Toward a demand forecasting model for preannounced new technological products

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Abstract

This paper develops a model to forecast demand for a new preannounced technological product that builds upon existing product positioning models. Our model incorporates (i) the factors of technological ability of a firm to design the preannounced product, and (ii) the impact of the preannouncement on the product acceptance behavior of channel members and the choice behavior of prospective customers. Such behavior is governed by credibility of the firm’s preannouncement and expectations about the availability of the new product; a channel member’s decision to accept the new product depends upon the expected sales and the product’s acceptance by other channel members. These issues lead logically to the interdependence between product positioning and preannouncement decisions of the firm. Our model also examines the trade-off between development time of a technologically superior product and preannouncement of a marginally better product. We conclude with a discussion of the data required to implement the forecasting model as well as implications for the product development process, competitive behavior, and future research.

Keywords. Technological products; Preannouncements; Demand forecasting

1. Introduction

Considerable recent progress in forecasting new product demand has focused almost exclusively on frequently purchased consumer goods and new products that are essentially modifications or evolutionary innovations (Urban and Hauser, 1980). These models assume that the new product is available. Although Urban et al. (1990) presented a model for prelaunch forecasting of new automobile models that draws on the ideas of pretest market models used for packaged consumer goods, much less guidance is available for forecasting demand for highly innovative technological products or specialty goods. This guidance seems essential because of shortening product life cycles (Qualls...
et al., 1981; Goldstein, 1989) and increasing development inputs that together lead to considerable risks. Demand forecasts for a new technological product depend naturally upon the decisions of product design and other marketing mix variables and need to be developed long before the product is available in the marketplace. This problem is further complicated when a firm preannounces products with advanced technology.

Outweighing risks such as cueing one’s competitors, cannibalizing the current product line, and damaging one’s own reputation, benefits from preannouncement include better positioning of the new product, access to efficient channels of distribution, early market feedback, forestalling customer purchases of rival products, and signaling the firm’s commitment to new technology. Preannouncements could thus be used by a firm in the product development and introduction process. This strategy will also affect the product choices of potential customers and the stocking decisions made by the channel intermediaries. This paper proposes a demand forecasting model for a preannounced technological product that incorporates both technological ability of the firm and the responses of the channel members and customers to the preannouncement.

By definition, preannounced products are not yet available and it is not certain that they will ever be available! In fact, in technologically fast-moving areas, such as computer software, many preannounced products may never reach the market. The firm’s reputation instills confidence that the preannounced product will be available in the foreseeable future. The realization of the preannounced product will depend directly upon its technological characteristics.

Both customers and channel members are affected by this uncertainty. Customers must decide whether to wait for the preannounced product, while channel members must decide whether to stock the product. Both decisions depend on the perceived likelihood of availability, which in turn depends on the degree of an advancement over the existing products.

Classical product positioning models for new products assume that the product is available and that the firm can with certainty design a product with any combination of product characteristics. Our modification takes into account uncertainty about whether the promised product can be delivered by the firm and considers consumer and channel uncertainty. We propose a single product positioning/forecasting model that incorporates these considerations.

Little research has been done on the choice of products under non-availability. We will thus formulate some ideas on consumer choice models and product positioning models. Because channel intermediaries affect potential demand for a new product, their behavior must be integrated into the forecasting model. These enhancements could be achieved using established modeling and data collection procedures. The new ideas should supplement and modify traditional approaches.
2. Foundations of a conceptual model

2.1. Firms' strategies

Firms that market new technological products develop several strategies to reduce risks and investments to the extent possible in the competitive environment. In general, four different strategies are employed:
(i) imitation of competitors (Schewe, 1992) or adaptation of innovations of lead users (von Hippel, 1986, 1988);
(ii) increase efficiency using methods such as reducing development time (by simultaneous engineering efforts or by increasing progress steps than is customary) (Clark, 1990);
(iii) phased distribution of new products (Gerybadze, 1988);
(iv) preannouncement of new products long before they are available.

We believe that a trade-off exists between development time and level of technology; this trade-off is not considered in classical product positioning models.

Preannouncing new products (Eliashberg and Robertson, 1988) could reduce risk because market feedback may be valuable for the final product design and because customers may consider to buy the new product long before it is available. More important, preannouncements can be considered psychological or virtual market introductions of new products before their physical availability. This may speed up the diffusion process reaching a larger number of customers and, thus, increase the total level of distribution. Both effects are beneficial for the preannouncing firm if they are not offset by cannibalization. Preannouncements could preempt competitors, which was of consideration in antitrust litigation in the computer industry (Fisher et al., 1983). It could also influence channel members' cooperation with the firm. A U.S. study (Eliashberg and Robertson, 1988) indicated that preannouncements were aimed at sales force (84%), customers (79%) and distributors (55%); while a recent study of four German industries (automobiles, consumer electronics, photography, household appliances) found that 63% of those firms that preannounce products aim at channel members as well as consumers (Preukschat, 1992). Preannouncement could also increase the risk of product failures if it gives too precise hints of future products to competitors at inappropriate times. In the German study, 23% of preannouncing firms took measures to avoid too early information to competitors. On balance, firms using preannouncements find that their benefits outweigh the costs (Preukschat, 1992).

The observed market reactions on preannouncement will depend on the credibility of the preannouncement or the likelihood that the product will become available. This, in turn, may depend on the amount of technological advance involved in the preannounced product as compared with present capabilities of the announcing firm.
Preannouncement strategies imply that consumers who become aware of the future product offers decide to buy the preannounced product with the unavailability of the future product in mind. Unavailability can result from other situations such as products out of stock because of production shortages or insufficient distribution. It may also give rise to decision processes that are different from the standard choice processes. This difference should be incorporated into a demand forecasting model. It is not known whether unavailability is more common among consumer goods, technological, industrial, or specialty goods. We conjecture, however, that product unavailability may be more widespread for technological goods for two basic reasons: first, strategic choice open to technological firms to reduce risks will naturally lead to unavailability and secondly, the relatively high value and small degree of standardization of the latter products will prevent some products from becoming available to customers.

2.2. Customer choice under conditions of unavailability

An immediate result of preannouncement is that customers may choose among products, some of which are not currently available. It is fair to assume that a preannouncement will imply that the customer is aware of the new promised product. A customer's actual choice will depend on whether or not a close substitute to the preannounced product is available. If a close substitute exists, the new product would be considered an evolutionary innovation, otherwise, it may be considered a revolutionary innovation. These differences could cause different reactions to the product under consideration. If the new product is evolutionary, the customer shopping for the product at an outlet is most likely to substitute another product available at the same outlet or the most preferred product available at another outlet. If the new product is revolutionary, the opportunity cost of buying the second best product immediately may appear rather high. Therefore, it is likely that the purchase may be postponed. This type of product may open up a new category of goods, particularly if trade channels for related products are either unable or unwilling to cope with the new item. Thus, product unavailability leads to options for the customer that can be unified by the opportunity cost argument and are not treated in the standard consumer choice models.

2.3. Channel behavior

Channel intermediaries influence the distribution of new products by their decision whether to accept the product. Their decision may depend on the characteristics of the new product: channel members may readily accept evolutionary rather than revolutionary items. Because channels also stock products from which customers may choose, existing stock is devalued when a new
product serves some of the customers of the old product better. Channel members must decide whether to stock the preannounced product and how to market present stock affected by the preannouncement.

Little empirical research has been conducted on explaining the probability of new product acceptance, through marketing intermediaries; existing research is aimed mostly at new consumer goods (Voigt, 1983). Rao and McLaughlin (1989) found that probability of acceptance of a new consumer product by a channel intermediary is significantly and positively related to the perceived product uniqueness as indicated by buyer judgments on a 10-point scale as well as the number of competing firms that have already adopted the same product. Furthermore, there exists an insignificant relationship with a variable that measures the association of a product with a family of currently sold products, which is a measure of synergy (see also Bayus and Rao, 1989).

3. A descriptive conceptual model

The preceding discussion of preannouncement and resulting impacts on channel behavior and the customer choice is shown as a descriptive conceptual model in Fig. 1. It shows the interplay between firms, channel members and

![Diagram](image-url)

Fig. 1. A paradigm for the demand for a new technological product.
customers within a contextual framework of competitive, regulatory, or other environmental forces.

The firm's behavior is guided by choosing an optimal combination of product characteristics to attract a maximum number of customers (or to maximize sales, which is the classical product positioning objective) for a specific market entry period. In the classical product positioning model (Albers, 1988; Choi et al., 1990), the choice of optimal product characteristics is made in relation to a certain price range in the market. This is also reflected in the design-to-cost philosophy in which the firm tries to achieve, at a given development cost, certain characteristics to match the future optimal product with a certain price level. We assume accordingly that price need not be addressed as an additional variable at this stage of model development.

Product positioning is influenced by flow of information from customers and competitors as well as the technological and regulatory environment of a firm. This information is transformed into the new product development decision on a combination of product characteristics. The classical product positioning model assumes that the attainment of any combination of product characteristics has equal probability. In reality, however, firms in some markets sequentially seek small improvements while other firms make larger but riskier changes. A forecasting model would consider interdependence between product positioning and the probability of achieving the position in the characteristics space. The information on the positioning decision guides the product development, which at some time before market entry of the new product may be communicated to the customers. Thus, the strategy of preannouncement is plausible for some reduction of risk in new product launching. Therefore, its influence on customer decision making must be considered, since it may affect the product positioning decision.

Next, the decisions of channel intermediaries would be taken into account. The impact of channel members follows the arguments similar to those for customers. The conceptual model may be used to predict demand in a more formal manner. We propose a single product positioning and forecasting model that incorporates the technology, customers and channel members.

3.1. Classical product positioning model

Let us assume that individual demand of the \( k \)th customer, \( s_k \), is weighted by the probability \( w_k \) of the \( k \)th customer choosing a new product. Total expected sales \( S \) for the new product would thus be:

\[
S = \sum_k s_k w_k.
\]

(1)

In this classical model, a firm seeks to determine the characteristics of a new product so as to maximize expected sales. But the probability of choice depends
not only on product characteristics relative to those of competing products and the ideal product perception but also on belief that the firm will make the product physically available, channel acceptance (product availability), and consumer awareness of the new product. First, we consider the firm's behavior to determine the product characteristics by optimal product positioning; this may have to be modified to resolve technological difficulties in designing a new product that would match the optimal solution at a specific point in time.

3.2. Firm behavior

This part of the model involves assumptions about development of consumer tastes (Brockhoff, 1978). Basically, the product positioning model describes the probability that a customer will accept a new product based on a comparative evaluation of product characteristics.

3.3. Customer choice probability

Assuming that a customer maximizes random utility composed of nonstochastic and stochastic parts that reflect individual tastes for a product alternative, McFadden (1974) derives a relative probability of purchase of a new product, \( y \), competing with a set of \( I \) alternatives\(^1\) for the \( k \)th customer \((q_{ky})\) as:

\[
q_{ky} = \frac{\exp(u_{ky})}{\sum_{i=1}^{I} \exp(u_{ki})},
\]

where \( u_{ki} \) is the utility derived for the \( i \)th product \((i = 1, 2, ... , I \text{ and } y)\) for the \( k \)th customer. Further, let the profile of the characteristics of the new product \( y \) be \((y_1, ..., y_j, ..., y_J)\). As a first approximation, we let \( w_k = q_{ky} \) in eqn. (1). The drawback of this model due to the assumption of independence of irrelevant alternatives (IIA) may not greatly influence our decision problem, as it is relevant if product alternatives are close substitutes. In fact, McFadden suggests that his model “should be limited to situations where the alternatives can plausibly be assumed to be distinct and weighted independently in the eyes of the decision-maker” (McFadden, 1974, p. 113). This corresponds to the assumption of heterogeneous technological products, especially those called “revolutionary”.

We now assume that the utility is related to distance of a product from an

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\(^1\)The problem of identifying items competitive to new products has been the subject matter of several research studies and can be resolved using selected qualitative and analytical marketing research techniques. (For a discussion, see Allenby 1989; Rao and Sabavala, 1981; Urban and Hauser, 1980).
ideal product perception, called $d_{ky}$ for the new product and $d_{ki}$ for the product alternatives. Further, if $u_{k} = b \cdot \ln d_{ky}$ or $u_{ki} = b \cdot \ln d_{ki}$, for all $i$, the model is equivalent to standard utility models such as the ideal point model, (see Trommsdorff, 1975 for empirical evidence of this assumption). Inserting these assumptions into the expression for $q_{ky}$, we arrive at the probability measure that is used in the product positioning model by Shocker and Srinivasan (1974):

$$q_{ky} = \frac{d_{ky}^b}{d_{ky}^b + \sum_i d_{ki}^b} \tag{3}$$

and

$$S(y) = \sum_k s_k q_{ky}. \tag{4}$$

The parameter $b < 0$ is assumed to depend on a product class (Shocker and Srinivasan, 1974, p. 931; see Albers and Brockhoff, 1979, for further discussion). The maximization of $S(y)$ ignores the issue of product availability. As argued above, the probability of making a product available at a given future date depends on product characteristics.

Advertising and related communication used by a firm to convey the characteristics of the new product will lead to the customer’s perception of the product. While the research, development, and product design activities in a firm are geared toward “objective” characteristics of a product, a customer’s probability of choice is essentially determined by the product’s perceptual characteristics. Thus, physical (or objective) characteristics corresponding to the optimal perceptual position of the new product must be identified. This is often referred to as reverse mapping. In the following, we assume that the reverse mapping is possible between these two sets of product characteristics.

3.4. Technological achievement

It can be assumed that the probability of achieving a specific product position at a given point in time decreases with the necessary technological advancement. Of the many measures for technological advancement suggested in the literature, one is particularly fitting for our purposes. Dodson (1970) suggested measuring state-of-the-art technology by searching for the mini

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2 Several methodologies exist to identify the physical characteristics corresponding to an identified perceptual location (for a discussion see Desarbo and Rao, 1986). One simple transformation to model the psychophysical transformations of objective characteristics is: Perceived characteristic = objective characteristic × scaling factor. We may model the scaling factor in terms of advertising as: $1/\left[1 + \exp(-\theta_0 - \theta_1 A)\right]$ where $A$ is the advertising and other communication expenditures and $\theta_0$ and $\theta_1$ ($>0$) are parameters. In reality, these parameters may be product characteristic dependent and, therefore, characteristic-specific scaling factors may need to be developed accordingly.
mum covering sphere of technical solutions that are represented as points in a technology space similar to products in a characteristics space. Technological advance can be measured as the distance between the future technological solution point and the edge of the technological performance space. Although this is largely an industry perspective, we can adopt it for a single firm.

Difficulties in the realization of new products arise because of their superiority to the most advanced product offered by the same supplier. Thus, even if the new product does not advance the state-of-the-art of an industry, its development, production and marketing may cause great difficulties for its producer. A supplier may, therefore, denote a product \( i^* \) with characteristics \((e_{i1}, \ldots, e_{iJ})\) in order to measure the necessary degree of technological advance to meet the optimal solution to \( S(y) \).

If \( y_{js} \) are the unknown coordinates of the new product, we arrive at a distance measure for technological advance:

\[
d(Y) = \left( \sum_j g_j |y_i - e_{ijs}|^m \right)^{1/m},
\]

where the \( g_j \)'s are weights that may be necessary to make different characteristics comparable with respect to technological advance; the metric parameter \( m \) is larger than or equal to 1.

The probability of achieving the position \( y_j \) may now be expressed as:

\[
P(y) = \exp[-\gamma d(y)],
\]

where \( \gamma > 0 \) is a constant whose value depends on the R&D expenditure devoted to product development.

Whereas the choice of the metric parameter \( m \) is confined to the usual values of \( m = 1 \) (city-block distance) or \( m = 2 \) (Euclidean distance), the parameters \( \gamma \) and \( g_1, \ldots, g_J \) would have to be determined empirically using nonlinear estimation.

3.5. Search procedure

Given the above considerations, the firm's problem should now be to maximize \( S(y)P(y) \) rather than \( S(y) \). Because \( S(y) \) is not a concave function, the same is true for the product \( S(y)P(y) \). Therefore, we suggest using the same grid-search procedures or gradient methods to find the maximum with respect to \( y_j \) as those suggested by Shocker and Srinivasan (1974). Possible consequences of the new objective function are shown in Fig. 2 for a one-dimensional characteristics space.

The larger the deviation of the optimal new product position (according to the original objective function) from the technological reference product \( e_{i*js} \), the smaller will be \( P(y) \). Consequently, the difference between the optimal solution (according to the new objective function) and the technological ref-
ference product will be smaller than the difference between the reference product and the original objective function maximum. Thus, the limited possibilities of a firm to attain arbitrarily far removed positions in the characteristics space favor evolutionary innovations over revolutionary alternatives. It may be more advantageous for the firm to make available a less technologically advanced product with greater certainty than to strive for a more advanced concept with lower probability of success. This discussion shows the interdependence of product positioning decision and availability of the new product to the customer. The problem becomes more complicated if one tries to optimize $S(y)P(y)$ also with respect to time, because changes in customer preference structures as well as different competitive strategies will have to be considered.

The search procedure may be illustrated with an example. Consider the two-dimensional characteristics space in Fig. 3, which shows positions of four real products P, Q, R, and S and twelve ideal product perceptions. The ideal product positions form two distinct clusters of customers. The real products are positioned in between the two clusters and cannot really satisfy either one. If we now apply a grid search procedure to find an optimal new product position according to eqn. (1) with $s_k = 1$, for all $k$, we arrive at the position $(0.85, 0.6)$.

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3Let us assume the following concave approximation to $S(y)$: $S(y) = hy^a \exp(-\beta y)$, with $y \equiv d(y)$, which implies measuring from an artificial zero point. The optimum of $S(y)$ with respect to $y$ is $y^* = \alpha/\beta$, as can be easily verified. Let us now assume $P(y) = \exp(-\gamma y)$, with $\gamma > 0$. Then, the optimum of $S(y)P(y)$ is found at $y^{**} = \alpha/\beta + \gamma$. From this we find $y^{**} < y^*$, which concludes the argument.
Fig. 3. A two-dimensional characteristics space with ideal (•), new (○), and real (×) product positions.

(labeled as A) that will lead to expected sales of 10.69. If we assume that the present state-of-the-art is described by the real product position of product R with characteristics, \(e_i = (0.1,0.3)\) and set the parameter \(\gamma\) at a value of 0.125, we would maximize \(P(y)S(y)\) at the product position B, with \(y = (0.80,0.55)\), and the value of the objective function is 9.67, and \(P(y) = 0.90\). If we increase \(\gamma\) to 0.25 we should expect to move the optimal new product position toward the position of the product that represents the current state-of-the-art. In fact, we find that C with \(y = (0.75,0.50)\) is the best result that could be achieved; the corresponding value of \(P(y)S(y)\) is 8.82 with \(P(y) = 0.825\). The optimal new product position is quite sensitive to the value of \(\gamma\). If its value is further increased towards 0.375, the optimum is almost indistinguishable from the position of the state-of-the-art product.

4. Channel acceptance of new product

Successful stores tend to develop ideal point perceptions for new products that match the ideal point perceptions of their customers. The probability of acceptance \(Q(y)\) of the item \(y\) (operationalized as a bundle of characteristics) could, therefore, be estimated from

\[
Q(y) = \frac{1}{1 + \exp(-\beta_0 - \beta_1 S(y) - \beta_2 x_1)},
\]

(7)
where $\beta_0, \beta_1, \beta_2 > 0$ are parameters and $x_1$ is the number of earlier adopters in the channel (as in Rao and McLaughlin, 1989) or a similar measure of earlier adoption success such as the cumulated first-time buyers modeled according to the Bass-type models of diffusion (Bass, 1969). Including these channel considerations, the sales potential of a new product now becomes $S(y)P(y)Q(y)$, which can be maximized with respect to product characteristics.

Neglecting $x_1$, we would expect a pull toward the traditional model's optimum solution from the application of $Q(y)$ on $S(y)P(y)$, if the influence of $P(y)$ is counteracted by the channel decisions. This assumes that the channel members do not discount product announcements for their probability of not being met by the producers. If such a discounting does occur, it may be captured by inserting $S(y)P_1(y)$ into the estimation formula for $Q(y)$ rather than $S(y)$. Here $P_1(y)$ is specified in a manner similar to that for $P(y)$ as:

$$P_1(y) = \exp[-\gamma_1 A(y)],$$

with a different parameter value ($\gamma_1$) that reflects the credibility of the announcement to the channel members. In other words, the parameter is a measure of the channel members' expectation of the firm's success in realizing the preannounced new product.

In general, the forecast must be based on either $y$ or $y_1$, given that both values are reliably estimated. The difference may be used to evaluate costs of different distribution strategies. While one might assume that the channel members are more critical about the delivery of the new product than the supplying firms (which infers $y < y_1$), this is not necessarily true.

5. Customer behavior

Previous research by Choffray and Lilien (1978) has shown that a custom-
er's probability of buying an industrial product is influenced by awareness, acceptance (dependent on product characteristics), and group decision processes. Further, Urban et al. (1990) have shown that the stepwise modeling of purchase probability is also relevant for industrial goods. They also demonstrate that customer behavior is shaped by knowledge of the product (which, in our case, can relate to a firm’s preannouncement strategy). While we abstract from the group decision process issue, we propose a two-stage process for describing customer behavior. First, the choice probability for the new product described in eqn. (3) assumes that the preannouncement is credible. It needs to be modified by the probability of availability of the new item and the believability of the announcement. The probability of availability is essentially the probability of acceptance of the product by the channel intermediary described in eqn. (7). The probability of belief of the preannouncement by any customer can be modeled as:

\[ P[\text{Believing the preannouncement}] = \frac{1}{1 + \exp(-\delta_0 - \delta_1 y - \delta_2 X_F)} \tag{9} \]

where \( y \) and \( X_F \) are, respectively, descriptors of the new product and the firm characteristics, \( \delta_1 \) and \( \delta_2 \) are associate vectors of parameters, and \( \delta_0 \) is a scalar parameter.

Combining these elements, we arrive at the expression for the choice behavior of the customer toward the new product given availability:

\[ P[\text{Choosing new item}] = P[\text{Choice|Believability}] \times P[\text{Believing the preannouncement}] \]

Thus, the modified probability of choice for any customer is:

\[ w_k^* = q_{ky} = \frac{d_y^b}{d_y^b + \sum_i d_{ki}^b} \cdot \frac{1}{1 + \exp(-\delta_0 - \delta_1 y - \delta_2 X_F)} \tag{10} \]

Various \( \delta \)-parameters in this expression can be idiosyncratic to the customers (or segments of customers).

6. Integration of various factors

The sales forecast expression for optimization for the product positioning now becomes:

\[ S(y) = \left( \sum_k s_k w_k^* \right) P(y) Q(y) \tag{11} \]

In this formulation, we assume that product availability in the channels and belief of preannouncement by customers are independent. This can now be
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related to the forecasting of the demand. Given that \(S(y)\) enters the expression for \(Q(y)\), an iterative procedure is necessary for solving this optimization problem.

7. Data requirements

The integrative model described above requires several pieces of information for calibration. These additional inputs can be collected as part of a research project on the product positioning model by a firm or in a project for a pre-test market. Table 1 shows the data required for our model. These data can be collected and analyzed using existing methods of marketing research.

As indicated in Table 1, additional data will include the trust by channel members in the preannouncement of a new product, how these preannouncements affect channel members' willingness to accept a new product and the customers' belief of the preannouncement. These data may be collected through surveys or conjoint analysis experiments (Green and Srinivasan, 1990) designed specifically for the new product or accumulated over time across several products. We recommend extensive use of conjoint analysis and related methods. For some parameters, the analyst will be able to draw on the experiences of management personnel. Undoubtedly, data and calibration methods will be refined as this model is implemented. Appropriate techniques will need to be developed to test the accuracy of various pieces of data and estimation methods.

8. Conclusions

The demand forecasting model developed in this paper incorporates several aspects that arise when a firm follows a preannouncement strategy. While our model draws upon several existing models of product positioning and customer and channel behavior, it specifically shows the effects of preannouncing a product long before it will be available on the market. We have shown the trade-off between waiting longer for a new product that is close to the technological frontier and risking the consequences of the preannouncement and introducing a marginally better product much sooner. Dynamic implications of this model should be studied because these could suggest that small steps are more advantageous than occasional large steps in product development.

The degree to which a firm’s strategy of preannouncement is credible will undoubtedly affect the acceptance by both the channel member and customer of the new product. We have shown specific ways of including these effects in

\(^{6}\)In a recent study, we elicited judgments on a rating scale from the laboratory personnel of a software development firm on “novelty” and ability of the firm to develop several of software packages. The novelty estimates were used as proxy for \(Ay\) and the function of \(P(y)\) was calibrated. (We did not decompose the problem to the level of characteristics.) We found this process to be quite reliable contrary to the literature on direct estimates of \(P(y)\) (Schröder, 1975).
the estimation of the potential demand for new products. The submodel implicitly shows the time-dependent effects on the intermediary's acceptance of the new product.

We have treated the effects of product unavailability and consumer's beliefs of preannouncements in a probabilistic manner. But various other aspects of consumer choice are relevant for new technological products. These include consumer's tendency to restrict choice to an evoked set of items (Narayana and Marklin, 1975; Silk and Urban, 1978), differential reactions to nonavailability of preferred choice alternatives (Bettman, 1979), and budget limitations (Lancaster, 1971). Future research is needed to develop a more comprehensive theory of consumer choice that accommodates these additional factors.

Our model will need to be validated in the field, which is quite difficult and time-consuming. However, specific experiments could explore particular relationships hypothesized in this paper. For example, an experiment using student or manager subjects could examine the relationship between a preannouncement strategy and the technological improvement of a product such as computer software or a laptop computer. Such an experiment could also contrast the credibility of a preannouncement by a well-known firm versus that of a start-up firm. The results may indicate an appropriate strategy for the start-up firm that intends to develop a revolutionary product. Sales growth of computer peripherals (Meyer and Roberts, 1986) as well as high-tech start-ups (Kulicke, 1987) is largest for some optimal degree of newness that is definitely smaller than the maximum degree of newness.

The authors are presently working on empirical analyses that support individual components of the model, such as credibility estimates for preannouncements. Newer methodologies will also be needed to identify sets of items that compete with a revolutionary product and to measure them on comparable attributes (Johnson, 1986). As these and other methods are developed, a full-scale implementation of our forecasting approach will be possible. Further, our approach may require some modifications to accommodate a firm's objective of maximizing profits (not sales) and other ways of integrating consumer information such as QFD and TQM (Hauser and Clausing, 1988; Griffin and Hauser, 1992).

The current model does not incorporate the dynamic effects of the decision process of the customers, "increased attractiveness", or the idea that many technological products seem more attractive the more they are adopted (Arthur, 1988). This has considerable strategic implications. If the adoption decision can be influenced by product preannouncements, this may determine whether a new product supersedes an existing product. Timing of the preannouncement is critical. A static equilibrium model that examines these issues was presented by Farrell and Saloner (1986). However, inclusion of dynamic aspects will be an important area for future research, that may help answer such questions as: What is the effect of the preannouncement strategy on the
development time for the new product? What is the optimal time to announce
the new product's future availability? What is the trade-off between the in-
vestments in research and development expenditures in ensuring the credibil-
ity of a preannouncement? What are the appropriate ways in which competi-
tors should react to firms that preannounce products? Answers to these
questions will enhance our understanding of the interrelationships between
technology strategy and marketing strategy of a firm selling new technological
products. We believe that the models presented in this paper will provide the
basis for these inquiries.

Acknowledgments

The authors thank the anonymous reviewers of JET-M, Professors Philip
Anderson and Barry L. Bayus for their helpful comments on this paper.

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