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For most firms producing fast-moving consumer packaged goods, line extension is central to their new product development (NPD) strategy. The authors present a decision-support system for managing the NPD process in this industry, which explicitly evaluates the financial prospects of new line extension concepts. The system developed is based on an in-depth analysis of 51 new product projects launched over a three-year period at a major food manufacturer. It embodies historical knowledge about the productivity of the firm's NPD process and captures some key research and development resource inputs that can affect this productivity. It also provides shipment forecasts at various stages of the NPD process and thus can be used at new product project review gates to evaluate line extension concepts systematically. Finally, the system also can be used to improve the practice of the NPD process by enabling its users to take a product line perspective, using incremental sales evaluation, and by facilitating cross-functional and inter-project learning. Although the system has been developed specifically for a packaged food company environment, its underlying design principles are generic and applicable to a wide range of industries.

An Anatomy of a Decision-Support System for Developing and Launching Line Extensions

For most industrial and consumer product firms, successful new products are engines of growth for sales and profitability. Although there is consensus about the strategic importance of new product development (NPD), no universal formula for success has been prescribed. Firms in different industries wrestle with different competitive imperatives and formulate different strategies to succeed in the marketplace.

In Cohen, Eliashberg, and Ho (1996), we present an analytical model for managing the trade-offs between a target level of product performance and the time to market, two critical factors for success in high-technology industries (e.g., computers, packaged software). Because objective measures for product performance can be determined in these industries fairly easily, the primary objective of a design team becomes launching a product with sufficiently high performance in the shortest time possible. We also show that the ability to achieve success in this type of industry, characterized by a high rate of product obsolescence and a narrow window of market opportunity, depends on the interaction of a number of factors, including the level of capital investment to support development (e.g., use of computer-aided design and engineering), the productivity of the engineering resource (i.e., how fast it can improve product performance), the number of engineering hours allocated to different research activities in the NPD process, an appropriate choice of a target level for product performance, and time to market.

The challenges faced by firms in the packaged goods (e.g., food, detergents) industry are somewhat different. Using an in-depth analysis of 51 new products launched over a three-year period at a major packaged goods company, we observed that it is often impossible to develop objective measures of product performance. Consequently, the drivers of success of NPD for packaged goods are different from those in the high-technology industry. Firms cannot perfectly determine customer wants ex ante (especially for truly new products), so they must invest relatively more time and effort as they move through the design process to capture the "voice of the customer," so that the new product will be more likely to meet customers' needs (Akao 1992).

Therefore, the critical input resources are those that help to identify, and later to influence, customers' wants. We have

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found that these inputs include the level of experience of the new product design team leader and the amount of customer-based information collected during the NPD process. In addition, a significant amount of promotion and advertising dollars must be invested to launch such products successfully.

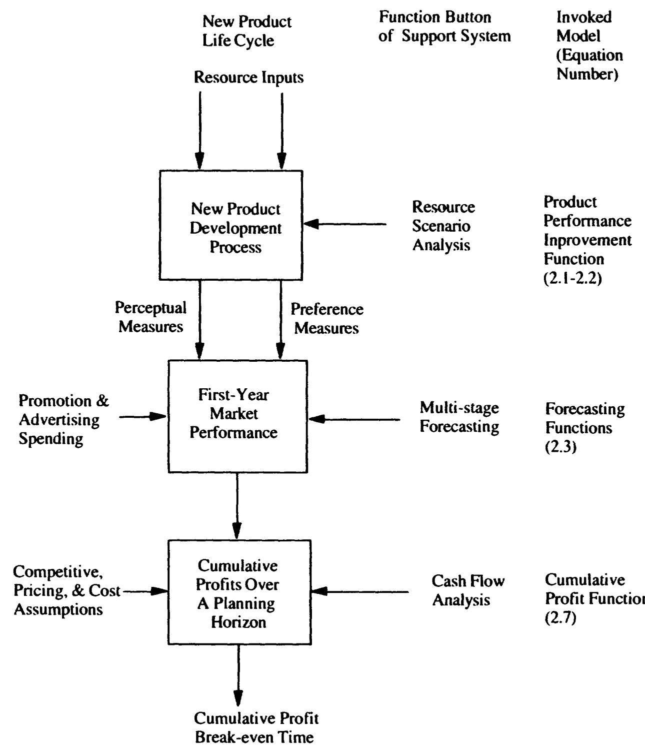
The difficulty and risk associated with determining customers' needs have prompted many firms in the fast-moving consumer goods industries to rely heavily on line extensions for stimulating demand for their brands. Indeed, a recent study of leading consumer packaged goods companies revealed that only 5% of new product introductions are new brands, 6% are brand extensions, and the remaining 89% are line extensions (Aaker 1991).[1] Many believe that line extensions will continue to be central to NPD strategy in consumer packaged goods markets (Aaker 1991). Therefore, the importance of effectively managing the line extension process is quite high. Moreover, despite the lower risk involved in line extensions, managers feel that their NPD process is successful less than 50% of the time (Group EFO Limited 1994).

One way to improve the NPD process is to rely on decision-support systems (DSSs). The use of computer-based support systems to improve decision making in marketing is not new. Several successful implementations of DSSs have been reported, supporting such activities as marketing mix (Little 1970, 1975), sales calling (Lodish 1971), retailing (Lodish 1981), consumer promotion (Keon and Bayer 1986), commercialization and communication of new products (Rangaswamy et al. 1987), new product launching (Choffray and Lilien 1986; Ram and Ram 1989), and market trends detection (Schmitz, Armstrong, and Little 1990).

We describe a DSS designed for packaged goods manufacturers to improve the evaluation and selection of new line extension concepts, the allocation of the necessary resources, and the promotion of links between research and development (R&D) and marketing decisions. The DSS is model-based and comparable to ADBUDG (Little 1970), CALLPLAN (Lodish 1971), and BRANDAID (Little 1975). Several empirical relationships, which can be developed from company historical records of line extension launches, are embedded into the system. These empirical relationships are used to predict the impact of alternative resource input mix choices on anticipated product performance and to generate sales volume forecasts at various stages of the NPD process. As a result, the system can help improve the selectivity of the NPD process so that inferior concepts can be screened out early on, thereby enabling superior concepts to be developed successfully (Kotler 1994; Wind 1982).

We illustrate how the system can be used to support a food company's line extension strategy. The article is organized as follows: First we describe the overall system design and its major functions and highlight its unique features. Next, we illustrate how the system was customized for use by the food company. The system currently is being evaluated as a basis for a corporatewide methodology to assess line extension concepts that have product-market characteristics similar to those of existing products. The process of developing it, in cooperation with the company, has already led to changes in the company's NPD procedures. We conclude by discussing the actual and likely future impacts of the system on the company, its managerial and research implications, and the conditions necessary for its successful implementation.

Figure 1
THE PS²'S OVERALL SYSTEM DESIGN



OVERALL SYSTEM DESIGN

Description of the System

The DSS we developed is called Product Portfolio Support System (PS^2). The PS^2 design is based on data available in the company and supports market research, brand managers, R&D managers, and manufacturing managers throughout the NPD process. The basic shell of the system was created in Hypercard 2.0 V2.

In Figure 1, we indicate the overall design of PS^2 and the way it supports resource allocation, as well as selection and evaluation of new product concepts, throughout the NPD process. The system has four features that are worth noting.

First, NPD is conceptualized here as a product performance improvement process. Thus, the manner and speed at which product performance is enhanced throughout the development process is modeled explicitly. This dynamic issue is often ignored in the marketing literature.

Second, our system allows for continuous assessment of a new product concept throughout its development process. As more information becomes available, the system provides updated and more accurate estimates of the prospects of the concept.

[1]A brand extension occurs when a successful product's brand name is used to enter a completely different product category (e.g., Ivory shampoo). A line extension occurs when an existing brand name is used to enter a new market segment in the same product category (e.g., Levi's Wrinkle-Free Dockers slack series).

Third, we adopt a life cycle perspective to NPD. With a given set of competitive, pricing, and cost assumptions, the PS^2 can estimate both the cumulative revenue and cost of the new product over its life cycle. In this way, the firm is encouraged to take a long-term perspective in evaluating the potential return on the investment in a new product concept.

Fourth, our experience suggests that management often focuses only on the individual new product project, ignoring product line considerations. The system developed here evaluates the performance of the entire product line with and without the new product under consideration and thus determines the incremental impact of the new product.

Our overall approach links R&D and marketing activities, thus promoting greater cross-functional integration between the two functions. Research and development resource inputs are evaluated in light of their ultimate incremental sales and profit contributions so that they are allocated to the development of the most promising product concepts. Advertising and promotion dollars are employed to launch only those products that score well with respect to product attributes and customer reactions, because they are the most likely to succeed in the market. As a consequence, we believe that PS^2 is likely to lead to the development of more effective new product strategies in the future.

PS^2's Functions

The system has four major functions: (1) product performance improvement and resource allocation analysis, (2) multistage forecasting, (3) cash flow analysis, and (4) concept ranking (see Figure 2). These functions are discussed in the following paragraphs in more detail.

Product performance improvement and resource allocation analysis. The system supports the allocation of necessary, and often scarce, development resources among competing NPD projects. This is done by assessing trade-offs explicitly through a product performance improvement function.

The underlying idea here, that the dynamics of NPD can be construed as a product performance improvement process, is not entirely new. The speed of product performance improvement is similar, for instance, to the speed of knowledge production studied by R&D economists (Griliches 1984; Kamien and Schwartz 1982). Griliches (1984) defines a firm's speed of knowledge production as the number of patents generated by the firm per unit time and shows that it increases with the firm's R&D investments.

If we measure the output of the NPD process in "units of performance," the speed of the new product performance improvement becomes similar to the speed of knowledge production used by R&D economists. The improvement function enables us to identify and quantify the relative importance of the various R&D resource drivers in improving the product's performance over time. As mentioned previously, the performance of a product in the packaged food industry is often subjective, and it is thus gauged, indirectly, by customers' preference measures (e.g., purchase intent and expected frequency of consumption) and by perceptions of the new product (e.g., taste and uniqueness).

Let R_i be the level of R&D resource input i per unit time assigned to the development process (i = 1, ..., I). Assume that product performance is gauged by a set of preference measures X_j (j = 1, ..., J) and a set of perceived performance measures Y_k (k = 1, ..., K). Denote the speeds (rates) of improvement of these measures by $\dot{X}_j$ and $\dot{Y}_k$. We chose the Cobb-Douglas forms to model the product improvement functions (for empirical support, see Bohem 1982; Ho 1993). They are given by

$$(1) \qquad \dot{X}j = K_j^X R_1^{\alpha_{j1}} R_2^{\alpha_{j2}}, \ldots, R_I^{\alpha_{jI}}, j = 1, \ldots, J,$$

$$(2) \qquad \dot{Y}_k = K_k^Y R_1^{\beta_{k1}} R_2^{\beta_{k2}}, \ldots, R_I^{\beta_{kI}}, k = 1, \ldots, K,$$

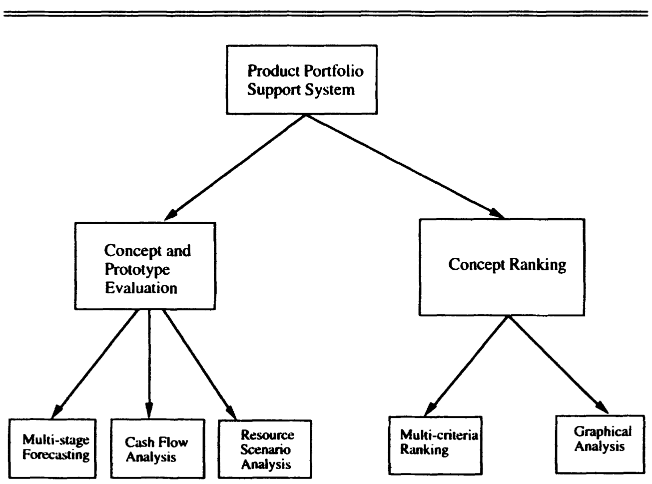
where K_j^X and K_k^Y are constants of porportionality and α_{ji} and β_{ki} are productivity parameters of resource i.[2]

Multiple-stage forecasting. The PS^2 system evaluates the prospects of a product concept during its development process. Our forecasting method combines three broad categories of methods to predict product sales (Choffray and Lilien 1986):

1. *Judgmental methods*, which include Delphi-like group judgment procedures, pooling of experts' opinions, and other qualitative forecasting techniques (Clemen and Winkler 1993; Wheelwright and Makridakis 1980).
2. *Product testing methods*, which include various pre-launch consumer focus groups, surveys, and test markets. Product samples are offered for evaluation on a test market basis, limited by geography or a selected group of targeted consumers. Prospective consumer reactions are recorded and used to forecast sales.
3. *Analog methods*, which identify similar product-market situations and assume that the way the new line extension will be accepted in the market is comparable to the way similar products have been accepted.

In our DSS, analogies and product testing methods are used to forecast initial post-launch performance (e.g., sales, shipments to retailers, profits). Judgmental methods, coupled with initial post-launch performance forecasts, are used to forecast subsequent performance. Let the sales (or ship-

Figure 2
THE FUNCTIONS OF PS^2



[2]This formulation does not imply that every resource input has an impact on every performance measure. For example, if α_{ji} is 0, then resource input i does not enter into the design production function of preference measure j.

ments) volume forecasts (in units) in the first time period after the product is launched (e.g., year or quarter) be denoted by S_1. Denote the level of marketing spending on a particular advertising and promotion method l by M_l (l = 1, ..., L). Then, we can invoke, for example, the widely accepted linear relationship:

$$(3) \quad S_1 = \theta_0 + \theta_1^X X_1 + \ldots + \theta_J^X X_J + \theta_1^Y Y_1 + \ldots + \theta_K^Y Y_K + \theta_1^M M_1 + \ldots + \theta_L^M M_L,$$

where Xs and Ys are consumers' preferences for and performance perceptions of the new product concept and prototype. These measures are collected *sequentially* as the product flows through the NPD process. In the next section, we use Equation 3 to obtain three best-fit models as more information (Xs, Ys, and Ms) becomes available at the three successive development stages.

The company's collected consumer preference measures for the new product concept include purchase intent, which is widely used in practice for sales forecasting for new products at the concept stage. Tauber (1981) suggests that the use of purchase intent to develop sales forecasts will continue to dominate in practice because of its simplicity despite the discrepancy between intent and actual behavior. Tauber (1975) shows that a concept's purchase intent relates positively to new product awareness and trial purchase but not to its repeat purchase. He concludes that a concept's purchase intent should not be used alone to make go/no go decisions at new product review gates. In addition to a concept's purchase intent, consumers' perceptions of taste and uniqueness for the concept, purchase intent for the prototype, and first-year advertising expenditure are employed in our sales forecasting equations.

The sales of the new product in the subsequent time periods (S_t, $t \geq 2$) can be estimated using the estimated first-period sales level (S_1) and managers' subjective judgments about the market environment. Denote the (unobservable) attraction of the new product by A. It is assumed that A is fixed at launch and remains unchanged throughout the life cycle. The total attraction of all other products in the category (i.e., all products except the line extension under consideration) is denoted by $TA_0(t)$. Note that the latter variable may vary over time.[3] Let D_t be the size of the product category at time t. Using the classic attraction model (Bell, Keeney, and Little 1975), we express the sales volume of the new product under consideration at time t, S_t, as

$$(4) \quad S_t = D_t \cdot \frac{A}{A + TA_0(t)}, t = 1, 2, ..., T.$$

Dividing Equation 4 by $S_{t-1} = D_t \cdot A/[A + TA_0(t + 1)]$ and rearranging terms, we have

$$(5) \quad S_t = S_{t-1} \cdot \frac{D_t}{D_{t-1}} \cdot \frac{A + TA_0(t-1)}{A + TA_0(t)} = S_{t-1} \cdot \frac{D_t}{D_{t-1}} \cdot \frac{\frac{A}{TA_0(t-1)} + 1}{\frac{A}{TA_0(t-1)} + \frac{TA_0(t)}{TA_0(t-1)}}, t = 2, ..., T,$$

where T is the sales cycle (e.g., end of the product life cycle). Let $r_t = A/TA_0(t) = S_t/(D_t - S_t)$ (from Equation 4), $r_t^o = [TA_0(t) - TA_0(t-1)]/TA_0(t-1)$, and $g_t = (D_t - D_{t-1})/D_{t-1}$. Then Equation 5 can be written as

$$(6) \quad S_t = S_{t-1} \cdot (1 + g_t) \cdot \frac{r_{t-1} + 1}{r_{t-1} + 1 + r_t^o}, t = 2, ..., T.$$

Using the recursive Equation 6 and S_1 (from Equation 3), we can estimate S_t for $t > 1$. Note that r_t is the relative attraction of the new line extension vis-a-vis all other products in the category, r^o_t is the growth rate of the total attraction of all other products in the category, and g_t is the growth (or decline if it is negative) rate of the size of the total product category at time period t. r^o_t and g_t can be determined, as in Little (1970), by using judgmental methods (e.g., pooling estimates from the appropriate brand managers). In Equation 6, r_{t-1} is computed using values of S_{t-1} and D_{t-1} obtained in the previous recursion.

We chose to rely mainly on judgmental methods to obtain r_t^o and g_t because the use of analog methods to forecast sales in the subsequent time periods presents some problems. On the one hand, products that have been launched recently are likely to be more representative of new product concepts under consideration, but sales for the distant future have yet to be realized. On the other hand, older products have all the needed sales data, but they tend to be less predictive of sales for the new product concepts under consideration, because the competitive environment for the new products is likely to be different from that of the old products. It is also worth noting that PS^2 consists of multiple forecasting equations and incorporates consumer reactions as they become available at the different stages of the NPD process. The system automatically adapts and improves forecasting accuracy by incorporating new information items into a revised forecasting equation. Thus, new product concepts can be reassessed for their potential payoff throughout their development process.

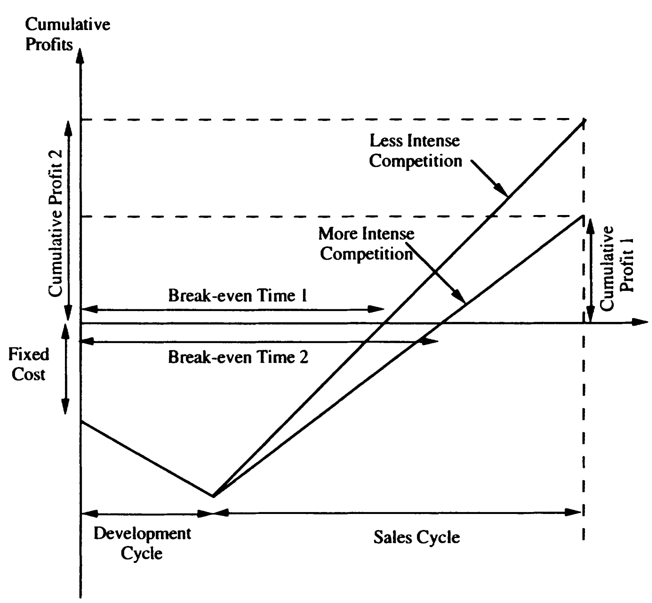
Cash flow analysis. The system also supports the construction of the so-called "well-curve": the cumulative profit projection of a product over a certain planning horizon given a set of competitive, pricing, and cost scenarios (see Figure 3). With the well-curve, it is possible to determine the cumulative profit of the product over the planning horizon. Thus, products can also be evaluated on the basis of their life-cycle profits. The cumulative profit realized by time period t is

$$(7) \quad \Pi_t = \sum_1^T (p_t - c_t)S_t - DC - MS,$$

where p_t and c_t are the unit price and cost of the product at time t, DC is the development cost, and MS is the market spending needed to launch the product. The specification of

[3]TA_0 varies over time because competitors too extend their product lines and the firm may launch more line extensions subsequently. A and TA_0 could also change as a result of changes in marketing mix. We assume A to be fixed over time here because our firm did not allocate much money for market spending to support the line extension after the first year.

Figure 3
THE WELL-CURVE, OR CUMULATIVE PROFIT PROJECTION UNDER TWO COMPETITIVE SCENARIOS



the pricing and cost scenarios are based on judgmental estimates obtained from managers. Anticipated competitive reactions (captured by r^o_t) affect sales volume S_t (see Equation 6), and hence the cumulative profits at time t.

In Figure 3, we show how this feature can enable the brand manager to evaluate the new product concept under two competitive scenarios. As a result of more intense competition, the new product is likely to have a longer break-even time and a smaller cumulative profit. The construction of the well-curve also makes it possible to generate several useful new product performance metrics, such as the break-even time and rate of return of the project. Firms frequently use these performance metrics to manage NPD. For example, Hewlett Packard's BET/2 strategy is directed toward reducing product break-even time (BET) by one-half for all its new products (House and Price 1991).

Ranking of concepts. Different criteria for evaluating a development project can be applied at different times during the NPD process in order to rank new product concepts, which involves using, for example, a concept's consumer-based scores, first-year sales, or total life-cycle profits. This feature permits the firm to change the evaluation criteria at different times to gain a balanced assessment of a new product concept. For example, a superior new product concept (i.e., high concept score) may be hard to operationalize and thus may score poorly as a prototype or have high expected unit cost. Such a concept may be rejected as a result of such an evaluation.[4]

For many line extensions, total sales may not be adequate for determining the success of the NPD process, because most line extensions cannibalize the sales of existing products in the same product category. Thus, consistent with a product line perspective, it is important to analyze the sources of sales volume to determine the incremental impact of the line extension. For mature product categories such as packaged food products, there is often little or no growth in the category volume. Thus, the sales volume of the line extension can come from either cannibalization of the firm's existing product line or reduced sales of competitive products. Our system enables users to develop an estimate of the degree of cannibalization and provides a forecast of the incremental sales.

Let $TA_f(t)$ be the total attraction of the firm's current product line (i.e., excluding the new concept) in the category in period t, and TS(0) be the firm's total shipment volume in period 0. Then, the total shipment volume of the firm in period 1 if the line extension under consideration is not launched, $TS^{no}(1)$, is

$$\text{(8)} \qquad TS^{no}(1) = D_1 \cdot \frac{TA_f(1)}{TA_o(1)},$$

$$= D_1 \cdot \frac{TA_f(0)}{TA_o(0)} \cdot \frac{TA_o(0)}{TA_o(1)},$$

$$= (1 + g_1) \cdot TS(0) \cdot \frac{1}{1 + r_1^o}.$$

If the line extension is launched, the total attraction of the firm's products in period 1 becomes $A + TA_f(O)$. Here the firm's total shipment volume in period 1, $TS^{Yes}(1)$, is

$$\text{(9)} \quad TS^{Yes}(1) = D_1 \cdot \frac{A + TA_f(0)}{A + TA_o(1)},$$

$$= D_1 \cdot \frac{A}{A + TA_o(1)} + D_1 \cdot \frac{TA_f(0)}{TA_o(1)} \cdot \frac{TA_o(1)}{TA_o(1) + A},$$

$$= S_1 + (1 + g_1) \cdot TS(0) \cdot \frac{1}{1 + r_1^o} \cdot \frac{1}{1 + r_1}.$$

Note that all terms on the right-hand side are either known or can be elicited from managers. The incremental shipment in period 1 due to the line extension is given by

$$\text{(10)} \qquad IS(1) = TS^{Yes}(1) - TS^{No}(1).$$

Equations 8 and 9 assume that Luce's choice axiom (which states that the ratio of the market shares between two existing products remains unchanged before and after the line extension) holds. Ho and Tang (1995) provide a procedure for estimating incremental sales when Luce's axiom does not hold.

The return from a new product concept in terms of total sales, incremental sales, or life-cycle profit should be assessed against its required level of development resources and marketing expense. We can easily formulate the overall resource allocation problem of the entire product line as a constrained optimization program. The objective of the resource allocation problem is to maximize the overall expected return of the product line subject to the given resource constraints.

User Interface

The PS^2 system is designed with the following principles in mind:

[4]To support managerial decision making further, the system also offers several graphical tools to allow visual comparison of new product concepts.

1. Modular: PS^2 is modular in that additional modules can be added easily. Additional empirical relationships can be added to PS^2 by using functional buttons (see the next item). This will reduce the lead time for modifying the system.
2. Button-driven: We use data and function buttons. Data buttons enable the firm to develop different levels of aggregation to view the data. For instance, a data button for unit product cost can be created if it is useful to break this aggregate cost into its components. There is no limit to the level of aggregation allowed. The function buttons invoke different embedded empirical models to analyze and evaluate product concepts. The embedded empirical models are "best-fit" relationships derived from the historical data of similar products in the product category (see multistage forecasting and resource allocation analysis).
3. Single-screen: The use of function and data buttons enables us to adopt a single screen design. By "calling" the name of a product concept, the system provides a "card" that captures all relevant aggregate data about the product concept. Additional details of a data item for the concept can be viewed by clicking the associated data button. In Figure 4, we show how the Market Spending data button is broken into its components.

IMPLEMENTATION ISSUES

Overall NPD Process

In this section, we describe how we customized the PS^2 system for a major food processor. Figure 5 is a schematic of the firm's NPD process. The development process, which interfaces with the screen illustrated in Figure 4, consists of four major steps: (1) concept development and selection, (2) prototype development and testing, (3) process development and production, and (4) promotion, advertising, and sales.

The concept development and selection step entails communicating and expressing the new product concept in terms that customers can understand and relate to (e.g., as a picture and/or a verbal description) to gauge market reaction.

The prototype development and testing stage is quite laborious and often occurs iteratively. First, initial product prototypes are assessed with an experimental design using focus groups. The reactions collected from the focus groups help to narrow the number of product prototypes targeted for

Figure 4

THE SINGLE-SCREEN DESIGN

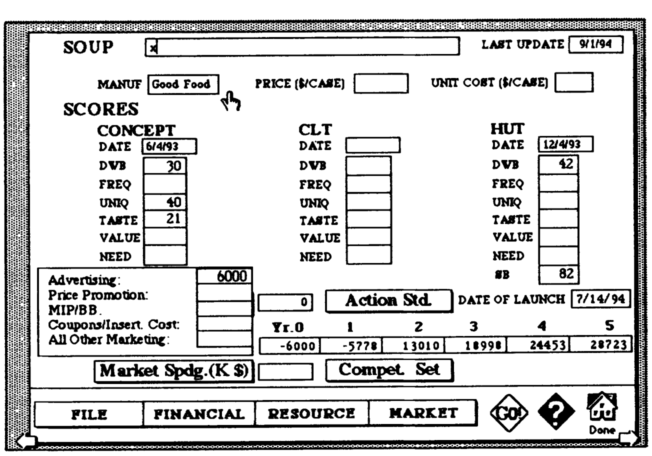
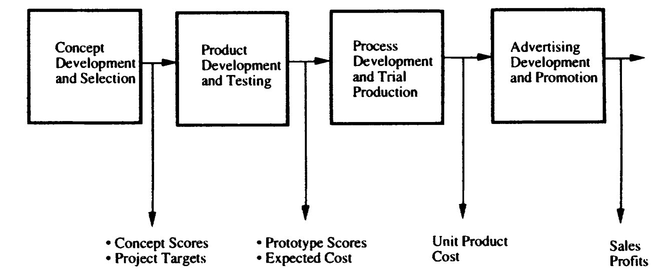


Figure 5

THE FIRM'S NPD PROCESS



further development. Various consumer-based tests are then conducted to evaluate customer acceptance for the product prototype. These include "taste and feel" surveys at central locations, such as a shopping mall, and direct consumption tests at consumers' homes. The tests generate information about consumer preferences (X_j) and perceptions (Y_k) of the proposed new product.

The process development and trial production step tests the feasibility of the proposed product for mass production and provides a more realistic unit cost estimate. The advertising development and promotion stage includes formulating plans for product launching. The plan includes selecting the appropriate level and mix of advertising and promotion to support launch of the product.

New Product Performance Improvement

Knowledge about the actual performance of a new product within a firm is often subjective and not always well defined. Thus, development teams do not know, a priori, which formulation of the product will best suit the target group of consumers. Indeed, the major objective of the NPD process is to determine the definition of a high-performance product. This is usually done by different product tests conducted during product development. These tests gather feedback and increase the chance of meeting the customer's wants.

Using the data made available to us by the company, we developed two performance measure improvement functions for the NPD process. We collected six independent variables (project scope, number of prototypes used in the focus group, sample size of the focus group, experience levels of the lead and secondary investigators, and total labor hours spent on the tests)[5] and analyzed their predictive roles on consumer perceptions of the developed prototype. Using a sample of 51 NPD projects launched over a three-year period, three significant independent variables were found: total labor hours (R_L) spent on the prototype development and testing, the sample size of the focus group (R_N), and the experience of the primary or lead investigator (R_E). Because the main purpose of the focus group is to understand the drivers of product success, as perceived by the consumer, the

[5]Project scope is measured on a nine-point scale and is judged subjectively by the R&D director. Experience levels of the lead and secondary investigators are measured by their years of experience in the food industry. Total labor hours spent on the tests is the sum of the labor hours of all members in the team. The sample size is measured by the total number of subjects interviewed in the focus groups.

total number of subjects used in the tests is a reasonable measure for the extensiveness of these tests. R_E is measured by the number of years of experience of the primary (R&D) investigator; presumably, more experience leads to better-quality information.

The two dependent variables in the performance measure improvement function are preference measures.[6] The first measures consumers' average liking for the product (i.e., the "scoreboard," $X_1 = SC$), and the second measures the consumers' purchase intent (i.e., the percentage checking "definitely will buy," $X_2 = DWB_p$) after a direct consumption test is administered. DWB_p (ranges from 0 to 100%) is measured by consumers' willingness to purchase the product when asked to evaluate the product in their own home. SC (ranges from 10 to 90%) is a measure of how much the consumers like the product.[7] Because all new products are developed under a one-year schedule to conform to an industry product-launching season, new product performance at the time of launch is used as a measure for the rate of the product performance improvement during that year. The total personnel hours expended is equivalent to the rate of the labor input. Equation 1, when applied to our data set, is thus given by

$$\dot{SC} = K_1^X R_L^{\alpha_{1L}} R_E^{\alpha_{1E}} R_N^{\alpha_{1N}}, \tag{11}$$

$$D\dot{W}Bp = K_2^X R_L^{\alpha_{2L}} R_E^{\alpha_{2E}} R_N^{\alpha_{2N}}. \tag{12}$$

In Figure 6, we show the results of the regression analyses fitted empirically to Equations 11 and 12. The parameters of the three independent variables were found to be statistically significant.[8] The total personnel year variable is less critical relative to the extensiveness of product guidance tests and experience of the primary investigator.[9]

Because all the regression coefficients are positive, the R&D resource inputs complement rather than substitute for each other. This design "production" function enables us to find the optimal mix of R&D resource inputs to be allocated to a NPD project to achieve a given level of output, either DWB_p or SC. To illustrate this, let us focus on the two more significant resource inputs, R_E and R_N, and the production of DWB_p. If the constant marginal costs for R_E and R_N are given by W_E and W_N, then it can be shown that the optimal levels of R_E and R_N obey the following ratio (Varian 1984):

Figure 6

THE FIRM'S NEW PRODUCT PERFORMANCE IMPROVEMENT FUNCTIONS

$$\mathrm{Log}(\dot{SC}) = \underset{(.0245)^{***}}{4.3495} + \underset{(.0175)^{**}}{.0348\,\mathrm{Log}(R_L)} + \underset{(.0033)^{***}}{.0348\,\mathrm{Log}(R_E)} + \underset{(.0037)^{***}}{.0123\,\mathrm{Log}(R_N)}$$

(Adj R-sq = .34)

$$\mathrm{Log}(D\dot{W}Bp) = \underset{(.0245)^{***}}{2.8874} + \underset{(.1860)^{*}}{.3263\,\mathrm{Log}(R_L)} + \underset{(.0923)^{***}}{.3611\,\mathrm{Log}(R_E)} + \underset{(.0392)^{**}}{.1188\,\mathrm{Log}(R_N)}$$

(Adj R-sq = .33)

*Statistically significant at 10% level.
**Statistically significant at 5% level.
***Statistically significant at 1% level.
+Numbers in the parentheses are standard errors of the estimated coefficients.

SC scoreboard measures how much subjects like the prototype (10–90)
DWBp percentage of subjects checking top box in a five-point purchase intent question (0–100%)
R_L total R&D labor hours involved in prototype development (in person-years)
R_E years of experience of the lead investigator involved in prototype development
R_N number of subjects involved in the focus group for soliciting feedback in prototype development

$$\frac{R_E}{R_N} = \frac{\alpha_{2E} W_N}{\alpha_{2N} W_E} = \frac{.3611 W_N}{.1188 W_E}, \tag{13}$$

where α_{2E} and α_{2N} are parameter estimates of the second regression equation given in Figure 6.

Multistage Shipments Forecasting

Nine independent variables were available for launched projects that went through all stages of the NPD process, to establish regressions for first-year shipments. They include consumer preference and perceptual measures generated during the concept test (purchase intent, expected consumption frequency, product uniqueness, expected taste, perceived value), consumers' preference measures collected at the prototype test (purchase intent, scoreboard), and the firm's marketing spending decisions (media spending and all other marketing spending).[10] The independent variables that turned out to have significant predictive power are the concept's purchase intent ($X_1 = DWB_c$), the concept's perceived taste (Y_1 = Taste), the concept's perceived uniqueness (Y_2 = Uniq), the prototype's purchase intent (X_2 =

[6]Unfortunately, the firm did not collect any perceptual measures about the product during the prototype development and testing stage. Some perceptual measures about the concept (e.g., taste and uniqueness) were collected during the concept development and screening stage, however. We could thus determine the impact of R&D resource inputs only on the preference measures collected during the prototyping stage.

[7]Customers were asked how likely they would be to buy the line extension at a store where they normally shop at a certain price point for a certain packaged size. A five-point scale is used (1 = Definitely would buy it; 5 = Definitely would not buy it). DWB_p is the percentage of subjects checking the top box (i.e., choosing 1). They were also asked to pick an expression best describing how much they liked the product overall on a nine-point scale (1 = dislike extremely; 9 = like extremely). Scoreboard is computed from subjects' responses to this question.

[8]Linear and semilog functional forms were also investigated. They did not provide a good fit of the data.

[9]R-squared drops from .34 to .29 and .33 to .30, respectively when R_L is removed from the regression.

[10]Purchase intent in the concept test is measured in the same way as that measured in the prototype test. Expected consumption frequency is measured on a five-point scale. Product uniqueness is the percentage of respondents checking the top box in a three-point scale question. Expected taste and perceived value are percentages of people checking the top boxes in a five-point scale question.

Figure 7

THE SALES FORECASTING FUNCTIONS

Concept Stage

$$\text{Sales} = \underset{(292.81)^{**}}{-932.54} + \underset{(4.34)^{**}}{14.65}(\text{DWBc} + \text{Taste}) + \underset{(5.27)^{**}}{21.48}\text{Uniq}$$

(Adj R-Sq = .44)

Prototype Stage

$$\text{Sales} = \underset{(337.13)^{**}}{-931.30} + \underset{(5.16)^{**}}{11.41}(\text{DWBc} + \text{Taste}) + \underset{(5.71)^{**}}{18.51}\text{Uniq} + \underset{(4.63)^{**}}{10.86}\text{DWBp}$$

(Adj R-Sq = .51)

Marketing Stage

$$\text{Sales} = \underset{(320.93)^{**}}{-872.38} + \underset{(4.90)^{**}}{12.85}(\text{DWBc} + \text{Taste}) + \underset{(5.82)^{**}}{13.37}\text{Uniq} + \underset{(1.48)^{**}}{2.85}\text{DWBp} + \underset{(30.88)^{**}}{79.39}\text{Media}$$

(Adj R-Sq = .66)

*Statistically significant at 5% level.
**Statistically significant at 1% level.
+Numbers in the parentheses are standard errors of the estimated coefficients.

At the concept stage, subjects were presented with a picture of the concept. The following were collected:

- DWBp percentage of subjects checking top box in a five-point question about purchase intent (0–100%)
- Taste percentage of subjects checking top box in a five-point question about expected taste (0–100%)
- Uniq percentage of subjects checking top box in a three-point question about uniqueness (0–100%)

At the prototype stage, subjects consumed the prototype at home. The following was collected:

- DWBp percentage of subjects checking top box in a five-point question about purchase intent (0–100%)

After first-year of launch, the following were collected:

- Sales first-year shipment volume (in thousands of cases)
- Media media spending during the first year of product launch (in millions of dollars)

DWB_p), and media spending (M_l = Media).[11] We experimented with various functional forms and found that the best-fit models are the linear regression models. We report on three empirical regression equations (i.e., Equation 3 with increasingly more independent variables as they are collected), which can be used to generate shipment prospects for the first-year after launch (S_l) throughout the NPD process (see Figure 7).

The first regression equation can be used to generate the first-year shipment forecast after the concept test is done for a new line extension. The second regression equation can be used to forecast the first-year shipment after both the concept and prototype tests are completed. Finally, if the media efforts are known, then the third regression equation can be used accordingly. Note that the goodness of fit increases as more information items become available over development process. At the marketing stage, we achieved an adjusted R^2 of value .66.[12]

Figure 8

PRODUCT X'S RESOURCE INPUTS AND CHARACTERISTICS

Item	*Level or Score*
Development Resources	
•Total R&D labor hours involved in prototype development (RL)	.6 person-year
•Years of experience of the lead investigator involved in prototype development (R_E)	1.5 years
•Number of subjects involved in the focus group for soliciting feedback in prototype development (R_N)	60 subjects
Concept Stage (Subjects were presented with a picture)	
•Percentage of subjects checking top box in a five-point question about purchase intent (DWBc)	30
•Percentage of subjects checking top box in a three-point question about purchase intent (Uniq)	40
•Percentage of subjects checking top box in a five-point question about purchase intent (Taste)	21
Prototype Stage (Subjects tried the prototype at home)	
•Percentage of subjects checking top box in a five-point question about purchase intent (DWBp)	42
•Average liking of subjects for the prototype (SC)	82
Promotion and Advertising	
•Media spending in million of dollars (Media)	$6.0 million

An Illustrative Example

In this section, we illustrate the use of PS^2 with data available from one real new product (X) that was launched by the firm (see the Appendix for a sample of interactions with the decision support system by the user). In Figure 8, we show the levels of various resource inputs, product and consumer testing scores, and the media spending of the product.

With the levels of resource inputs, using the regression equations given in Figure 6, the predicted SC and DWB_p are 81 and 29 (the actual scores were 82 and 42, respectively). It follows from the regression equations given in Figure 7 that the first-year shipment forecasts at the three different stages are 671K, 847K, and 913K cases, respectively. The actual shipments for the first year were 840K cases. In Figure 9, we show an illustrative set of subjective estimates of growth rates in product category, competitive, pricing, and costing scenarios. In addition, the volume of the category in period 0, D_0, is estimated to be 3,530K cases. With these subjective estimates, we can construct the well-curve for a five-year sales cycle (T = 5; note that the development cycle is one year).

[11]DWB_c and Taste are highly correlated; we group them into a single measure. The reliability of the construct appears reasonable (Cronbach's alpha = .81).

[12]Regression parameters have been rescaled to preserve confidentiality. R&D resource inputs play a significant but not as important role as media spending through DWB_p. We provide two caveats here. First, our sample consists entirely of product launches, whose DWB_p and SC scores are above certain thresholds. This "biased" sample might limit the effects of the two measures somewhat. Second, we are unable to determine the effects of R&D inputs on other product measures (e.g., Taste and Uniqueness) in the prototype stage because these measures are not collected.

Figure 9
A SET OF SUBJECTIVE ESTIMATES

Item	*Time Period* 1	2	3	4	5
Grow Rate of Category Demand, g_t	0%	0%	0%	0%	0%
Grow Rate of Total Attraction, TAo(t),r_t^o	20%	20%	20%	20%	20%
Unit Price, p_t(in \$)	25.2	20.2	19.2	19.2	19.2
Unit Cost c_t(in \$)	12.3	11.1	10.5	10.0	10.0

If we adopt the estimate for S_1 from the last regression equation, then S_1 = 913K cases. With this estimate, using Equation 6,

$$S_2 = 913 \cdot (1+0) \cdot \frac{\frac{913}{3,530 - 913} + 1}{\frac{913}{3,530 - 913} + 1 + .2} = 795\text{K}.$$

Similarly, S_3 = 688K, S_4 = 593K, and S_5 = 475K. Because S_t, p_t, and c_t are known, using Equation 7, we can compute the cumulative profit. The project is expected to break even in the middle of the second year (1.5 years from the time the product concept was conceived). The cumulative profits by the end of five years is \$28.7 million (see Figure 10).

The firm had 78% of the market share in period 0 (i.e., prior to the time period at which the new product is under launching consideration). Thus, TS(0) = 78% · 3,530 = 2,753K. Using Equation 8, we have $TS^{no}(1) = 1 \cdot 2{,}753 \cdot 1/1.2$ = 2,294K cases. From Equation 9, we obtain $TS^{Yes}(1)$ = 913 + 2,294{1/[1+ (913)/(3530 – 913)]} = 2,614K. Thus the incremental shipment volume in period 1, IS(1), is 2,614 – 2,294K = 320K cases. Consequently, 35% of the sales volume for the line extension in the first year come from reduced sales of competitive products, and 65% come from cannibalization of the firm's existing product line.

Wind, Mahajan, and Cardozo (1981) suggest that the diagnostic power of a forecasting model should be taken into account in assessing its practical value. In addition to estimating the degree of cannibalization, PS2 provides diagnostic insights into the relative impact of various R&D resource strategies on anticipated product performance. For example, the performance improvement functions given in Figure 6 suggest that if the experience level of the lead investigator is five years instead of one and one-half years, then new predicted SC and DWB_p are 84.6 and 59.6, respectively. In addition, the system generates conditional well-curve estimates under alternative competitive and environmental scenarios. These alternative scenarios can be captured by different values of r_t^o and g_t. Finally, with reliable probability estimates of these scenarios, the user can construct the risk profile associated with the rate of return for launching the line extension.

DISCUSSION

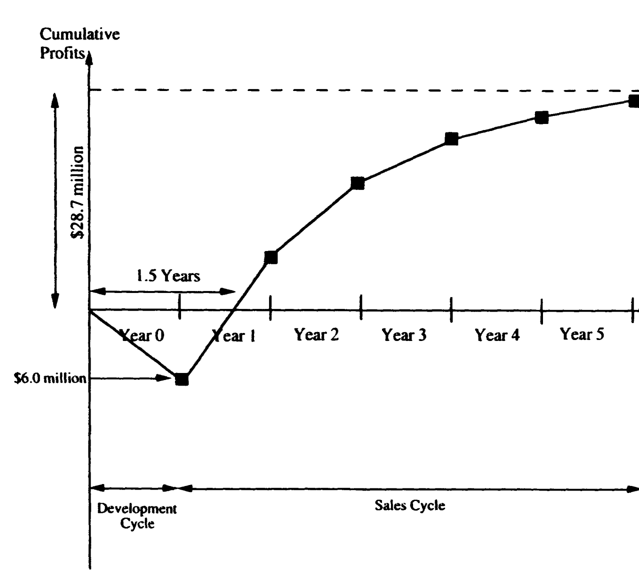
We describe the design and development of a decision support system to enhance the management of the NPD process in fast-moving package goods industries. The approach described here has had an impact on the practice of NPD within the specific application site of the food company. It has also led to several managerial and research findings, which are described in this section.

Actual and Likely Impact

Although PS2 has not been fully implemented, its principles and qualitative implications have had an impact on the food manufacturer for which it was customized. Our approach has provided this company with several links to best practices in the following ways:

1. The process of developing the system, with the active participation of functional managers and the dissemination of its results, has led to significant changes in the firm's concept and prototype screening procedures for new products. Commonly held beliefs concerning the relative predictive value of different variables, based on consumer response data, collected at different stages in the development process, have been challenged by the empirical results. Overall, the dissemination of the system concept and its empirical foundations have helped to enhance the level of rigor and consistency in the firm's NPD process across both product and geographical divisions.
2. Product strategy has been affected. The company's approach for acceptance and rejection of concepts and prototypes involves the use of a "hurdle rate" for an aggregate metric based on various consumer responses. Only those concepts and prototypes that clear the hurdle are accepted or continued. The PS2-based approach naturally leads to an overall product line perspective in which line extensions are evaluated in terms of their incremental financial impact on the existing product line (i.e., incremental revenue). As a consequence, the company has added incremental sales volume as an input to the screening process for product concepts. Ultimately, with PS2, a life cycle financial return will become required for each stage gate review of a development project.
3. The development of the system also has led to the design of a unified global product development protocol, which combines best practice from within the company with the normative insights of our model-based system as well as with observations of best practice by other leading package goods companies.

Figure 10
THE PRODUCT X'S WELL-CURVE



This global protocol, to be used worldwide, is currently being rolled out by the company.
4. PS2 can easily generate multiple performance metrics for product development. The company now has expanded its evaluation for new products to include some of these metrics. For example, rate of return and break-even time derived from the well-curve are currently used routinely by the senior managers in new product planning.
5. The role of cross-functional teams for product development has long been recognized a key factor of best practice. The development of the PS2 system indicated that there were challenges within the company concerning such integration. In particular, coordination between R&D and marketing and among different divisions has not always been effective; hence, gaps between concept and product (in terms of consumer evaluations) sometimes can arise. The system supports the use of a common database and the sharing of information across functions and divisions. It thus supports more effective team performance and is likely to lead to the elimination of such gaps. This common database is currently being implemented by the company.

Other likely impacts of the system include the following:

1. The system provides a means to specify resource allocation trade-offs explicitly. For example, the design production functions given in Figure 6 can be used to determine the optimal mix of R&D resource inputs to be allocated to a NPD project. In addition, the relative value of each resource input can now be determined by its relative contribution to product performance enhancement (see Equation 13).
2. As indicated in "An Illustrative Example," the system can be used to generate diagnostic insights concerning the impact of alternative resource, competitive, and environment scenarios. These insights can be used to better allocate the scarce development resources.
3. The system, by design, encourages the application of different forecasting and business proposition formulations at different project stages. Our empirical results indicate that the significance of sales forecasting predictor variables changes with the development stage and that information and knowledge are important drivers of product performance improvement. The system also illustrates the role of forecasting a product's life cycle performance on project management. It, therefore, can be used as an effective learning tool.
4. The system supports post-mortem analyses of failure and successes and thus can enhance organizational learning within the company across projects and over time.

Managerial Implications

From a generic managerial perspective, our work has several implications. First, it provides a framework for R&D and brand managers to understand the linkages and impact of their decisions on the success of a NPD project. With design production functions, R&D managers can now focus on key resource drivers for product performance enhancement. Similarly, sales forecasting equations enable brand managers to focus their attention on critical product performance measures for improved sales.

Second, our framework integrates information inputs from multiple stages of NPD and thus provides a systematic way to ensure that good product concepts are not "killed" arbitrarily and that only "the best of the best" products are launched at the end of the NPD process.

Third, the designed system estimates the cash flow of the project over a life cycle planning horizon, and thus new products can be evaluated for the long term on a financial basis. Simple and powerful performance measures, such as break-even time, rate of return, and net present value, can be constructed from these cash flow estimates at each stage of a project. Consequently, stage gate reviews can be carried out throughout the development process, thereby increasing the effectiveness of scarce development resources.

Finally, a product line perspective is adopted so that users can evaluate line extension concepts with respect to their incremental impact on the entire product line. This is particularly relevant in consumer packaged goods, where cannibalization often represents a significant source of sales volume for the line extension.

Research Implications

From a research perspective, we also make several contributions. First, we provide further empirical evidence for the existence of crucial concepts underlying the NPD process, such as the performance improvement function. In Cohen, Eliashberg, and Ho (1996), this function was introduced at the conceptual level and shown to be a major driver of strategic decisions such as time to market. Here we demonstrate that such functions are estimable.

Second, our modeling approach identifies research areas that have been considered separately in the past. For example, variables such as total labor hours and purchase intent were traditionally considered to belong to the operations and marketing functions, respectively. They are considered here simultaneously, and, hence, the analysis contributes to the evolving marketing/operations interface discipline.

Third, our empirical findings, though preliminary and suggestive, provide some guidance for formulating and empirically testing some interesting research hypotheses. For example, the trade-off between the sample size of the focus groups employed and the experience level of the lead R&D employee raises an intriguing empirical question about the extent to which the voice of the customer can be substituted by an experienced project team.

Finally, our preliminary findings suggest that differential attention should be given to alternate predictor variables (e.g., uniqueness, definitely will buy) at different stages of the NPD process. We can argue that scoring too high or too low on a uniqueness scale may be detrimental to the actual performance of the new product. This suggests another interesting research avenue: defining the "optimal" level of uniqueness and the stage (e.g., concept, prototype) at which it should be considered as the most critical to the NPD team.

Conditions for Applicability

The PS2 system was developed with a particular domain in mind. The new product concepts of interest here are not revolutionary in nature, so that histories of NPD projects can be used effectively to forecast sales of the new product. This assumption does not hold if a particular new product is truly new and revolutionary. Thus, our system will work well for line extension projects that frequently occur in packaged food companies. Our approach is restricted by the data set needed to derive the empirical relationships. Many firms may not collect the needed data to implement such a system; however, we believe that the benefits of a systematic and disciplined approach to NPD will outweigh the costs of such data collection. Last, the approach requires brand managers to provide estimates for the size of the product category, its growth rate, and the evolution of competitive product performance over time. These estimates may be subjective, but their inclusion forces managers to consider relevant strategic factors.

We believe that our PS[2] system can have a wider applicability. The system can easily be customized to suit other packaged goods companies. Our system will also be valuable to other industries that have the following characteristics:

- •Objective product performance measures are difficult to obtain. The NPD process, therefore, is a process of continuously testing the extent to which consumers' wants and needs are met.
- •The major investment in NPD occurs at the launch of the new product (i.e., advertising and promotion) so that new product concepts can still be killed after the prototype stage. This will increase the value of the sales forecasting equations. The potential impact of the system will be smaller if the cost of development prior to launch is a substantial part of the total cost of the new product.

Line extension represents a substantial portion of the new product activities. This will increase the predictive value of the empirical relationships derived from the existing products.

APPENDIX

We illustrate the use of PS[2] with a concrete example (see Figure 11). The four major steps, listed in likely order of usage pattern, follow:

1. *Concept Test*: When PS[2] icon is clicked or activated (recall that PS[2] is Hypercard based), the user is presented with Screen S1. Assume that Concept X has been developed and tested with potential customers. The user wants to create a record to capture these concept test scores and evaluate its sales volume prospect. Clicking the concept button in Screen S1 brings up a concept menu, one item of which is labeled NEW. Because this is a new concept, the user clicks NEW and is presented with a record template given in Screen S2. The user enters the concept name (in this case it is called X) and the test scores for the concept (DWB_C, Taste, and UNIQ). Screen S3 shows the sales volume forecast that is obtained by clicking the MARKET button and Button 1 in the forecasting menu, which consists of seven options based on information inputs. Screen S3 shows that the forecast of first-year shipments, SI at the concept stage, is 674K, 35% of which are incremental.

2. *Resource Allocation*: If the concept is selected for prototype development at the review gate, the user can test alternative resource allocation strategies on product performance measures (SC and DWB_p) by clicking the RESOURCE button. After entering planned levels for the resources, the user clicks the GO button to obtain the predicted DWB_p and SC (see Screen S4 under the HUT [home use test] column). At the given levels of resource inputs, the predicted DWB_p and SC turn out to be 29 and 81, respectively.

3. *Prototype Test:* At any time during the NPD process, new information can be added to the record by clicking the Concept button and Concept X, which is now part of the concept menu. Assume that Concept X has been tested in a home-use test. The test reveals that $DWB_p = 42$. The user enters this score. At this point, the user can provide a better sales volume forecast that makes use of both concept and prototype tests scores by clicking MARKET and button 4 in the forecasting menu (see Screen S5). As shown, the revised forecast for SI at the prototype stage is 847K, of which 296K are incremental. The user keys in planned advertising dollars by clicking the market spending button (see Figure 4). Another forecast of the sales volume can be obtained by clicking button 7 of the forecasting menu (see Screen S6).

4. *Business Proposition:* A major management tool for project evaluation is the use of a well-curve. The user constructs the project's well-curve by clicking the FINANCIAL BUTTON; the table in Figure 9 appears on the screen. The user enters alternative market growth, competitive, pricing, and cost scenarios. Activating the GO button will generate cumulative profits over a six-year planning horizon (see Figure 4).

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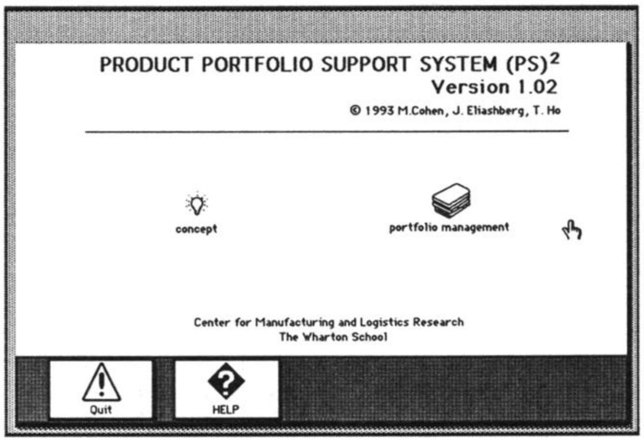
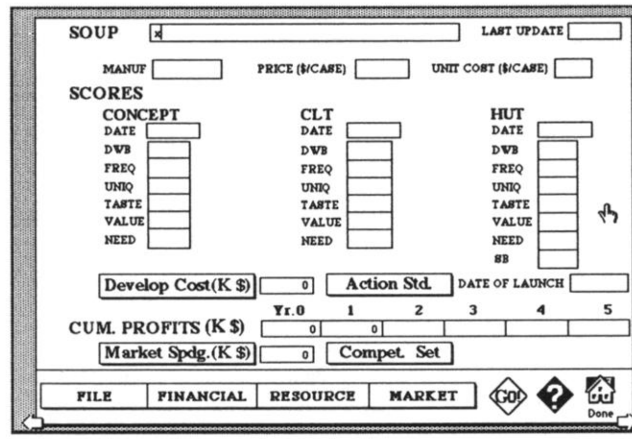
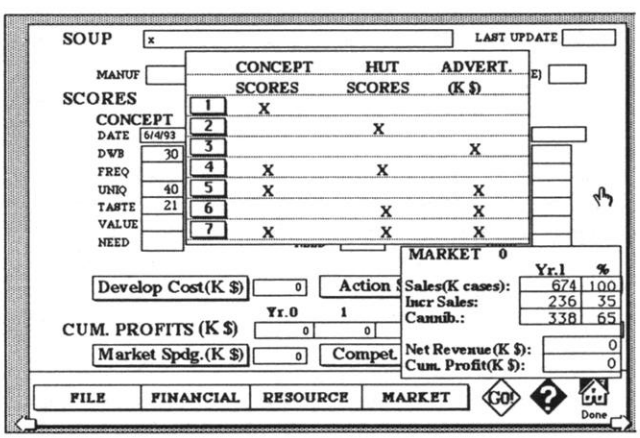
Figure 11
USAGE SCREENS ILLUSTRATION



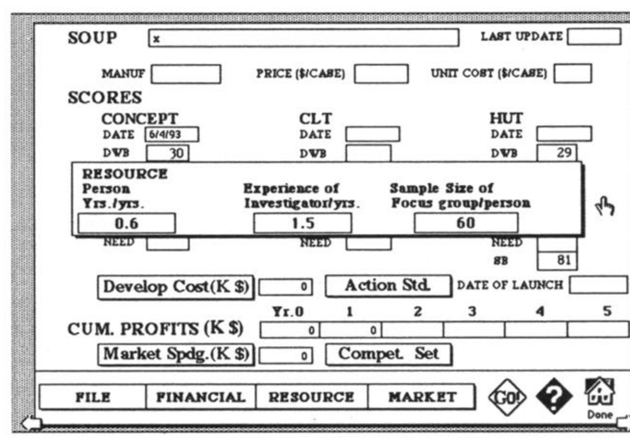
Screen S1



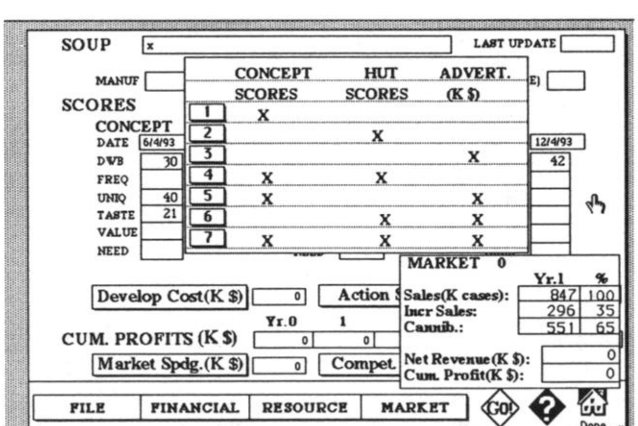
Screen S2



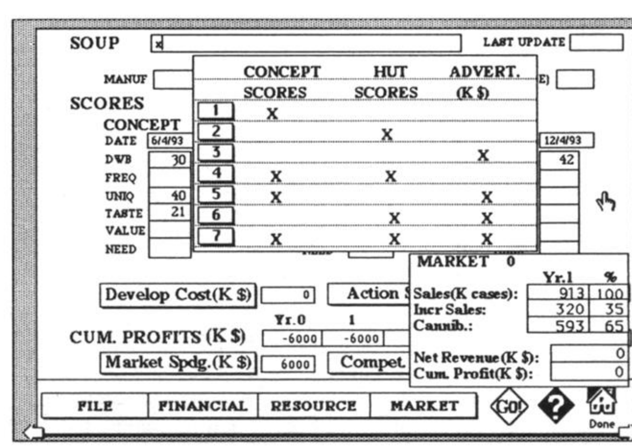
Screen S3



Screen S4



Screen S5



Screen S6

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