Alleviating feature fatigue of multi-generation products

Jinze Chai, Liya Wang, Quanlong Shi and Mingxing Wu
Department of Industrial Engineering and Logistics Management, Shanghai Jiao Tong University, Shanghai, China

Received 30 March 2015
Revised 17 June 2015
12 July 2015
Accepted 16 July 2015

Abstract

Purpose – Feature fatigue (FF) will lead to negative Word-Of-Mouth (WOM), which damages the brand's long-term profit and ultimately decreases the manufacturer's customer equity (CE). It becomes severer in multi-generation products because of the significant impacts of earlier generation products on the CE of later ones. The purpose of this paper is to alleviate FF, it is imperative for designers to decide what features should be integrated to balance initial revenue and long-term profit so as to maximize CE.

Design/methodology/approach – In this paper, a novel method based on the Norton-Bass model is proposed to alleviate FF of multi-generation products to help designers find optimal feature combination that maximizes CE. The authors take the effects of adding features on product capability and usability into account, and integrate product capability, usability, WOM and earlier-generation product's effects into the Norton-Bass model to predict the impacts of FF on CE in current product development. A case study of a virtual product is presented to illustrate and validate the proposed method.

Findings – The advantage of the proposed method is highlighted in the cases of large feature number, high-product complexity (low-product usability) and multi-generation products. The experiments show that the earlier generations do affect the later ones from the perspective of maximizing CE. The superiority of the proposed method compared with the traditional way to put all potential features into a product during the product development is demonstrated. And the more features, the larger CE obtained using the proposed model than the one obtained by traditional way.

Originality/value – Although, there are reports attempting to analyze and alleviate FF, most of these studies still suffer the limitations that cannot point out what features should be added to the product with the objective of maximizing CE. In addition, few studies have been carried out to alleviate FF of multi-generation products. A novel method based on the Norton-Bass model and a genetic algorithm is proposed to alleviate FF of multi-generation products to help designers find optimal feature combination that maximizes CE.

Keywords Feature fatigue, Customer equity, Multi-generation product, Norton-Bass model

Paper type Research paper

1. Introduction

Nowadays, manufacturers (especially in high-tech or electronic industries) persist in offering customers an ever-increasing number of features, aiming to improve product capability and attractiveness (Angelis, 2008; Thompson *et al.*, 2005). Customers are indeed seduced by high-feature products at the purchase moment (before use). However, once they start using the products (after use), they become dissatisfied with the complexity of these feature-overloaded products. Their dissatisfaction will lead to negative Word-Of-Mouth (WOM), and ultimately decrease manufacturer's long-term profit (Li and Wang, 2011; Li *et al.*, 2013; Thompson *et al.*, 2005). Therefore, a problem of balancing the benefit of increasing "capability" with the cost of decreasing "usability" exists.

Thompson *et al.* (2005) used "feature fatigue" (FF) to represent the phenomenon of customers' inconsistent satisfaction with high-feature products before and after use.

This research was supported by the National Natural Science Foundation of China under Grant No. 71072061/G020801 and 70932004/G0209.

Industrial Management & Data Systems
Vol. 115 No. 8, 2015
pp. 1435-1456

0263-5577
DOI 10.1108/IMDS-03-2015-0104

Many cases have been reported to show this problem (Li and Wang, 2011; Li *et al.*, 2013). A typical example is the BMW 745 car, whose dashboard alone has more than 700 features. This high-capability car is indeed attractive initially but, after use, most of the owners are frustrated by the multi-function displays and the complicated iDrive system (Li *et al.*, 2013; Thompson *et al.*, 2005). A survey in USA indicated that after purchasing a high-tech product, 56 percent of the purchasers are dissatisfied with its complexity (Rockbridge Associates, 2004; Thompson *et al.*, 2005). Another study showed that 63 percent of smartphone returns in UK have no hardware or software fault but the reported problems related to product usability (Keijzers *et al.*, 2008; Li *et al.*, 2013). Therefore, it is imperative for manufacturers to decide what features should be integrated when developing a new product to make the product attractive enough and not so difficult to use, thus alleviating FF.

Adding product features is a "double-edged sword" (Figure 1). On one hand, adding features increases product capability and attractiveness, which will increase initial acquisition rate and thus improve manufacturers' initial revenue (IR) (Li *et al.*, 2013; Rust *et al.*, 2006; Thompson *et al.*, 2005). On the other hand, adding too many features will decrease product usability and lead to customer dissatisfaction (or decrease of satisfaction) (Li *et al.*, 2013; Thompson *et al.*, 2005). Consequently, dissatisfied customers will take their business elsewhere in the future (Rust *et al.*, 2006), thus reducing customer retention rate. Furthermore, customer dissatisfaction will lead to wide-spread negative WOM, and severely damages the reputation of the product and even of the manufacturer (Jokela, 2004; Thompson *et al.*, 2005), thereby having a detrimental impact on acquiring new customers in the future, which will reduce future acquisition rate. Therefore, adding product features will increase manufacturers' IR, but adding too many features may decrease manufacturers' long-term profit and even their Customer Equity (CE) (Thompson *et al.*, 2005; Wu and Wang, 2011). Here CE is defined as the sum of Customer Lifetime Value (CLV, the net present value) of all customers (Blattberg *et al.*, 2001).

Traditionally, manufacturers pay much more attention to maximizing initial sales than to the deleterious impacts of usability problems on long-term profit, thereby leading to FF (Rust *et al.*, 2006; Thompson *et al.*, 2005). Yet the evolution of just restricting new product to fewer features is non-optimal due to the decrease of IR (Keijzers *et al.*, 2008; Li *et al.*, 2013). The right way to alleviate (or even eliminate) FF is to make a trade-off between product capability (which affects IR) and usability (which affects long-term profit) to add a suitable number of features to the product so as to maximize CE (Li *et al.*, 2013; Thompson *et al.*, 2005).

There are reports in the literature on attempts to analyze and alleviate FF (Li and Wang, 2011; Li *et al.*, 2013; Thompson *et al.*, 2005; Wu and Wang, 2011). Most of these

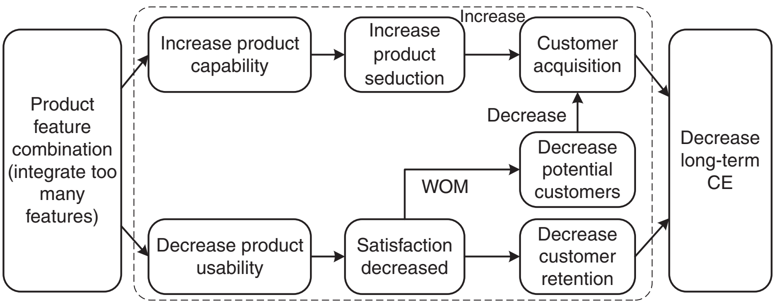

Figure 1.
FF effects on CE

studies still suffer the limitations that cannot point out what features should be added to the product with the objective of maximizing CE. Wu *et al.* (2013) proposed a new method based on the SIR epidemic model to solve the problem, but they only considered one generation of the product (see discussions of the related work review in the next section).

In this paper, we propose a novel method based on the Norton-Bass model to predict and alleviate FF, which will help designers find an optimal feature combination in current product development considering successive earlier generations. Product capability, usability, inter-generation and WOM effects (positive and negative) are integrated into the Norton-Bass model to predict the impacts of adding features on customer acquisition process (i.e. acquisition and retention). Simultaneously, we predict the impacts of product usability on customer retention. Based on the above analysis, CE can be calculated in the early stages of product development according to the customer transition model. Designers can get decision supports to decide what features should be added to the product so as to maximize CE, thus alleviating FF. The main contributions of this paper are: first,the proposed method can help designers decide what features should be added instead of only deciding the optimal number; second, Our model takes multi-generation products into consideration while combining FF and CE in the process of product development.

The remainder of this paper is organized as follows. In Section 2 we review the related works in the literature. The FF analysis method based on the Norton-Bass model is proposed in Section 3. In Section 4, a case study of virtual product development is presented. Discussions and conclusions are presented in Sections 5 and 6, respectively.

2. Related work

The term CE was first used by Blattberg and Deighton (1996), and they defined CE as the ideal balance between what companies spend on acquiring customers and what they spend on retaining them. To calculate CE, Blattberg and Deighton suggested that a company measure expected contributions from each customer, taking into consideration their life expectancy. Later, the company should discount these expected contributions (at the discount rate that the company expects to earn on its investments) to compute their net present value. Afterwards, other authors enhanced the definition of CE or even proposed different concepts and ways of measuring CE. Gupta *et al.*'s (2004) study extended the work of different researchers (e.g. Blattberg *et al.*, 2001; Niraj *et al.*, 2001; Reinartz and Kumar, 2000; Rust *et al.*, 2000) and followed the traditional model, adopting a financial approach of discounted cash flow to determine CLV for every customer, and then to estimate CE (sum of all CLVs of the firm). The basis of their approach is that CLV is the net discounted cash flow of future income derived from the acquisition, retention and expansion of the customer base minus their associated costs. The computation of cash flow used data obtained only from secondary sources, including actual information on the retention rate of customers over time. However, this information is often unavailable from secondary sources. In fact, Gupta *et al.* (2004) use estimations of this rate in their own paper. A point worth noting is that in Gupta *et al.*'s model, the acquisition of customers is possible at all times since the acquisition and loss of customers occur in a continuous process.

The term "feature fatigue" was first used by Thompson *et al.* (2005) to represent the phenomenon of customers' inconsistent satisfaction with high-feature products before and after use. There are reports in the literature on efforts to explain FF. Hamilton and Thompson (2007) used construal-level theory to explain the reason for FF. They found that indirect experience triggers more abstract mental construal and increases preference of high-desirability (capability) products, while direct experience triggers more concrete mental construal and increases high-feasibility (usability) products. Gill (2008) classified product features into hedonic category (which is associated with experiential consumption, pleasure and excitement) and utilitarian one (which is related to more instrumental/practical considerations), and showed that different categories of product features have different effects on customers' perceived capability and usability. Yet, neither of above studies points out how to determine how many and what features should be added to the product so as to alleviate FF.

There are other reports on efforts to analyze or alleviate FF. Thompson *et al.* (2005) proposed an analytical model to show the influence of the number of features on manufacturer's long-term profit and, to determine a suitable number of features to be added so as to maximize CE, and they suggested that firms should offer a wider assortment of simpler products instead of all-purpose and feature-rich products. But they just focussed on the total "number" of features and considered all the features to be equal, ignoring the differences between them, however, in practice different features have different effects on FF. Li and Wang (2011) proposed a probability based methodology for FF analysis in which Bayesian network technique was used to analyze the uncertain relationships among product features and the combination effects. But the method cannot find out how many and what specific features should be added to the product so as to alleviate FF. Li *et al.* (2013) considered the feature addition problem as a multi-objective decision-making problem, in which product capability and usability are two conflicting objectives; and a FF multi-objective genetic algorithm was proposed for solving the problem. Wu *et al.* (2013) proposed a new method based on the SIR epidemic model to solve the problem, but they only considered one generation of the product. Actually, products of earlier generations will affect the attractiveness and the usability of the products of the later generations. Meanwhile, the later generation products will also affect the earlier ones. For example, people will become confused and dissatisfied if the later generation products are more complex than earlier ones, as the usability of these products will decrease. Also, the sales of the earlier generation will decrease if the later one is much better than the earlier one. Therefore, FF of different generations has important impacts on CE. When predicting the diffusion of a certain multi-generation product considering FF, the effects of earlier-generation product should also be taken into account, which is precisely ignored by other researchers.

In this paper, a novel method based on Norton-Bass model is proposed in order to overcome the limitations of previous research and help designers to find an optimal feature combination which will alleviate FF to maximize CE.

3. Predicting FF based on Norton-bass model

The framework of the proposed approach is shown in Figure 2. It consists of two modules: first, customer purchase analysis; second, feature combinations optimization. In the first module, the Norton-Bass model is utilized to depict WOM effects on customer purchase behavior (in this paper we use customer transition processes, including acquisition, retention and defection, to represent customer purchase behavior). Then, a quantitative customer transition model considering WOM effects is proposed to analyze customer purchase behavior under different feature combinations. In the second module, a GA is used to search an optimal feature combination that maximizes CE. CE is used as the fitness function of the GA that can be calculated on the basis of the first module.

A chromosome represents a feature combination which will be inputted into the first module for the calculation of CE. So the two modules form an iterative cycle, and the iteration will stop when the optimal feature combination has been found. The details of the proposed approach are presented in the following subsections.

Note that, in Figure 2 C_i and U_i are the capability and usability of feature i respectively; *PC* and *PU* are the capability and usability of the product, respectively.

3.1 Customer purchase analysis

3.1.1 WOM effects on customer purchase. WOM has significant effects on customer purchase. Positive WOM will facilitate customers' acquisition, while negative WOM will make many potential customers be "removed," which in return decelerates customer acquisition (Charlett *et al.*, 1995; Anderson, 1998; Bansal and Voyer, 2000). Nowadays, due to the developments in information technology, the increase in communication between customers, has amplified WOM effects (Bughin *et al.*, 2010). To model WOM effects on customer purchase, we impose two restrictions. First, individuals affected by WOM in one period start to purchase in the next period. Second, the spread of WOM is restricted to those who have actually purchased the product (Hogan *et al.*, 2004). That is, we just consider experiential WOM which derives from a customer's direct experience with a product, ignoring those individuals who hear about the product, tell others, but do not purchase themselves. Actually, experiential WOM is the most common and powerful form of WOM, typically accounting for 50-80 percent of WOM activities in any given product category (Anderson, 1998; Bughin *et al.*, 2010).

WOM effects on customer purchase based on Norton-Bass model are shown in Figure 3. The population of the target market can be classified into four groups of individuals with respect to the states of their relationship with the manufacturer:

- *prospects*: potential customers;
- *first-timers*: newly acquired customers;

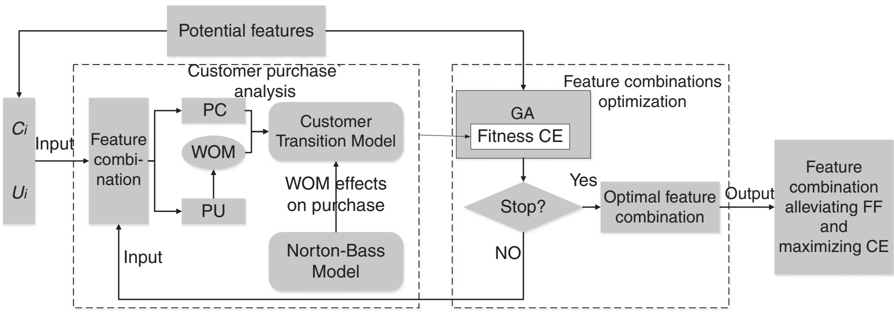

Figure 2. Framework of the proposed approach

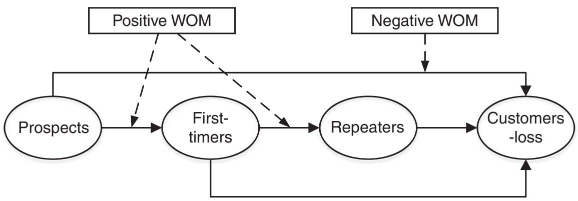

Figure 3. The Norton-Bass model of WOM effects

- *repeaters*: customers who will repurchase the product; and
- *customers-loss*: the customers who are not retained and the individuals who will never be acquired.

The positive WOM can make prospects transfer to first-timers, and also make first-timers become repeaters; while the negative WOM will lead to customers-loss. The WOM effects on customer purchase reflect in the determination of Norton-Bass parameters. The quantitative WOM effects will be given in Section 3.1.2.

Market potential m affected by product capability is not fixed. It means that market potential is different for different products actually. We consider successive-generation products in this paper, hence, it is reasonable to assume that the market potential is fixed for each generation of a product.

3.1.2 Customer transition model. Customer transition means individuals can transfer from one group to another with a certain probability (or "rate"; hereinafter, we consider the two concepts of "rate" and "probability" to be equal). Possible transition directions or paths are shown in Figure 4.

The rates of customer transitions are affected by many factors, such as product capability and usability, advertising (Wang and Moon, 2013), WOM, product price, product quality and customer service. According to the definition and the characteristic of FF, in this paper we only consider the impacts of product capability and usability on customer transition rates, assuming all else being equal. And we assume that customer transition rates are homogeneous across individuals.

Customers are often seduced by high-capability products at the purchase moment, which is independent of previous adopters (Angelis, 2008; Thompson *et al.*, 2005; Rust *et al.*, 2006). According to the Norton-Bass model, external influence is independent of previous adopters (Bass, 1969; Bass *et al.*, 1994). Therefore, product capability can be seen as external influence (p) that affects customer acquisition rate (p_F) and will affect the market potential (m) which equals to the number of prospects at time $t=0$ (Figure 4). On the other hand, usability problems caused by too many features will decrease customer satisfaction, thus leading to a drop of strength of positive WOM, or even

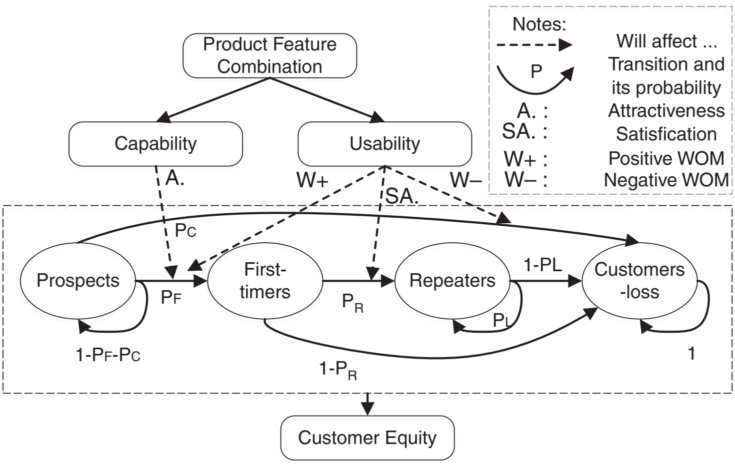

Figure 4.
FF-CE framework

leading to negative WOM. Dissatisfied customers and potential customers affected by negative WOM will take their business elsewhere in the future, moving into the group of Customers-loss (Rust *et al.*, 2006; Thompson *et al.*, 2005; Wu and Wang, 2011). Thus, product usability has impacts on future acquisition rate (p_F, at time $t > 0$), customer retention rate (p_R), and prospects' defection rate (p_C) which in turn affects future acquisition rate (p_F, at time $t > 0$) (Figure 2). In light of the definition of FF, we assume that repeaters are "immune" from FF and will move into Customers-loss with a constant rate of $1-p_L$. CE is determined by the parameters of m and p_F, p_C, p_R, p_L.

The following subsection will discuss the determination of the above parameters which will affect the transition of customers based on the Norton-Bass model.

(1) Determining positive WOM effects. We propose the equations of positive WOM based on the theory of Norton-Bass model and classic Bass model considering the FF to describe the customer transitions between different generations of products. Equation (1) refers to products which contain two generations, Equation (2) refers to three generations:

$$\begin{cases} n_1(t)_+ = \left[p_1 + q_1 \frac{N_1(t)}{m_1}\right][m_1 - N_1(t) - S_{12}(t)] \\ n_2(t)_+ = \left[p_2 + q_2 \frac{N_2(t)}{m_2}\right][m_2 - N_2(t) + N_1(t)] \end{cases} \tag{1}$$

$$\begin{cases} n_1(t)_+ = \left[p_1 + q_1 \frac{N_1(t)}{m_1}\right][m_1 - N_1(t) - S_{12}(t)] \\ n_2(t)_+ = \left[p_2 + q_2 \frac{N_2(t)}{m_2}\right][m_2 - N_2(t) + N_1(t) - S_{23}(t)] \\ n_3(t)_+ = \left[p_3 + q_3 \frac{N_3(t)}{m_3}\right][m_3 - N_3(t) + N_2(t)] \end{cases} \tag{2}$$

where p_i and q_i can be obtained from Equation (8) and (7) respectively, i means the index of the generation. $n_i(t)_+$ presents the customer acquisition in each time period for positive WOM; $N_i(t)$ is the cumulative customer acquisition. $S_{12}(t)$ refers to the customer transition from the First generation to the second generation. $S_{23}(t)$ refers to the customer transition from the second generation to the third generation. The customer transition refers to the customers switching from the earlier generation to the later generation (Norton and Bass, 1987). Obviously, the value of the transition is based on the adopters of the earlier generation. Based on the Bass model, we use the cumulative adopters as the potential to calculate the transition. Thus, the customer transitions can be acquired by the below Equation (3):

$$\begin{cases} S_{12}(t) = \left[p_2 + q_2 \frac{N_2(t)}{m_2}\right] N_1(t) \\ S_{23}(t) = \left[p_3 + q_3 \frac{N_3(t)}{m_3}\right] N_2(t) \end{cases} \tag{3}$$

(2) Determining negative WOM effects. Negative WOM will cause customers loss instead of customer acquisition. We consider three successive generations here. The equations can be extended to more generations actually.

For the first generation, the customer acquisition in each time period can be presented as:

$$\begin{cases} n_1(t) = [m_1 - N_1(t) - L_1(t) - S_{12}(t)]p_1 \\ L_1(t) = \sum_{i=1}^{t} l_1(i) = \sum_{i=1}^{t} q_1 \frac{N_1(i)}{m_1}[m_1 - N_1(i) - S_{12}(t) - L_1(i-1)] \end{cases} \quad (4)$$

For the second generation, the customer acquisition in each time period can be presented as:

$$\begin{cases} n_2(t) = [m_2 - N_2(t) - L_2(t) - S_{23}(t) + N_1(t)]p_2 \\ L_2(t) = \sum_{i=1}^{t} l_2(i) = \sum_{i=1}^{t} q_2 \frac{N_2(i)}{m_2}[m_2 - N_2(i) - S_{23}(t) - L_2(i-1) + N_1(i)] \end{cases} \quad (5)$$

For the third generation, the customer acquisition in each time period can be presented as:

$$\begin{cases} n_3(t) = [m_3 - N_3(t) - L_3(t) + N_2(t)]p_3 \\ L_3(t) = \sum_{i=1}^{t} l_3(i) = \sum_{i=1}^{t} q_3 \frac{N_3(i)}{m_3}[m_3 - N_3(i) - L_3(i-1) + N_2(i)] \end{cases} \quad (6)$$

l_j (t) refers to the customers loss in each time period, and $L_j(t)$ is the cumulative customers loss till time t.

(3) Determining internal coefficient. The internal coefficient (coefficient of imitation), q, is determined by the level of customer satisfaction (Stahl *et al.*, 2003). For the purpose of FF analysis, in this paper, customer satisfaction or dissatisfaction can be derived from product usability. So the coefficient of imitation can be seen as a function of product usability.

The piecewise function could be like the one below:

$$q = \begin{cases} q_W\left(1 - e^{-\lambda_q|U-U_0|}\right), & U \geqslant U_0 \\ -q_W\left(1 - e^{-\lambda_q|U-U_0|}\right), & 0 \leqslant U < U_0 \end{cases} \quad (7)$$

q_w refers to a coefficient which could also be described as the maximum of q; U_0 is the threshold in the piecewise function; λ_q is the coefficient which can adjust the curve of the function. These parameters (q_w, λ_q, U_0) can be obtained by customer survey or data mining, or determined by designers. Product usability U can be obtained through some usability testing methods (Dumas and Redish, 1993; Li *et al.*, 2013).

(4) Determining external coefficient. As discussed in the preceding, the external coefficient (coefficient of innovation) p, can be seen as a function of product capability (say $p = f(C)$). Like Blattberg and Deighton's (1996) acquisition model, p does not

increase without limit as product capability increases and has a characteristic of Diminishing Returns. We assume that the external coefficient will increase faster in the initial stage than the later ones, which means the curve of the function is a sigmoid curve. Consider the differential equation $(dp/dC) = \lambda p(p_A - p/p_A)$, p_A is the maximum of the coefficient. Therefore, by solving the equation, the function can be presented as below:

$$p = \frac{p_0 p_A}{p_0 + (p_A - p_0)e^{-\lambda(C - C_0)}} \tag{8}$$

where p_0 is the minimum of the external coefficient, p_A is the maximum. C_0 is the initial capability of the product without adding any additional features, C is the sum of the capability for the product. λ is the adjustment coefficient. The parameters here can be obtained by customer survey or data mining, or determined by designers.

(5) Determining Customer retention. Through the above analysis, retention rate (p_R) can be seen as a function of product usability (all else being equal). Once again, like Blattberg and Deighton's (1996) retention model, p_R does not increase without limit as product usability increases and has a characteristic of diminishing returns. Therefore, we propose:

$$p_R = L_R \times [1 - \exp(-K_R \times U)] \tag{9}$$

Where L_R is the ceiling rate (the ultimate rate) of p_R under certain conditions (e.g. certain customer service and marketing expenditure); K_R is a constant that controls the steepness of the curve. L_R and K_R can be obtained through customer survey or data mining, or determined by designers.

With respect to the definition of FF, an individual moving into the group of Repeaters means that he/she has not suffered from FF. So we consider the repeaters to be "immune" from FF. However, not all repeaters will be retained by a manufacturer (Reichheld, 1996). They will move into the group of Lost-for-goods with a certain rate of $1-p_L$, which is determined by other factors such as Customer Relationship Management that is out of our research in this paper. So we consider p_L as a constant value:

$$\begin{cases} R(t) = R(t-1)p_L + n(t-1)p_R, & t \geqslant 2; \\ R(1) = 0 \end{cases} \tag{10}$$

3.3 Feature combinations optimization using a GA

Different feature combinations lead to different product capability and usability, further resulting in different customer transition and CE. So it is a Combinatorial Optimization Problem (COP) to find an optimal feature combination that maximizes CE. Many methods have been reported in the literature to solve a COP, such as ant colony (Liu *et al.*, 2013), simulated annealing (Mirsanei *et al.*, 2011), branch and bound method (TemIz and Erol, 2004), Tabu-search (González *et al.*, 2012), swarm intelligence (Aydin, 2012) and GA (Ventura and Yoon, 2012). Among these methods, GA is a particularly well-suited method for combination optimization problems because of the characteristics of GA such as global search ability, easy operation, flexibility, short computing time (Guan *et al.*, 2009; Li *et al.*, 2013) and simplicity of encoding the current problem into chromosome. Therefore, in this paper, we use a GA to solve the feature combinations optimization problem.

3.3.1 Procedure. The procedure of feature combinations optimization based on a GA is shown in Figure 5. CE is used as the fitness function of the GA. Each chromosome generated in the GA represents a feature combination that will be inputted into the customer transition model for CE calculation.

3.3.2 Chromosome coding. Each possible solution is represented by an encoded chromosome. The genotype representation of the chromosome is outlined in Figure 6. The binary value (x1, x2, …, xF) of each gene indicates whether the corresponding feature is integrated into the product: "1" means YES and "0" means NO (assume that all the features are uncorrelated with each other). The length of the chromosome string is the total number of potential features, F.

3.3.3 Fitness evaluation. In this paper, the fitness is evaluated by CE that can be calculated according to the customer transition model. As illustrated in Figure 5, after defining potential features, designers should evaluate the capability and the usability of each potential feature. Some methods can be used to evaluate

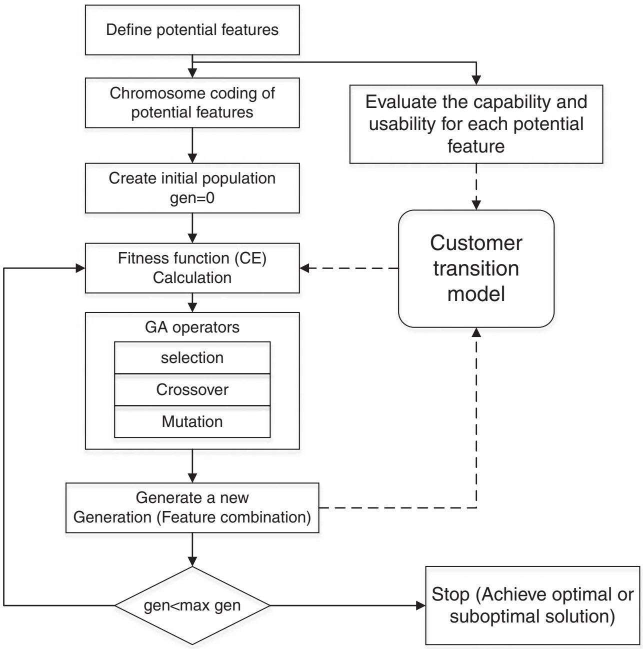

Figure 5.
Procedure of feature combinations optimization

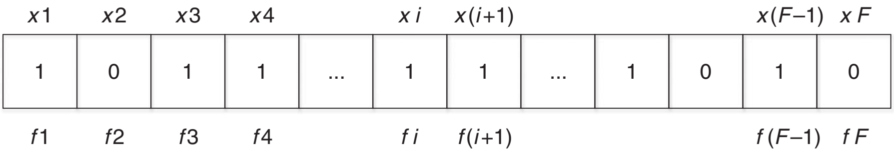

Figure 6.
Chromosome coding

a feature's capability and usability (see details in Section 4.4). Product capability, C, and the number of selected features, B, can be calculated according to the chromosome:

$$C = \sum_{i=1}^{F} C_i \times x_i$$

$$B = \sum_{i=1}^{F} x_i$$

Based on the previous analysis, we propose a formula to calculate the CE over a T-year time.

$$CE = \sum_{t=1}^{T} \frac{n(t)M_F + R(t)M_R}{(1+d)^t} \tag{11}$$

$$\begin{cases} R(t) = R(t-1)p_L + n(t-1)p_R, t \geqslant 2; \\ R(1) = 0 \end{cases} \tag{12}$$

where M_F and M_F are the average yearly margin of a first-timer and a repeater, respectively; d is the yearly discount rate; $n(t)$ and $R(t)$ are the number of first-timers and repeaters at time t, respectively.

Using appropriate GA operators (selection, crossover, mutation), the proposed approach can theoretically find out an optimal feature combination that maximizes CE, therefore, designers can get decision supports for deciding what feature combination should be integrated in the process of product development.

4. Case study

4.1 Case description

As is mentioned previously, we provide a case to show the process of our method. Suppose a virtual product can contain 20 features at most, including the initial feature. We need to predict the CE five years later considering both the effects of FF and the two earlier generations. Also, we will find a good enough feature combination of current product in development considering the two earlier generations. There are three parts in this section. First part is the parameters estimation of our case and model. The second one is the prediction of CE for different feature combinations. The last one is to find an optimal solution for current product development.

4.2 Parameters estimation

Some methods like Kano's model or AHP can be used to evaluate feature's and product's capability (Jiao and Chen, 2006; Li *et al.*, 2013; Wu and Wang, 2012). Product usability can be obtained through some usability testing methods (Dumas and Redish, 1993; Li *et al.*, 2013). The other parameters of the proposed approach can be estimated by nonlinear least squares regression (Srinivasan and Mason, 1986), or "guessing by analogy" (Bass, 2004). Since the work of parameters estimation is not the focus of this paper, we estimate the parameters of the case study based on previous research (Table I).

In Table II, we have ranked the feature capabilities already. We suppose that the earlier two generations take the initial feature and the 0-8 feature combination respectively.

All the parameters are calculated as previously mentioned. In the remaining part, we will show the calculation of the parameters in Table I. In our case, we assume that the market is fixed, say $m = 1{,}000$.

According to previous research (Hogan *et al.*, 2003; Parker, 1994; Sultan *et al.*, 1990), the value of the coefficient of innovation (p) ranges from 0.0001 to 0.06 and averages 0.03. So we set $p_A = 0.06$, $p_0 = 0.03$, $\lambda = 1$. Thus Equation (8) reduces to:

$$p = \frac{0.03 \times 0.06}{\left(0.03 + 0.03 \times \exp\left(-(C-10)/10\right)\right)} \tag{13}$$

Table I. The parameters of the model in this case

Features	C	ΣC	U	p	P_R
0	*10.0000*	*10.0000*	*0.1379*	*0.0300*	*0.6734*
1	*0.2906*	10.2906	*0.1309*	0.0343	0.6570
2	*0.2840*	10.5746	*0.1231*	0.0384	0.6372
3	*0.2753*	10.8499	*0.1187*	0.0420	0.6254
4	*0.2453*	11.0952	*0.1108*	0.0450	0.6029
5	*0.2232*	11.3184	*0.1038*	0.0473	0.5814
6	*0.2217*	11.5401	*0.0994*	0.0494	0.5669
7	*0.2201*	11.7601	*0.0945*	0.0512	0.5503
8	*0.1919*	*11.9520*	*0.0899*	*0.0525*	*0.5338*
9	*0.1879*	12.1399	*0.0851*	0.0537	0.5158
10	*0.1340*	12.2739	*0.0805*	0.0544	0.4976
11	*0.1242*	12.3981	*0.0762*	0.0550	0.4801
12	*0.1229*	12.5210	*0.0728*	0.0555	0.4656
13	*0.1125*	12.6335	*0.0704*	0.0560	0.4549
14	*0.0851*	12.7185	*0.0669*	0.0563	0.4390
15	*0.0681*	12.7866	*0.0646*	0.0565	0.4282
16	*0.0472*	12.8338	*0.0620*	0.0567	0.4157
17	*0.0453*	12.8791	*0.0598*	0.0568	0.4050
18	*0.0365*	12.9155	*0.0572*	0.0569	0.3919
19	*0.0183*	*12.9338*	*0.0549*	*0.0570*	*0.3802*

Notes: C is the feature capability, ΣC is the product capability, U is the product usability, p is the external coefficient, p_R is the retention rate, $q$is the internal coefficient

Table II. The parameters of two earlier generation

Features	ΣC	U	p	p_R	q
0	10.0000	0.1379	0.0300	0.6734	0.0454
0~8	11.9520	0.0899	0.0525	0.5338	−0.0002

Previous research shows that in a typical firm customers are defecting at the rate of 10-30 percent per year (Reichheld, 1996). Thus we assume $L_R = 0.9$ and set $K_R = 10$ for convenience. Then Equation (9) reduces to:

$$p_R = 0.9 \times (1 - \exp(-10 \times U)) \tag{14}$$

Also, we set $q_w = 0.03$, $U_0 = 0.09$, $\lambda_q = 1$. Then Equation (7) reduces to:

$$q = \operatorname{sign}(U - 0.09) \times 0.03 \times (1 - \exp(-50 \times |U - 0.09|)) \tag{15}$$

With respect to the definition of FF, an individual moving into the group of Repeaters means that he/she has not suffered from FF. So we consider the repeaters to be "immune" from FF. However, not all repeaters will be retained by a manufacturer (Reichheld, 1996). They will move into the group of Customers-loss with a certain rate of $1 - p_L$, which is determined by other factors such as Customer Relationship Management that is out of our research in this paper. So we consider p_L as a constant value.

4.3 Prediction of CE

Assume the expected yearly margin is \$1 per customer (first-timer or repeater, which means $M_R = M_F = 1$). And we assume a yearly discount rate of 10 percent, an average yearly repeaters' retention rate of $p_L = 0.08$, and a time horizon for the customer lifetime of five years as suggested by Berger and Nasr (1998). Adopting an elitist model combining roulette wheel selection of the GA, one point crossover, 60 percent crossover rate, 5 percent mutation rate, a population size of 100, maximum generation of 500 (for stop condition of the GA).

We take the 0~19 feature combination for an example (which is bold in Table I). The figures below show the result of the prediction. Figure 7 shows both the customer acquisition of each time period of earlier generations and the prediction of current generation. The left figure of Figure 8 shows the CE of earlier generations and the predicted CE of current product as time goes on. The other figure of Figure 8 shows the sum of the earlier generations CE and the current one which is called the total CE as time goes on. All the figures seem to be so called s-type-functions. These figures prove the validity of the proposed model in some ways. Based on this method, we can use a GA to find a better solution compared to the integration of all features which has been shown in Figure 8 (As it is not a large-scale problem with 20 features, so in this part we will calculate CEs of all feature combinations to illustrate the validity and accuracy of the proposed model).

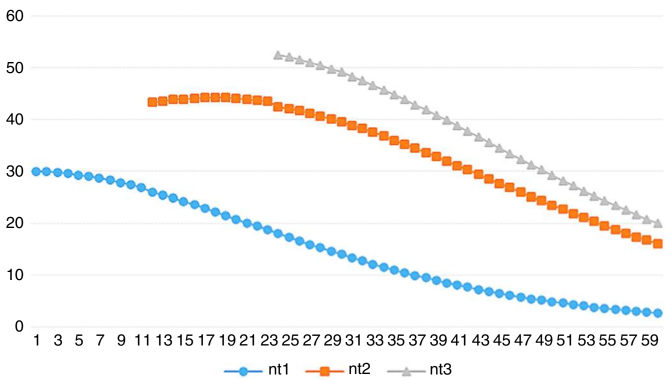

Figure 7.
Customer acquisition of each time period

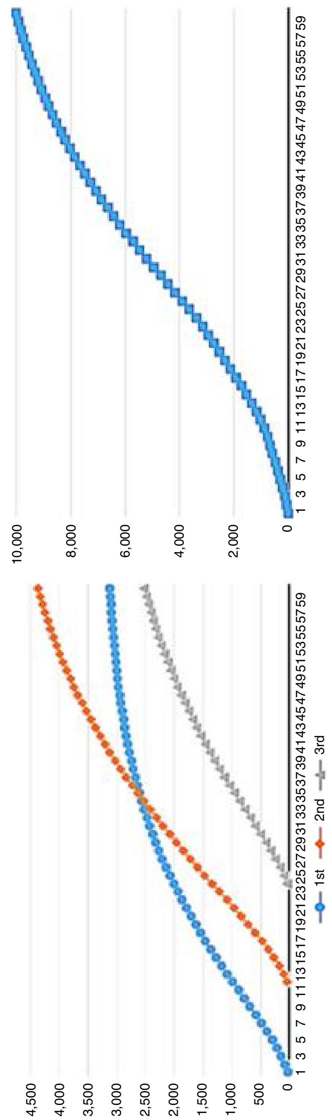

Figure 8.
CE of each product generation (left) and total (right)

4.4 Optimization of feature combination

We have realized the goal to predict the CE of current product with the effect of earlier generations as time goes on, in other words, we have realized the goal to predict the FF effects on CE considering the effect of earlier generations. But prediction is not enough, we would like to do some optimization to help the decision making in the product development. Considering the best way to alleviate FF is to maximize CE (Thompson *et al.*, 2005; Li *et al.*, 2013).

Based on the previous formula, we can get the CEs of different feature combinations for the Third generation product. Thus we can find an optimal solution. Table III shows the final CE (5 years later) of the first and the second generation considering different feature combinations of the third generation. The initial and final CE of the 3rd generation are also shown in Table III. The total CE of three generations is placed in the last column.

5. Discussion

From the case study, we can suppose a situation that, a product designers need to design a new generation product, and there are 20 potential features, they must decide which features should be added in the new product. In addition, there are already two earlier generation products in the market of the same company. The designers have to consider the effects of earlier generation products on the later ones. As discussed in former sections, whether a product being successful or not has significant effects on CE even the development of a company. Our approach is exactly aimed at solving this kind of problem, helping the designers to find an optimal feature combination that will maximize CE considering FF.

According to traditional methods that focus on maximizing initial sales, in the case study, designers should add all the 18 potential features besides the initial features, which makes manufacturers gain the highest IR of \$30.9 (Figure 9(b)). However, this makes manufacturers gain a CE of only \$1,748.7, while the highest CE is \$2,135.546 (Figure 9(c)). The optimal feature combination is 1~6 when considering CE of the third generation only. It may be better to take the total CE into consideration in product development for a company. In this case, the optimal solution is 1~4, which is different from the third generation. Thus with respect to the evolution of just maximizing total long-term profit, designers should add only 1~4 features. Adding further more features leads to negative WOM that decreases long-term profit (Table III and Figure 7).

Feature	Third initially	First	Second	Third finally	Total
1	18.63908	2,545.454	2,564.605	1,966.445	7,076.505
2	20.84429	2,545.456	2,558.625	2,047.175	7,151.256
3	22.82261	2,545.458	2,553.131	2,118.616	7,217.204
4	24.41299	2,545.459	2,549.229	2,133.926	*7228.614*
5	25.70138	2,545.46	2,546.200	2,131.088	7,222.748
6	26.82718	2,545.461	2,543.416	*2,135.546*	7,224.422
7	27.79654	2,545.461	2,541.162	2,125.274	7,211.897
…	…	…	…	…	…
16	30.84500	2,545.463	2,536.602	1,815.666	6,897.731
17	30.90385	2,545.463	2,536.752	1,780.575	6,862.79
18	30.93264	2,545.463	2,536.945	1,748.734	6,831.142

Table III. CE of each generation and total with different features

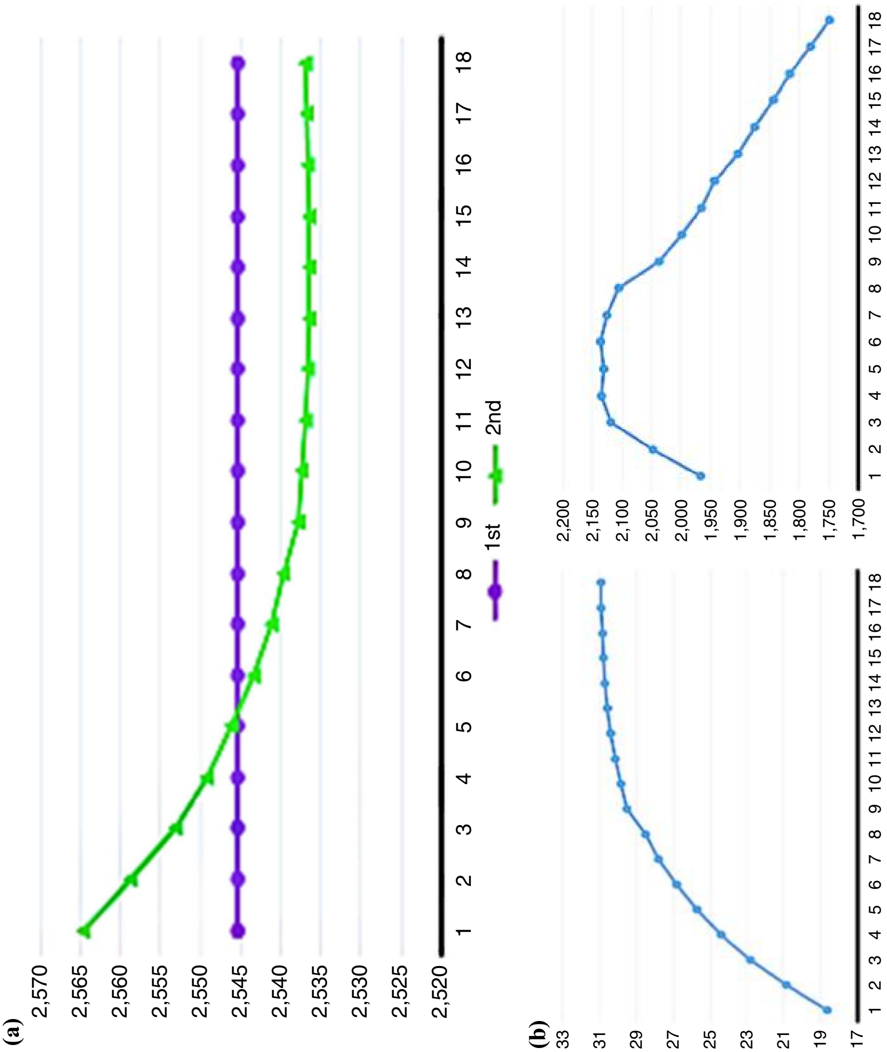

Figure 9.
CE of earlier two generations, (a) 3rd generation, (b) initially and (c) finally

The results show that the earlier generations do affect the later ones. It becomes more complicated when the optimization of the total CE is taken into consideration. Also the results of the case study demonstrate that adding more features indeed increases initial sales; however, adding too many features ultimately decreases CE due to usability problems. There is an optimal feature combination a product should include to balance capability and usability so as to maximize CE and total CE. This case study considers only 18 potential features. In reality, some products have much more features. Thus, FF problem may be more significant in most industries in real life (Figure 10).

Since the effect of one customer passing WOM to another is known as a "ripple effect" (Hogan *et al.*, 2004), adoptions of durable products may be more significantly influenced by WOM than that of short life-cycle products. Thus designers of durable products should pay more attention to alleviating FF relative to that of short life-cycle products.

Thompson *et al.*'s (2005) model can find the "optimal number" of features a product should include with the objective of maximizing CE. But their model focusses only on the total number of features. Actually, different combinations of features will lead to different CE, although they consist of the same number of features, as shown in Table IV. Therefore, Thompson *et al.*'s (2005) model cannot give a suggestion of what specific feature combination should be integrated. In this paper, the results in Table V show that the proposed approach can point out what specific feature combination should be integrated to maximize CE and thus alleviate FF.

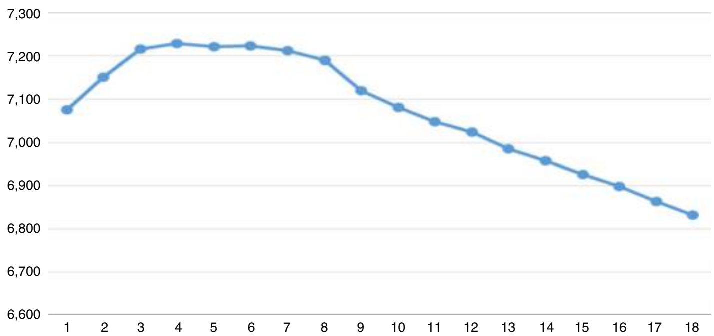

Figure 10.
Total CE

Table IV.
CEs of different combinations with the same feature number

Solutions	Feature combinations	NoF	IR($)	CE($)
1	11111011011101111101110111100110001101110011101111	36	69.3701	323.8400
2	11111111010110111001001101111110010111111010111101	36	68.8020	*330.1833*
3	01100010111011011111111011011011111110111010011111	36	51.0641	294.3052

Table V.
Compared results

Methods	Feature combinations (solutions)	NoF	IR($)	CE($)
Traditional	11111111111111111111111111111111111111111111111111	50	86.4604	276.4932
Proposed	11111111010110111001001101111110010111111010111101	36	68.8020	*330.1833*

Though product tests may somewhat moderate FF problem (Thompson *et al.*, 2005), product iterations will extend the cycle time of product development (Ozer and Cebeci, 2010). The proposed method can help designers predict FF in the early stages of product development. Therefore, it is believed that the proposed method provides decision supports for designers to alleviate FF.

In order to evaluate the robustness of the proposed approach, we performed numerical experiments with five different problem sizes, each of which has five sets of random data (feature capability and usability). In this part, we use the method proposed by Wu *et al.* (2013) to calculate the usability and capability of each feature dynamically, which might only influence the concrete value of CE but will not affect the trend. The "Traditional" method represents the traditional and common way to put all potential features into one product and "Proposed" method represents the way proposed in this paper, which aims at maximizing CE while considering FF. As shown in Table VI, on average, the proposed approach increases the CE about 18 percent relative to the traditional method. Besides, Figure 11 shows that the more the features, the larger the increase of CE (15.48 percent for $F=40$ while 27.9 percent for $F=200$). This indicates that the more features a product includes, the more likely it will lead to FF, which agrees with Thompson *et al.*'s (2005) study. Therefore, the proposed approach can help manufacturers significantly improve their CE, especially when there are too many features.

Table VI.
Results of different problem sizes

Data sets	Methods	$F=30$	$F=40$	$F=50$	$F=60$	$F=70$
1	Traditional	233.3932	226.7812	247.9043	318.7648	286.5552
	Proposed	261.6391	268.7817	306.2249	359.4612	362.3160
2	Traditional	200.0839	244.0753	279.4796	268.9315	311.7899
	Proposed	247.3726	285.0477	323.8400	335.1096	367.8696
3	Traditional	182.3553	220.3532	272.8542	292.7887	295.5262
	Proposed	223.7783	265.8221	304.9796	347.5220	351.6339
4	Traditional	219.2415	268.3587	276.4932	286.9500	307.4543
	Proposed	253.8708	292.2475	330.1833	342.8159	364.3486
5	Traditional	198.9859	261.1604	248.0092	291.8017	295.8350
	Proposed	234.0940	297.8394	294.3052	354.8753	346.3264
Mean	Traditional	206.8120	244.1458	264.9481	291.8473	299.4321
	Proposed	244.1510	281.9477	311.9066	347.9568	358.4989
	Increase	18.05%	15.48%	17.72%	19.23%	19.73%

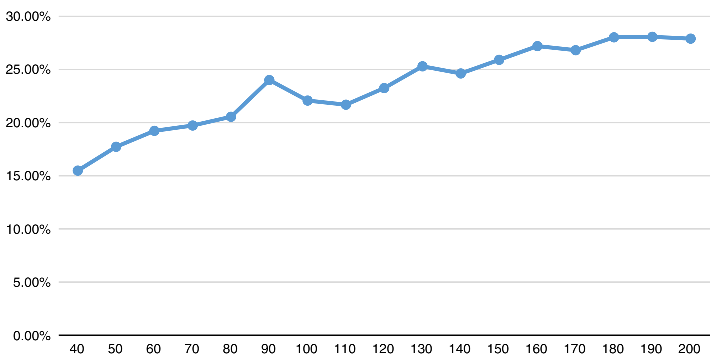

Figure 11.
Percentage of CE increase with feature numbers

6. Conclusion

In this paper, we propose a novel method based on the Norton-Bass model to predict and alleviate FF in product development considering the earlier generations. We focus on predicting the impacts of adding features on CE considering the effects of earlier generations, thereby providing decision support for designers to decide what features should be added so as to maximize total CE and alleviate FF.

We firstl consider the market potential as an *S*-type-function of product capability with diminishing returns. Then we adopt the Norton-Bass model to predict the impacts of adding features on customer acquisition considering the earlier generations, where the coefficients of innovation and imitation are considered as a function of product capability and usability, respectively. And we consider first-timers' retention rate as a function of product usability. Based on the above analysis, predictive CE is calculated in the early stages of product development. Designers can get decision supports using a GA to search an optimal feature combination to be added.

The advantage of the proposed method is highlighted in the cases of large feature number, high-product complexity (low-product usability) and multi-generation products. The experiments show that the earlier generations do affect the later ones from the perspective of maximizing CE. The superiority of the proposed method compared with the traditional way to put all potential features into a product during the product development is demonstrated. And the more features, the larger CE obtained using the proposed model than the one obtained by traditional way.

Nowadays, most of the current studies still suffer the limitations that cannot point out what features should be added to the product with the objective of maximizing CE. In addition, few studies have been carried out to alleviate FF of multi-generation products. So the main contributions of this paper are: first, the proposed method not only can decide the optimal feature number in a new product but also can help designers decide what features should be added so as to maximize total CE; second, our model takes multi-generation products into consideration while combining FF and CE in the process of product development. As far as we know, it is still a new study point, we have not seen similar studies until now.

Some limitations call for further research. First, most studies of FF assume that the features are non-structural and there are not interactions among them, which may not be realistic. In this paper, we still only consider the effects of feature number, so based on the conclusion of this paper, we can further take the feature structure into consideration to improve our study. Second, in this paper, we calculate CE based on static usability, capability and other parameters, but in practice, market information changes in real time especially for fast upgrading product. So for further study, data mining can be applied into our current model to identify customers' needs dynamically so as to revise design in time. Third, the population is considered to be homogeneous, and some functions of the proposed method are based on previous researches of customer behavior or marketing literature. However, the population is heterogeneous with respect to valuation of the product in real life (Kalish, 1985). Customers' behaviors may change in some cases, which may influence decision making.

References

Anderson, E.W. (1998), "Customer satisfaction and word of mouth", *Journal of Service Research*, Vol. 1 No. 1, pp. 5-17, doi: 10.1177/109467059800100102.

Angelis, M.D. (2008), "The effect of adding features on product attractiveness: the role of product perceived congruity", PhD, University of Bologna, Bologna.

Aydin, M. (2012), "Coordinating metaheuristic agents with swarm intelligence", *Journal of Intelligent Manufacturing*, Vol. 3 No. 4, pp. 991-999.

Bansal, H.S. and Voyer, P.A. (2000), "Word-of-mouth processes within a services purchase decision context", *Journal of Service Research*, Vol. 3 No. 2, pp. 166-177.

Bass, F.M. (1969), "A new product growth for model consumer durables", *Management Science*, Vol. 15 No. 5, pp. 215-227.

Bass, F.M. (2004), "Comments on 'a new product growth for model consumer durables': the bass model", *Management Science*, Vol. 50 No. 12, pp. 1833-1840.

Bass, F.M., Krishnan, T.V. and Jain, D.C. (1994), "Why the bass model fits without decision variables", *Marketing Science*, Vol. 13 No. 3, pp. 203-223.

Berger, P.D. and Nasr, N.I. (1998), "Customer lifetime value: marketing models and applications", *Journal of Interactive Marketing*, Vol. 12 No. 1, pp. 17-30, doi: 10.1002/(sici)1520-6653 (199824)12:13.0.co;2-k.

Blattberg, R.C. and Deighton, J. (1996), "Manage marketing by the customer equity test. (Article)", *Harvard Business Review*, Vol. 74 No. 4, pp. 136-144.

Blattberg, R.C., Getz, G. and Thomas, J.S. (2001), *Customer Equity: Building and Managing Relationships as Valuable Assets*, Harvard Business School Press, Boston, MA.

Bughin, J., Doogan, J. and Vetvik, O.J. (2010), "A new way to measure word-of-mouth marketing", *McKinsey Quarterly*, No. 2, pp. 113-116.

Charlett, D., Garland, R. and Marr, N. (1995), "How damaging is negative word of mouth?", *Marketing Bulletin*, Vol. 6, Research Note 1, pp. 42-50.

Dumas, J.S. and Redish, J.C. (1993), *A Practical Guide to Usability Testing*, Ablex Publishing Corporation, Norwood, MA.

Gill, T. (2008), "Convergent products:what functionalities add more value to the base?", *Journal of Marketing*, Vol. 72 No. 2, pp. 46-62.

González, M., Vela, C., González-Rodríguez, I. and Varela, R. (2012), "Lateness minimization with Tabu search for job shop scheduling problem with sequence dependent setup times", *Journal of Intelligent Manufacturing*, Vol. 24 No. 4, pp. 741-754, doi: 10.1007/s10845-011-0622-5 (Published online).

Guan, X., Wang, Y. and Tao, L. (2009), "Machining scheme selection of digital manufacturing based on genetic algorithm and AHP", *Journal of Intelligent Manufacturing*, Vol. 20 No. 6, pp. 661-669.

Gupta, S., Lehmann, D.R. and Stuart, J.A. (2004), "Valuing customers", *Journal of Marketing Research*, Vol. 41 No. 1, pp. 7-18.

Hamilton, R.W. and Thompson, D.V. (2007), "Is there a substitute for direct experience? Comparing consumers' preferences after direct and indirect product experiences", *Journal of Consumer Research*, Vol. 34, No. 4, pp. 546-555.

Hogan, J.E., Lemon, K.N. and Libai, B. (2003), "What is the true value of a lost customer?", *Journal of Service Research*, Vol. 5, No. 3, pp. 196-208, doi: 10.1177/1094670502238915.

Hogan, J.E., Lemon, K.N. and Libai, B. (2004), "Quantifying the ripple: word-of-mouth and advertising effectiveness", *Journal of Advertising Research*, Vol. 44 No. 3, pp. 271-280.

Jiao, J. and Chen, C.H. (2006), "Customer requirement management in product development: a review of research issues", *Concurrent Engineering Research and Applications*, Vol. 14, No. 3, pp. 173-185.

Jokela, T. (2004), "When good things happen to bad products: where are the benefits of usability in the consumer appliance market?", *Interactions*, Vol. 11 No. 6, pp. 28-35.

Kalish, S. (1985), "A new product adoption model with price, advertising, and uncertainty", *Management Science*, Vol. 31 No. 12, pp. 1569-1585.

Keijzers, J., Ouden, E.D. and Lu, Y. (2008), "The'double-edged sword'of high-feature products: an explorative study of the business impact", paper presented at the Proceedings of the 32nd Annual Product Development and Management Association (PDMA) International Research Conference, Orlando, FL, September 15-17.

Li, M. and Wang, L. (2011), "Feature fatigue analysis in product development using Bayesian networks", *Expert Systems With Applications*, Vol. 38 No. 8, pp. 10631-10637, doi: 10.1016/j.eswa.2011.02.126.

Li, M., Wang, L. and Wu, M. (2013), "A multi-objective genetic algorithm approach for solving feature addition problem in feature fatigue analysis", *Journal of Intelligent Manufacturing*, Vol. 24 No. 6, pp. 1197-1211, doi: 10.1007/s10845-012-0652-7.

Liu, X.-J., Yi, H. and Ni, Z.-H. (2013), "Application of ant colony optimization algorithm in process planning optimization", *Journal of Intelligent Manufacturing*, Vol. 24 No. 1, pp. 1-13.

Mirsanei, H.S., Zandieh, M., Moayed, M.J. and Khabbazi, M.R. (2011), "A simulated annealing algorithm approach to hybrid flow shop scheduling with sequence-dependent setup times", *Journal of Intelligent Manufacturing*, Vol. 22 No. 6, pp. 965-978.

Niraj, R., Gupta, M. and Narasimhan, C. (2001), "Customer profitability in a supply chain", *Journal of Marketing*, Vol. 65 No. 3, pp. 1-16.

Norton, J.A. and Bass, F.M. (1987), "A diffusion theory model of adoption and substitution for successive generations of high-technology products", *Management Science*, Vol. 33 No. 9, pp. 1069-1086.

Ozer, M. and Cebeci, U. (2010), "The role of globalization in new product development", *Engineering Management, IEEE Transactions on*, Vol. 57 No. 2, pp. 168-180.

Parker, P.M. (1994), "Aggregate diffusion forecasting models in marketing: a critical review", *International Journal of Forecasting*, Vol. 57 No. 2, pp. 353-380.

Reichheld, F.F. (1996), *The Loyalty Effect: The Hidden Force Behind Growth, Profits, and Lasting Value*, Harvard Business School Press, Boston, MA.

Reinartz, W. and Kumar, V. (2000), "On the profitability of long-life customers in a non-contractual setting: an empirical investigation and implications for marketing", *Journal of Marketing*, Vol. 64 No. 4, pp. 17-35.

Rockbridge Associates (2004), *National Technology Readiness Survey*, Rockbridge Associates Inc, Great Falls, VA.

Rust, R.T., Thompson, D.V. and Hamilton, R.W. (2006), "Defeating feature fatigue", *Harvard Business Review*, Vol. 84 No. 2, pp. 98-107.

Rust, R.T., Zeithaml, V.A. and Lemon, K.N. (2000), *Driving Customer Equity*, The Free Press, New York, NY.

Srinivasan, V. and Mason, C.H. (1986), "Nonlinear least squares estimation of new product diffusion models", *Marketing Science*, Vol. 5 No. 2, pp. 169-178.

Stahl, H.K., Matzler, K. and Hinterhuber, H.H. (2003), "Linking customer lifetime value with shareholder value", *Industrial Marketing Management*, Vol. 32 No. 4, pp. 267-279, doi: 10.1016/s0019-8501(02)00188-8.

Sultan, F., Farley, J.U. and Lehmann, D.R. (1990), "A meta-analysis of applications of diffusion models", *Journal of Marketing Research*, Vol. 27 No. 1, pp. 70-77.

TemIz, I. and Erol, S. (2004), "Fuzzy branch-and-bound algorithm for flow shop scheduling", *Journal of Intelligent Manufacturing*, Vol. 15 No. 4, pp. 449-454.

Thompson, D.V., Hamilton, R.W. and Rust, R.T. (2005), "Feature fatigue: when product capabilities become too much of a good thing", *Journal of Marketing Research*, Vol. 42 No. 4, pp. 431-442.

Ventura, J. and Yoon, S.-H. (2012), "A new genetic algorithm for lot streaming flow shop scheduling with limited capacity buffers", *Journal of Intelligent Manufacturing*, Vol. 24 No. 6, pp. 1185-1196, doi:10.1007/s10845-012-0650-9 (Published online).

Wang, B. and Moon, Y.B. (2013), "Hybrid modeling and simulation for innovation deployment strategies", *Industrial Management & Data Systems*, Vol. 113 No. 1, pp. 136-154.

Wu, M. and Wang, L. (2011), "Feature fatigue analysis based on behavioral decision making", paper presented at the Industrial Engineering and Engineering Management (IEEM), 2011 IEEE International Conference, Singapore, December 6-9.

Wu, M. and Wang, L. (2012), "A continuous Fuzzy Kano's model for customer requirements analysis in product development", *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, Vol. 226 No. 3, pp. 535-546, doi: 10.1177/0954405411414998.

Wu, M., Wang, L., Li, M. and Long, H. (2013), "An approach based on the SIR epidemic model and a genetic algorithm for optimizing product feature combinations in feature fatigue analysis", *Journal of Intelligent Manufacturing*, Vol. 26 No. 1, pp. 199-209.

Further reading

Yang, C., Lee, S.-G. and Lee, J. (2013), "Entry barrier's difference between ICT and non-ICT industries", *Industrial Management & Data Systems*, Vol. 113 No. 3, pp. 461-480.

Corresponding author
Professor Liya Wang can be contacted at: wangliya@sjtu.edu.cn