Issues and Cases in User Research for Technology Firms

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Introduction

We describe aspects of market research conducted in technology companies that make technology product research different from that of traditional consumer products. These include differences in both the products themselves and the business environments in which they are developed. Although many traditional market research techniques are appropriate in technology companies, they may be poorly utilized due to these structural differences. We explore these factors and offer brief case studies from projects at Microsoft. Finally, we provide certain recommendations for the implementation of preference modeling in the new technology environment.

Technology Products Are Unlike Shoes, Soda, and Detergent

We characterize traditional marketing research as occurring when three conditions are met: (1) products are well-defined in their real or potential characteristics; (2) research methods allow marketers to gauge interest in those products for potential markets; and (3) business structures enable development decisions to be made based on this research. Such conditions occur to a reasonable degree in most consumer product categories. Among traditional consumer goods, specifying potential product configurations is not difficult (at least in principle) because the universe of product attributes is largely contained. For instance, a new running shoe product has a limited array of potential materials, colors, general shapes, and sizes. Similarly, the general composition and manufacturing methods for sodas, detergent, clothing, televisions, automobiles, and most other consumer products are well understood.

However, technology products often are not so well-specified. Even their general characteristics (e.g., the product category) may be poorly-defined, and researchers may not know which features of a product are feasible. Even where these characteristics are well understood by the firm, they may not be understood among consumers. This exposes the firm to considerable research risk where understanding of product characteristics differs from respondent to respondent.

Nevertheless, quantifying consumer interest in innovation can be especially valuable for firms selling technology products. Since new technology products and new features are very costly to develop in time and money, early market intelligence can help firms to allocate effectively resources between development projects. Also, small differences in given features may have a large impact on cost-of-goods, particularly when dealing with such features as onboard memory, image resolution, and screen size. Further, interaction effects between features may be substantial. The value of image resolution, for example, will depend substantially on the viewable image size. Finally, technology products typically follow highly truncated lifecycles, typically no more than 5 years and sometimes much less. This puts additional pressure on firms to develop the correct set of features in the initial version.

Technology Products Can Be Difficult to Research

Traditional marketing research techniques rely upon consumers' capability to understand new products, but discontinuous innovations presented by technology products often cannot be understood by consumers until the product is actually created. Since the outcomes of such research is, or should be, a primary input into the product definition and development, this creates something of a chicken/egg paradox for technology firms. Product features cannot be well understood by research subjects without some degree of experiential context, and such a context cannot easily be provided without at least a working prototype available. In most cases, high cost and development time preclude firms from developing prototypes without a some degree of confidence that the product will ultimately reach the market.

Consider for instance the concept of a digital pen, which captures ordinary handwriting with an ink pen on paper and makes it digitally available to various PC applications (for classroom notes, sketches, appointments, etc.). When Microsoft researched this concept in 2004, customers' perceptions of the product's capabilities were highly inaccurate, and this led to extreme variance in their appraisal of its value. After 1.5 hour focus groups discussing the concepts, respondents were enthusiastic and stated high levels of value (up to $500). However, after using such a product and becoming familiar with its limitations (such as poor handwriting recognition and the need to use special paper), no customer stated that they would pay more than $25. Microsoft opted not to pursue commercialization of that digital pen. Other firms have released their own versions of the product, although great apparent success.

Because the level of consumer interest has often been unknown(and in many cases unknowable) at critical points in product development, business decisions for technology projects are often based on "macro" adoption models, such as the well-known Bass model(c.f, Bass 1969). These models are highly sensitive to assumptions about market size and adoption coefficients related to the behavioral characteristics of likely purchasers. These coefficients are themselves difficult to estimate ex ante, and a common approach is to estimate by analogy, i.e., by using the adoption coefficients from what at believed to be similar products that have already reached the market.

Marketers have a strong tendency toward choosing analogous products that have achieved some degree of commercial success, especially where similar products that have not succeeded are difficult to identify.

This general approach can bias organizational thinking in favor of products that are entrenched in engineering or management, even when evidence suggests that customers do not want such a product. A common retort is, "Of course they don't want it because they've never seen anything that can do what this will do. Once it's real, they will want it!" Lacking effective customer-level research methods, the only way to disprove this is to develop and manufacture the product. In such an environment, the role of marketing becomes one of developing channel and promotional strategies for products that are defined by engineers.

Consumer Reference Price Effects

It has long been held in marketing literature that consumers evaluate the attractiveness of a product's price relative to some reference price (Niedrich et al. 2001). Where a product is price below the reference price, the price tends to be deemed attractive. Where it is priced above the reference price, it is considered unattractive. This effect is asymmetrical; the negative impact of prices above the reference price is generally greater than the positive impact of prices below the reference price.

Two general categories of reference prices have been modeled: memory-based and stimulus-based. Each has been shown to be predictive of consumer preference.

Memory-based reference prices: These references, sometimes referred to as internal reference prices, are developed based on the consumer's previous purchases and other experience within the product space (Kalyanaram and Winer 1995; Monroe and Lee 1999; Vanhuele and Dreze 2002). In essence, the consumer develops an estimate of the dollar value of the product prior to entering the purchase process.

Stimulus-based reference prices: Stimulus-based reference prices are formulated at the time of purchase. These are references are highly dependent on cues, such as the observed prices for comparable products, and context, such as the store environment.

In general, researchers have investigated the influence of either one or the other of the reference prices. These reference prices are sometimes modeled as single values such as the weighted average of observed prices. More recent research, however, has modeled reference prices as being drawn from a distribution of values at the time of purchase (Kalwani et al. 1990; Sherif M 1958), and hybrid memory-based/stimulus based reference price models are being developed (Park et al.).

When a consumer encounters a really new product, it is believed that they seek out one or more exemplar product(s) upon which to base a reference value (Mao and Krishnan 2006). Where no environmental stimulus is available, this exemplar will be sought in the individual's memory. It will therefore be highly dependant on the individual's experience and will vary from person to person. Where the product is extremely new, this variance can result in dramatic differences in perceived value. Should researchers provide cues as to the appropriate reference set, then they may bias their results.

We have found that technology products are in fact quite sensitive to consumer experience with a related product. In studies using webcams and digital music players as the product stimuli, we found that current owners of products respond in systematically different ways than customers who intend to buy the product but do not yet own one. In general terms, it appears that owners rate features highly when they extend current use cases or apply to core product experience features, whereas intenders rate features highly when they provide new use cases. Intenders do not distinguish as clearly as owners do between crucial features and relatively insignificant features. This suggests that product experience may be informative regarding the true comparative value of the product features.

There is also good reason to believe that there exist reference feature levels. These may be construed as expected levels of performance (Love and Okada In progess). Where product features do not meet their expected level of performance, then demand drops off dramatically. When a product feature meets the expected level of performance, however, there is diminishing sensitivity among consumers to further improvements to that aspect of the product. As with reference prices, these levels of performance expectation vary between groups of consumers.

The Preference/Experience tradeoff

Features may also appeal to users even when they would have no effect on the underlying product experience. Consider, for example, that consumer webcams today offer a maximum resolution of 2.0 megapixels. In a small study with 40 respondents, we found that higher resolution (in megapixels) was the most strongly preferred of 14 potential webcam features. However, this improvement would be largely irrelevant in a new product, because Internet bandwidth, PC processing power, and USB interface bandwidth cannot stream such a video signal.

This creates a serious resource allocation problem for the firm. Should it choose to develop features that are preferred by respondents but add no experiential improvement, the product will provide lower long-term satisfaction and value. Should it choose to ignore stated preferences and develop features that it believes will most enhance product value, then the product may be perceived as deficient by consumers. Developing both types of features will make the product noncompetitive in yet another dimension: price.

In the case of the webcam (as in many other cases), the megapixel number provides a convenient measure of comparison between products. A consumer choosing between a 2 megapixel camera and a 4 megapixel camera may be assured that they are getting more megapixels with the latter than the former, which they implicitly associate with greater image detail and higher overall quality. The user preference must be reinterpreted: users are communicating that they want better video experience than current products offer, and the feature score is a measure of that desire. As researchers, we are challenged to make the correct inferences from the data.

Adapting Market Research to Novel Technology Products

The solution to these problems, we believe, is found in the combination of traditional market research techniques with the methods of user research (aka usability engineering). User research focuses on how to understand users' needs behaviorally and bring that understanding into an engineering process. In this process, product concepts begin as vague ideas and gradually become more and more specific until the final product is delivered. This approach is generally engineering focused and may occur in relative isolation from executive decision making and consumer research.

We have found that when choice-modeling is carefully integrated into user research and matched with other market research methods, product viability may be determined much more rapidly and product feature sets may be specified with greater confidence.

Furthermore, insights gained from this approach may then be rolled into macro models that may provide much more realistic adoption estimates. Where these models are developed in combination with reliable demographic, psychographic, and behavioral survey information, it becomes possible to create product performance scenarios and to test the sensitivity of such scenarios to different product, market and promotional characteristics. It also becomes possible to make predictions regarding competitive response.

Choice-based research techniques have proven highly informative in our research by helping to narrow the field of possible products and features of those products. For instance, scaling methods (such as MaxDiff) can be used to quantify customers' stated needs, dissatisfactions with current products, interest in general product concepts, and usage cases. Instead of asserting that a concept is "exciting" on the basis of speculation or focus group discussion, it can be objectively evaluated against other concepts and user needs. However, these techniques must be applied carefully; because features of new products are not well understood, customer data can be unstable and easy to misinterpret.

In one example, we conducted an online survey of 1008 respondents that asked about a novel webcam feature that would enable new use cases. We used both a conjoint format and MaxDiff format. Respondents showed significant interest in the feature in conjoint analysis ($p < .01$), as shown in Chart 1.

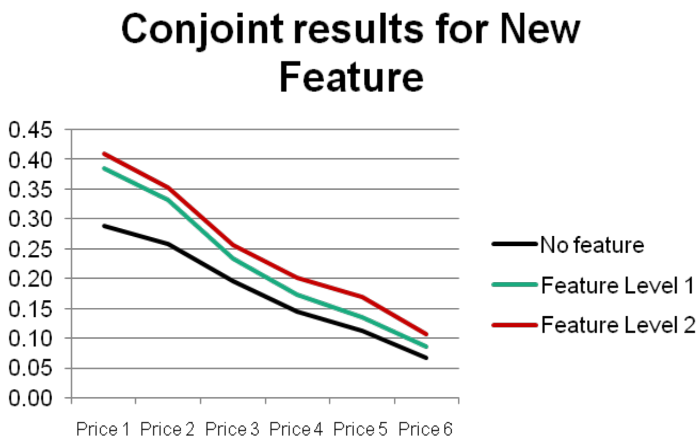

Chart 1

However, that same feature ranked 8th of 22 features in the MaxDiff exercise, as shown in Chart 2, scoring no better than would be expected from a random response set with 22 items (average scaled score of 4.9).

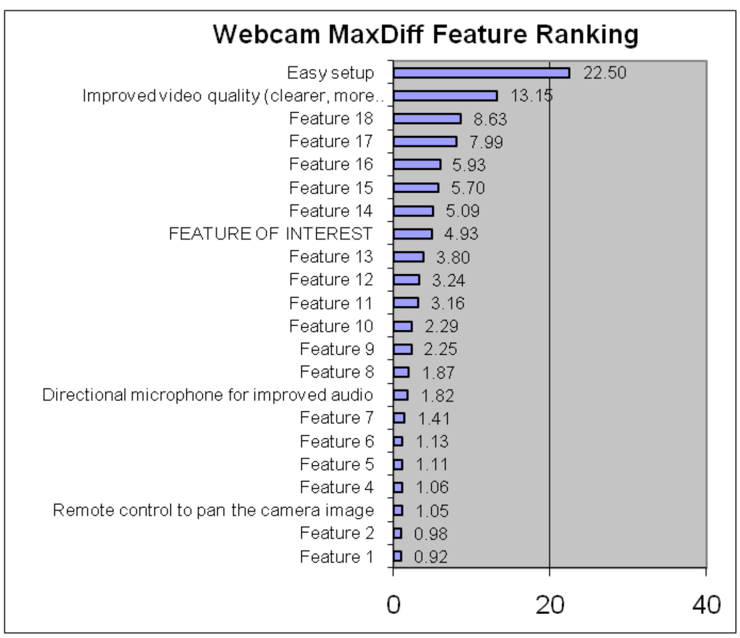

Chart 2

Such a result can appear puzzling, but is explained by four factors. First, they assessed a slightly different set of attributes between the conjoint and MaxDiff, and we may not be able to assume independence to the non-included alternatives. Second, because MaxDiff items can be non-specific they may have been so vague as to skew the results. In the present case, the top-scoring MaxDiff concept was "Easy Setup". When a concept applies to every possible customer and use case, it is not surprising that it would score well and consequently depress the scores of more specific product concepts.

Uncertainty in the product feature set implies uncertainty in the value product value proposition. Therefore, pricing research must be conducted with caution. In general, we opt to include a broad range of price levels that provide information regarding the relative impact of changes in other features. When price is considered in this way as a relative attribute, the results are not necessarily indicative of exact market pricing.

Clearly, such effects may lead to pitfalls in the interpretation of choice-based research. We therefore suggest the following general rules for applying such methods in early product research:

- Assess concepts and features in multiple ways, using multiple methods. We have found that qualitative and quantitative methods can be used together in order to achieve results that are both interpretable and actionable. Multiple methods are particularly important where features are not well understood.
- Choice-based research in the early part of lifecycle must be combined with careful behavioral analysis. Features must be rationalized with regards to real product experience, which users may not be able to anticipate. Selecting features to maximize choice preference may yield an experientially inferior product, and a "superior" product may not be maximally preferred. Make inferences regarding stated preferences where necessary.
- Careful attention must be paid to systematic differences that affect specific population subgroups. In particular, for technology products, customers who have experience in a product space may make markedly different choices than potential customers without such experience.
- Eliminate vague or poorly defined features from quantitative analysis. Such features may skew respondents' evaluations of other features. Also, response to such features may create the illusion of specific value where none exists.
- If price is used as a product attribute, determine early whether it will be used purely as a relative gauge of value, or whether it will be viewed as corresponding to actual product pricing. Investigating actual pricing of new technology products requires careful design and we believe it generally benefits from multiple measures, involving multiple methods of measurement (conjoint, willingness to pay methods, auction or allocation methods, etc.)

Future Work

The issues discussed here present several opportunities for future work. Some of these areas are suitable for research projects conducted as part of work for individual clients or projects, while others would benefit from exploration across multiple projects and clients. We suggest the following areas for investigation:

- How to apply methods for rapid prototyping in order to obtain more realistic consumer evaluations. There are several approaches available for creating consumer prototypes of technology products, including: (a) evaluation of similar existing products; (b) early engineering prototypes of a product in development; (c) creation of visual demos such as interactive user interface models; (d) construction of prototypes from platform development products (such as mocking up a mobile product using a mobile PC); and (e) information acceleration alternatives (e.g., creating 3D virtual representations of products and purchasing or usage environments (Urban et al. 1997)).
- Exploration of market segmentation models with regard to product familiarity. If, as we suggest, consumer choices are markedly affected by general technology enthusiasm as well as direct experience in a product space, then such factors should be taken into account in market segmentation. One research question here is whether such factors apply in general across many product spaces, and if so, how they may best be characterized.

- Integration of market exploration in a systematic fashion with iterative behavioral research. We postulate that market research in technology companies should be integrated with behavioral design at the earliest time of a design process. However, to date, there is no systematic model for such integration. This is the subject of an upcoming work (Chapman and Love 2008).

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