are taken after each major information exposure and then integrated in a model to predict the growth of sales of the new product based on assumptions of the changes in the environment and the managerial introduction plan.

Intent-to-purchase scales. After concept exposure, after the respondent exits an information source, and at the end of an IA search -- for the target car and for any competitive vehicles, we ask the respondent to judge the probability that he or she would purchase the car. This subjective probability asks the respondent to estimate an action fully recognizing that search will continue. To make a judgment, the respondent must assess his or her likelihood of acting based on currently available information and, implicitly, assess what information will become available prior to choice. The basic scale is a thermometer scale with the eleven verbal anchors commonly used in purchase intent scales (Juster 1966). The respondent estimates a probability by using a pointing device to drag a pointer from the prior value obtained from an earlier question to the subjective probability that applies based on the respondents' current information state. See figure 3a. To evaluate the strengths and weaknesses of the EV, respondents rated the EV and their preferred cars on eight attributes (chosen from prior market research). To evaluate whether they were confident in these ratings we also asked them to indicate the certainty with which they make these judgments. See figure 3b.

Table 2. Judged and Adjusted Probabilities of Purchase from the Information Accelerator

	Judged Purchase Estimate	Adjusted Purchase Estimate
Apex	0.53	0.24
Celica	0.39	0.17
Geo (Future)	0.35	0.19
Geo (1991)	0.30	0.15

[1]For the Buick Reatta the percentages for showroom, advertising, magazines, and word-of-mouth were 48%, 9%, 24%, and 19% for first visit and 100%, 59%, 65%, and 68% for percent using.

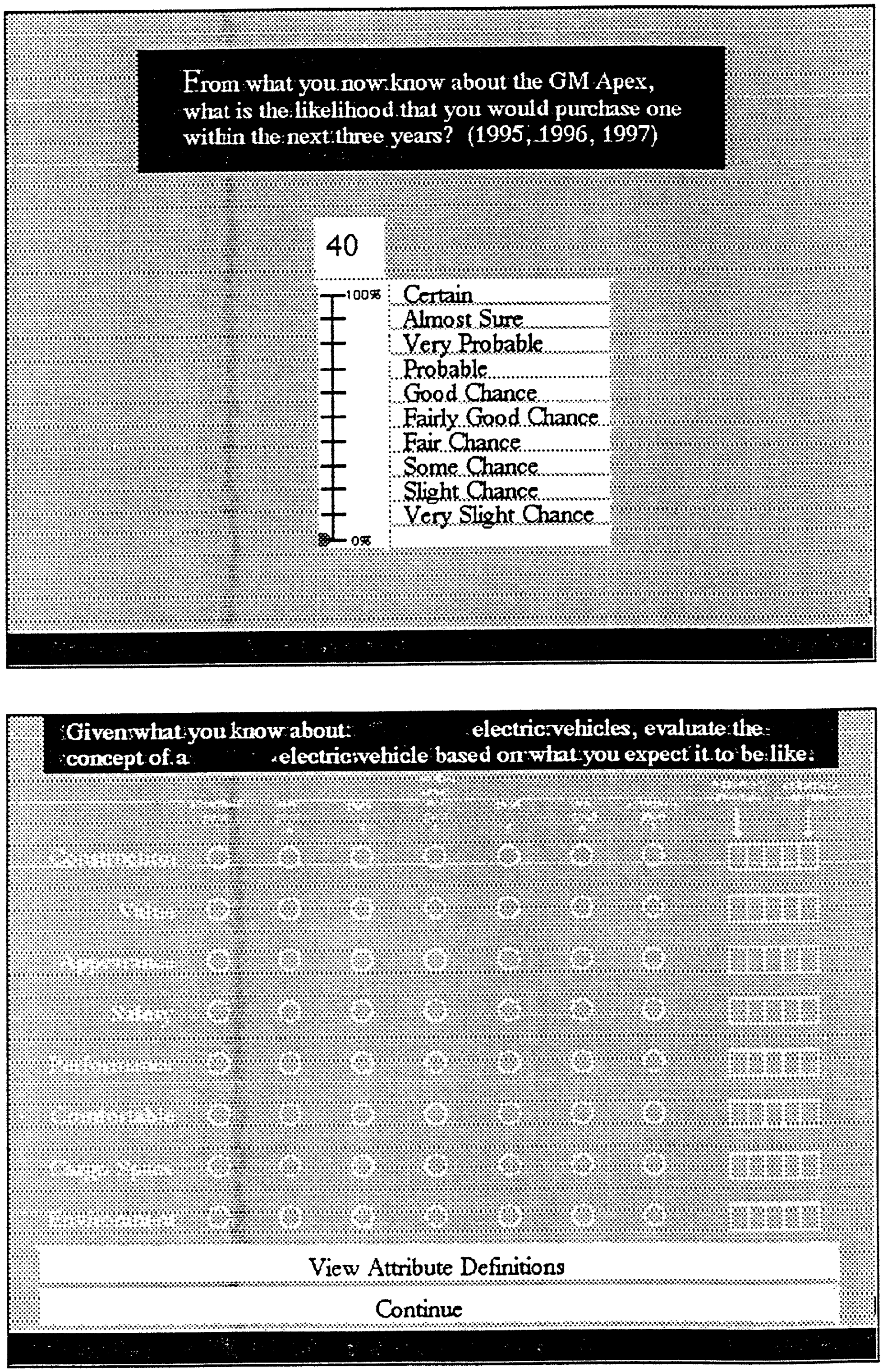


Figure 3. Measures of Likelihood of Purchase and Perceptions. (a) Likelihood of Purchase and (b) Perceptions of Relevant Attributes

Table 2 reports the average full-information judged probabilities (respondent exits last chosen information source) for each of the test and control cells. The judged probabilities are based on the IA. Intent scales are indicators of true probabilities (Juster 1966, McNeil 1974, Morrison 1979, Kalwani and Silk 1983, Jamieson and Bass 1989), but must be adjusted to provide specific predictions. Our first adjustment, shown in table 2, is made by normalizing the stated probabilities by the stated intent probabilities for all the cars in the respondent's consideration set. This has proven accurate in previous studies (Urban, Hauser, and Roberts 1990). Our second adjustment is based on comparing the reported probabilities for the Toyota Celica in the IA to actual sales of the Toyota Celica. To make this adjustment we use proprietary data on the sales volume of the Toyota Celica, the size of the target market for the Celica, and information on the success of the marketing campaign for the Toyota Celica. See methods in Urban, Hauser and Roberts (1990). Based on comparing the actual and predicted 1991 sales of the Toyota Celica, we found that the model over estimated sales by 10%. (Predictions depend upon measures of awareness, dealer-visit likelihoods, and segment sizes. These predictions are obtained from proprietary data and management judgment.)

We must also estimate the impact of future conditioning. Based on table 2 we estimate that future conditioning (Metro with future conditioning vs. Metro without future conditioning) introduces a 26% increase in the judged probabilities. At this point it is difficult to know whether this is simply a demand effect or reflects a true change in probabilities due to the change in the future environment. It becomes a managerial judgment to determine how much of this increase to attribute to each effect. In our case management chose a 13% increase as a demand effect and the remainder as the increase in purchasing that reflects the change (induced by the IA) between the state of the world in 1991-1992 and the state of the world in 1994-1995.

By putting the 10% intent inflation and the 13% future-conditioning inflation together and assuming an additive model, management chose to adjust all forecasts downward by 23%. Thus, an 0.813 multiplier (1.0/1.23 = 0.813) was applied to all forecasts.

Diffusion/decision-flow models. Information has an effect. To use the data in table 2 we must model the impacts of awareness from marketing and word-of-mouth, the likelihood of a dealer visit, the impact of infrastructure, and the limitation of the population to those who satisfy the screening constraints.

To forecast for an actual scenario we estimate the conditions that describe the marketplace of 1994-1995. To do this we use the decision-flow diagram in figure 4. A decision-flow diagram is a map of the conditional probabilities that are used to forecast based on consumer information acquisition and market conditions. We estimate as many of the conditional probabilities as possible from the information accelerator. Others, such as the percent aware due to advertising are based on the marketing plans of the firm using the IA to evaluate the Apex. Still others, such as the size of the market and the percent who would consider an EV are based on information available from other sources. For more details and examples in the auto industry, see Urban, Hauser and Roberts (1990).

For example, the firm conducted a market-research survey to determine the percent of the population which would consider an EV. For this paper we can not report the actual number, so we use a disguised number of 48%. Similarly we disguise the percent who pass the remaining screening criteria as 45%. The total number of automobiles sold per year in California averaged approximately 1.2 million in 1990 and 1991 (Statistical Abstract). For this paper we use the round number (for 1995 model-year sales) with a 1% per year growth -- the firm used the actual numbers. The firm estimated (disguised for this paper) a 30% awareness of Apex in the first year and a 40% awareness of Apex in the second year growing to 50% by 1998. The firm defined awareness as a state of knowledge comparable to the information obtained by searching one or more sources in the IA. These numbers represent a substantial marketing campaign. The firm estimated that 80% of the respondents would be near sufficient service and recharging infrastructure by 1995 with this number growing to 100% by 1999. (Again these are disguised numbers.)

The probability of visiting a dealer was measured as 0.30 as stated above and did not depend strongly on the number of sources visited. The adjusted probability of purchasing an Apex was 0.24 in table 2, it remained at 0.24 when we condition on the respondent having "visited a dealer."

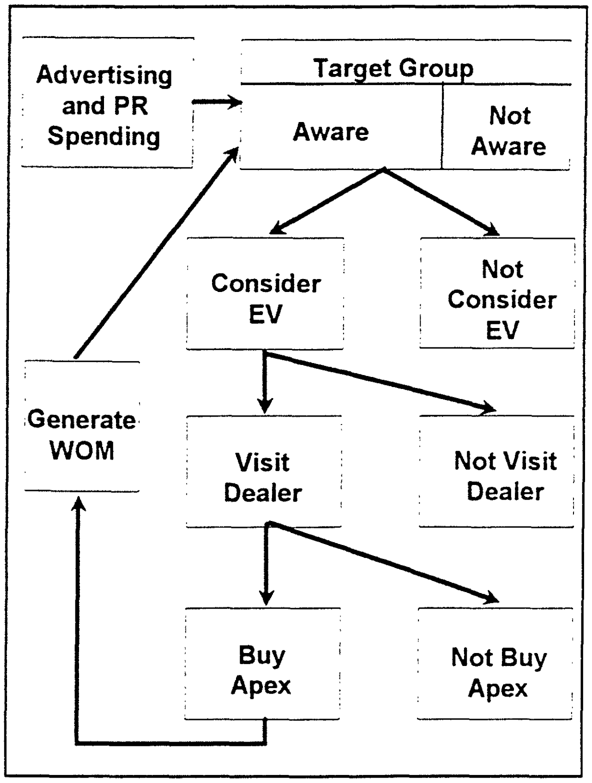


Figure 4. Decision-Flow Diagram for Apex Forecast

Putting these numbers together, we forecast a first-year sales of 6,743 units. (1,200,000 units in market x .45 pass screening criteria x .30 awareness x .48 consider an EV x .80 near infrastructure x .30 visit a dealer x .24 purchase probability after drive x .813 adjustment = 3,641 units.)

We now return to the managerial issues to illustrate how the conditional forecasts influenced the decision whether to launch the really-new product.

Managerial Results

Based on the data and the assumptions above we estimate the sales of the Apex for the model years 1995 through 1999. See figure 5. Unfortunately while these base case forecasts were sufficient to generate the sales required to meet the California regulations in 1998, these sales would not be sufficient to produce the profit stream necessary to justify the investment that the firm would have to make in development. If the firm were to price the vehicle to meet a long-term break-even point, the resulting sales

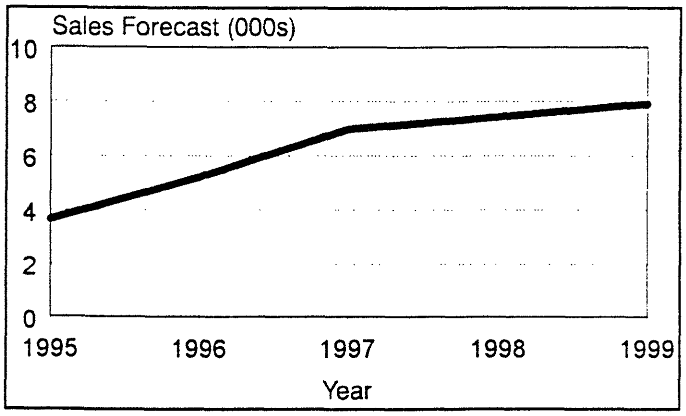


Figure 5. Base Case Forecast for the Apex

would not be sufficient to meet the regulations. (Price elasticities were obtained from a conjoint analysis administered following the IA.)

Competitive Vulnerability

In the experimental design 80 respondents participated in an IA for competitive two-seat EVs immediately following the IA for the Apex. When a competitive two-seat EV was introduced in the IA two effects were observed. First the market for EVs expanded 39% because some people who had not chosen the Apex selected a competitive EV. (The adjusted purchase probability for at least one EV was 0.346.) Second, some of the respondents who had chosen the Apex switched to the competitive EV -- the Apex share of these choices was 59%. Together these effects imply that the Apex sales would be 81% of the level that would be achieved if it were the only EV in the market (0.59 x 1.38 = 0.81). This reduces the sales forecast for the Apex to 2,950 units in the 1995 model year and 6,015 units in the 1998 model year. These forecasts lower the expected rate of return on the firm's investment in research and development and make it more difficult to meet the regulations at a break-even price. (We report all significant digits in the forecast so that the reader can reproduce our arithmetic. Managerial planning is based on a reasonable understanding of the accuracy of the forecasts.)

Product-line Potential

At the time of the IA experiment, management had already begun development of the two-seated sporty car. They hoped that this EV would be ready by for the 1995 model year. But since the sales of the two-seat EV were below those necessary to meet the mandated levels, the effect of adding a van or sedan was of interest to management. In the experimental design 204 respondents participated in an IA for a line of EV vehicles. Specifically, they were allowed to search for information on a sedan and a van after they completed the search for the two-seat EV. For these respondents we forecast an 83% market expansion due to the availability of the sedan and van. (83% more respondents selected an electric vehicle when three body types were available.) Of those who had purchased the Apex, 19% switched to a van or sedan when given the opportunity in the IA. With this product-line expansion and if there were no competition, our disguised data would forecast sales of 13,588 units in the 1998 model year. However, with competition this would be reduced to 11,007 units. These disguised numbers would meet the California mandates if the firm could design the sedan and/or van in time and if it could reduce costs.

The undisguised numbers were more pessimistic. The firm could come close to the mandated levels in 1998 but the rate of return on investment was still below minimums due to the additional fixed costs of design and the production of the van and sedan. If any reasonable estimate of competitive impact were included, even the firm's mandated sales requirements could not be met.

Qualitative Insights

The autos presented in this study were powered by lead-acid batteries. These batteries limit the range (75 miles city and 100 miles highway for the two-seat EV, 70 miles city and 90 miles highway for the sedan, and 62 miles city and 80 miles highway for the van). The EVs are expensive relative to their ICE alternatives (1991 price levels were $16,000 for two-seat EV, $17,000 for the sedan, and $17,500 for the van). To understand better the qualitative reaction to the EVs, we collected perceptual ratings on eight scales (construction quality, value, appearance, safety, performance, comfort, cargo space, and environment -- "is the car environmentally friendly"). Review figure 3b.

The EVs were rated much higher on environment but lower on the other attributes than the control car (Toyota Celica). The differences were more pronounced when respondents rated the EV versus their current first choice cars. However, when respondents were asked to rate the importance of the eight "consumer needs," they rated environment to be the lowest (4.7 on a 7-point scale). While consumers felt environmental impact was moderately important, they did not want to give up other car attributes to get it. Specifically, many attributes, such as the driving range of the EV, would have to be increased substantially before the auto could succeed financially in California. Qualitative interviews completed by the firm confirmed these interpretations.

Management's Decisions

Based on the IA study reported here and supporting market research, management concluded that the sales of the Apex two-seat vehicle would not be profitable. The emerging conclusion was to delay the Apex launch. The delay would enable them to concentrate on improving battery technology and on the production and design improvements that could reduce the cost of the vehicle. In order to develop the core capability to enter the EV market when the technology was ready, the firm decided to maintain a demonstration program based on prototype use and to conduct a nation-wide study to determine the responses of customers in other parts of the country. This nation-wide study included a combined conjoint analysis and IA to estimate the effects of modifying the design.

Other Applications and Initial Validations

The EV application demonstrates most of the features of an IA and how it can be used to provide managerially relevant forecasts. In addition to the EV application we have completed four other IA applications -- the Buick Reatta, a new camera, a home information system, and a medical instrument. Although the Reatta was not a really-new product it did enable us to compare the IA showroom to a showroom with an actual vehicle and an actual salesperson. The camera application (also not a really-new product) enabled us to compare the forecasts from the IA with actual sales results. In this section we describe these initial validations and the managerial situations of the home information system and the medical instrument.

Reatta -- IA Compared to a Real Vehicle and Real Salesperson in a Showroom

Our first application of IA was to test consumer reaction to a new internal-combustion two-seated sporty car, the Buick Reatta convertible. As in the EV study, we used a test car/control car design. In this case two-thirds of the sample, chosen randomly, searched for information on the Reatta and one-third searched for information on a Mazda RX-7. As part of that application, we wanted to test whether the IA could reproduce forecasts based on a conventional forecasting clinic in which consumers where allowed to view the actual vehicle in a showroom setting and to talk to an actual salesperson. As in the EV study IA was used to simulate showroom visits, newspaper and television advertising, magazine articles, and word-of-mouth. However, for one-third of the sample, chosen randomly, when respondents selected the showroom in the IA they received a message to call for an attendant. They were then taken to view the actual automobile in a simulated showroom. The same Boston-area Buick salesman, who had been videotaped for the IA, was in the showroom and answered questions from a script. When respondents were finished in the simulated showroom the attendant took them back to the computer to complete the IA.

The initial sample was chosen from the registration records of consumers who had purchased a sports car in the last two years. Respondents were pre-screened via telephone on whether they would consider purchasing a two-seated sports car as their next car and whether they planned to spend at least $20,000 on the purchase. Those who qualified were invited to participate in the study, given a time and location at which to appear, and promised a $25 incentive for participation. The final sample was:

Reatta, computer showroom	71
Reatta, real-car showroom	43
RX-7, computer showroom	40
RX-7, real-car showroom	23

We used the same purchase intent scale for the Reatta IA as for the EV IA. Two measures are relevant for comparing experimental treatment effects: (1) the full-information judged probabilities and (2) the change in judged probability measured before and after the showroom visit. Figure 6 plots the treatment effects for both measures. In each case there is a main effect for vehicle -- consumers prefer the RX-7 to the Reatta, but the difference between the computer showroom and the real-car showroom is not significant. Table 3 reports the analysis of variance. We also measured the time that respondents allocated to the showroom search not counting the time going to and coming from the real-car showroom. For the IA the average total time was 3 minutes and 25 seconds; for the real-car showroom it was 3 minutes and 23 seconds. This difference was not significant at the 0.01 level ($t = 0.11$).

Table 3: Analyses of Variance

SOURCE OF VARIATION	FINAL PROBABILITY			CHANGE IN PROBABILITY		
	D.F.	MEAN SQ.	F-STAT.	D.F.	MEAN SQ.	F-STAT.
Main Effects						
Video vs. Real	1	144.3	0.22	1	10.4	0.05
Reatta vs. RX-7	1	2835.1	4.33	1	653.8	2.96
Interaction	1	392.7	0.60	1	0.1	0.00
Residual	171	655.4	-	173	220.8	-

While these comparisons do not guarantee that either the IA or the real-car showroom are valid representations of consumer information search in real automobile showrooms, they

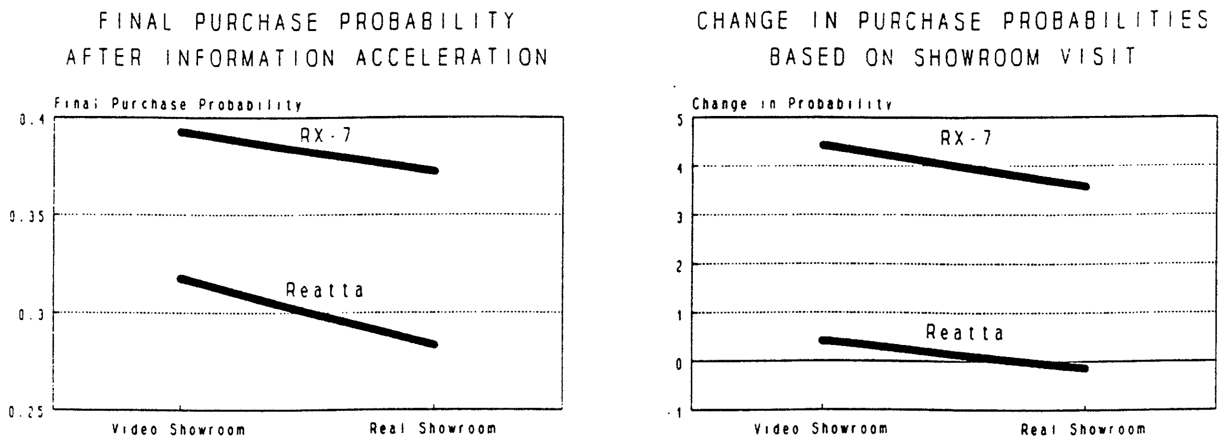


Figure 6. Comparing the Effects of Reatta vs. RX-7 and IA vs. Real-car

do suggest that the IA is as good a forecasting tool as a clinic-based real-car showroom. This is an important managerial result because forecasting clinics have been validated (Urban, Hauser, and Roberts 1990) and are the primary market-measurement means used to forecast the sales of new automobiles. The advantage of IA relative to a prelaunch clinic is that IA is less expensive, faster, and can be applied to concepts that are available only as computer images rather than pre-production models.

Camera -- Forecasts vs. Early Sales

Our second application of IA was to a new camera in an existing line. The new camera was a new brand positioned for gift-giving and personal use with improved picture quality and a lower price (about $59). The sample was 200 respondents who were unaware of the new camera. The IA included television advertising, consumer-reports articles, and word-of-mouth. User experience was simulated by allowing the respondent to browse a shelf containing 18 competitive cameras. The respondent could ask an attendant for a demonstration of any of the cameras[2]. One-half of the respondents were allowed to search for information for the new camera while one-half searched for information on an existing camera.

The forecast was based on calibrating the judged probabilities of the existing camera to actual sales and comparing those modified probabilities to that for the test camera. The actual advertising and distribution, which was known at the time of the forecast, was used in a decision-flow diffusion model to adjust the full-information probabilities. The forecast proved to be within 10% of actual sales eighteen months after market launch. Estimates of cannibalization of the other cameras in the product line were equally accurate.

The camera IA was not an application to a really-new product and the marketing plan was known. However, the forecast accuracy is encouraging. (The IA also identified opportunities

[2]In this IA 42% visited the store first, 27% examined magazines first, 22% examined word-of-mouth first, and 7% examined the advertising first.

to improve profit by 25% by lowering advertising and increasing in-store promotion.)

Applications to a Home Information Service and a Medical Instrument

The IA has been applied to a new home information service based on an enhanced telephone, interactive television, or computer screen interface. None of the devices tested generated sufficient volume for a go decision. Although the devices were functional, the service plans were not sufficiently powerful or sufficiently easy-to-use to gain customer acceptance at the prices tested. The regional telephone company is now redesigning the service packages and exploring partnerships to underwrite the product-development effort to create software for the applications.

The final IA application was to a CBC (Cell Blood Count) medical instrument based on a new optical technology. The IA forecast good sales penetration in the target segment of small independent practices, but the segment was smaller than expected and declining. The low sales potential plus uncertainty about government reimbursement policies led this project to be shelved. See Bohlmann, Qualls, and Urban (1994).

Research Challenges

Information acceleration is one method to tap the power of multimedia computing to address the really-new new-product forecasting challenges of future conditioning, full information, user experience, user control, and active search. Based on the applications to date to somewhat-new products we believe that the forecasting accuracy is promising. Based on the application to a really-new product we believe that IA has the potential to address the forecasting challenges, but much remains to be done. We sketch here a few of the major challenges remaining.

Cost

As implemented in the EV study IA is expensive. A typical application costs $100,000 to $300,000. IA is expensive because, besides programming the computer, one must assemble professionally produced advertising, word-of-mouth video, and simulated showroom footage as well as create believable newspaper articles, magazine articles, and product brochures early in the design process. As a result, the applications to date of IA have been sponsored by manufacturers who have a large financial stake in forecasting for the new or really-new product. Within these applications we have been able to test some of the concepts, but further scientific testing must await a substantial reduction in cost.

Fortunately that cost reduction is coming. The IA described in this paper was implemented with "video pass-through." That is, actual video footage was produced and pressed on a videodisc. The computer then controlled the videodisc in order to access the video as needed. Recently, compression breakthroughs and fractal conversions coupled with increases in computer speed and data storage are enabling an alternative technology called "video capture." With video capture video footage is digitized and stored on either a hard disk or a CD-ROM disk. The computer then reads the information as a data file, decompresses the information, and plays the video. Not only does video capture promise to reduce the cost of playback, but the ability to edit digital files promises to reduce dramatically the cost of authoring an IA system. For example, to create a simulated showroom with video pass-through we must photograph a mockup of an automobile body by moving a video camera through different locations and angles using professional photographers to maintain consistency. With video capture we could take fewer pictures and use the computer to create alternative views. Alternatively, we might even use computer-aided design (CAD) methods to create the images without a physical model. See Adamjee and Scaife (1993) for an initial video-capture application.

Given the rapidity with which multimedia computing is advancing we expect that IA will be within the budgets of many academic researchers in the next few years. It is at that time that we expect many of the following issues to be addressed.

Future Conditioning -- What is real?

When developing the future conditioning for the EV scenarios we tried a variety of formats and information content. The format and content that we chose passed a series of pretests in which the respondents reported that they could image themselves in 1994. Our induction had strong face validity. It is also clear that future conditioning had a measurable effect on judged probabilities. However, it is likely that mass-produced EVs will not be introduced for a number of years and the infrastructure may not be available until the end of the century. (At the time of this writing, the Apex is delayed.) At this point in time there is no way to assess the validity of the future conditioning. To test future conditioning we recommend experiments in which respondents are recruited for a situation with which they are not familiar but for which they can be made familiar soon after using the IA. For example, one might use IA to test on-board amenities for cruise ships using as respondents consumers who have never cruised but plan to do so in the near future. Alternatively, one might use an IA to test HDTV just before it is introduced.

User Control and Active Search -- External Validity

In real decision environments consumers do not visit all information sources because, among other things, the time cost and out-of-pocket costs do not justify the value of the information they obtain from those sources. In the IA the cost of visiting a source is much less than in a real decision environment. We address this problem by limiting the time available to the respondent in the IA and modeling their search process. We first ask potential consumers what information sources they normally visit. We then adjust the time they have available such that they can visit roughly as many sources in the IA as they would in a real decision environment. Similarly we are able to adjust each information source so that respondents split time among information sources roughly in proportion to how they would behave normally. See details in Hauser, Urban, and Weinberg (1993).

However, there is no guarantee that matching the number of sources visited and the split among sources is sufficient to insure external validity. The ratio of acceleration varies among sources. For example it is much faster to visit a showroom in the IA than in real life when one takes travel (and sales pressure) into account. On the other hand, reading *Consumer Reports* may take about as long in the IA as in real life. It is incumbent upon the IA developer to model these effects, but there is certainly room for further development to test the external validity of the sources and to develop means to maximize external validity.

User Experience

The IA provides simulated experience. With the EV we combined a simulated showroom with a driveable prototype. However, some products require much more consumer experience. For example, a user would be better able to use a radical new computer keyboard if allowed to use that keyboard for a week or more. The user would learn how best to use the new keyboard and might even customize it for maximum comfort and efficiency. For discussions of the user-active paradigm of product development see von Hippel (1988).

Fortunately a number of engineering breakthroughs promise to enhance our ability to test user experience. Among these developments are rapid prototyping systems which tie CAD systems to forming, molding, and cutting machinery. With rapid prototypes and IA we could provide information to the customer and give a prototype to the customer which he or she could use for a period of time. Another interesting development is "smart" prototypes. Already many products such as photocopiers and automobiles provide feedback to customers and repair technicians on the product's past use. By coupling this technology with rapid prototyping we could monitor customer use quickly and use it both to modify designs and forecast use. Smart prototypes have the potential to enhance (1) flexible design -- products are designed so that they can be changed readily based on user experience, (2) robust design -- products are designed to work well in a variety of environments, and (3) IA -- getting information to the user rapidly so that the user's experience is accelerated. See Eppinger and Ulrich (1994) for a discussion of these developments.

Another direction might be to move the IA to a full virtual reality in which the drive itself (say for a car) is simulated. Flight simulators are in common use to train pilots. Virtual reality "amusement parks," now touring the US, include race-car simulators which combine computer controlled screens and centrifuges to give both the look and the feel of driving a car. Today these simulators are costly, but tomorrow they may be cost-effective.

Multiperson IA

Many business-to-business products are sold to groups not individuals. IA is now being extended to group decision processes in which each individual receives full information and in which interactions among decision makers (and influencers) are accelerated with groupware and interactive media. See Bohlmann, Qualls, and Urban (1994).

Summary

IA is an exciting new technology. It has the potential to enhance product development success by providing forecasts early for really-new products. In this paper we have tried to report on the status of IA in the hopes that the reader can evaluate this technology and develop new research directions to test and improve IA. IA also has the potential to explore new areas of consumer behavior. By accelerating information researchers might use IA to study how consumers search for information, use information, and learn how to use products. Naturally many hurdles remain, but some of these hurdles are falling to the advancement of engineering and computer technology and others will fall to the creative experiments of marketing researchers[3].

[3]Many research staff members helped on this project. Special thanks to Vince Barabba, John Bohlman, Ivan Cavero, Roberta Chicos, John Dables, Scott Halstead, Sheung Li, Michael Kusnic, Sean MacNamarra, Dave Newhouse, Matt O Mera, Sanjay Parthasarathy, and John Scaiffe. This research was supported by grants from the manufacturer and from the International Center for Research on the Management of Technology. May 1994.

References

Adamjee, Hafiz H. and John H. Scaife (1993), "The Face of the Customer: The Use of Multimedia in Quality Function Deployment," Master's Thesis, Sloan School of Management, M.I.T., Cambridge, MA 02142.

Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science,* 15, (5) (January), 215-27.

_______ (1980), "The Relationships Between Diffusion Rates, Experience Curves, and Demand Elasticities for Consumer Durable Technological Innovations," *Journal of Business*, 53, 3 (2), (July), S51-S67.

Blattberg, Robert, and John Golanty (1978), "TRACKER: An Early Test Market Forecasting and Diagnostic Model for New Product Planning," *Journal of Marketing Research,* 15 (2), (May), 192-202.

_______ and Scott Neslin (1990), *Sales Promotion: Concepts, Methods and Strategies*, (Englewood Cliffs, N.J.: Prentice Hall).

Bohlmann, Jon, William Qualls, and Glen Urban (1994), "Information Acceleration and Decision Unit response to New High Tech Industrial Products," Working Paper, Sloan School of Management, M.I.T., Cambridge, MA, May.

Cattin, Phillipe. and Dick R. Wittink (1982), "Commercial Use of Conjoint Analysis: A Survey," *Journal of Marketing*, 46, 44-53.

_______, Gerard Hermet, and Alain Pioche (1982), "Alternative Hybrid Models for Conjoint Analysis: Some Empirical Results," in *Analytical Approaches to Product and Market Planning: The Second Conference*, (Marketing Science Institute: Cambridge, MA), (October), 142-152.

Charlton, P., A. S. C. Ehrenberg, and B. Pymont (1972), Buyer Behavior under Mini-Test Conditions," *Journal of the Market Research Society,* 14 (3) (July), 171-83.

Choi, Audrey and Margaret Studer (1994), "Daimler-Benz's Mercedes Unit to Build a Car With Maker of Swatch Watches," *Wall Street Journal*, (February 23), A14.

Claycamp, Henry and Lucien E. Liddy (1969), "Prediction of New Product Performance: An Analytical Approach," *Journal of Marketing Research,* 6 (3), (November), 414-20.

Dodson, Joseph A., and Eitan Muller (1978), "Models of New Product Diffusion Through Advertising and Word of Mouth," *Management Science,* 15 (November), 1568-78.

Dolan, Robert and Abel Jeuland (1981), "Experience Curves and Dynamic Demand Models:

Implications for Optimal Pricing Strategies," *Journal of Marketing*, 45, (Winter), 52-62.

Eppinger, Steven and Karl Ulrich (1994), *Methodologies for Product Design and Development*, (New York: McGraw-Hill)

Eskin, Gerry J. (1973), "Dynamic Forecasts of New Product Demand Using a Depth of Repeat Model," *Journal of Marketing Research,* 10 (2), (May), 115-29.

Furse, David H., Girish N. Punj, and David W. Stewart (1984), "A Typology of Individual Search Strategies Among Purchasers of New Automobiles," *Journal of Consumer Research*, 10, (March), 417-431.

Fourt, Louis A., and Joseph W. Woodlock (1960), "Early Prediction of Market Success for Grocery Products," *Journal of Marketing*, 25 (2), (October), 31-38.

Gatignon, Hubert Jehoshua Eliashberg, and Thomas S. Robertson (1989), "Modeling Multinational Diffusion Patterns: An Efficient Methodology", *Marketing Science*, 8 (3), (Summer 1989), 231-247.

Green, Paul E. (1984), "Hybrid Models of Conjoint Analysis: An Expository Review," *Journal of Marketing Research*, 21,2. (May), 155-169.

_______, Abba M. Krieger, Manoj K. Agarwal, and Richard M. Johnson (1991), "Adaptive Conjoint Analysis: Some Caveats and Suggestions, Comment," *Journal of Marketing Research*, 28, (May), 215-225.

_______ and V. Srinivasan (1978), "Conjoint Analysis in Consumer Research: Issues and Outlook," *Journal of Consumer Research*, 5 (2), (September), 103-123.

_______ and _______ (1990), "Conjoint Analysis in Marketing Research: New Developments and Directions," *Journal of Marketing*, 54, 4, (October), 3-19.

Hauser, John R. and Kenneth J. Wisniewski (1982), "Application, Predictive Test, and Strategy Implications for a Dynamic Model of Consumer Response," *Marketing Science*, 1, 2, 143-179.

_______, Glen L. Urban, and Bruce Weinberg (1993), "How Consumers Allocate Their Time When Searching for Information," *Journal of Marketing Research*,

Hirokazu, Takada and Dipak Jain (1991), "Cross-National Analysis of Diffusion of Consumer Durable Goods in Pacific Rim Countries," *Journal of Marketing*, 55 (April), 48-54.

Horsky, Dan (1990), "A Diffusion Model Incorporating Product Benefits, Price, Income and Information", *Marketing Science*, 9 (4), (Fall), 342

Jamieson, Linda F. and Frank M. Bass (1989), "Adjusting Stated Intention Measures to Predict Trial Purchase of New Products: a Comparison of Models and Methods", *Journal of Marketing Research,*, 26 (August), 336-345.

Jain, Dipak, Vijay Mahajan and Eitan Muller (1991), "Innovation Diffusion in the Presence of Supply Restrictions," *Marketing Science*, 10 (Winter), 83-90.

Juster, Frank T. (1966), "Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design," *Journal of the American Statistical Association*, 61, 658-696.

Kalwani, Manohar U. and Alvin J. Silk (1983), "On the Reliability and Predictive Validity of Purchase Intention Measures," *Marketing Science*, 61 (September), 243-286.

Kiel, Geoffrey C. and Roger A. Layton (1981), "Dimensions of Consumer Information Seeking Behavior," *Journal of Marketing Research*, 18, (May), 233-239.

Lenk, P. and Amber G. Rao (1990), "New Models from Old: Forecasting Product Adoption by Hierarchical Bayes Procedures", *Marketing Science*, 9 (1), (Winter), 42-53.

Louviere, Jordan J. and George Woodworth (1983), "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data", *Journal of Marketing Research*, 20 (November 1983), 350-367.

Mahajan, Vijay and Eitan Muller (1979), "Innovation Diffusion and New Product Growth Models in Marketing," *Journal of Marketing,* 43 (4), (Fall 1979), 55-68.

_______, _______, and Frank M. Bass (1990), "New Product Diffusion Models in Marketing: A Review and Directions for Research", *Journal of Marketing*, 54 (1), (January), pp. 1-26.

_______ and Yoram Wind (1986), Editors, *Innovation Diffusion Models of New Product Acceptance*, (Cambridge, MA, Ballinger Publishing Company).

_______ and _______ (1988), "New Product Forecasting Models, Directions for Research and Implementation", *International Journal of Forecasting*, 4, 341-358.

Mason, Charlotte H. (1990), "New Product Entries and Product Class Demand," *Marketing Science*, 9, (Winter), 58-73.

McNeil, John (1974), "Federal Programs to Measure Consumer Purchase Expectations, 1946-73: A Post-Mortem," *Journal of Consumer Research*, 1 (December), 1-10.

Morrison, Donald G. (1979), "Purchase Intentions and Purchase Behavior, *Journal of Marketing*, 43 (Spring), 65-74.

Newman, Joseph W. and Richard Staelin (1972), "Prepurchase Information Seeking for New Cars and Major Household Appliances," *Journal of Marketing Research*, 9, (August), 249-257.

Parfitt, J. H., and B. J. K. Collins (1968), "Use of Consumer Panels for Brand Share Prediction,"*Journal of Marketing Research,* 5 (2), (May), 131-46.

Pessemier, Edgar M., P. Burger, R. Teach, and D. Tigert (1971), "Using Laboratory Brand Preference Scales to Predict Consumer Brand Purchases," *Management Science,* 17 (February), B-371 to B-385.

Pringle, Lewis, R. Dale Wilson, and Edward I. Brody (1982), "NEWS: A Decision-Oriented Model for New Product Analysis and Forecasting," *Marketing Science*, 1 (Winter), pp. 1-30.

Punj, Girish N. and Richard Staelin (1983), "A Model of Consumer Information Search Behavior for New Automobiles," *Journal of Consumer Research*, 9, (March), 366-380.

Roberts, John H., and Glen L. Urban (1988), "Modeling Multiattribute Utility, Risk and Belief Dynamics for New Consumer Durable Brand Choice," *Management Science*, (February), 34 (2), 167-185.

Robinson, B., and C. Lakhani (1975), "Dynamic Price Models for New-Product Planning," *Management Science,* 21 (10), (June), 1113-22 .

Robinson, Patrick J. (1981), "Comparison of Pre-Test-Market New-Product Forecasting Models," *New-Product Forecasting: Models and Applications*, Edited by Yoram Wind, Vijay Mahajan, and Richard N. Cardozo, (Lexington, MA: Lexington Books, D.C. Heath and Company), pp. 181-204.

Scaife, John and Hafiz Adamjee (1993), "The Face of the Customer: The Use of Multimedia in Quality Function Deployment," Master's Thesis, Sloan School of Management, M.I.T., Cambridge, MA 02142 (May).

Schmittlein, David C., and Vijay Mahajan (1982), "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance", *Marketing Science*, 1, 57-78.

Sheridan, Thomas B. and David Zeltzer (1993), "Virtual Reality Check," *Technology Review*, 96, 7, (October), 20-28.

Shocker, Allan D. and V. Srinivasan (1979), "Multi-attribute Approaches for Product Concept Evaluation and Generation: A Critical Review," *Journal of Marketing Research*, 16, (May), 159-180.

Silk, Alvin J. and Glen L. Urban (1978), "Pre-Test-Market Evaluation of New Packaged Goods:

A Model and Measurement Methodology,"*Journal of Marketing Research,* 15 (2) (May), 171-91.

Srinivasan, V. and Gordon A. Wyner (1988), "Casemap: Computer-Assisted Self-Explication of Multi-attributed Preferences," in W. Henry, M. Menasco, and K. Takada, eds., *Handbook on New Product Development and Testing*, (Lexington, MD: D. C. Heath).

Taguchi, G. and Don Clausing (1990), "Robust Quality," *Harvard Business Review*, (1), (January-February), 65-75.

Tauber, Edward M. (1977), "Forecasting Sales Prior to Test Market," *Journal of Marketing,* 41, (1) (January), 80-84.

Urban, Glen L., and John R. Hauser (1993), *Design and Marketing of New Products, 2nd. Ed.*, (Englewood Cliffs, NJ: Prentice-Hall, Inc.)

_______, _______, and John H. Roberts (1990), "Prelaunch Forecasting of New Automobiles: Models and Implementation", *Management Science*, 36 (4), (April), 401-21.

_______, John S. Hulland, and Bruce Weinberg (1993), "Premarket Forecasting of New Consumer Durables: Modeling Categorization, Elimination, and Consideration Phenomena," *Journal of Marketing*, 57, (April), 47-63.

_______, and Gerry M. Katz (1983), "Pre-test-Market Models: Validation and Managerial Implications," *Journal of Marketing Research*, 20 (August), 221-34.

Von Hippel, Eric, *The Sources of Innovation*, (New York, N.Y.: Oxford University Press 1988).

Westbrook, Robert A. and Claes Fornell (1979), "Patterns of Information Source Usage among Durable Goods Buyers," *Journal of Marketing Research*, 15, 3, (August), 303-312.

Wind, Yoram (1982), *Product Policy: Concepts, Methods, and Strategy*, (Addison-Wesley: Reading, MA).

_______, Paul E. Green, Douglas Shifflet, and Marsha Scarbrough (1989), "*Courtyard by Marriott:* Designing a Hotel facility with Consumer-Based Marketing Models," *Interfaces*, 19, (January-February), 25-47.

_______, Vijay Mahajan, and R.N. Cardozo (1981), Eds. *New Product Forecasting*, (Lexington, MA: Lexington Books).

Wittink, Dick R. and Philippe Cattin (1989), "Commercial Use of Conjoint Analysis: An Update," *Journal of Marketing*, 53, (July), 91-96.