Glen L. Urban, Bruce D. Weinberg, & John R. Hauser

Premarket Forecasting of Really-New Products

The authors illustrate how a firm can face the challenge of forecasting consumer reaction for a really-new product. For the case of an electric vehicle, the authors describe how one firm combines managerial judgment and state-of-the-art market measurement to determine whether (1) the really-new product would be a viable business venture at its target launch date, (2) the firm should plan for improvements in technology that would reduce price and/or increase benefits enough so that the business venture would be profitable, or (3) the firm should stop development. The new market measurement system combines existing methods with a multimedia virtual-buying environment that conditions respondents for future situations, simulates user experience, and encourages consumers to actively search for information on the product. The authors comment on the advantages and disadvantages of the methodology and summarize the lessons they have learned from this application.

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 (e.g., Lexus) of luxury automobile. In general, market researchers can forecast the potential sales of new variants and new brands well.

However, some products revolutionize product categories or define new categories. Hewlett-Packard's Laserjet printers, Apple's (then IBM) personal computers, Sony's Walkman, beta-blockers (i.e., hypertension medicine), Visicalc (then Lotus, Quattro, and Excel) spreadsheets, Black & Decker's Dustbuster, Swatch (i.e., 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.

We address some of the challenges of forecasting for really-new products by describing how a major automobile manufacturer, General Motors (GM), combined a new measurement methodology, *information acceleration* (IA), with existing marketing research methods to forecast the potential sales of a new electric vehicle—possibly the first full-scale production electric vehicle to be introduced to a mass market. In this case, the multimedia-based market research information was a key influence, but not the only influence, on the strategy that the manufacturer adopted to enter the market. To help the reader evaluate the methodologies, we describe as much of the managerial situation as confidentiality considerations allow. We state where the numbers came from, but disguise the actual numbers.[1]

Because this is a real application with real cost and time constraints, management made a number of trade-offs. For example, some inputs are based on market measurement, and some are based on managerial judgment. We describe the trade-offs that were made, comment on the uncertainty introduced by these trade-offs, and suggest options that could have been explored with more time and money. We

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[1]Electric vehicles are based on new technologies. If successful, they will have a major impact on the U.S. automobile market and the environment. Their development entails scrutiny by government, the press, and the public, as well as major commitments of resources by automobile manufacturers. Sales forecasts are considered strategic information that firms do not wish to reveal to their competitors. On the other hand, we believe the reader can best evaluate the methodology and its generalizability within the managerial context. To balance these considerations we disguise the data. We attempt to keep the numbers internally consistent and qualitatively appropriate. The values reported cannot be used for purposes other than demonstration of the IA methodology. We report the disguised forecasts to all of their significant digits so that the reader can reproduce the calculations that led to the forecasts. In the application, management recognized that the forecasts were made with many aspects of uncertainty.

comment on where we feel the information acceleration methodology succeeded, how it could have been improved, how it augments existing methods, and what we learned from the experience. We hope the reader joins us in a critical evaluation of the application.

Electric Vehicles

Electric vehicles (EVs) are really-new products in many ways. 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, limited driving range on a charge, potential stranding, and perceived hazards due to high amperages, become important. There are new levels of existing attributes, such as noise (the engine is *extremely* quiet), smooth acceleration, no need to shift gears, and size (usually small). Acceptance depends on new scenarios (tax breaks, greater environmental awareness, government mandates) and infrastructure (charging stations at work, "tow" services to replace battery packs) and could vary with new technologies (lithium polymer or nickel batteries replacing lead-acid batteries as technologies with greater range or lower cost).

Furthermore, EVs are of major management interest. Regulation in California and 12 other states mandates that by 1998 2% of all new cars sold by the "top-7" manufacturers be zero-emission vehicles[2] (California Environmental Protection Agency 1994). This percentage will increase to 5% in 2001 and 10% by 2003. If consumers purchase this number of EVs, then EVs could become a $10 to 20 billion market in the United States—and an almost $1 to 2 billion one in California. Manufacturers will be assessed a $5,000 penalty per unit below the target and will earn credits against this penalty for sales prior to 1998. (Credits can be bought and sold, and extra credits are given for cars sold in 1996 and 1997.) Competition is keen with many U.S., 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. (However, hybrid vehicles do not affect the zero-emission targets.) The propulsion system could be made available in sedan, two-seater, or van configurations. Even Swatch, in partnership with Mercedes Benz, has entered the market for an environmentally sound city car (Choi and Studer 1994).

In this application, GM developed an initial two-seater EV concept called *Impact*. At the time, multipassenger EVs required further research and development. General Motors 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 fiberglass body and interior. An existing 1991 model-year vehicle was retrofitted with an electric power train to enable the customer to experience driving an EV. If the program were to be continued it would require a commitment of several hundred million dollars. The goal of the new product forecast was to make a "go/on/no go" decision on the basis of the ability of Impact to meet the California legal regulations and the firm's strategic goal of developing a market for EVs and reflecting its stockholders' interests.

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 multipassenger vehicle increase the sales penetration.
- How vulnerable is the two-seater automobile sales level to the entry of competitive two-seater cars?

The First Study

To address these questions, GM chose to combine existing forecasting methods (i.e., concept evaluation, decision-flow models, prelaunch forecasting models, and conjoint analysis) with the new IA method. The basic idea behind IA is to place the consumers in a virtual buying environment that simulates the information that is available to the consumer at the time he or she makes a purchase decision. For this application the basic technology was a Macintosh II computer, with a Sony 14" Trinitron video monitor, a RasterOps STV video card, and a Pioneer 4200 laser videodisc. The software was written in Macromind Director.[3] 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, because video responses are provided to questions the respondents selected. State-of-the-art surrogate travel technology enables consumers to interact with virtual prototypes. These are combined with driveable partial prototypes. (The manufacturer hopes that 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].) We begin by describing the details of the first IA study. This study led to several managerial decisions, including a decision to collect more data following a similar format. We subsequently describe how the additional data collection augmented the first IA study.

Sample and Design

The first study was performed in Los Angeles in the fall of 1991. The sample for the EV test was drawn randomly from consumers who would consider spending enough to buy a

[2]The regulations refer to any manufacturer with 35,000 or more vehicles sold in California. This includes Chrysler, Ford, GM, Honda, Mazda, Nissan, and Toyota. Beginning in 2003, the mandate will apply to any manufacturer selling more than 3000 vehicles. Electric vehicles are the only Zero Emission Vehicle technology expected to be ready by 1998. Of the 13 states with mandates, only California, Massachusetts, and New York require EVs.

[3]A videotape illustrating the computer laboratory is available from the authors.

premium automobile the next time they bought a car, who 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 environmentally friendly vehicle. Respondents were given a $50 incentive for participation. Of the 606 respondents who agreed to participate, 587 were interviewed.

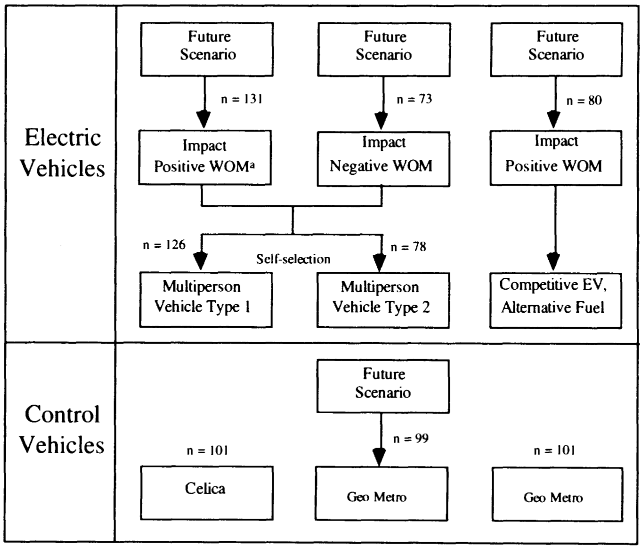
We selected an experimental design that enabled us to measure some of the potential biases induced by the IA. For example, we selected a popular internal-combustion-engine (ICE) car, a 1991 Toyota Celica, to serve as a control. The respondents who experienced the IA for the Celica received an IA conditioning corresponding to the 1991/1992 environment. By comparing the forecasts from the IA to actual Celica sales for the target population, we estimated the bias introduced by the IA laboratory. (The screening criteria for the "control" sample was appropriate for the Celica. Celica sales within the target population were available from the EV manufacturer.)

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, namely, the high-mileage version of the 1991 Geo Metro. To provide further insight, roughly half of the Geo Metro respondents received the same future conditioning as the Impact respondents, whereas the other half of the Geo Metro respondents received an IA conditioning corresponding to the 1991/1992 environment.[4]

The experimental design is summarized in Figure 1. Of these 585 respondents interviewed, 284 experienced an IA for the Impact, 101 experienced an IA for a popular ICE car, and 200 experienced an IA for a high-mileage ICE car. Of the 200 who experienced an IA for the high-mileage ICE car, 99 received the same future conditioning as did the Impact respondents, and 101 received conditioning that corresponded to the 1991/1992 environment.

All of the 284 Impact respondents were exposed to an additional IA for a second environmental vehicle. Two hundred and four respondents were asked to indicate what type of multiperson style they preferred and then were given a complete IA for an all-EV in that body type. The remaining 80 respondents were exposed to two additional vehicles. One vehicle was a competitive two-seater EV (competitors chosen randomly), and the second vehicle was the respondent's choice of alternative-fuel vehicles (high-mileage ICE, methanol, hybrid, and compressed natural gas). In all cases, the exposure and the measures were placed after all measures on the Impact were completed. This enabled us to compare the Impact respondents to the Celica and Geo respondents. Although GM recognized that some biases might be introduced by presentation-order effects and respondent fatigue, they believed that the additional information could be used with suitable caveats. One justification given by the manufacturer was that the Impact was expected to be the first major EV on the market and, hence, the presentation-order effect would be in the same direction as the order-of-entry effect.[5]

FIGURE 1
Experimental Design: First Information Acceleration Study



aWOM = Word-of-Mouth.

Future Conditioning

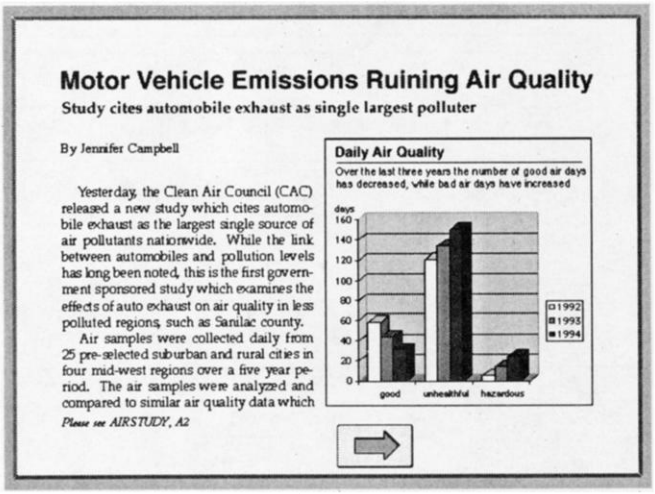
The acceptance of EVs depends on an infrastructure to support them, not unlike the infrastructure of gas stations and repair shops that supports internal combustion vehicles. Although the study was conducted in September 1991, we wanted the respondent to imagine the infrastructure and EV specifications that could be available for the target introduction year—the 1995 model-year. To accomplish this 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 imagine him- or herself in the future. Specifically:

- Time frame was extended by text that 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

[4]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. Because our measurement cannot attribute how much of the difference between the Geo with conditioning and the Geo without conditioning is due to the environmental hype and how much is due to the change in the state of the world, we relied on the judgment of the managers to allocate a percentage of this difference to environmental hype.

[5]In other applications, we can investigate the presentation-order effect by increasing the sample size to allow an experimental design in which one-half of the respondents were exposed to the Impact after, rather than before, the alternative body type, alternative fuel, or competitive vehicle.

FIGURE 2
Newspaper Article



Motor Vehicle Emissions Ruining Air Quality

Study cites automobile exhaust as single largest polluter

By Jennifer Campbell

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 Sanilac county.

Air samples were collected daily from 25 pre-selected suburban and rural cities in four mid-west regions over a five year period. The air samples were analyzed and compared to similar air quality data which

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could read them at their own speed. See Figure 2 for an example in which they click on arrows to turn pages forward or backwards.[6]

- Information about EVs that would be common knowledge was provided.

In this study, GM wanted a forecast for the most likely scenario. This decision was driven, in part, by budget considerations and, in part, by GM's belief that it could modify this forecast for other scenarios. A more robust design expands the IA design to obtain observations for a range of feasible scenarios. Actions could then be based on formal decision analysis (Keeney and Raiffa 1976) or the tenets of robust design (Taguchi and Clausing 1990). For example, when alternative designs or marketing strategies are evaluated, forecasts for multiple scenarios enable the product team to choose the design and marketing strategy that does well in the most and/or the most likely scenarios.

Full Information

Electric vehicles are complex products. They might be more attractive to a customer if regulations favor EVs (tax breaks), consumer magazines (e.g., *Consumer Reports*) report that they are reliable, environmental imperatives are more severe, and, most important, the consumer gets a chance to drive a vehicle. Advertising and concept descriptions may not be sufficient to provide the consumer with enough information with which to make a choice. Thus, 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; Westbrook and Fornell 1979), we chose showroom visits, advertising (television, magazine, and newspaper), magazine articles, 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 simulated as follows:

- *Showroom visits.* We used surrogate travel (Figure 3, part A) on a computer monitor. By clicking on the appropriate arrows the respondent 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 based on the manufacturer's planned marketing strategy; the respondent could select from a range of questions and observe (video and sound) the salesperson's response.
- *Advertising.* By clicking on an icon, the respondents could watch a potential television advertisement (produced from stock footage of wilderness scenes chosen to evoke an environmental image). Another icon used "beauty shots" of the EV with the tag line, "The Impact for those who feel personally responsible for the environment" (see Figure 3, part B). A third icon gave newspaper advertising (Figure 3, part C), which provided information on price and availability. In each case, the advertising appeared in the same form that the respondent is used to seeing.
- *Articles.* The respondents could view, at their own pace, simulated articles about the Impact from consumer-guide and automobile magazines (Figure 3, part D). These articles provided information on construction, value, appearance, safety, performance, comfort, cargo space, environment, and price—the attributes that respondents in qualitative interviews had previously indicated were important.
- *Word-of-mouth.* Professional improvisational actors took on the characters of five representative consumers. The five consumer profiles were chosen on the basis of a psychographic segmentation study and voice-of-the-customer interviews conducted by the automobile manufacturer. The respondent viewed a menu of video clips in which each menu item is represented by a still shot of the word-of-mouth consumer and a short quote from that consumer (Figure 3, part E). After clicking on the icon, the respondent sees a full screen image of the consumer and a set of topics. The respondent can choose video clips on any or all of the topics (Figure 3, part F).

We do not know whether the word-of-mouth in 1995 will be positive or negative. Thus, we created two experimental treatments for the EV—a positive and a negative treatment (review Figure 1). Two-thirds of the Impact test sample was exposed to a positive treatment and one-third to a negative 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. Because people cannot purchase an EV without visiting a dealer, we asked respondents to assess the probability that they would visit an actual dealer after gaining awareness from advertising, articles, or word-of-mouth.

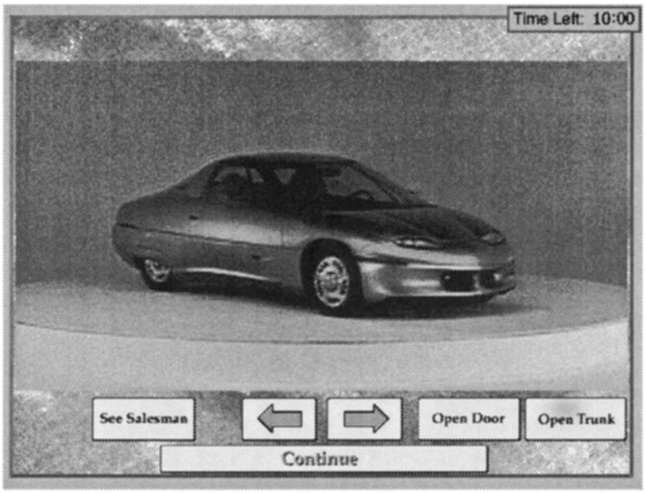
User Experience

An electric power train drives differently than internal combustion vehicles. They shift easily, accelerate well, handle nicely, and are silent. However, if a full prototype or an initial production vehicle were available, most of the capital investment that is at risk for the really-new product would have been committed. The challenge of the IA simulation was to give the user enough simulated experience with an EV for management to rely on the consumers' stated intentions. In this application, after respondents exited the virtu-

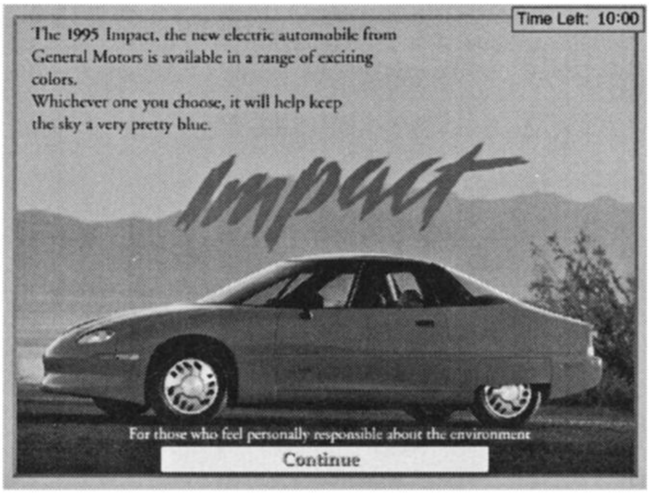
[6]Figures 2 through 4 represent graphic displays used in the original and follow-up EV studies.

FIGURE 3
Information Acceleration Computer Screens

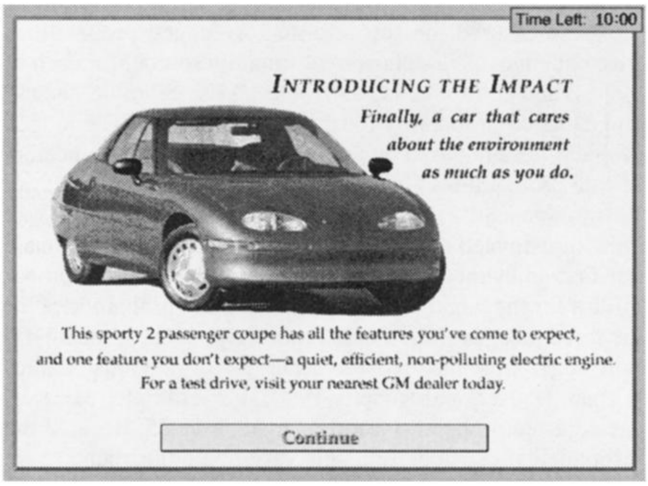
A. Showroom Surrogate Travel



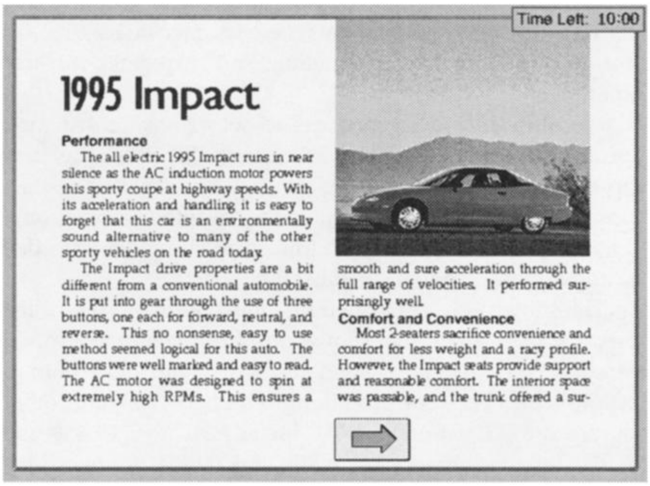
B. Magazine Advertisement



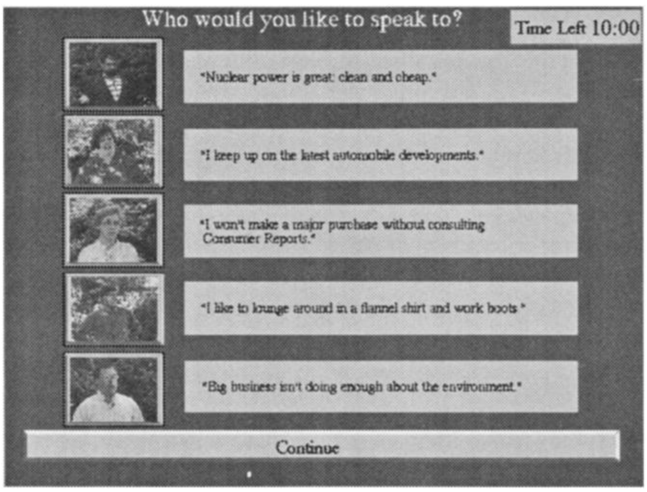
C. Newspaper Advertisement



D. Magazine Article



E. Word-of-Mouth Selection



F. Word-of-Mouth Questions

al dealer visit, they were allowed to test drive a 1991 Geo Storm that was retrofitted with an electric power train. We instructed respondents to evaluate the drive vehicle with respect to *only* its drive characteristics, that is, acceleration, braking, and so on.

Full information and user experience could induce a demand effect. By comparing the Impact respondents to the Celica respondents, we estimated the laboratory bias and corrected our forecasts accordingly.

User Control and Active Search

Some consumers read magazines, test drive vehicles, and talk to many friends and acquaintances before buying a car. Others do not. Existing methods (e.g., Urban, Hauser, and Roberts 1990; 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, an active search helps the customer internalize future conditioning, full information, and surrogates for user experience.

We allowed the respondents to 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 any source as often as they wanted, subject only to a constraint on total search time. The computer recorded the time in each source (or subsource).

The showroom was visited first most often (44.0% of the respondents visited the showroom first) and most often overall (99.6% of the respondents visited the showroom at least once). The corresponding numbers for the other sources are 27.8% and 64.4% for advertising, 19.4% and 66.9% for magazines, and 8.8% and 69.0% for word-of-mouth. This is generally consistent with results reported in Hauser, Urban, and Weinberg's (1993) study for the Buick Reatta.[7]

Measurement and Modeling

Future conditioning, full information, user experience, user control, and active search constitute the core of IA. After we put respondents in the virtual future buying environment, measures are taken of their likelihood of purchase, their perceptions, and their 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 on the basis of assumptions about the changes in the environment, the managerial introduction plan, and the projected competition.

Intent-to-Purchase Scales

After both concept exposure and the respondent's exit from an information source, as well as at the end of an IA search—for the target car and for any competitive or alternative fuel vehicles—we asked 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 an IA search will continue. To make a judgment, the respondent must assess his or her likelihood of acting on the basis of currently available information and, implicitly, assess what information will become available prior to choice. The basic scale is a thermometer scale with the 11 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 4, part A). 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 made these judgments (see Figure 4, part B).

We measured the full-information judged probabilities (respondent exits last chosen information source) for each of the test and control cells (see Table 1). For example, the average judged probability for the Impact was .53. The judged probabilities are based on the IA. Intent scales are indicators of true probabilities (Jamieson and Bass 1989; Juster 1966; Kalwani and Silk 1983; McNeil 1974; Morrison 1979), but must be adjusted to provide specific predictions. We made our first adjustment by normalizing the stated intent probabilities for the target car by the stated intent probabilities for the three most-preferred cars in the respondent's consideration set.[8] This has proven accurate in previous studies (Urban, Hauser, and Roberts 1990). For example, the average adjusted probability for the Impact was .25. Because the respondents' consideration sets vary, the adjustments were made at the individual level and then were aggregated. This means that the ratio of adjustment is not constant across cells in the experiment.

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 used proprietary data on the sales volume of the Toyota Celica within the target population, 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.) On the basis of comparisons between the actual and predicted 1991 sales of the Toyota Celica, we found that the model overestimated sales by 10%.

We also estimated the impact of future conditioning. On the basis of the adjusted probabilities, we estimated that future conditioning (Metro with future conditioning versus

[7]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 percentage using, respectively.

[8]For each respondent we compute (adjusted probability) = (measured probability)/[(measured probability) + (sum of measured probabilities for that respondent's three most-preferred cars)].

TABLE 1
Conditional Purchase Intents Given Full Information

	Judged Full-Information Purchase Estimate	Adjusted Full-Information Purchase Estimate
Impact	.53	.25
Celica	.39	.17
Geo (Future)	.35	.19
Geo (1991)	.30	.15

Metro without future conditioning) introduces a 26% increase in the judged probabilities. At this point it was difficult to know whether this was simply a demand effect or reflected a true change in probabilities due to the change in the future environment. It became 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 .813 multiplier (1.0/1.23 = .813) was applied to all forecasts.

Diffusion/Decision-Flow Models

Information has an effect. To use the data from the IA, we must model the effects 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.

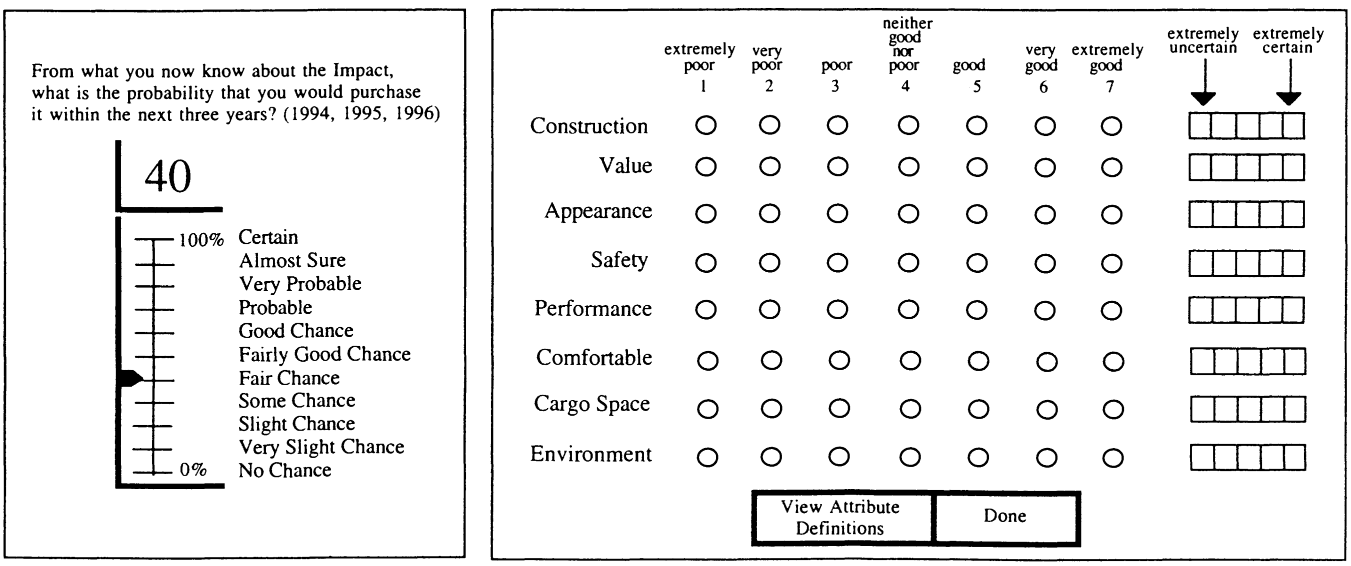
To forecast for an actual scenario, we estimated the conditions that describe the marketplace of 1994/1995 with the decision-flow diagram in Figure 5. A decision-flow diagram is a map of the conditional probabilities that are used to forecast on the basis of consumer information acquisition and market conditions. We estimated as many of the conditional probabilities as possible from the IA. Others, such as the percentage aware because of advertising, were based on the marketing plans of the firm using the IA to evaluate the Impact. These, in turn, can be based on management experience or on analytical models. Other conditional probabilities, such as the size of the market and the percentage who would consider an EV, were based on information available from other sources. (For more details and examples in the automobile industry, see Urban, Hauser, and Roberts 1990).

For example, the firm conducted a market-research survey to determine the percentage of the population that would not reject an environmentally friendly vehicle. We cannot report the actual number, so we use a disguised number of 48%. From previous survey data, the firm obtained the percentage who pass the remaining screening criteria of our study. We disguise that percentage here as 45%. The total number of automobiles sold per year in California averaged approximately 1.2 million in 1990 and 1991. We here use the round number (for 1995 model-year sales) with a 1% per year growth—the firm used the actual numbers.

The firm estimated (all numbers here are disguised) a 30% awareness of Impact in the first year and a 40% awareness of Impact 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 are based on the amount that the firm had budgeted for marketing the EV—a

FIGURE 4
Measures of Likelihood of Purchase and Perceptions

A. Likelihood of Purchase **B. Perceptions of Relevant Attributes**



substantial marketing campaign. Budgets can be transformed to awareness estimates through managerial judgment (in this case) or formal models (Blattberg and Golanty 1978; Silk and Urban 1978). 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.

To purchase an automobile, consumers must visit a dealer. In the IA, respondents were asked to estimate the probability that they would visit a dealer to search for the EV. The average judged probability is disguised as .30. The resulting estimate of visiting an Impact dealer is .30. Recall that the average adjusted probability of purchasing an Impact was .25; it remained at .25 when we conditioned for the respondent having visited a dealer.

Putting these numbers together, we forecasted a first-year sales of 3793 units (see Figure 5). (1,200,000 units in market × .45 pass screening criteria × .30 awareness × .48 do not reject environmentally friendly vehicle × .80 are near infrastructure × .30 visit a dealer × .25 purchase probability after drive × .813 adjustment = 3793 units.) The calculations follow the same formula for years 2, 3, 4, and 5.

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 in the first IA study, we estimated the sales of the Impact for the model-years 1995 through 1999 (see Figure 6). Although these coded base-case forecasts imply it may be possible to generate the sales required to meet the California regulations in 1998,

FIGURE 5
Decision-Flow Diagram for Impact Forecast and First-Year Probabilities

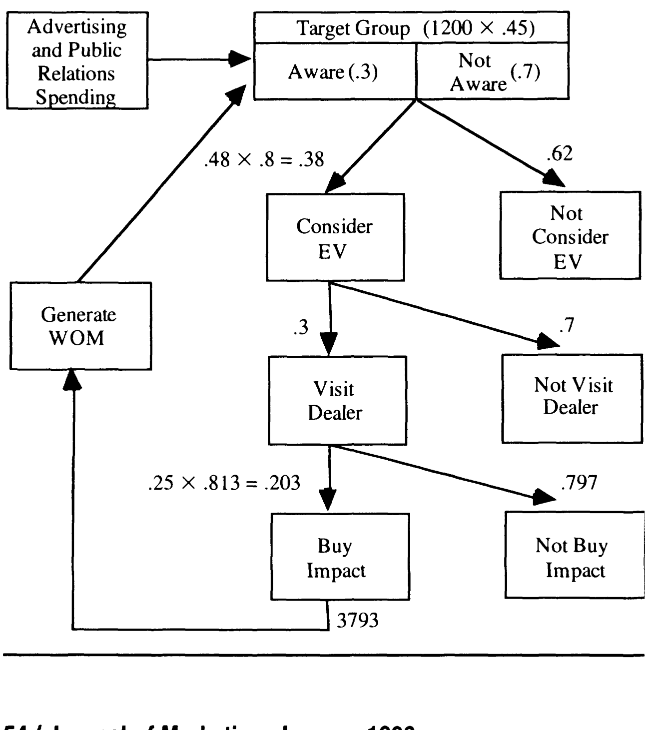
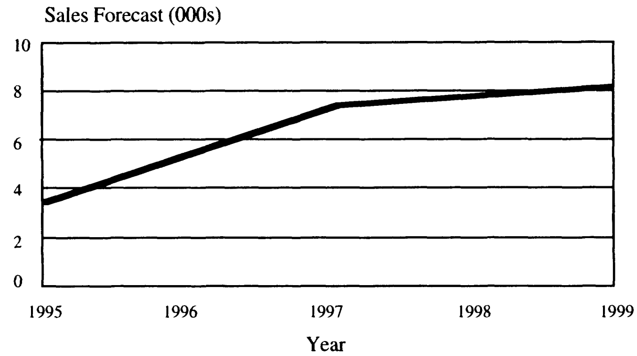


FIGURE 6
Base-Case Forecast for the Impact[a]



[a]Data are disguised (see footnote 1).

these sales (at the planned price) would not be sufficient to produce the cash flow necessary to justify the investment that GM would need to make to develop and launch the new vehicle while protecting the long term assets of their shareholders. More important, the base-case forecasts do not take into account competition that reduces the forecast or a (potential) product line of EVs.

Competitive Vulnerability

In the experimental design, 80 respondents participated in an IA for competitive two-seater EVs immediately following the IA for the Impact. When a competitive two-seater EV was introduced in the IA, two effects were observed. First, the market for EVs expanded 38%, because some people who had not chosen the Impact selected a competitive EV. (The adjusted purchase probability for at least one EV was .346.) Second, some of the respondents who had chosen the Impact switched to the competitive EV—the Impact share of these choices was 59%. Together, these effects imply that the Impact sales with one competitor would be 81% of the level that would be achieved if Impact were the only EV in the market (.59 × 1.38 = .81). This reduces the sales forecast for the Impact to 3072 units in the 1995 model-year and 6265 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.

A 1995 launch of the Impact would make it the first major EV in the market. In the first few years, the firm expected few major competitors. However, because the California regulations apply to the top seven manufacturers, we expect there will be many competitors by the year 2000. Thus, though the 81% might be an appropriate factor for the first few years, it would be only an upper bound on Impact sales in subsequent years. If the Impact were not the first EV on the market, then it would lose its first-mover advantage. This would further lower the 81% factor. Finally, because GM focused on getting an accurate base-case estimate, the experimental design in Figure 1 always presents the Impact prior to the competitive vehicle. Thus, there might be a presentation-order effect that favors the Impact relative to competition. Such an effect would lower still further the 81% factor.

Putting these phenomena together it is likely that the estimate of 6265 units in 1998 is too high. These considerations reinforce the conclusion that the Impact would not be profitable.

Product-Line Potential

At the time of the IA experiment, management had already begun development of the two-seater sporty car. They hoped that this EV would be ready by the 1995 model-year. But because the forecast sales of the two-seater EV might have been below those necessary to meet profitably the mandated levels, the effect of adding a multiperson vehicle (i.e., greater than two people) was of interest to management. In the experimental design 204 respondents participated in an IA for a line of EV vehicles. (Note, however, that sample sizes for pair-wise comparisons are smaller, though all respondents completed the conjoint task.) Specifically, respondents were allowed to search for information on a multiperson vehicle after they completed the search for the two-seater EV. For these respondents, we forecast an 83% market expansion because of the availability of the multiperson vehicle. (83% more respondents selected an EV when three body types were projected to be available.[9]) Of those who had purchased the Impact, 19% switched to a multiperson vehicle when given the opportunity in the IA.[10] With this product-line expansion and if there were no competition, our disguised data would forecast sales of 14,155 units in the 1998 model year. However, with competition this would be reduced to 11,465 units. These disguised numbers would meet the California mandates if the firm could design the multiperson vehicle in time, if it were first on the market, if there were only modest competition, and if it could reduce costs.

Based on the undisguised numbers, GM could come close to the mandated levels in 1998, but the rate of return on investment is still below minimums because of the additional fixed costs of designing and producing a multiperson vehicle. If any reasonable estimate of competitive impact were included, even the firm's mandated sales requirements could not be met.

Qualitative Insights

The automobiles presented here were powered by lead-acid batteries, and these batteries limit the range substantially. The EVs are expensive relative to their ICE alternatives (premiums of $5,000 to $15,000). 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—of consumer needs (see Figure 4, part B).

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). Although consumers believed 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 need to be increased substantially before the automobile could succeed financially in California. Qualitative interviews confirmed these interpretations.

Management's Decisions

Based on the first IA and supporting market research, management concluded that the sales of the Impact two-seater vehicle would not be sufficient to create the desired scale in the EV market at a fair return to stockholders. The emerging conclusion was to delay the Impact launch. The delay enables them to concentrate on improving battery technology and the production and design improvements that could reduce the cost of the vehicle. To develop the core capability to enter the EV market when the technology is ready, GM decided to maintain a demonstration program based on prototype use and conduct a second IA study to improve their understanding of consumer response to competition and improvements in technology and to test the acceptance of an EV outside California.

The Second Study

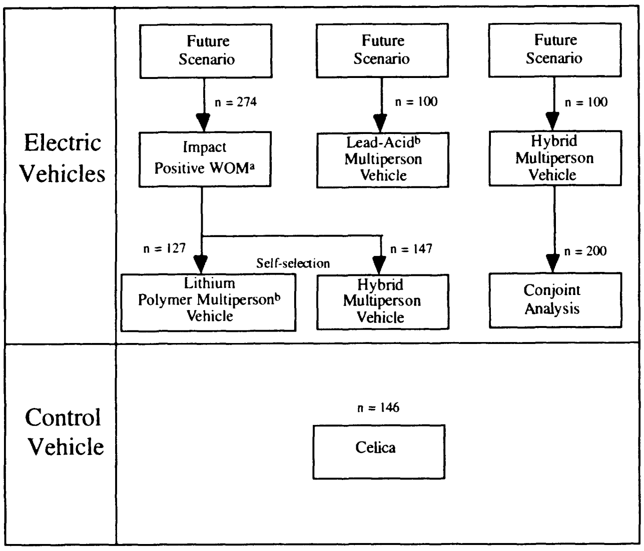
Although the first IA study was sufficient for the initial go/on/no go decision, management believed they would need more information to proceed. Among the questions they wished to address were:

1. Did the California estimates apply nationwide? How would they extend to 2010?
2. What would be the effect of more than one competitor?
3. Would improved battery technology make the business proposition viable?
4. Should development include hybrid vehicles as well as zero-emission vehicles?
5. How would the estimates vary if the EV's features (and body style) changed?
6. How would the estimates vary if the price changed?

[9]To avoid respondent fatigue, respondents were given the choice of searching for information on either a sedan or a van. By allowing self-selection we approximate the choice from the set {two multiperson vehicles and Impact} with a two-stage choice. In other words, respondents chose from the set {two multiperson vehicle styles} prior to search and then from the set {winner among the two multiperson styles, Impact} after the search. This may represent a slight underestimate because respondents did not search on the losing body style. However, the estimate should be sufficient for an initial estimate stage. Improved estimates were obtained in the study described subsequently.

[10]This 19% might be downwardly biased because of presentation-order effects. However, in the first study, the management focus was on the combined sales of the two-seater and two multipassenger vehicles. The presentation-order effect for the alternative body style should approximately offset the (upwardly biased) presentation-order effect for the Impact. If the primary focus of the IA had been on the market for body styles, a better design would have been to rotate randomly the body styles and have the customer search for all three body styles. See also the second IA described subsequently.

FIGURE 7
Experimental Design: Second Information Acceleration Study



[a]WOM = Word-of-mouth.
[b]Lead Acid and Lithium Polymer are battery technologies.

The first question is important because it relates to the economies of scale necessary to drive costs down. The second addresses one of the weaknesses of the first IA, the single competitor. The third tests the managerial decision to wait for new battery technology. Answers to the fourth and fifth questions enable management to plan for consumer response to different technologies and body styles. Answers to the sixth question enable management to determine the break-even price necessary to justify further investment.

To address these questions, the firm designed and implemented a second IA study in a location outside of California. The methodology was essentially the same except that (1) hybrid vehicles were included, (2) vehicles based on lithium polymer batteries were included, and (3) 40% of the sample completed a computer-aided adaptive conjoint analysis exercise after finishing the IA search.[11] The attributes in the conjoint analysis design included different brand names, body styles, prices, ranges, battery recharge times, and battery replacement costs. By anchoring the conjoint analysis to the IA search (for the appropriate vehicle), the firm was able to simulate consumer response to different technology-based features, body styles, price points, and competitive sets. Figure 7 provides the experimental design for the second IA.

General Motors considered the experimental designs in Figures 1 and 7 as a master design. For example, by comparing the positive Impact in Figure 1 with the positive Impact in Figure 7, we can estimate a city/time main-effect. Once this effect is taken into consideration, the lead-acid multiperson vehicle first versus the hybrid multiperson vehicle first gives the hybrid versus lead-acid effect; the lithium polymer multiperson vehicle second versus the hybrid multiperson vehicle second gives the lithium polymer versus hybrid effect and the implied hybrid versus lead-acid effect; the hybrid multiperson vehicle first versus the hybrid multiperson vehicle second gives part of the presentation-order effect and would have given the entire presentation-order effect had an Impact search replaced the conjoint analysis; and so on. In this way, the firm can estimate various baselines that are then extended with the conjoint analysis.

To forecast nationwide sales through 2010, management must make assumptions about the rate at which distribution (car dealers) would grow, the growth of the infrastructure (e.g., recharging stations), the product line that the firm could develop and fund, and the nature and timing of competitive entries—all on a nationwide basis. Because the forecasts depend on these assumptions, GM not only performed sensitivity analyses, but also was forced to recognize that the forecasts contain considerable uncertainty. Because the decisions to be made were qualitative, such as which technology to bet on or when to launch each component of the line, rather than quantitative, such as how much to invest or how many dealerships to franchise, the firm believed that the IA/conjoint analysis combination provided a sufficient indicator of demand.

Distribution was based on management's best estimate of their plans for expanding the dealership structure. Infrastructure was based on GM's best assessment of the political and social changes during the next 15 years (GM has another staff unit that provides input to these estimates). In some cases, the estimates are based on purely managerial judgment; in other cases the estimates are based on econometric submodels developed by the staff. Management needed to estimate which competitors would enter when and with which attribute profiles. Once these estimates were made, we were able to use the conjoint analysis choice simulators (for descriptions of conjoint analysis simulations, see Green and Srinivasan 1990; Urban and Hauser 1993; Wind 1982; Wittink and Cattin 1989). The flow model in Figure 5 was expanded to include conditional estimates that depend on the entry of competition and on the changing attribute profiles that result from new technologies. Because the firm had validated the conjoint analysis methodology many times with new, but not really-new, vehicles, it felt comfortable with relying on the conjoint analysis to modify the IA estimates.

Figure 8 is one of the many simulations that were run. (We have removed the numbers on the vertical axis and changed the shape slightly to protect confidentiality.) This simulation reflects assumptions that the Impact would be first on the market, competition would begin to enter in 1997, and the infrastructure and dealerships would grow steadily. The "scalloped" changes in the total-market forecast reflect new technologies, such as lithium polymer batteries, with projected new model introduction dates of 1999, 2004, and 2009. Other simulations made assumptions about the product line, dealership and infrastructure growth, entry of competition, and development of new technology. (The details are still considered confidential, but the methodolo-

[11]The conjoint analysis was implemented by Applied Decision Analysis, Menlo Park, Calif. See Smallwood and Weber (1994).

gy follows that described here, coupled with the methodology described in the conjoint analysis references.)

Based on the simulations and information on technology, infrastructure, and competition, management decided that a new battery technology was one key to profitability. General Motors had joined with Ford, Chrysler, and the Department of Energy in a joint venture called the United States Advanced Battery Consortium to develop such new technologies. Subsequent to the simulations, GM joined Ovoric Battery Company to investigate commercialization of nickel-metal hydride technologies.

Sales forecasts at various price points coupled with estimates of component costs suggested that GM's sales alone would not provide sufficient economies of scale. To generate economies of scale, GM announced a new business unit to sell EV (and hybrid) components to itself *and* other manufacturers. This could reduce the cost and price of future EVs and improve the sales potential.

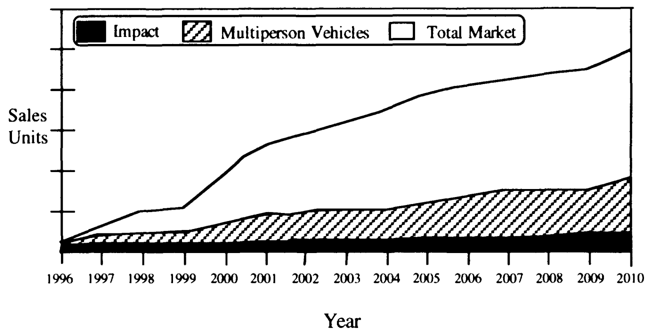
The projected sales and market share depend on how consumers perceive the Impact's features and the type of word-of-mouth that they will generate. To gain further information on these critical variables, GM placed ten EVs with 80 consumers in California to determine in-use technological capabilities (e.g., range, durability) to measure word-of-mouth and the needs of more-experienced consumers. Plans call for testing in 12 cities over 24 months, with 30 vehicles and 900 respondents. Early feedback from the in-use placement was encouraging. Final forecasts depend on the actual achievement of the design specifications.

General Motors remains serious about becoming one of the major manufacturers of EVs. It's EV program goals include being the technical leader in EVs, fulfilling GM's corporate environmental responsibility to create a market for EVs at a profit to its stockholders, and forming a new partnership between industry, utilities, and government to develop the infrastructure, incentives, and technology for EVs. Although the two IAs provide valuable consumer-response information, the in-use test, the components division, and further technological development will continue to guide the firm's strategy.

Other Applications and Initial Validations

The EV application demonstrates most of the features of an IA and how it is used to provide managerially relevant forecasts. In addition to the EV application, we know of eight other IA applications—the Buick Reatta, new cameras, a home information system, new telecommunications products, and a medical instrument. Although the Buick Reatta was not a really-new product, it did provide partial validation of the methodology. In that application the sample was split on two factors: (1) the new car versus a control car and (2) a computer showroom versus a real-car showroom with a real salesperson. Although there were significant differences in the forecasts between the two cars, there were no significant differences in the forecasts between the computer showroom and the real-car showroom (Weinberg 1992). The first camera application was also not a really-new product, but subsequent market tracking enabled us to compare the IA forecasts with actual sales—they were within 10% when the actual advertising and distribution (known at the time of the validation) were used in the decision-flow model.

FIGURE 8
15-Year Sales Forecast of GM EVs



Note: Based on IA, conjoint analysis, and decision-flow model.

The final partial validation tested the ability to include people who influence purchase decisions. The product was a Complete Blood Cell medical instrument based on new optical technology. In approximately one-half of the sample, both a physician and his or her laboratory technician went through the IA separately and then met to decide on a judged purchase probability. In the other half of the sample, the physician and technician went through the IA separately and reported their probabilities of purchase separately. In this second half of the sample, for the physician, the face-to-face meeting was replaced with a simulated staff recommendation matched to the technician's actual recommendation. The favorableness of the technician's recommendation had a significant impact on the physicians' reported purchase probabilities, but the experimental treatment, a face-to-face discussion versus a computer simulation, did not (Urban, Qualls, and Bohlman 1994).

Comments and Research Opportunities

In the EV application, the two IA studies provided valuable data on which to base managerial decisions, but these studies were not without weaknesses.

Comments

Cost. As it was implemented in the EV study, IA is expensive. A typical application costs \$100,000 to \$300,000. Information acceleration is expensive, because, besides programming the computer, a person 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. The EV manufacturer believed that the cost of the IA was justified for the EV, but the firm continues to use a combination of conjoint analysis and prelaunch forecasting clinics for more conventional internal combustion vehicles.

Experimental designs. A direct implication of an IA's cost is that management is forced to make a number of trade-offs between the experimental design that would provide the cleanest, most scientific estimate and the experimental design that can be cost-justified. In the EV application, management judged that the cost of three control cells was justified in the first IA, but not in the second IA in which the firm simply applied the measured multipliers from the first IA. In the first IA, management was most concerned with the Impact's forecast and was willing to use smaller samples and a confounded (presentation-order) design for modeling competitive vulnerability and product-line implications. As a result, the forecasts relied on judgment to untangle effects. The managerial goal was to obtain qualitative indicators. For the decisions in 1991, these indicators were sufficient, but for subsequent decisions, the firm needed the data from the second IA/conjoint analysis study.

Such trade-offs are typical of managerial applications and are similar to those we faced when applying pretest market models (Silk and Urban 1978), defensive strategy models (Hauser and Gaskin 1984), and prelaunch forecasting models (Urban, Hauser, and Roberts 1990).

Managerial judgment. The EV forecast depends on the measures taken in the IA (judged purchase probabilities, word-of-mouth, and dealer-visit probability), measures available from other market research data (EV consideration and target market size), and measures of competitive and product-line preference. But the forecast also depends on managerial judgments that reflect the planned marketing campaign, planned dealer network, and forecasts of infrastructure growth. The last estimates can have effects that are comparable to the IA and market research measures. This requires that IA-based estimates be used by managers who have the data and experience with which to make the estimates and who realize the implications of the uncertainties these estimates provide. For example, the IA can measure consumer response uncertainty, but the manager must also recognize the uncertainty in forecasting competitive response and new technologies.

One aspect of a methodology such as IA is that it highlights the sensitivity of the estimates. For example, in the first IA, the firm needed to estimate the impact of lithium polymer batteries, but in the second IA, it measured the impact through the research design. In both IAs, the results were sensitive to the type of word-of-mouth generated and the consumer perceptions of the EV's technological capabilities. In the in-use placement, the firm measures these variables.

Order of entry. The sales of the Impact depend on whether it is the first EV on the market. In the IA, we measured how forecasts change if there are two vehicles on the market. However, we could not simulate order-of-entry effects that might result from earlier vehicles gaining name recognition, initial adoptees, and so on. Current estimates rely on judgmental order-of-entry, but could use scale factors from other categories. In addition, if budgets were larger, an additional subsample could be exposed to a competitive EV before the Impact. This experimental design enables the firm to measure the presentation-order effect more completely.

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 we chose passed a series of pretests in which the respondents reported that they could imagine themselves as being in late 1994. Our induction had strong face validity. It is also clear that future conditioning had a measurable effect on judged probabilities. However, it is possible that mass-produced EVs will not be introduced for several years, and the infrastructure may not be available until the end of the century. 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, a researcher might use IA to test on-board amenities for cruise ships using consumers who have never cruised, but plan to do so in the near future, as respondents. Alternatively, a researcher might use an IA to test High Definition Television 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 by modeling their search process. We first ask potential consumers what information sources they normally visit. We then adjust the time they have available so that they can visit roughly as many sources in the IA as they would in a real decision environment. Similarly, we adjust each information source so that respondents split their 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 ensure 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 a person 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 on the IA developer to model these effects, but there is certainly room for further development to test the external validity of the sources and develop means to maximize this external validity. (The test versus control design protects the overall forecast from gross errors. This caveat becomes more important if IA is used to study the differential effects of information sources.)

User experience. The IA provides simulated experience. With the EV, we combined a simulated showroom with a driveable prototype that could provide experience with some, but not all, of the EV's attributes. However, some products require much more consumer experience. For example, a user would be better able to evaluate a radically new computer keyboard if he or she is 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.)

Research Opportunities

Complementarity to existing research methods. Information acceleration represents new opportunities, but those opportunities complement, rather than replace, existing research methods. For example, estimates in the second IA were coupled to a conjoint analysis simulator to model consumer response to a full competitive set and to changes in the technology. In both IAs, we used decision-flow diagrams, which are a form of diffusion model (Bass 1969; Mahajan and Wind 1988), to model the impact of word-of-mouth, the dealership network, and the infrastructure.

Cost reduction. The IA described here was implemented with *video pass-through;* that is, actual video footage was produced and pressed on a videodisc. The computer then controlled the videodisc 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 also 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, while using professional photographers to maintain consistency. With video capture we can take fewer pictures and use the computer to create alternative views. Alternatively, we might even use computer-aided design methods to create the images without a physical model (for an initial video-capture application, see Adamjee and Scaife 1993). Because of 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.

User experience. Fortunately, a number of engineering breakthroughs promise to enhance our ability to test user experience. Among these developments are rapid prototyping systems, which tie computer-aided design 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 on the basis of 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 (for a discussion of these developments, see Eppinger and Ulrich 1994).

Another direction might be to move the IA to a full virtual reality in which the drive itself (e.g., for a car) is simulated. Flight simulators are commonly used to train pilots. Virtual reality amusement parks now touring the United States include race-car simulators that 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.

Summary

The prelaunch forecasting of really-new products is an important managerial problem. We attempt to illustrate with an application a new multimedia-based method of measurement and the challenges it faces in a managerial environment. We hope the reader evaluates this application critically and adopts those aspects of the methods that improve the state-of-the-art in forecasting for really-new products.

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, Massachusetts Institute of Technology.

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

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

California Environmental Protection Agency (1994), "Technical Support Document: Zero-Emission Vehicle Update," (April), Sacramento, CA: State of California.

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.

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

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), 417–31.

Green, Paul E. and V. Srinivasan (1990), "Conjoint Analysis in Marketing Research: New Developments and Directions," *Journal of Marketing,* 54 (October), 3–19.

Hauser, John R. and Steven P. Gaskin (1984), "Application of the 'DEFENDER' Consumer Model," *Marketing Science,* 3 (Fall), 327–51.

———, Glen L. Urban, and Bruce D. Weinberg (1993), "How Consumers Allocate Their Time When Searching for Information," *Journal of Marketing Research,* 30 (November), 452–66.

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), 336–45.

Juster, Frank T. (1966), "Consumer Buying Intentions and Purchase Probability: An Experiment in Survey Design," *Journal of the American Statistical Association,* 61 (315), 658–96.

Kalwani, Manohar U. and Alvin J. Silk (1983), "On the Reliability and Predictive Validity of Purchase Intention Measures," *Marketing Science,* 61 (September), 243–86.

Keeney Ralph L. and Howard Raiffa (1976), *Decisions with Multiple Objectives: Preferences and Value Tradeoffs.* New York: John Wiley & Sons.

Kiel, Geoffrey C. and Roger A. Layton (1981), "Dimensions of Consumer Information Seeking Behavior," *Journal of Marketing Research,* 18 (May), 233–39.

Mahajan, Vijay and Yoram Wind (1988), "New Product Forecasting Models, Directions for Research and Implementation," *International Journal of Forecasting,* 4 (3), 341–58.

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), 249–57.

Punj, Girish N. and Richard Staelin (1983), "A Model of Consumer Information Search Behavior for New Automobiles," *Journal of Consumer Research,* 9 (March), 366–80.

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

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 (May), 171–91.

Smallwood, Richard and Lynne J. Weber (1994), *Applied Decision Analysis Capabilities and Experience.* Menlo Park, CA: Applied Decision Analysis, Inc.

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

Urban, Glen L., John R. Hauser, and John H. Roberts (1990), "Prelaunch Forecasting of New Automobiles: Models and Implementation," *Management Science,* 36 (April), 401–21.

——— and ——— (1993), *Design and Marketing of New Products,* 2d ed. Englewood Cliffs, NJ: Prentice-Hall, Inc.

———, 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.

———, William J. Qualls, and Jonathan D. Bohlman (1994), "Information Acceleration of High Tech Industrial Products: A Market Feasibility Test," working paper, International Center for Research on the Management of Technology, Sloan School of Management, Massachusetts Institute of Technology.

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

Weinberg, Bruce D. (1992), "An Information-Acceleration-Based Methodology for Developing Preproduction Forecasts for Durable Goods: Design, Development, and Initial Validation," doctoral thesis, Sloan School of Management, Massachusetts Institute of Technology.

Westbrook, Robert A. and Claes Fornell (1979), "Patterns of Information Source Usage among Durable Goods Buyers," *Journal of Marketing Research,* 15 (August), 303–12.

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

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

LINKED CITATIONS

Premarket Forecasting of Really-New Products
Glen L. Urban; Bruce D. Weinberg; John R. Hauser
Journal of Marketing, Vol. 60, No. 1. (Jan., 1996), pp. 47-60.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28199601%2960%3A1%3C47%3APFORP%3E2.0.CO%3B2-Z

References

A New Product Growth for Model Consumer Durables
Frank M. Bass
Management Science, Vol. 15, No. 5, Theory Series. (Jan., 1969), pp. 215-227.
Stable URL:
http://links.jstor.org/sici?sici=0025-1909%28196901%2915%3A5%3C215%3AANPGFM%3E2.0.CO%3B2-4

Tracker: An Early Test Market Forecasting and Diagnostic Model for New Product Planning
Robert Blattberg; John Golanty
Journal of Marketing Research, Vol. 15, No. 2. (May, 1978), pp. 192-202.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197805%2915%3A2%3C192%3ATAETMF%3E2.0.CO%3B2-O

A Typology of Individual Search Strategies Among Purchasers of New Automobiles
David H. Furse; Girish N. Punj; David W. Stewart
The Journal of Consumer Research, Vol. 10, No. 4. (Mar., 1984), pp. 417-431.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28198403%2910%3A4%3C417%3AATOISS%3E2.0.CO%3B2-Y

Conjoint Analysis in Marketing: New Developments with Implications for Research and Practice
Paul E. Green; V. Srinivasan
Journal of Marketing, Vol. 54, No. 4. (Oct., 1990), pp. 3-19.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28199010%2954%3A4%3C3%3ACAIMND%3E2.0.CO%3B2-3

LINKED CITATIONS

Application of the "Defender" Consumer Model
John R. Hauser; Steven P. Gaskin
Marketing Science, Vol. 3, No. 4. (Autumn, 1984), pp. 327-351.
Stable URL:
http://links.jstor.org/sici?sici=0732-2399%28198423%293%3A4%3C327%3AAOT%22CM%3E2.0.CO%3B2-4

How Consumers Allocate Their Time When Searching for Information
John R. Hauser; Glen L. Urban; Bruce D. Weinberg
Journal of Marketing Research, Vol. 30, No. 4. (Nov., 1993), pp. 452-466.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28199311%2930%3A4%3C452%3AHCATTW%3E2.0.CO%3B2-6

Adjusting Stated Intention Measures to Predict Trial Purchase of New Products: A Comparison of Models and Methods
Linda F. Jamieson; Frank M. Bass
Journal of Marketing Research, Vol. 26, No. 3. (Aug., 1989), pp. 336-345.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28198908%2926%3A3%3C336%3AASIMTP%3E2.0.CO%3B2-0

Dimensions of Consumer Information Seeking Behavior
Geoffrey C. Kiel; Roger A. Layton
Journal of Marketing Research, Vol. 18, No. 2. (May, 1981), pp. 233-239.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28198105%2918%3A2%3C233%3ADOCISB%3E2.0.CO%3B2-Z

Federal Programs to Measure Consumer Purchase Expectations, 1946-1973: A Post-Mortem
John McNeil
The Journal of Consumer Research, Vol. 1, No. 3. (Dec., 1974), pp. 1-10.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28197412%291%3A3%3C1%3AFPTMCP%3E2.0.CO%3B2-Z

Purchase Intentions and Purchase Behavior
Donald G. Morrison
Journal of Marketing, Vol. 43, No. 2. (Spring, 1979), pp. 65-74.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28197921%2943%3A2%3C65%3APIAPB%3E2.0.CO%3B2-4

LINKED CITATIONS

Prepurchase Information Seeking for New Cars and Major Household Appliances
Joseph W. Newman; Richard Staelin
Journal of Marketing Research, Vol. 9, No. 3. (Aug., 1972), pp. 249-257.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197208%299%3A3%3C249%3APISFNC%3E2.0.CO%3B2-T

A Model of Consumer Information Search Behavior for New Automobiles
Girish N. Punj; Richard Staelin
The Journal of Consumer Research, Vol. 9, No. 4. (Mar., 1983), pp. 366-380.
Stable URL:
http://links.jstor.org/sici?sici=0093-5301%28198303%299%3A4%3C366%3AAMOCIS%3E2.0.CO%3B2-Y

Pre-Test-Market Evaluation of New Packaged Goods: A Model and Measurement Methodology
Alvin J. Silk; Glen L. Urban
Journal of Marketing Research, Vol. 15, No. 2. (May, 1978), pp. 171-191.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197805%2915%3A2%3C171%3APEONPG%3E2.0.CO%3B2-P

Prelaunch Forecasting of New Automobiles
Glen L. Urban; John R. Hauser; John H. Roberts
Management Science, Vol. 36, No. 4. (Apr., 1990), pp. 401-421.
Stable URL:
http://links.jstor.org/sici?sici=0025-1909%28199004%2936%3A4%3C401%3APFONA%3E2.0.CO%3B2-N

Premarket Forecasting for New Consumer Durable Goods: Modeling Categorization, Elimination, and Consideration Phenomena
Glen L. Urban; John S. Hulland; Bruce D. Weinberg
Journal of Marketing, Vol. 57, No. 2. (Apr., 1993), pp. 47-63.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28199304%2957%3A2%3C47%3APFFNCD%3E2.0.CO%3B2-7

Patterns of Information Source Usage among Durable Goods Buyers
Robert A. Westbrook; Claes Fornell
Journal of Marketing Research, Vol. 16, No. 3. (Aug., 1979), pp. 303-312.
Stable URL:
http://links.jstor.org/sici?sici=0022-2437%28197908%2916%3A3%3C303%3APOISUA%3E2.0.CO%3B2-2

LINKED CITATIONS

Commercial Use of Conjoint Analysis: An Update
Dick R. Wittink; Philippe Cattin
Journal of Marketing, Vol. 53, No. 3. (Jul., 1989), pp. 91-96.
Stable URL:
http://links.jstor.org/sici?sici=0022-2429%28198907%2953%3A3%3C91%3ACUOCAA%3E2.0.CO%3B2-4