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Abstract

Most new product adoption models have focused on single-generation products. Only recently have researchers begun to focus on the importance of analyzing consumers' purchase demands in multi-generation products. This paper proposes a model that incorporates both initial and repeat purchases and allows for leap-frogging behavior for multi-generation technological products. Whereas most new product adoption models are based on aggregate market sales, the proposed model is estimated and validated on individual consumer data. Within a logistical modeling framework, the model combines a purchase incidence (buy/not buy) component and "generation" choice components for each time period. These model components allow for individual heterogeneity. Purchase probabilities for buyers are captured as a function of purchase history, buyer expectations of future generations, and preferences for the currently available options. The proposed model is parsimonious. It requires relatively simple data for estimation. It is empirically tested using individual-level purchase data from an illustrative pilot study in the multi-generation personal computer (PC) market. The model fits and explains individual consumers' actual purchase behaviors reasonably well.

Keywords: Consumer decision-making; Choice; Individual consumer; Purchase incidence; Generation

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1. Introduction

Since the basic model for adoption of technological innovations was introduced by Bass (1969), there has been a steady stream of research related to demand dynamics, culminating in an explosion in research activities in the recent past. However, these research efforts have typically focused on the front end of single-generation product life cycles (PLCs). Issues important in later stages of the diffusion process such as repeat/replacement sales, adoption of new generations of technology, and leap-frogging behavior have received only limited attention.

PLC analyses have important implications on resource allocation decisions governing capital, manpower, and R&D investments among inter-related product lines. In the case of multi-generation technological products, for example personal computers (PCs), as the length of PLC for each generation gets shorter it becomes appropriate to examine and model a succession of inter-related "product form life cycles" (Kotler, 1988). And, in order to develop more realistic models of market behavior, it is important to capture repeat/additional purchases of technological products (Mahajan et al., 1990a; Srivastava, 1991). Of late, some progress has been made in two research streams — multi-generation technological substitution/replacement and repeat purchase models.

Multi-generation technological substitution or replacement models typically estimate/predict sales for each generation of technological products. Technological substitution models for two generations of products, originated by Fisher and Pry (1971) and developed further by several researchers (Blackman, 1974; Stern et al., 1975; Bretschneider and Mahajan, 1980; Kamakura and Balasubramanian, 1987) fall in this category. Multi-generation technological substitution models (Norton and Bass, 1987; Mahajan and Muller, 1996) and normative models based on dynamic optimization principles that address issues such as market entry timing or pricing strategies for successive generations (Kalish, 1985; Wilson and Norton, 1989; Lilien and Yoon, 1990; Bayus, 1992; Mahajan and Muller, 1996) can also be considered to be part of this stream.

Repeat purchase models describe multiple purchases in a product category as a function of product attributes, marketing efforts of firms, and word-of-mouth impact. Typically, these models divide the population of potential adopters into several homogeneous groups according to purchase status — for example, non-repeaters and repeaters (and, within repeaters, sub-categories such as early versus late adopters). Ultimately, these models trace the movement of individuals between pre-defined groups and capture aggregate sales at a time period by adding up sales from different adopter groups (Lilien et al., 1981; Mahajan et al., 1988; Rao and Yamada, 1988; Hahn et al., 1994).

Existing technological substitution models do not consider repeat purchase for individual consumers (Norton and Bass, 1987) or assume perfect replacement of generations (Mahajan and Muller, 1996). On the other hand, repeat purchase models tend to deal with frequent purchases only. Neither model can separately describe purchase behavior of individual buyers of multi-generation technological products. The proposed model integrates these two modeling approaches into a multi-generation adoption model that captures both technological substitution and repeat purchase behaviors for individual consumers.

Because most existing models are for aggregate market behavior, this paper addresses an important objective: to develop individual-level adoption timing models. The aggregate market diffusion models based on a homogeneity assumption for consumer characteristics among potential adopters only provide information on what the market looks like in general but cannot provide insights into the variance of individual adopter behavior. Individual-level adoption models, on the other hand, capture heterogeneity in motivations for adoption based on differences in individual characteristics. This is important for a multi-generation market prediction and will enhance the scope for insights that may result in improved marketing efforts.

The purpose of the model is to help understand the factors that affect individual buying behavior for multi-generation technological products and to analyze the directions and magnitudes of those influences. In doing so, the model also confirms some of existing theories of consumers' purchase motivations (e.g., Rogers, 1983; Zaltman et al., 1973) in the context of technological product markets. More specifically, this paper proposes an individual-level purchase logit model that captures adoption and substitution patterns for successive generations of technological products.

As individual-level adoption models intend to predict purchase timing, it is theoretically sound to incorporate the consumer's technological expectation and leap-frogging behavior (i.e., skipping over generations of technology in expectation of an improved future product) into a multigenerational adoption model (Weiss and John, 1989). Analyzing the pattern and motivation of leap-frogging behavior is also managerially important because it will help firms determine the optimal launch time and marketing mix of successive generations (Doyle and Saunders, 1985). Additionally, leap-frogging analysis provides a significant input for effective resource allocation among multiple generations in terms of the timing of R&D investment, pre-announcement, and advertising/promotion (Eliashberg and Robertson, 1988; Brockhoff and Rao, 1993; Urban et al., 1993). For example, leap-frogging may explain why pre-announcements of new items forestall purchases of current products even though the current products are technologically advanced and are affordable (Weiss and John, 1989; Bridges et al., 1995).

Despite these theoretical and managerial implications, the literature on the leap-frogging phenomenon or technological expectation is relatively sparse for multi-generation product markets (Balcer and Lippman, 1984; Gatignon and Robertson, 1985). Again, this is partly because most existing studies on generational dynamics are based on the aggregate diffusion modeling framework (e.g., Norton and Bass, 1987), which does not incorporate customer expectations of future technologies (Bridges et al., 1995). The current research attempts to fill in this gap by drawing on individual-level multi-generational adoption modeling. The proposed model incorporates both initial and repeat purchases at the individual level and allows for leap-frogging behavior. These behaviors are modeled as a function of derived buyer expectations of newer generations of PCs on dimensions such as price and performance relative to the product generation currently owned as well as a function of consumer characteristics such as technology sensitivity, price sensitivity, and annual income. The model fits the purchase timing and the purchase probabilities for each generation of multi-generation technological products at the individual level.

The proposed model is parsimonious and requires relatively simple data (e.g., purchase histories (type/generation of PCs purchased, prices paid, and purchase timing), and some individual attitudes) for estimation. The model is estimated and tested based on multi-generation IBM-compatible and Macintosh market survey data. It yields reliable parameter estimates and reasonable fit to each individual consumer's (re)purchase history. This is an important contribution because most existing models deal with aggregate behavior only and, thus insights related to population heterogeneity are lost.

This paper is organized as follows. The next section furnishes the assumptions for our model development with a review of prior research on individual-level new product adoption models. In Section 3, we develop the proposed model. In Section 4, we discuss data collection and design for model calibration and estimate the model using data on individual purchase histories for multi-generation PCs. In Section 5, we validate the model by (i) examining model construct and validity of variables and (ii) showing the 1- year-ahead model fits. In Section 6, we discuss contributions and managerial implications of the current study. Finally, we present the limitations of our model and provide future research directions.

2. Assumptions for a multi-generation adoption model based on individual-level approach

In this section, we provide and discuss assumptions for our model development and compare them with those of the existing individual-level adoption models.

First, we assume that K_t options are available to potential buyers in a technological product market at time t. The buyers may purchase any one of the K_t options (generations) or may postpone their purchase. The main reasons for not buying any option could be one or more of the following: (i) consumers could wait for future options that are expected to perform better than those presently available (in the multi-generation product markets, e.g., the PC market, this waiting behavior is called "leap-frogging"), (ii) they may wait until the prices of the available options decrease to more acceptable levels, or (iii) they may wait because they want to amortize the cost of a recent purchase in the product category.[1] When the consumers do not buy any of the incumbent selections, they are assumed to be willing to accept the inconvenience caused by not having any of the product selections available at that time. This is a trade-off between the inconvenience and the expected performance/ price of the future selections. The buyers' decision to postpone purchase is simply treated as another option, resulting in $K_t + 1$ possible options at time t. We refer to this last alternative as the purchase-postponement option.

Previously, Roberts and Urban (1988) developed a Bayesian updating procedure for information uncertainty about a specific brand and developed a risk-adjusted utility function. Here, uncertainty/risk is mitigated by information search that, hence, affects brand purchase probabilities. Using a logit formulation, they describe the probability of choosing a specific brand for each time period, which leads to a dynamic market share forecast. However, because their model focuses on uncertainty reduction associated with only one brand, it would have to be modified to handle a multiple-generation setting (where each generation is treated as a "brand").

Second, we assume that individual consumers are utility maximizers in purchasing specific options (including the purchase-postponement option) at time t and that the buy/not buy decision and choice of generation occur simultaneously. The logic is that when consumers consider a PC purchase, the buy/not buy decision is usually affected by the availability of PC generations. For example, the decision to replace an existing PC depends on how much better new models are relative to the one owned within the individual consumer's price range. If the consumer finds available alternatives unsatisfactory, he will postpone the purchase until prices come down or until a more desirable PC generation becomes available.

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[1] Consumers could also wait simply because they do not need the product at all. But, if we deal with only the potential purchase population, this reason is inappropriate. So the proposed model does not include this kind of waiting.

When consumers do decide to buy a PC, it is reasonable to assume that they have a specific generation in mind. We therefore assume that the distribution of disturbance term for the purchase-postponement option is the same as that for the other product generations. This leads us to a multinomial logit model formulation.

Contrary to our assumption about simultaneous decision-making, Weerahandi and Dalal (1992) have developed a two-stage individual choice-based model where customers face purchase occasions according to a conventional aggregate new product adoption model and at each purchase occasion they buy according to a binary choice model (buy or not). They deal with population heterogeneity in purchase probabilities via customer-specific demographic variables. However, these demographic variables are dummy variables representing the identity of a group to which a customer belongs, resulting in a segment-level estimation (not an individual-level analysis as in our model).

Third, we assume that the utility of all options is conditional on the most recent purchase. For example, a consumer who already owns a PC386 machine tends to assess other PCs available in the market relative to the PC386 in terms of performance and income-adjusted price (Phister, 1979; Gordon, 1990; Horsky, 1990; Hitt and Brynjolfsson, 1994). If he finds an appropriate option, he will buy it. If he is not satisfied with any of the available PCs on their performance/price or he reasons that he bought his PC quite recently so the second PC is not immediately needed, he does not have to purchase a PC at this time — he will postpone the purchase and wait.[2] This relative performance/price of one generation of PC (to be purchased) over another generation (the owned PC) is captured in the model by a conditional utility function. That is, the most recent purchase is assumed to be a good proxy for a reference point for the next purchase (Kahneman and Tversky, 1979; Kameda and Davis, 1990).

Similarly, Lattin and Roberts (1988) posit in their study that a consumer will adopt a new product if his risk-adjusted utility is greater than the utility from maintaining the status quo (without the new product). They assume a distribution for the difference between the utility expected from the product and the utility from the status quo to derive the number of the potential customers who will adopt the product at any time period. Although their model predicts the timing of the buying decision, it does not explain which option to buy, resulting in only a binomial (buy/not buy) decision model.

Fourth, the purchase probability of a product generation (say, generation j) at time t is assumed to be influenced by the cumulative number of adoptions of the generation until that time (see C_{jt} and C_{jt}^2 in Eq. (2) of Section 3). We have two reasons for including the cumulative number of adoptions of the generations into the utility function formulation. (i) Communication (file exchange, co-work on programs) with other PC users will be much easier if they own the same PC generation. This is because computer files and programs are dependent on software compatibility and most software operations are dependent on the PC generation (for example, Windows and Excel run better on the PC386-compatible machine or more advanced generations). Therefore, we assume that the utility of a generation can be enhanced by the proportion of adopters who use it. (ii) Psychological utility may increase due to lower perceived risk associated with products that have broader acceptance. The increase in each individual's utility due to network externalities (e.g., compatibility with other users, lower perceived risk associated with leading

[2] From now on, we use the term "generations" instead of "options" or "selections" for the proposed model development, which is for the multigeneration technological products.

formats or standards) associated with growth in the installed base (i.e., number of adopters) has been widely recognized (Katz and Shapiro, 1985, 1986; Esser and Leruth, 1988; Shurmer, 1993; Thum, 1994).

In addition, we adopt a concave form ($a_{11}C_{jt}+a_{12}C_{jt}^2$ in Eq. (2) of Section 3) for the effect of the cumulative generation adoption, expecting a negative coefficient for its square term (C_{jt}^2). We contend that the cumulative adoption of a generation will affect utility positively in the early part of the generation's life cycle and negatively in the later part of the life cycle. This is because of the influence of technological substitution — a new generation's market expansion (Norton and Bass, 1987) and an older generation's image of being relatively out-of-date. This logic is similar to that of Mahajan et al. (1984) in that the word-of-mouth effect for a new product/generation increases while the product dominates the market but it starts to decrease when a newer product/generation with a reputation superior to the existing one is introduced. Carpenter and Nakamoto (1989, 1990) also suggest a concave form based on the logic that pioneering advantages (for example, a reputation effect) will increase with product uniqueness in the early stages of a product's (generation's) life cycle but decrease again after similar (or better) competing products are introduced. This change in the word-of-mouth effect is well captured by a concave form.

Finally, we assume that the utility for the purchase-postponement (leap-frogging) is affected by four factors: (i) performance/price expectations of future generations relative to existing options (Phister, 1979; Gordon, 1990; Hitt and Brynjolfsson, 1994), (ii) the timing of past purchases, (iii) the cumulative adoption of the product category (all generations), and (iv) buyer attitudes. When the expectation of the performance/price ratio of future generations is greater than the performance/price ratio of any generation currently available, the utility for the purchase-postponement option is relatively high. De Jonge and van Veen (1976) examined purchase behavior based on buyers' purchase histories and future expectations and concluded that the gap between satisfaction with the current option and anticipation based on future options is a motivation for a new purchase. Further, in the case of repeat purchases, the longer the time since the last purchase, the stronger the desire for and likelihood of upgrading and, therefore, the lower the utility for the purchase-postponement option (Bayus and Gupta, 1992). Issues related to inter-purchase time are enumerated in Helsen and Schmittlein (1993). Also, if a potential buyer has not yet bought any generation (i.e., when modeling an initial purchase), social pressure is expected to increase with the cumulative adoption of the product category (Mahajan et al., 1990b) and the utility for the purchase postponement will decrease. In addition, consumers' individual attitudes may influence purchase timing. We have included three buyer attitude variables (technology sensitivity, insensitivity to new product information, and price sensitivity) that influence the tendency to wait for future generations (i.e., choose the purchase-postponement option). Although Bayus (1988, 1991) conducted an exploratory study to examine how replacement purchase behavior is influenced by a buyer's existing technology and price preferences, choice models that incorporate these variables explicitly have yet to be implemented. Clearly, development of models incorporating purchase history and price preferences will help capture heterogeneity across customers.

3. The model

In this section, we develop a purchase timing and generation choice model for initial and repeat purchases of multi-generation technological products using an individual level approach. Based on the assumptions in Section 2, the proposed model has a logit formulation where the purchase probability for the j-th generation conditional on prior purchase of generation i is:

$$P_{jtn|it'} = \frac{e^{U_{jtn|it'}}}{\sum_{k=1}^{K_t+1} e^{U_{ktn|it'}}} \tag{1}$$

where $P_{jtn|jit'}$ is the probability of purchasing generation j at time t given the last purchase was generation i at time t' for a potential buyer n, $U_{jtn|jit'}$ is the utility for purchasing generation j at time t given the last purchase was generation i at time t' for a potential buyer n, for i=0 to K_t, j=1 to K_t+1[3], t=1 to T (discrete time periods in the model) and n=1 to N (total sample size of potential buyers).

Eq. (1) models the conditional likelihood of purchase of a generation of technology given prior purchases. This approach is consistent with using individual purchase histories to explain repeat purchase behavior (e.g., Jones and Zufryden, 1981).

We capture the utility for a potential buyer n to choose one of the K_t generations that are available (the formulation for the purchase-postponement option, K_t +1, is presented subsequently) conditional on the buyer's most recent purchase from K_t +1 options (0, 1, 2,. . ., K_t; generation 0 represents non-ownership) by Eq. (2) below. If a buyer purchases the product category for the first time, the "most recent purchase" of the buyer is the non-ownership or 0-th option. This allows the proposed model to include the initial purchase as a special case of repeat purchases. The utility function formulation for choosing any one of the available generations (i.e., not choosing the purchase-postponement option) at time t is given by:

$$U_{jtn|it'} = (b_{0jtn} - b_{0itn}) + a_{11}C_{jt} + a_{12}C_{jt}^2 + \varepsilon_{jtn|it'} \tag{2}$$

where $b_{0jtn} = b_j/(\text{PRICE}_{jt}/\text{INCOME}_{tn})$, $b_{0itn} = b_i/(\text{PRICE}_{it}/\text{INCOME}_{tn})$, b_j is the performance of generation j, b_i is the performance of generation i, PRICE_{jt} is the price of generation j at time t, PRICE_{it} is the price of generation i at time t, INCOME_{tn} is the annual household income for individual n, C_{jt} is the cumulative number of adoptions of generation j till time t, a_{11} and a_{12} are coefficients, and $\varepsilon_{jtn|it'}$ is the Gumbel-distributed disturbance term, i.i.d., for j=1 to K_t, i=0 to K_t, t=1 to T, and n=1 to N.

In Eq. (2), b_j represents the performance parameter for generation j (under consideration) and b_i is the performance parameter for the most recently purchased generation i.[4] Then b_{0jtn}, given by dividing the performance parameter of the generation (b_j) by its current income-adjusted price for consumer n at time t ($\text{PRICE}_{jt}/\text{INCOME}_{tn}$), is presented as the performance/price ratio of generation j at time t. This type of performance/price ratio is frequently used for technological product markets, especially in the computer industry, to measure relative performances of the different models/generations (Phister, 1979; Gordon, 1990; Hitt and Brynjolfsson, 1994). As is clear from Eq. (2), the performance/price ratio (b_{0jtn}) changes with the time period even though the performance parameter (b_j) is constant because the price of the generation (PRICE_{jt}) changes with time t. It is also varies across individual consumers since each individual has different value of INCOME_{tn}. This is one of the factors that provide for consumer heterogeneity for the model. Similarly, b_{0itn} is the performance/price ratio of the generation i at time t. This approach incorporating performance, price and income is consistent with the logic that choice

[3] Option (generation) zero, non-ownership, is used to describe only prior purchase conditions (here, i), not a current purchase option. On the other hand, option/generation K_t +1, purchase-postponement, is used only as a current purchase option (here, j), not as a prior condition. Again, generations 1 to K_t (actual available generations at time t) are used to describe present purchase options as well as last purchase conditions

[4] The current prices in this model are projected (fitted) ones. More details are discussed in Section 5.3.

probabilities are influenced negatively by price (Guadagni and Little, 1983; Tellis, 1988; Tellis and Zufryden, 1995), that higher prices retard replacement behavior in the context of consumer durables (Bayus, 1988), and that higher incomes lead to higher repeat purchase probabilities (Jones and Zufryden, 1981; Bayus, 1991).

The term $b_{0jtn} - b_{0itn}$ in Eq. (2) can be interpreted as the relative performance/price ratio of generation j to generation i at time t perceived by potential customer n. A reasonable buyer is likely to purchase one of the new generations that has the best performance/price ratio. Accordingly, in estimating performance parameters, which affect purchase probabilities, we can expect the estimated value of b_j to be larger than that of b_i if generation j is an upgraded version of generation i in its functions or performance. The effects of the cumulative number of generational adoptions (C_{jt} and C_{jt}^2 in Eq. (2)) are based on the assumptions in Section 2.

Because consumers pondering a purchase/upgrade decision are likely to evaluate the available generations on their performance, prices, features, and reputation, the utility for the purchase-postponement option (K_t+1) at time t is represented in Eq. (3) as a linear combination of the relative performance/price ratio of expected future generations, the time since the purchase, three attitudinal variables, and the cumulative adoption of the product category:

$$\begin{aligned} U_{K_t+1,tn|it'} = {} & (b_{0Etn} - b_{0itn}) + a_2 T^*_{tn} + a_3 CT_t \\ & + a_4 TS_n + a_5 II_n + a_6 PS_n + \varepsilon_{K_t+1,tn|it'} \end{aligned} \qquad (3)$$

where b_{0Etn} is the income-adjusted expected performance/ price ratio of future generations, T_{tn}* is the time since the last purchase for individual consumer n at time t, CT_t is the cumulative adoption of product category at time t, TS_n is the technology sensitivity of individual consumer n, II_n is the information insensitivity of individual consumer n, PS_n is the price sensitivity of individual consumer n, a_2, a_3, a_4, a_5, and a_6 are the coefficients, $\varepsilon_{K_t+1,\text{tnjito}}$ is the Gumbel-distributed disturbance term, i.i.d., for i=0 to K_t,[5] t=1 to T, and n=1 to N.

Here, b_{0Etn}, the income-adjusted expected performance/ price ratio of future generations, is assumed to be increasing with time because consumers expect higher performance/ price ratios for generations as they are upgraded. This implies that larger values of $b_{0Etn} - b_{0itn}$ in Eq. (3) result in a higher probability of waiting. T_{tn}* in Eq. (3) represents the time since the last purchase for individual consumer n if the purchase at this time is a repeat purchase. This captures the pressure on owners of current generations of technology to update products via "repeat" (or replacement) purchases as in studies of innovation adoption timing based on the hazard function approach (e.g., Sinha and Chandrashekaran, 1992). The social pressure to make an initial purchase for first-time buyers is captured by CT_t, the cumulative adoption of the product category, and buyer attitudes are included based on the three variables — TS_n, II_n, PS_n — as discussed in Section 2.

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[5] The performance/price ratio for a consumer's "non-ownership" status (i.e., a null most recent purchase) is represented as b00tn in Eqs. (2) and (3). This is the case when the consumer has not yet bought any generation and the purchase at this time is the initial purchase. In the model estimation b00tn and b0, the performance parameter for "non-ownership," are set equal to zero, implying that there is no performance-related utility associated with not owning a PC. However, this is simply for estimation convenience without loss of generality. We can set any value for this "non-ownership" status and estimate other performance parameters relative to this value.

In summary, we developed the proposed model based on two utility function specifications, one for choosing available generations (Eq. (2)) and the other for the purchase-postponement option or decision to wait for a future generation (Eq. (3)). After substituting Eqs. (2) and (3) into Eq. (1), we estimated the model (Eq. (1)) based on the maximum likelihood principle.

4. Empirical test of the proposed model

In this section, we present an empirical study based on the model developed in Section 3. First, we describe the data collection procedure and the final data form used for model estimation. Second, we show the model estimation results using the data from 1980 to 1992.

4.1. Data collection

Actual model estimation was based on four generations of IBM-compatible PCs (PC86/88, PC286, PC386, PC486) and three generations of Macintosh (Apple, Mac and Mac II series). For this purpose, we developed a questionnaire and sent 370 copies of the questionnaire by mail to randomly selected SOHO (small-office/home-office) business owners listed in the American Home-Based Business Association Directory. These SOHO business people make their own decisions on the model and generation of PCs to buy and pay for the purchases themselves. We also asked in the questionnaire that they report only the PC purchases that were for professional (business) purposes.

A total of 141 responses were received, resulting in a response rate 38.1%. Upon elimination of respondents with missing data on variables used in the model, we ended up with 129 responses, which are used for the model estimation. The questionnaire was composed of four sections. The first section focused on the respondent's PC usage behavior and the decision-making process/purchase attitude for his/ her most recent PC purchase. Variables from this section were used to estimate the price sensitivity factor (PS_n), one of the individual attitude variables in Eq. (3). The second section dealt with the respondent's PC purchase history. The data on the PC generations bought, prices paid, and purchase timing are available from this section. The third section deals with personal attitudes that yielded the technology sensitivity (TS_n) and information insensitivity (II_n) factors in Eq. (3). The last section of the questionnaire covered personal demographics.

4.2. Design of panel-type data set

As it is directly related to the multi-generational choice context, we explain the second section of the questionnaire (PC purchase history) in further detail. First, we asked about the most recent PC purchase regarding (i) the year of purchase, (ii) brand name, (iii) model/processor type (providing seven alternatives to choose from: PC86/88, PC286, PC386, PC486, Apple, Mac, and Mac II series), (iv) the price paid, (v) peripherals/options purchased at the same time as the PC, and (vi) purchase outlet. Then, we repeated the same set of questions for the next to the most recent purchase and two earlier purchases. To clarify, if the respondent had bought only one PC, he/she was supposed to answer for the most recent purchase case only. In this way, each respondent may describe a maximum of four cases of PC purchases.

To convert this purchase-history questionnaire into a panel-type data set, we first generated a time-series horizon over 1980 to 1992 for each individual respondent and provided seven choice options (models/generations) to each individual for each year, resulting in 1677 records of data (13 periods multiplied by 129 respondents) containing seven variables. We added one more option—purchase-postponement— to each record so that each respondent had altogether eight options to choose from. For example, if a respondent bought a PC286 in 1986 and Mac II in 1991, this consumer is considered to choose the purchase-postponement option from 1980 to 1985 and then to choose PC286 in 1986 and again select the purchase-postponement from 1987 to 1990 and then Mac II in 1991, and finally he/she is supposed to take the purchase-postponement option for 1992.

Through this procedure, we have built a panel-type time-series data set that can be used in our model estimation. It contains the PC purchase history data and the attitude variables for each of 129 individual consumers, covering 13 time periods for each consumer (1980–1992), and 8 PC generations (including the purchase-postponement option) for each consumer and each time period. Even though this is not a "real" panel data set, it is a highly recommended type of data design for the case of non-frequently purchased product categories such as technological durables (Hsiao, 1986). Other time-dependent variables in the model — cumulative number of adoptions of generations (C_{jt} in Eq. (2)), and price, income, inter-purchase time (T_{tn}* in Eq. (3)) and cumulative adoption of product category (CT_t in Eq. (3)) — were included in each individual record. Finally, buyer attitude variables — TS_n, II_n, PS_n, which are of the cross-sectional type, were pooled to the time-series data by adding them to the corresponding respondent's record across the years as suggested by Hsiao (1986).

4.3. Model estimation based on the data

The model estimation program is written in SAS using the non-linear least square (NLIN) procedure. The estimation results of the model are presented in Table 1.

In Table 1, we see that parameter estimates of the proposed model are quite reasonable.

First, as mentioned in Section 3, the non-ownership performance parameter (used for the last purchase condition only; b_0 in Table 1) is set to zero. The performance parameter for the first generation PC (PC86/88), b_1, is fixed arbitrarily at 5 so that performance parameters for other generations are estimated as relative values. This allows us to capture more stable estimation results than if the case b_1 was unconstrained. Because b_4 represents the performance parameter for the most recent generation in the IBM compatible PC market (that is, for PC486 machine), it is expected to be larger than the performance parameters for the previous generations. As a consequence, we expect $b_4 \geq b_3 \geq b_2 \geq b_1$ in the PC market and $b_7 \geq b_6 \geq b_5$ in the Macintosh market. The results in Table 1 support expectations regarding the sizes of performance parameters (except for b_2, which is statistically insignificant).

Table 1: Parameter estimates for the proposed model

Parameter	Definition	Estimated values

	Performance for	
b_1	PC86/88	5.000 (given)
b_2	PC286	1.601
b_3	PC386	12.107*
b_4	PC486	51.280*
b_5	Apple series	5.010*
b_6	Mac series	5.018*
b_7	Mac II series	16.953*
b_0	non-ownership	0.000 (given)
	Coefficient for	
a_{11}	cumulative adoption of generation (C_{jt})	0.001
a_{12}	cumulative adoption of generation (C_{jt}^2)	-0.001*
a_2	purchase time interval (T_{tn}*)	-0.100*
a_3	cumulative adoption of category (CT_t)	-0.007*
a_4	technology sensitivity (TS_n)	-0.841*
a_5	information insensitivity (II_n)	-0.417*
a_6	price sensitivity (PS_n)	0.001

*Indicates that the parameter is significant at $p < 0.05$

Second, as in the fourth assumption in Section 2, it is worth noting that a_{12}, the coefficient for the quadratic term of cumulative adoption of a generation (C_{jt}^2), is estimated to be negative and is statistically significant. Hence, the inverted-U shape effect of the cumulative adoption on the utility of a specific generation (discussed in Section 2) is confirmed empirically.[6]

Third, as discussed in Section 3, CT_t, the cumulative adoption of category is included to represent the social pressure to make an initial purchase for first-time buyers and T_{tn}*, the purchase time interval, reflects the repeat (or replacement) purchase pressure for upgrading. Accordingly, as T_{tn}* and CT_t increase, the utility (consequently, the probability) of purchase-postponement decreases. Hence, the coefficients a_2 and a_3 are estimated to be negative in Table 1.

Fourth, technology-sensitive persons are likely to upgrade more frequently and are expected to have a lower utility for waiting (see related discussions in Rogers, 1983, p. 258). So a_4, the coefficient of TS_n (technology sensitivity of individual consumer n), is estimated to be negative. If a consumer is insensitive to information regarding new products/ generations (i.e., does not care how or why it works and merely wants to "get the job done"), he is likely to buy/ update earlier because informational inputs are less critical (Rogers, 1983, pp. 258 and 260). Hence, a_5, the coefficient for II_n (information insensitivity of individual consumer n), is estimated to be negative as expected.

On the other hand, price-sensitive persons will shop around to find better deals and are likely to wait for lower prices (Rogers, 1983; Horsky, 1990, pp. 260 and 259). Accordingly, the probability of purchase-postponement is high for these buyers. Therefore, a positive sign is expected for a_6, the coefficient of PS_n (price sensitivity of individual consumer n). In Table 1, a_6 is estimated to be positive as expected, but it turns out to be statistically insignificant. The validity of these attitudinal variables is discussed in Section 5.2.

[6] For estimation purposes, a discrete time analog is used so Cjt is measured by the cumulative number of adoptions of generation j until time t–1.

In sum, although estimates for three parameters are not statistically significant (b_2 for PC286 performance, a_{11} for the linear effect of cumulative adoption of a specific generation (C_{jt}), and a_6 for price sensitivity (PS_n)), all have expected signs and reasonable magnitudes when compared to coefficients with significant effects. All other parameters are significant and have expected signs and magnitudes. Consequently, the estimation results support the model and are consistent with our previous discussion in Section 2.

5. Model validity

As we discussed the validity of data in Sections 4.1 and 4.2, we also focus on the model validity in this section. We first discuss the model construct and the validity of model variables. Next, we provide the 1-year-ahead model prediction based on five consecutive years of hold-out samples.

5.1. Model construct and variables

The major factors of the model are (i) the relative performance/price ratio among the available options and expected future generation, (ii) social impact for the first and repeat (replacement) purchases, and (iii) buyer's attitudes to purchase.

First, by including the relative performance/price ratio in Eqs. (2) and (3), our model captures both the upgrading and downgrading purchase behavior in a flexible manner. For example, a PC486 owner could buy a PC386 machine for simple clerical work. This downgrading purchase has not been captured by the previous repeat-purchase framework or technological substitution models, which assumed structurally the upgrading or replacement by newer generations (Norton and Bass 1987; Mahajan et al., 1990a; Bayus, 1991). This also adds consumer heterogeneity to the model as discussed in Section 3.

Second, based on the logic in the previous studies by Carpenter and Nakamoto (1989, 1990) and Mahajan et al. (1984), our model captures a concave form of the word-of-mouth effect evidenced in Table 1. This social impact between adopters and non-adopters of technology generations is also consistent with that suggested by the aggregate diffusion models (Norton and Bass, 1987; Mahajan et al., 1990).

The third variable group — buyer's purchase attitude variables — has been continuously researched in the literature dealing with the impact of adopter characteristics on the innovation adoption (Rogers, 1983). Our model also includes these attitudinal variables as important covariates that explain individual consumers' purchase timing. One validity issue arising from including these individual specific variables is that they are measured at the micro level whereas other variables such as CT_t (cumulative adoption of category in Eq. (3)) and C_{jt} (cumulative adoption of generation *j* in Eq. (2)) are based on macro (industry)-level data. This is closely related to the issues of (i) measurement error of independent variables and (ii) combining individual heterogeneity into choice modeling. For the measurement error, although there have been studies on estimation biases caused by heterogeneous variance distributions for different levels of variables (Levi, 1973), the literature generally supports the combined regressors approach for predicting the dependent variable (McCallum, 1972; Kennedy, 1989). Practically, this approach of combining macro- and micro-level variables is used in forecasting because researchers would be willing to accept some possible biases than suffer from huge errors by omitting either group of the variables (Makridakis et al., 1983; Kennedy, 1989). On the heterogeneity issue in choice modeling, there have been efforts to combine individual variables and market variables and to show that a maximum likelihood estimation procedure based on logit modeling provides reliable estimates (Guadagni and Little, 1983; Dalal and Klein, 1989; Manrai, 1995). Based on this literature, we may contend that our model estimation could be valid and reliable even though it is not totally free from possible biases. Three constructs of the attitude variables and performance/price issues are discussed further in the following.

5.2. Factor analysis for the consumer attitude variables

The three attitudinal variables (TS_n, II_n, and PS_n) in Eq. (3) were obtained by two separate runs of principal component analysis with varimax rotation. The first analysis was based on 20 five-point Likert-scaled items concerning personal attitudes toward adoption of new technologies. Four factors that explained 46% of the variance of the original items were retained based on the scree test. Among these four factors, we identified two that were meaningful for the proposed model (technology sensitivity (TS_n) and information insensitivity (II_n)). The second analysis was based on 10 five-point Likert-scaled items on a consumer's decision-making attitudes related to the most recent PC purchase. Based on the scree test, three factors jointly explaining 56% of variance of the original items were selected. From the three factors, we identified one dimension that was relevant for the proposed model (price sensitivity (PS_n)). The three factors for the proposed model (TS_n, II_n, and PS_n) and the original items with corresponding factor loadings are represented in Table 2.

Table 2: Factor analysis on attitudinal and purchase decision variables

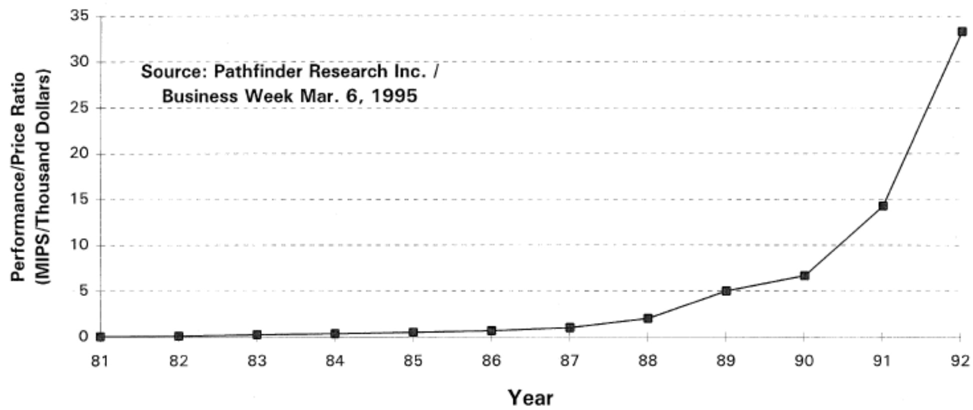
Factors	Items loading on factor (factor loadings)
Technology sensitivity (TS_n)	I am one of the first to become aware of new technologies/products. (0.79580) Because I like to have the latest and best equipment and features, I am likely to upgrade high-tech products sooner than others. (0.73920) I am one of the first to purchase new technologies/products. (0.81106)
Information insensitivity (II_n)	Learning new ways to do things does not excite me very much. (0.56791) It is enough for me that something gets the job done; I do not care how or why it works. (0.71482) The best way to learn something is by "getting your hands dirty." (-0.59170)
Price sensitivity (PS_n)	I visited retail stores to examine and compare different brands. (0.68934) I "shopped" around for prices. (0.65760) I put a lot of effort into deciding whether or not buy a PC. (0.74494)

5.3. Performance and price variables

5.3.1. Expected performance/price ratio of future generations (b_{0Etn})

The income-adjusted expected performance/price ratio in Eq. (3) is calculated from the market expected performance/ price ratio adjusted by each individual's household income per annum. The market performance/price ratio was obtained from the industry data where it is measured in MIPS (millions of instructions per second) per dollar (see Fig. 1). For purposes of model estimation, we use the next year's market performance/price ratio as the expected value for the purchase-postponement option.

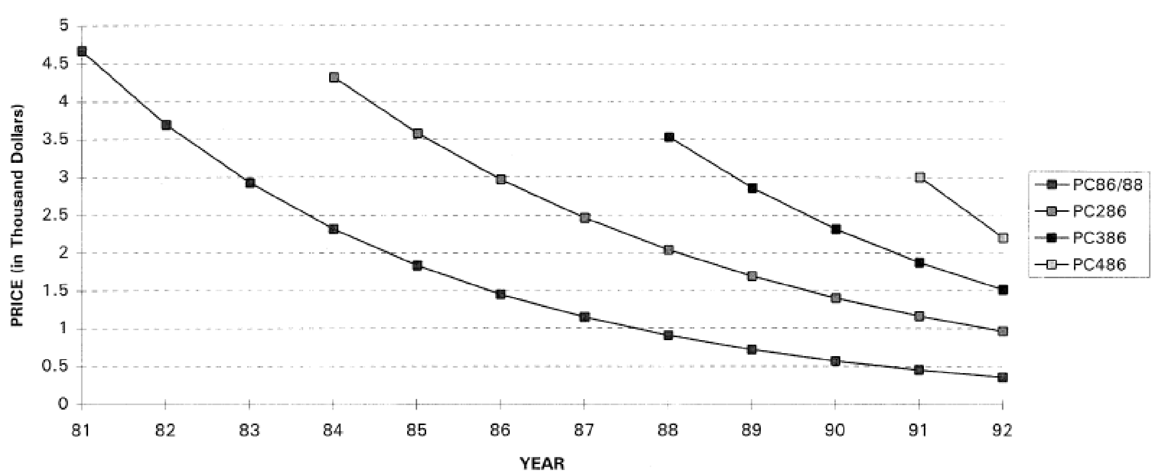
Fig. 1: PC market performance/price ratio



5.3.2 Prices of PCs

As was briefly discussed in Section 3, income-adjusted performance/price ratios in the equations for utility are computed by dividing estimated performance parameters by individual consumers' income-adjusted actual prices. Unfortunately, the definition of a PC's price was different from person to person. For example, some included several peripherals in the PC purchase price whereas others only included the central processing unit (CPU). Because individual price estimates were not comparable, we used externally projected price estimates. As is common practice in forecasting demand for durable products such as PCs, TVs, VCRs and other home electronic appliances (see Bayus, 1992, 1993), price trends were captured as an exponential function of time. Projected price trends for IBM-compatible PCs and Macintoshs are presented in Figs. 2 and 3 based on industry data.

Fig. 2. Projected price trends for IBM-compatible PCs



5.4. One-year-ahead prediction of individual purchase behavior

Finally, to validate the predictive power of the model, we performed 1-year-ahead predictions of individual consumer's PC purchase behavior. Using the parameter estimates from the model, we predicted the next year purchase behavior for each consumer on different PC generations. For example, for each individual consumer, we used the parameter estimates obtained from 1980 to 1991 data to predict purchase behavior for 1992 and the parameter estimates from 1980 to 1990 data to predict purchase behavior in 1991, and so on. We exhibit the predictive power of the proposed model by calculating the hit ratio between the actual versus predicted purchases (and non-purchases) for each PC generation. The results are presented in Table 3. Table 3 shows good hit between the predicted versus actual purchases except in the case of purchase-postponements. This is because we have relatively few actual PC purchases embedded in our data. For example, if a consumer's initial (first time) purchase is a PC386 in 1991, he/she is considered to have "bought" the purchase-postponement option continuously from 1980 to 1990. As a result, the model has difficulty in fitting this "loyalty-to-purchase-postponement" behavior. This kind of phenomenon can occur often in the technological and durable product markets where purchases are infrequent. In Table 3, we also see that some prediction errors are overstated for cases when a new generation was launched in the year for which predictions were made. This is to be expected since the estimation sample (ending the previous year) did not include that (new) generation option. Hence, this new generation option is often predicted as a purchase-postponement option in the 1-year-ahead forecast. When this is compared to the actual data for the forecasted year, the newly launched PC generation purchases are counted as prediction errors.

Table 3. Performance of the model in 1-year-ahead prediction of individual PC purchases (and postponements)[a] (measured by hit ratio between the actual versus predicted adoption status)

	Hit ratio in predicting the PC purchase of the year (in %)				
PC generations	1992	1991	1990	1989	1988
PC86/88	100	99.1	98.1	97.0	90.0
PC286	98.3	97.3	97.2	92.8	97.7
PC386	94.1	85.0	97.2	95.9	98.8[b]
PC486	88.1	90.3[c]	NA[d]	NA	NA
Apple series	100	100	100	99.0	100
Mac series	98.3	91.2	95.3	92.8	93.0
Mac II series	95.8	92.0	94.3	91.8	89.5[e]
Purchase-postponement	76.3	60.2	82.1	69.1	68.6
Total	93.9	89.4	95.5	92.3	92.2

[a] Based on 129 respondents and 8 options of the PC generations (including wait-for-expectations); a "hit" is when there is a match for actual and predicted states (for both purchase and postponement).

[b] Hit ratio is underestimated since PC386 was not available in 1987.

[c] Hit ratio is underestimated since PC486 was not available in 1990.

[d] This PC generation was not available (NA) at that time.

[e] Hit ratio is underestimated since Mac II series was not available in 1987.

6. Discussion and managerial implications

In this paper, we have developed and empirically estimated an individual-level initial and repeat purchase logit model that captures adoptions and substitution patterns for successive generations of technological products. In this section, we first examine the contributions of the current study by comparing our modeling approach to existing models in terms of assumptions, comprehensiveness, and implementability, and then we discuss the managerial implications of our model.

First, the proposed model includes both technological substitution and initial and repeat purchase phenomena, providing a more comprehensive scheme than previous models that deal with either technological substitution or repeat purchase only. Generally, repeat purchase models have been used to explain market penetration of nondurable products. On the other hand, technological substitution or replacement models have been developed to describe substitution among generations of technological products. Different research directions of the two areas show the difficulty of combining the concepts of repeat purchase and product generations. Our approach, in this respect, successfully integrates the two concepts of repeat purchase and multiple product generations using a dynamic choice model where generations are dealt with as “brands” to be selected and the choice is repeatedly permitted over the time periods. More succinctly, the proposed model integrates brand-choice and purchase-timing models to provide a framework for multi-generational dynamic choice modeling. In doing so, the proposed model captures various types of purchase behavior such as initial purchase, replacement, simple additional buying, technological upgrading, and leap-frogging. Such constructs are often ignored in aggregate models of multi-generation adoption processes. Hence, unlike existing approaches, the proposed model incorporates the timings of initial, repeat, and technological upgrading purchases.

Second, in the individual-level (micro-modeling) approach context, the proposed model has several advantages over the previous studies in this area. Previously, Chatterjee and Eliashberg (1990) explained one-time purchase only and included only one dimension, the amount of information for adoption, to describe consumer heterogeneity in purchase behavior. The suggested model is more consistent with individual heterogeneity assumptions as it includes individual attitudinal variables (technology sensitivity, information insensitivity, price sensitivity), annual household income, and inter-purchase time, which have specific values for each individual consumer. In addition, by using the income-adjusted price of the consumer, the proposed model shows that the generation specific performance/price ratio changes over time and across individual consumers.

Third, the proposed model builds upon the Lattin and Roberts model (1988) in that it expands the utility comparison between the new product and the status quo (in the Lattin and Roberts model) to utility comparisons between any two different generations, including the purchase-postponement option to provide a motivation for leap-frogging behavior. As a result, by introducing the concept of relative performance/price ratio among multi-generation products, the proposed model includes the Lattin and Roberts model as a one-generation buy/not buy choice situation. Also, the proposed model also builds upon the Chatterjee and Eliashberg model (1990) because it includes the social utility (demand inter-dependency) effect, social pressure for purchase, and the performance/price ratio concept to allow for “risk hurdles” and “price hurdles.”

Fourth, the proposed model uses easy-to-obtain data on PC purchase times, models, and consumers’ purchase attitudes. As demonstrated, such information can be readily assimilated via surveys. Based on these data, we generated a panel-type purchase history for each individual consumer and each PC generation option at every time period. Traditionally, panel-type purchase history data are not used in technological/durable product markets because such data are very difficult to obtain. The proposed model is successfully estimated based on the utility maximization principle using survey-generated panel- type purchase data.

In addition to its contributions to the literature, the current research has important managerial implications. First, the proposed model explains the motivation of leap-frogging behavior because it allows an individual consumer to choose a "future generation" or the purchase- postponement option in every time period. In doing so, it helps managers select profitable target markets to expedite sales based on the current technology (for example, marketing managers may well focus on more technology-sensitive and information-seeking groups such as research institutes or scientific professionals as their major target markets).

Second, by analyzing purchase timing and relative purchase probabilities, our model provides a guideline for determining the optimal launch time and marketing mix of successive generations of a product. Specifically, our study demonstrates that mangers could extend a relatively old generation's life cycle by a heavy price promotion of the generation targeted for technologically less-sensitive or non-professional customer groups. Recently, this strategy has been used by many PC manufacturers. For example, in facing the maturity stage of a generation, they usually set in place a basic model market with a huge price-cut for late adopters who do not need sophisticated additional functions.

Third, managers are cautioned that some strategic variables will affect the competition among generations whereas others may influence the total market potential across generations. From Eqs. (2) and (3) and Table 1, we have found that price promotion for a specific PC generation may contribute to increasing its market share but will not expand the total market potential for all PC generations. This is because the effect of price sensitivity is not significant in explaining potential consumers' purchase timing. In addition, we also note that a market penetration pricing strategy may work better than a skimming strategy for multi-generation markets in the sense that continuous price-cuts will be more effective during the stage of sales growth. The reason is that the price promotion of a generation is supposed to increase its sales, which again increase the choice probability of the generation through a positive word-of-mouth effect (Eq. (2) and Table 1). This effect is salient until the peak of generation sales; after the sales peak, the effect of a price-cut is offset by a negative word-of-mouth effect based on the image of an obsolete technology.

Fourth, our model is quite useful in capturing heterogeneity in individual consumers' purchase behaviors and in providing insights into their future purchases. Insights into future purchase behavior of individual customers based on their purchase histories have important implications for customer management and database marketing, especially since the model captures changing customer preferences for each PC generation. Such analyses are essential in guiding resource allocation decisions across generations in multi-generation technological product markets. In relation to this customer management issue, the purchase time interval in the proposed model also provides a meaningful managerial implication. Because a long-term purchase time interval increases new sales opportunities in the form of upgrading and/or replacement purchases, marketers are well advised to keep track of the sales data for each of their current customers. Intensive promotion programs targeted for "potential upgraders" will encourage their purchase decision and, consequently, increase sales of the currently available generations.

Finally, our individual adoption model can be extensively applied to the purchase of multi-category/multi-generation technological products for which consumers make infrequent purchase decisions. For these products, individual consumers are assumed to maximize the "value per dollar" with their choice sets for each purchase occasion. Replacement/upgrading purchases and leap-frogging behavior are usually observed in these product industries. Examples of such industries include (i) the wireless telecommunications industry where consumers may choose from the pager, CT2 (Cordless Telephone 2), and the cellular phone services, (ii) the home entertainment industry where the VOD (Video-On-Demand), satellite TV, and the cable TV technologies compete for a higher market share, and (iii) the display monitor industry that provides various sizes of Braun tubes and LCD monitors for PC users.

7. Limitations and future research

The current study/model is not without limitations. These limitations, however, could provide directions for future research in multi-generation choice dynamics.

First, the proposed model estimates the parameters without segmenting the total population in order to capitalize on the information content represented by individual heterogeneity. While the proposed model provides a reasonable trade-off between theoretical soundness and practical implementability, segment-level models are inherently more tractable and estimable. Future research may include segmenting consumers into manageable numbers of groups and calibrating the model based on each group segment. This approach will also render comparative analyses possible between heterogeneous customer groups in terms of consumer demographics, purchase incidence, and product knowledge. Chatterjee and Eliashberg's (1990) study sheds light on this area of research where they have incorporated each individual consumer's purchase information requirement as a basis of grouping. Future research results in this area will help multiple-generation line managers forecast and respond to different consumer reactions by heterogeneous consumer groups. Consequently, they may contribute to developing strategic planning for selected target markets based on a company's competitive assets and competencies (Aaker, 1998).

Second, we did not compare the results of aggregating individual consumers' purchase occasions with market sales patterns to examine the external validity of the model. This is because the 129 individual consumers seemed too small a group to represent multi-generations of the US PC market. Further, a few illogical outliers from the reasonable purchase behavior can make the aggregation results quite misleading. While we do not provide a comparison between the actual market sales and aggregate fitted/predicted market sales, we do describe the dynamics of individual consumers' purchase behaviors and successfully fit their purchase patterns based on heterogeneous purchase histories. Related to the first issue above, this aggregation issue may also be tackled by sensible market segmentation. Even though Chatterjee and Eliashberg (1990) and Urban et al. (1993) demonstrated their aggregation procedure based on consumer experimentation results, generalizability and implementability still remain difficult issues. Research efforts combining individual purchase forecasting into aggregate sales diffusion in multi-generation markets are highly desirable.

Finally, our model does not incorporate the impact of strategic variables other than price. The current and lagged effects of advertising, customer services, and channel support are not dealt with in the model despite their theoretical/managerial significance in multi-generation technological product markets. Besides, the model may be extended to include the effects of different features/ benefits of PCs that are currently captured by a single performance parameter for each generation. For example, the performance of each generation can be represented as a function of its RAM size, CPU capacity, hard-disk size, and bus speed. This extended model will provide richer explanations on an individual consumer's trade-off between his/her benefit-seeking and affordable prices. Again, it also could offer a market segmentation scheme based on the benefits sought by consumers. Developing a comprehensive framework that includes the impact of these important strategic options on purchase occasions is recommended for future research.

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