The Predictive Power of Internet-Based Product Concept Testing Using Visual Depiction and Animation[#]

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Biographical Sketches

<u>Ely Dahan</u> is Assistant Professor of Management Science in the Marketing group of MIT's Sloan School of Management. He is currently completing his dissertation in the Operations, Information and Technology program at Stanford Business School. At Stanford, Dahan was selected to participate in the Future Professor of Manufacturing program sponsored by the Stanford Integrated Manufacturing Association (SIMA). He held an Integrated Manufacturing fellowship from the Department of Energy, a National Doctoral Fellowship from the American Association of Collegiate Schools of Business (AACSB), and a Jaedicke Fellowship for scholarly achievement from the Stanford Business School. His research interests include internet-based market research methods, mathematical models of parallel and sequential prototyping, and the economics of cost reduction during product design. Prior to returning to academia, Dahan received a Bachelor's degree in Civil Engineering from MIT and an MBA from Harvard Business School. He worked as national product manager for W.R. Grace & Company and NEC Information Systems in Massachusetts until 1984 when he founded a computer networking company in Maryland, serving as CEO until the firm was acquired in 1993. Dahan presented the work described herein at the October, 1998 PDMA research conference in Atlanta.

<u>Professor V. "Seenu" Srinivasan</u> received his Bachelor's degree in Mechanical Engineering from the Indian Institute of Technology, Madras, and was the gold medallist in his graduating class. He worked for two years as a production planning engineer prior to joining Carnegie-Mellon University where he received his M.S. and Ph.D. in Industrial Administration. For three years he was on the faculty of the University of Rochester. He is currently the Ernest C. Arbuckle Professor of Marketing and Management Science at the Graduate School of Business, Stanford University. He was formerly the director of Stanford Business School's Ph.D. program. His primary research interest is in the measurement of customer preference structures and its role in new-product development. He has also contributed to other quantitative marketing areas such as market structuring and sales force compensation. Professor Srinivasan has been a consultant to several companies and has won best-teacher awards. He is an associate editor of the *Journal of Marketing Research* and *Marketing Science*. He has published extensively in many journals and is the recipient of two O'Dell awards, an ORSA award, and the John Little award. Professor Srinivasan is a recipient of the Parlin and Churchill awards, the highest awards from the American Marketing Association, for outstanding contributions to marketing research.

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Abstract

We measure the predictive accuracy of Internet-based product concept testing that incorporates virtual prototypes of new products. The method employs a two-factor conjoint analysis of prototypes and prices to enable a design team to select the best of several new concepts within a product category. Our results indicate that virtual prototypes on the Web provide nearly the same results as physical prototypes. As virtual prototypes cost considerably less to build and test than their physical counterparts, design teams using Internet-based product concept research can afford to explore a much larger number of concepts. In short, the Web can help to reduce the uncertainty and cost of new product introductions by allowing more ideas to be concept tested in parallel.

1. Introduction

One of the more challenging decisions faced by a new product development team is concept selection, the narrowing of multiple product concepts to a single, "best" design. A key input to this process is the predicted market performance of a product concept were it to be launched.

Pugh's [8] method of controlled convergence and Burchill's [2] concept engineering represent two approaches to concept selection in which a design is chosen prior to detailed engineering, prototyping, and testing. In contrast, Srinivasan, Lovejoy and Beach [10] demonstrate that, depending on the cost of developing each concept into a customer-ready prototype, it would be optimal to carry multiple product concepts into the prototyping and testing phase, and to select the best of those designs later in the process, as depicted in Figure 1.

Figure 1
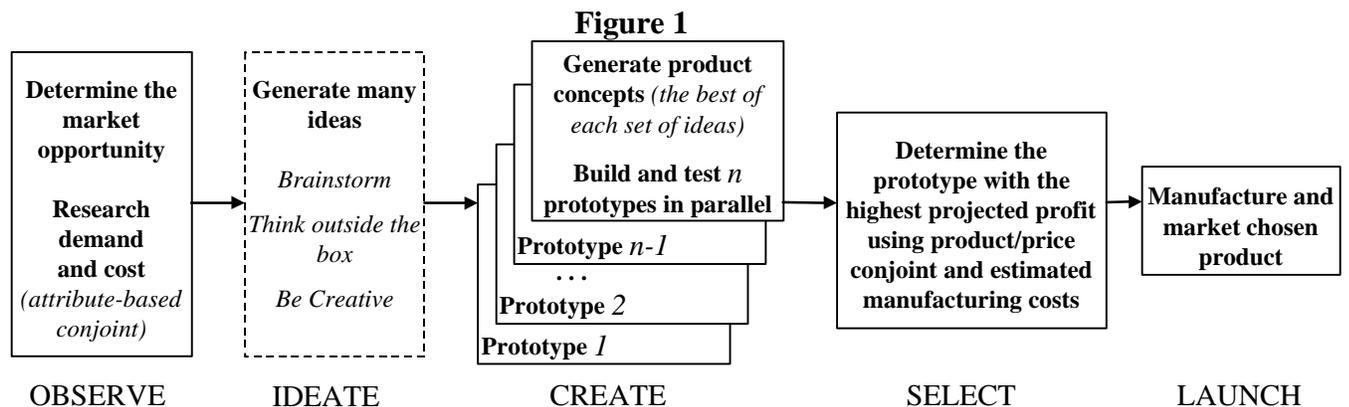
Dahan and Mendelson [3] use extreme value theory to determine the optimal number, n, of parallel prototypes under uncertainty and compare the parallel approach to an iterative, sequential one. They show how the optimal number of designs to carry forward (and the expected profit resulting from that effort) increases when time-to-market is critical and the cost

to build and test each design decreases. Product design teams benefit from lower per unit prototype costs since more concepts can be tested for their profit-generating ability without delaying product development. Stevens and Burley [11] point out the need to consider many product concepts since only a small percentage of new product ideas ultimately prove to be profitable. Furthermore, as Iansiti [5] points out, keeping multiple product concept options open and freezing the concept late in the development process affords the flexibility to respond to market- and technology shifts and may actually shorten total product development time. In short, there is a pressing need for low-cost, parallel testing of new product concepts.

In order to carry forward multiple product concepts a number of competing ideas must first be generated. We assume that prior to generating multiple product concepts, qualitative market research (e.g. focus groups or one-on-one customer interviews) is conducted, measurable product attributes are identified, and quantitative market research in the form of attribute-based conjoint analysis [4] is completed. (We use the term attribute-based conjoint analysis to refer to the understanding of customer trade-offs on multiple product attributes and price, and distinguish it from the two-factor product/price conjoint analysis for testing prototypes, described later.) The design team generates multiple product concepts that address customers' needs for both quantifiable performance attributes (guided, in part, by the attribute-based conjoint analysis) and qualitative attributes such as aesthetics and ease-of-use, and manufacturing cost considerations.

Srinivasan, et. al. [10] explain that while attribute-based conjoint analysis explains a significant portion of the variability in product preferences, it does not adequately explain preferences resulting from design issues such as aesthetics and ease-of-use. Vriens, et. al. [16] show that pictorial representations, as opposed to purely verbal ones, lead to increased

importance of what they term "design-attributes," i.e., non-quantifiable aesthetic or ease-of-use elements of a design. Srinivasan, et. al. [10] suggest that customer-ready prototypes provide customers the additional, non-attribute-based information. But what form, exactly, need a design concept take in order to make accurate predictions a new product's market potential? Are physical, customer-ready prototypes really necessary or will visual depictions or virtual animations suffice?

Urban, et. al. [13], [15] describe a powerful method of forecasting new product success called *information acceleration* (IA), in which virtual product representations are combined with a complete virtual shopping experience. The major limitation of the IA approach is the high cost of "building" and testing each prototype. A related limitation is that IA requires voluminous information to make the shopping simulation.

The World Wide Web offers a particularly attractive environment for new product market research [7]. First, the cost of "building" and testing virtual prototypes is considerably lower than that for physical prototypes, thereby allowing more product concepts to be tested within the same market research budget. Second, access to respondents is efficient and expedient. (Of course, there is a serious risk of sample bias from using Web-based respondents. We suggest reducing this risk somewhat by carefully pre-selecting panelists and reweighting the sample to correspond to the characteristics of the relevant market.) One can envision a day when paid consumer panels, "Nielsen Web Families" so to speak, respond instantaneously to market research studies over the Internet. Currently, such panels have been formed by market research firms to study consumer preferences for Web-based products and services. It is natural to extend these efforts to products outside of the traditional Internet domain. Third, new technologies available on the Web such as three-dimensional VRML (Virtual Reality Markup Language)

viewing, streaming video, and interactive sensory peripherals allow visual, auditory and tactile information to be disseminated and retrieved in rather powerful ways. Finally, several prototypes can be market-tested in parallel without increasing costs significantly.

In summary, if virtual prototypes evaluated over the Web result in nearly the same market share predictions as physical, customer-ready prototypes, then the economics of product concept testing will radically change. Many product concepts can be carried forward and evaluated in order to choose the best product to launch.

In this paper, we explore an approach in which static and animated virtual prototypes are displayed over the Web using three-dimensional VRML representations and the shopping experience is limited to a simple, interactive Web page. The spirit of Information Acceleration remains, but in a form that even smaller firms can economically implement. We compare the predictive accuracy of purely verbal attribute-based conjoint analysis, Internet-based static visual depiction, and Internet-based virtual animation against the standard of physical, customer-ready prototypes. Verbal, attribute-based conjoint is only provided as a benchmark and is not expected to be as accurate as the later-stage visual tests since it omits such important information as product aesthetics and method of operation. The more direct comparison made in the paper is between the virtual tests and the physical prototype standard.

Web-based approaches featuring greater interactivity and media richness have been shown to enhance user experiences. Ariely [1] and Klein [6] demonstrate the importance of interactivity and media richness in engaging and influencing Web users. Specifically, they show that respondents' decision quality and memory improve with greater interactivity and media richness. Urban, Sultan and Qualls [14] demonstrate that a well-designed Web site not only

provides useful information to customers, but may actually engender trust. We would expect that improvements in decision quality, memory and trust while evaluating virtual products would increase the accuracy of predictions of actual market shares.

The rest of the paper proceeds as follows. The next section outlines the methodology used to create and test multiple product concepts. Details of a Web-based research method follow. Finally, results from the alternative methods are compared and evaluated.

2. Method

In commercial situations, it is rare that multiple concepts in a product category are fully developed into customer-ready prototypes and market-tested in parallel. We are fortunate to have just such a situation in a graduate-level product design course. In the 1997 edition of this course, nine student teams, each comprised of two graduate-level engineering students and two MBA students, designed, built and tested a portable bicycle pump. Two commercially available portable bicycle pumps were used as standards; i.e., market share for each student-designed product was determined in a three-product competition in which the student product was pitted against the two commercial products.

Prior to the product design and prototype fabrication phases of the course, the students conducted an attribute-based conjoint analysis. The five product attributes, which were identified through qualitative, one-on-one interviews with potential bicycle pump consumers, were (1) size, (2) durability, (3) time for inflation, (4) ease of inflation, and (5) price. After analyzing the attribute-based conjoint results, each team independently designed and built a customer-ready bicycle pump prototype. The measurable attribute levels of the eleven bicycle pump designs are summarized in Table 1. The products in the first two columns, AirStik and Solibloc, are the

commercially available products. The performance numbers were determined through engineering measurement of the physical prototypes, with time of inflation ("Fast") being measured in minutes needed to inflate a tire to 60 psi and the other three attributes measured on a scale of 1 to 3, with 1 representing the best performance (see Figure 5 to see how these scales were presented to survey respondents). The engineering measurements were then translated into simpler, *Consumer Reports*-style rating dots as shown in the table.

Table 1: Attribute levels for each bicycle pump
*(Lower scores mean better performance; products leading each attribute are **bolded**)*

	AirStik	Solibloc	Cyclone	Gear-head	Silver Bullet	TRS	Gecko	Epic	Skitzo	Rim-Gripper	2wister
Price	$30.00	**$12.00**	$43.00	$29.90	$21.50	$30.00	$31.99	$26.50	$21.69	$23.50	$25.00
Fast	**1.5** ●	3.4 ◑	5.3 ○	5.3 ○	3.4 ◑	5.3 ○	5.3 ○	5.3 ○	3.4 ◑	3.4 ◑	3.4 ◑
Compact	**1.1** ●	2.0 ○	2.0 ○	2.5 ◐	**1.1** ●	2.0 ○	2.0 ○	1.5 ◑	**1.1** ●	2.0 ○	2.0 ○
Easy	**1.6** ◑	2.6 ◐	2.1 ○	**1.6** ◑	2.6 ◐	2.1 ○	2.6 ◐	**1.6** ◑	2.1 ○	2.6 ◐	2.6 ◐
Durable	1.7 ◑	2.1 ○	2.5 ◐	2.1 ○	**1.3** ●	2.1 ○	1.7 ◑	1.7 ◑	1.7 ◑	2.5 ◐	2.1 ○

Worst   ● ◐ ○ ◑ ●   Best

Each student team determined its price using cost calculations and conjoint simulations with the objective of maximizing profit. Product costs were calculated based on a detailed bill of materials and an activity-based process cost model.

The attribute-based conjoint study was conducted in October of 1996 and three visual (product vs. price) conjoint studies were conducted in 1997. The attribute-based conjoint study, having been conducted by the whole class, had a larger sample size of approximately 250 respondents. The three other conditions had a target sample size of approximately 100 each. In each case, the respondents were students of the same university and were screened for bicycle use. Respondents only participated in one study each and samples were controlled for relevant (based on the attribute-based conjoint analysis) demographic criteria. The attribute-only study

included the five product attributes listed earlier, each of which allowed a low, medium and high

attribute level. Since 243 attribute-level combinations were possible ($3 \times 3 \times 3 \times 3 \times 3 = 243$),

the attribute-based conjoint was conducted using a fractional factorial design of 18 profiles.

Respondents ranked the 18 profiles, which were printed on individual cards, in order of their

likelihood of purchase. The rank order was recorded and input into conjoint LINMAP software.

The attribute-only conjoint analysis was completed *before* the teams began designing products,

and served as one basis for their future design efforts.

In the three visual conjoint studies, only two factors were included: product and price.

Product had eleven levels, namely the nine student-team-designed bicycle pumps plus the two

commercially available ones, and price had three levels: $10, $20, and $40. Therefore,

33 (11×3) combinations of product and price were possible and respondents sorted all 33

combinations in the visual conjoint surveys. The performance of each product on the other four

attribute dimensions was measured and included for informational purposes, so that respondents

had information on all verbal attributes, product aesthetics and ease-of-use. The only difference

between each of the three visual conjoint studies was the visual depiction method used, as

described in Table 2.

Table 2: Summary of the Survey Methods Tested

Conjoint study	Number of Respondents (n)	Nature of Prototype Depiction	Task Description
Attribute-only, Full-Profile (AF)	257	Written attribute levels	Fractional-factorial, rank 18 full-profiles, 3 levels each of 5 verbal attributes (no visual)
Web Static (WS)	87	Static color rendering on the Web showing pump in two positions (open & closed)	Click on 33 price tags on a web page with 11 renderings and all attribute information
Web Animated (WA)	78	Animated color rendering on the Web	Click on 33 price tags on a web page with 11 bike pump animations and all attribute information
Physical Prototype (PP)	102	Physical Customer-ready prototype	Sort 33 price cards after observing 11 physical product demonstrations and seeing all attribute information

The final conjoint study, Physical Prototype (PP), is the standard that determined "actual" market share potential since it provided full information to the survey respondents and most closely simulated an actual shopping experience. In this study, 102 respondents witnessed demonstrations of and could examine each bicycle pump, then sorted price cards in the order they were *likeliest to buy* the products. The 33 price cards were placed in eleven stacks of three ($10 on top, $20 in the middle, and $40 on the bottom) on a paper sort board that featured color renderings, product logos, short verbal descriptions, and *Consumer Reports*-style product ratings of the eleven portable bike pumps. Respondents recorded the order in which they lifted the 33 price cards from the sort board. It was this sort order that was input into the conjoint LINMAP software.

Creating the Visual Depictions

All of the color renderings (done in Alias SketchTM) and animations (done in Silicon Graphics' Cosmo WorldsTM) were created by the same computer artist to maintain uniformity. The images in Figure 2 illustrate the nature of the visual depictions employed in the conjoint studies. A key breakthrough in being able to conduct this study across the Web was the advent of VRML authoring tools that could produce realistic 15 to 20-second animations within very compact data files. The innovation of the VRML approach is that the bulk of the image processing is conducted at the user's computer (by a VRML plug-in viewer such as SGI's Cosmo Player which must be installed in addition to the Web browser software) rather than across the Web. For example, the animations shown only required between 25 Kilobytes and 80 Kilobytes to be downloaded and the entire Web site fit on a 1.44-Megabyte diskette. Since the file sizes were small, the bandwidth limitations of the Web did not cause long download times. Had the animations consisted of video or other non-VRML methods, each would have exceeded 1 Megabyte in file size and download time would have been excessive. In short, the use of currently available VRML technology allowed simple animations to be downloaded quickly, while preserving image quality. Newer Web browsers such as Netscape Communicator 4 include VRML viewers, so this method of representing products on the Web may gain widespread acceptance.

Figure 2: Examples of Static Renderings and Animations

Product	Web Static (WS)	Web Animation (WA) Schematic[1]
AirStik		
Epic		
2wister		

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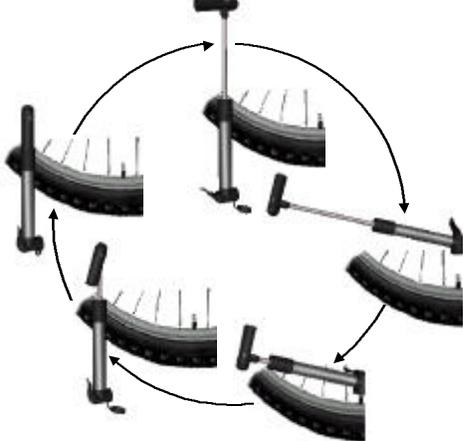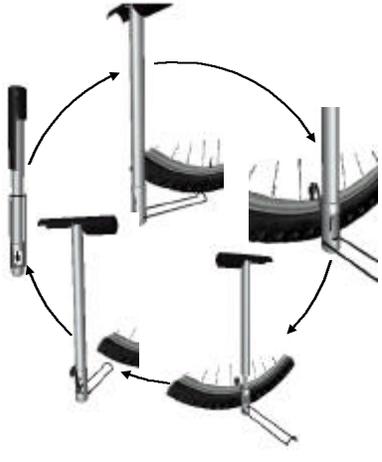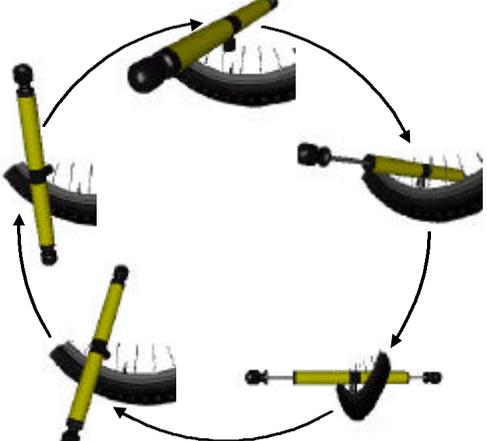
[1] The "snapshots" shown in these schematics do not capture the smoothness of motion provided by SGI's Cosmo Player VRML plug-in, which enabled respondents to view realistic-looking product animations on the Web.

Designing the Web Page

Figure 3 depicts the web page screen on which the conjoint survey was accomplished.

Figure 3: Web page used in Web surveys (WA and WS)
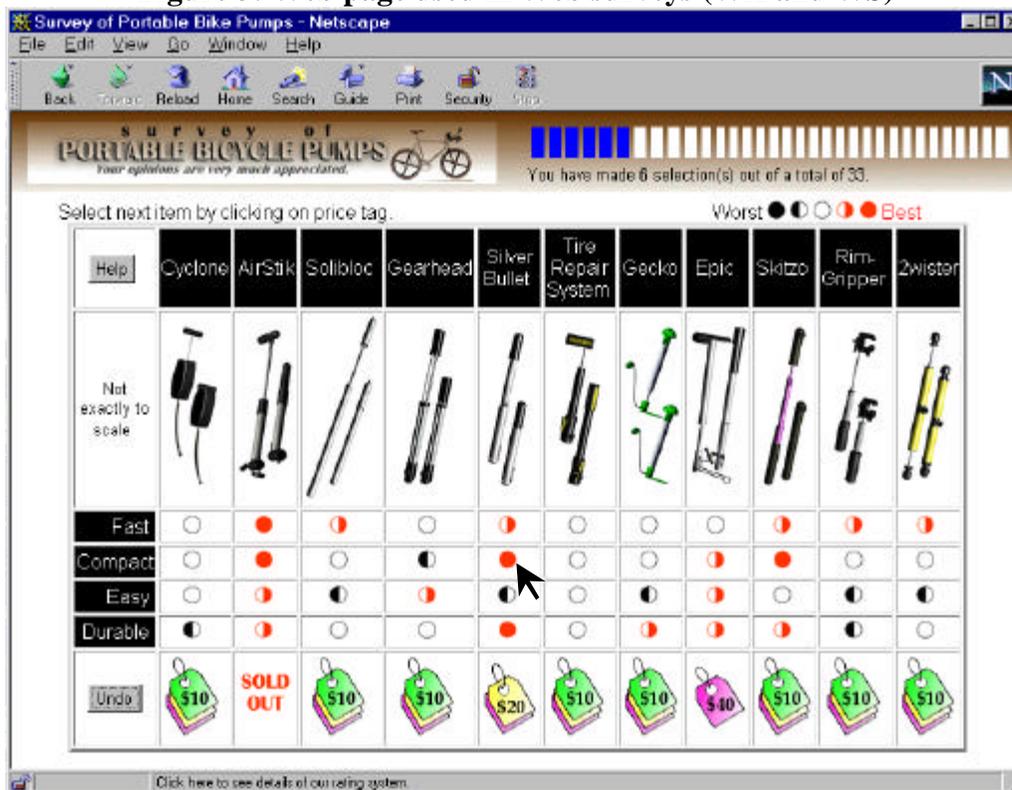
Additional screens featuring instructions preceded the one in Figure 3. First, the respondent

entered simple demographic data and information to prevent repeated participation in the survey.

He or she then received instructions describing the conjoint exercise and could return to these

instructions by clicking on the "Help" button. Next, respondents were given a "virtual tour" of

the eleven portable bicycle pumps in which an enlarged rendering (in WS) or animation (in WA)

of each pump was displayed along with its logo, a brief written description, and its four non-

price performance ratings. Every respondent, therefore, viewed the visual information for every

product, and the duration of this activity was consistent across respondents. Respondents could

review or replay product depictions while on the tour or could return to these enlarged images by

clicking on a product's name or small image as in Figure 4, where the small RimGripper image

has been clicked.

Figure 4: WS Enlarged Depiction
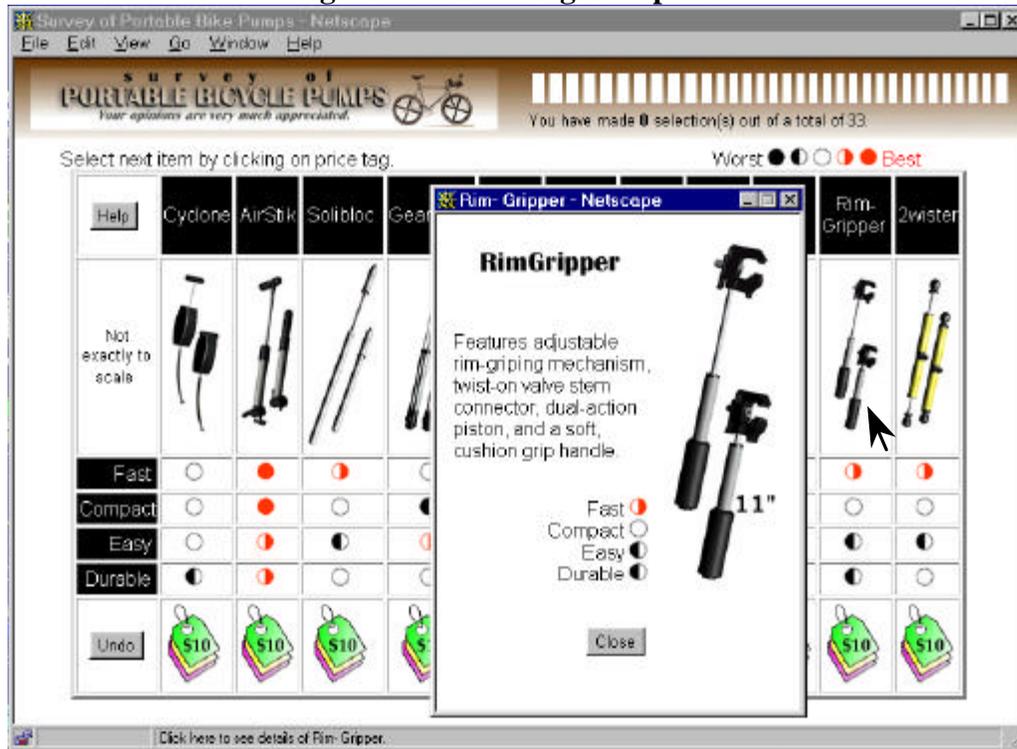
In this way, multiple products could be displayed in greater detail, overcoming the graphic

resolution limitations of personal computer monitors. Clicking on any of the red or black rating

dots causes the ratings key in Figure 5 to appear. The ratings key translates the measurable

engineering attributes quantified in Table 1 into the *Consumer Reports*-style rating dots that

appear in Figure 3.

Figure 5: *Consumer Reports*–**style rating screen**
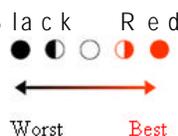
Respondents express their preferences by clicking on the price tags below the eleven

products in Figure 3. Each product has three price tags below it, viz., $10 on top, $20 in the

middle, and $40 on the bottom. Initially the respondent chooses among all eleven products, each

priced at $10. Suppose the respondent chooses AirStik. By clicking on the $10 price tag under

AirStik, the selection is made and the price of AirStik goes up to $20. (The "Undo Selection"

button enables the respondent to change his or her mind and return the most recently selected

price tags to their original location.) The next selection for the respondent is therefore to choose

among the eleven products with AirStik at $20 and all others at $10. In this case, suppose the

respondent chooses Epic at $10. Epic's price increases to $20 and the next choice has nine

products at $10 and the two others at $20, etc. In Figure 3, note that the respondent has clicked

on six price tags so far, the $10, $20 and $40 tags for AirStik, the $10 and $20 tags for Epic, and

the $10 tag for Silver Bullet. It is the ordering of these price selections (which is recorded by a

background CGI script) that results in the part-worths for the eleven products and the price utility functions for each respondent.

Market Share Predictions

For the AF (attribute-only, full profile) condition, market shares were forecast by a conjoint simulation using the individual-level max-choice rule (i.e., the individual chooses the product with the highest utility). The simulations used the part-worth functions estimated by the attribute-based full profile study of 257 respondents. (The part-worth function for each attribute used linear and quadratic terms to permit interpolation.) The simulator, in each case, compared three products, viz. the student product and the two commercial products, using the attribute values and prices given in Table 1.

For the three other cases (WS, WA and PP) the conjoint analysis had two part-worth functions, one for product (11 levels, one corresponding to each product) and a linear and quadratic part-worth function for price. (Recall, though, that respondents were also aware of the attribute levels for each product so that both verbal and visual information could influence their choices.) Market shares were forecast by a conjoint simulation using the individual-level max-choice rule. The simulation had three products in each case, viz. the student product and the two commercial products, using the prices given in Table 1.

3. Results

Table 3 summarizes the market share predictions for each bicycle pump when competing directly against the two commercially available products. The results are depicted graphically in Figure 6. Recall that the physical prototype (PP) condition is the standard against which the other methods (AF, WS and WA) are to be compared. The top three products using physical

prototypes were Skitzo, Silver Bullet and Epic. All three methods (AF, WA and WS) identified the top three products correctly. (WS reversed the first and second place products, however, possibly because Skitzo's telescoping feature was more obvious in animation than in the static rendering.)

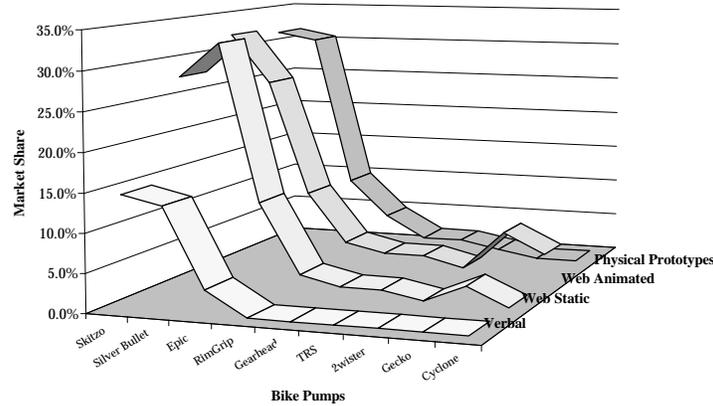**Figure 6: Market Share Predictions from Verbal versus Virtual Methods**

**Table 3: Market Share Predictions for Nine Product Concepts for Each Survey Method**

	Skitzo	Silver Bullet	Epic	Rim Gripper	Gear-head	TRS	2wister	Gecko	Cyclone
Physical	31.4%	30.4%	9.8%	4.9%	2.0%	2.0%	1.0%	0.0%	0.0%
Animation	32.1%	25.6%	10.3%	3.8%	2.6%	2.6%	1.3%	6.4%	3.8%
Static	27.6%	32.2%	11.5%	2.3%	1.1%	1.1%	0.0%	2.3%	0.0%
Verbal	14.4%	13.2%	3.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

The attribute-only, full-profile (AF) conjoint analysis predicted that all of the products except Skitzo, Silver Bullet and Epic would achieve *zero* market share when competing against the two commercially available products. The physical prototype (PP) survey, in contrast, revealed that all products except Cyclone and Gecko achieve at least some market share. In one sense, the attribute-only outcome is quite impressive in that it identifies the top three products, in correct order, in sharp relief to all of the lower performers. For a product development effort in which winners are to be separated from losers for more refined testing in a subsequent phase, e.g. as part of Thomke's [12] mode-switching approach, attribute-only results might be sufficient. But

the Web-based tests performed better in quantifying the degree to which a winner won and a

loser lost. This could be important when attempting to improve particular designs or when

forecasting the level of new product profitability. For example, although AF suggested that

Skitzo would achieve the highest share versus the competition, it predicted 14.4% market share

potential rather than the 31.4% predicted by PP. At 32.1% and 27.6%, respectively, the market

share predictions based on Web-based animations (WA) and renderings (WS) more closely

duplicated the physical prototype results. (Recall that the attribute-only (AF) case provided no

information on the products' aesthetics and ease-of-use.) We note that, in general, neither WA

nor WS dominate each other with greater accuracy.

As Figure 7 illustrates, the Web-based methods using animations and static renderings do

a significantly better job of predicting the absolute levels of performance, that is fitting the 45-

degree line that equates predicted and actual market shares. The verbal attribute-only method

consistently predicted market shares well below those actually achieved.

Figure 7: Market Share Predictions from Verbal versus Virtual Methods
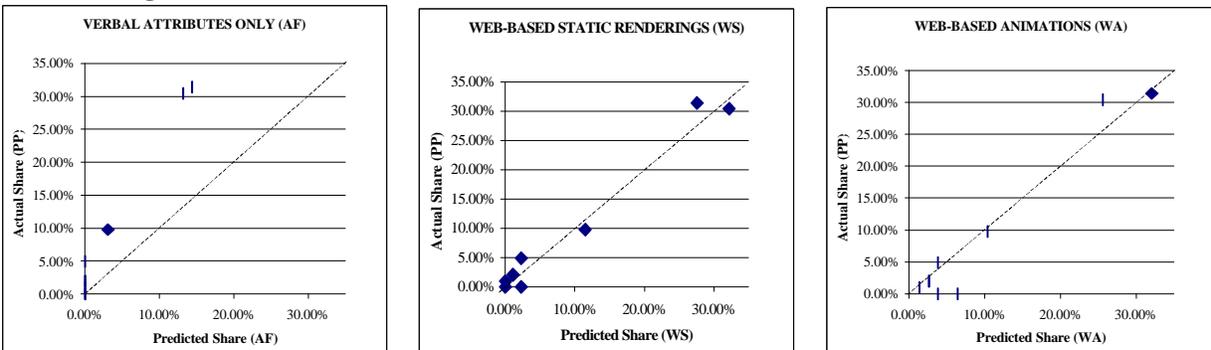
Applying the standard statistical test of the difference between two proportions (Spurr

and Bonini [9]), we observe in Table 4 that, for the top three products, the differences between

AF and PP are statistically significant, but that the differences between the Web results (for both WS and WA) and PP are not significant.[2] This is consistent with our earlier expectation that the Attribute-only test would not perform as well as the visual tests that inform respondents more fully.

Table 4: Statistical Significance of Differences Between Each Method and PP

|	Silver Bullet	Epic	Skitzo
AF	$p < 0.01$	$p < 0.05$	$p < 0.01$
WS	*ns*	*ns*	*ns*
WA	*ns*	*ns*	*ns*

ns = not significant

The Web-based methods sometimes revealed an interesting disconnect between virtual products and physical ones.

Figure 8: Web Depiction of Gecko

For instance, the Web-based surveys (WA and WS) predicted that Gecko, the product concept shown in Figure 8, could compete against the two commercially available products and achieve a fourth place ranking as seen in the market share results in Figure 9. But when customers handled the physical prototype, Gecko was unable to achieve any market share and was ranked last.

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[2]   The six trailing products were not included because they did not meet the requirement that $n \times p \geq 5$, where n

Figure 9: Market Share Predictions for Gecko
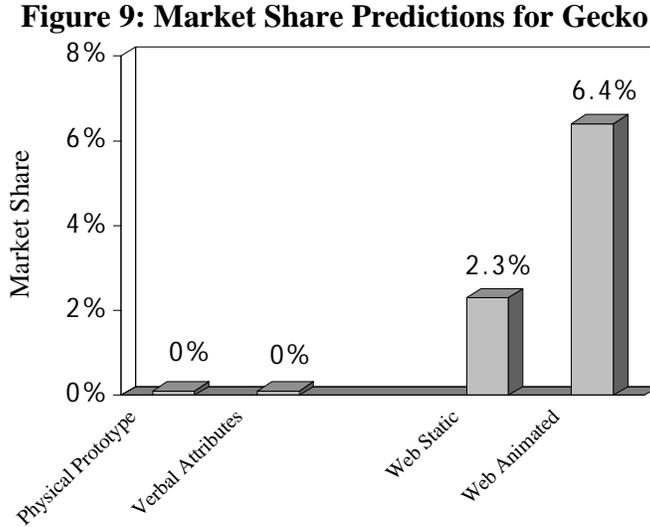
One explanation for the disconnect between virtual and physical prototype testing was that the Web-based color renderings and animations made Gecko look and feel better in virtual reality than it did in physical reality. Simply put, the fit and finish of the rubber material that gave Gecko its green, lizard-like texture and appearance was not of high quality, but this could only be perceived when the prototype was actually *touched* by consumers. Computer renderings and animations may *disguise* imperfections in fit-and-finish, texture, and smoothness of motion.

Table 5 and Figure 10 report the mean absolute differences between the market shares predicted by each method and those predicted by the PP method. The column labeled "0% Δ" summarizes the mean absolute differences in market share prediction when the products were priced at profit-maximizing levels. (The price of a product was varied in the simulation against the two benchmark products so as to maximize profit given the costs of each product.)

is the sample size and *p* is the proportion of the sample (in this case the market share prediction).

Figure 10: Web-Based Market Share Predictions are More Robust to Pricing Changes
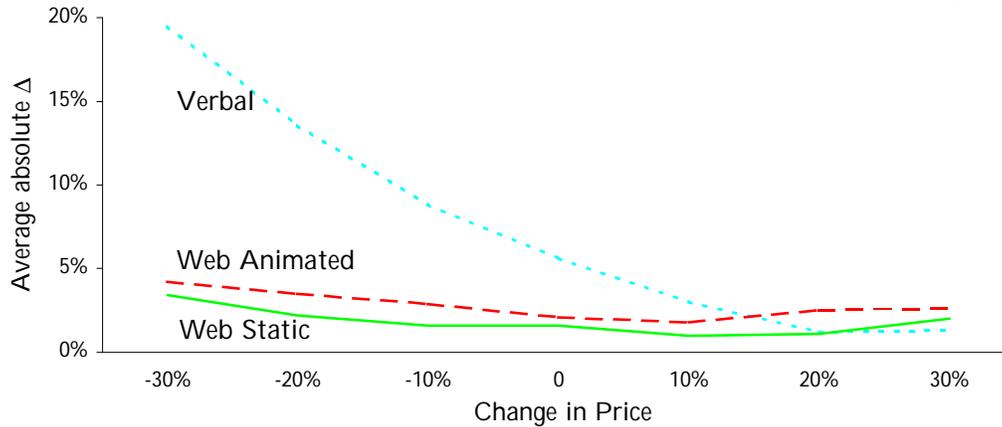
Table 5: Market Share Prediction Errors as Price Varies

Price Δ	Mean absolute deviation from PP shares as price varies							
	-30%	**-20%**	**-10%**	**0% Δ**	**+10%**	**+20%**	**+30%**	**Average**
AF	19.5%	13.6%	8.8%	5.6%	3.0%	1.2%	1.3%	7.6%
WS	3.4%	2.2%	1.6%	1.6%	1.0%	1.1%	2.0%	1.9%
WA	4.2%	3.5%	2.9%	2.1%	1.8%	2.5%	2.6%	2.8%

Since the profit-maximizing prices used to calculate market shares were determined *assuming known product costs*, we further evaluated the average absolute share differences as prices vary (i.e., as optimal prices might change in response to lower or higher actual product cost). While the Web-based predictions were quite robust to price changes in both directions, the attribute-based predictions lost accuracy when prices were reduced by 10% to 30%. Once again, both Internet-based methods performed equally well.

Our results suggest that the static and animated forms of Web-based depiction produce nearly equal accuracy. If this result is replicated in other contexts, one might choose the less expensive static method. When should the firm spend the extra time and money to develop animated depictions? Products might require animations to reveal hidden features (e.g. AirStik's dust cap), aesthetics (e.g. Epic's reflective aluminum texture), or ease-of use (e.g. 2wister's two-handed pumping through the spokes). Additionally, respondents may become more engaged in

the survey when the images are animated and interactive. As new software is developed and more computer artists are trained, the incremental cost and time required for animated computer rendering will decline. In any case, firms seeking to reduce the market risk inherent in new product introductions should consider exploiting the virtual parallel prototyping market-research opportunities available on the Internet.

4. Summary

This research indicates that virtual parallel prototyping and testing on the Internet provides a close match to the results generated in person using costlier physical prototypes for the bicycle pump product category. Can the virtual approach be generalized to product categories beyond bicycle pumps? Replication of our results with other product categories would be worthwhile. It remains to be seen which goods are best suited to virtual, visual testing, but we expect that many durable good categories can be accurately represented using VRML animation and compared using the simulated shopping experience described here. Further, attribute levels in the form of Consumer Reports ratings are familiar to many consumers and are frequently used to aid purchase decisions. The crucial question, therefore, is which product characteristics affecting customer choice are only properly communicated through physical prototypes? Sensory experiences such as smell, touch and taste are yet to be easily replicated in a virtual environment, making more difficult the task of testing experience goods over the Web at present.

The future of the virtual approach to product concept testing is quite promising. Firms can quickly generate multiple virtual prototypes and gather consumer preference data rapidly, and at very low cost. This should encourage a greater degree of parallel prototyping and creativity while enhancing the expected profitability of new product launches.

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