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Abstract

With the development of the Internet and Electronic Commerce (EC), enterprises have overcome the space and time barriers and are now capable of serving customers electronically. However, it is a great challenge to attract and retain the customers over Internet. One approach is to provide the responsive personalized service to satisfy the customer demand and promote sales at the first time. Hence, in this paper, we propose a decision support system which develops best promotion products based on combinations of different marketing strategies, pricing strategies, and customer behaviors evaluated in terms of multiple criteria. Data mining techniques are utilized to help the business discover patterns to develop on-line sales promotion products for each customer for enhancing customer satisfaction and loyalty.

The proposed system consists of four components: (1) establishing marketing strategies, (2) promotion pattern model, (3) personalized promotion products, and (4) on-line transaction model. A simple example is given to illustrate the implementation and application of proposed decision support system.

Keywords: Decision support systems, electronic commerce, personalized promotion, data mining

1. Introduction

The growth of the internet and the expansion of on-line shopping have forced traditional business to rethink over their marketing promotion programs because on-line shopping changes customer behavior dramatically. On-line personalized promotion provides business returns based on its ability to retain current customers and increase the value of customers [8].

On-line personalization of sales promotions can be executed at various levels of sophistication. There are two major approaches to provide personalized information [13]. In the content based approach, it provides items that are similar to what the user has favored in the past. In the collaborative filtering approach, it identifies other users that have showed similar preference to the given users and provides what they would like. The purpose of this research is to well formulate marketing strategies for offering customers promotions related to product categories they have purchased.

Besides, the effectiveness of promotions can be expected to increase if customers receive promotions that most attract them. Another purpose of this research is to study how to use data mining techniques to analyze historical on-line purchase data of a large group of customers to characterize all customers, customer cluster, and individual customers' shopping behavior. Accordingly, an intelligent on-line personalized promotion decision support system is proposed in this paper.

Simply stated, data mining refers to extracting knowledge from large amounts of data [4]. Kleissner [7] defined that data mining is a new decision support analysis process to find buried knowledge in corporate data and deliver understanding to business professionals. Hence, decision makers can quickly and correctly make decisions via data mining analysis.

The organization of the paper is as follows. Section 2 proposes an intelligent on-line personalized promotion decision support system. It is classified into five parts: (1) system architecture, (2) establishing marketing strategies, (3) creating a promotion patterns model, (4) generating personalized promotion products, and (5) proceeding with on-line transaction model. Finally, we conclude the paper and present directions for future research in Section 3.

2. An Intelligent On-line Personalized Promotion Decision Support System

In this paper, we present an intelligent on-line personalized promotion decision support system, which uses the data mining techniques to help the business discover suitable promotion products for each individual customer.

2.1 System architecture

Figure 1 shows the architecture of the system, which consists of the following components：(1) marketing strategies, (2) promotion patterns model (3) personalized promotion products, and (4) on-line transaction model. Each component of the proposed system is described in details as follows.

2.2 Marketing strategies

The marketing strategies include promotion strategies and the pricing strategies with business life cycle.

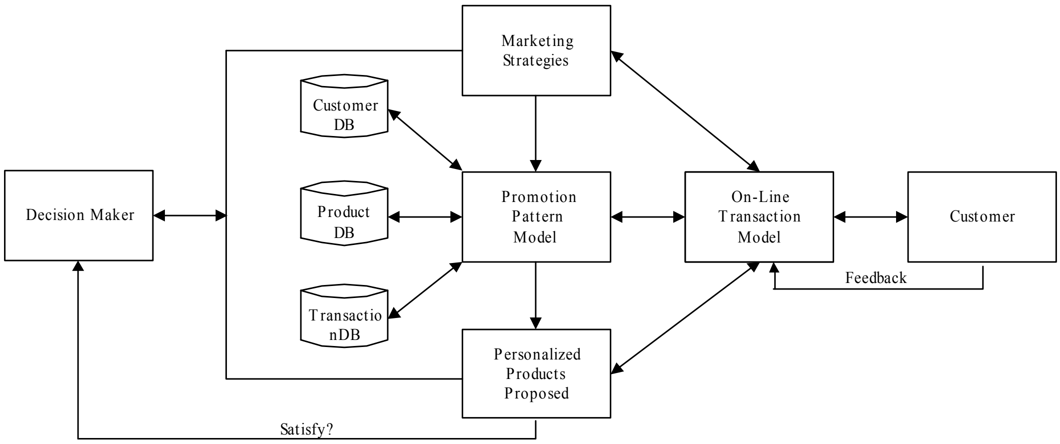

Figure 1. An intelligent on-line personalized promotion decision support system

2.2.1 promotion strategies

Most scholars believe that sales promotion can give the promoted objects immediate incentives and excite their interest. Davis [3] considered that sales promotion strengthens the marketed effect and increases the sales volume in short-term. Some other scholars subsumed the objects of sales promotion under the definition of promoted activities. Hence the promoted activities include customer promotion, trade promotion, and sales-force promotion.

In this paper, we focus on customer promotion in Internet. According to the classification of on-line customer promotion proposed by Hsu [5], on-line promotion models can be divided into cash discount, commodity presentation, and rewards drawing activities. Promotion models are listed in Table 1. Here, in our proposed system, sales promotion strategies including general promotion, cross-selling, and up-selling strategies are presented in Table 2. The three strategies utilize two promotion models, which are cash discount and commodity presentation.

Table 1. Promotion models [5]

Promotion model		Promotion manner
Cash discount	Universal price discount	Price-offs
		Price discount
	Differential price discount	Quality discount
		Total discount
Commodity presentation	Same kind Commodity presentation	Bonus packs
	Different kind Commodity presentation	Premiums
		Bundling
Rewards drawing activities		Trading stamps and sweepstakes

2.2.2 pricing strategies with business life cycle

For the pricing strategy, we define the promoted price based on two factors. One is the price strategy for each stage in business life cycle, and the other is the original price of product. In addition, the promoted price will be adjusted dynamically with time; that is to say, when the business situation or the product profit changes, the system will automatically, on the basis of the two factors, to refresh a new promoted price. First, we propose an approach which assesses business life cycle based on the capital growth ratio, employee growth ratio, and sales volume growth ratio and sets up the pricing strategies for each stage. The idea comes from the methods presented by Chow [2] and Smith et al.[11]. The pricing strategy for each stage of business life cycle strategy is shown in Table 3. It divides the business life cycle into four stages including introduction, growth, maturity, and decline stages. The value of growth ratio differentiates at each stage in the business life cycle. The growth ratio is defined by Chow [2] as the following formula.

$$R_i = \frac{G_i}{|G_{i-1}|} \quad , \quad G_i = \frac{S_i - S_{i-1}}{S_{i-1}} \times 100\% \quad ,$$

where R_i is the *i-th* period growth ratio, G_i is the *i-th* period growth rate, and S_i is the *i-th* period value of capital, employee and sales volume.

Next, we hope to consider two factors, pricing strategy for each stage and product price, in finalizing the final promoted price. Generally, the product price depends on the desired profit for business. Similarly, the promoted price should be adjusted according to the final profit that the business expects to yield. Here, let the final profit be P, the cost be C and the final promoted price be PP. Then $PP = C(1+P)$.

Table 2. Proposed sales promotion strategies

Strategy	Product categories	Promotion condition	Price manner	Applied technique
General promotion	· Best-selling · Worst-selling · Seasonal product · Festival product	· Purchased quantity · Purchased total amount	· Price discount	· Cross analysis
Cross-selling	· Association product · Sequential product	· Bundling · Purchased total amount		· Association mining · Sequential pattern mining
Up-selling	· Up-selling product · New product	· Bundling · Purchased total amount		· Cross analysis

Table 3. Pricing strategy for each stage of business life cycle

Business life cycle / Characteristic	Introduction	Growth	Maturity	Decline
Growth Ratio （Capital, Employee and Sales Volume）	R_i>=2	2> R_i >=1	1> R_i >=0	R_i <0
Price strategy for each stage	Low	Highest	High	Medium

In this research, by using a fuzzy set theory [13], an approach is proposed to help the business to decide the final promoted price. Two steps involve in the decision of final promoted price. One is to define the membership function for the profit, and the other is to utilize the fuzzy rule-based inference to obtain the final profit.

(1) defining the membership function for the profit

In fuzzy logic, a fuzzy set *A* on universe *X* is defined by the ordered pair (x, $\mu_A(x)$), where x is the object on *X*, and $\mu_A(x)$ is called the membership function of *A*. The membership function can be any value in the range of [0.0, 1.0]. Now, we define the membership function for profit as shown in Figure 2.

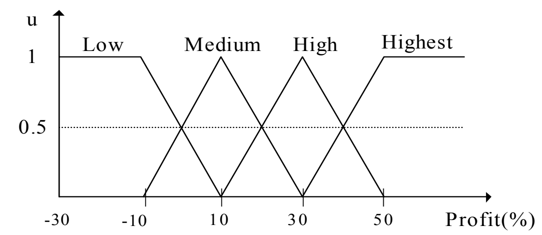

Figure 2. Membership function for profit

(2) utilizing the fuzzy rule-based inference to obtain the final profit

In this step, the promoted price will be obtained by combining the following two fuzzy rules. Firstly, assuming that a product ‘A’ has a profit of 15% and its cost is *C*. Secondly, assuming that the business life cycle stage is ‘Introduction’ and the pricing strategy for this stage is ‘Low.’ Therefore, the first fuzzy rule (say, MF_1) is “if the profit of product ‘A’ is Medium then the final profit is Medium,” according to the membership function for profit of Figure 2. Then, the second fuzzy rule (say, MF_2) is “if business profit is Low then the final profit is Low.”

Finally, an output value can be generated from a membership function merged from the two fuzzy rules mentioned above. The inference process consists of three basis steps and one optional step [6]. The first three steps are fuzzy matching, inference, combination, and the optional one is defuzzification.

(a) fuzzy matching step

Firstly we define the fuzzy matching function as *MF(p)=d*, where *MF*() is a fuzzy membership function such as MF_1 or MF_2, the original product profit *p* is an input of *MF*(), and the matching degree *d* is an output of *MF*(). We assume that two inputs are 15 and -4 respectively. Figure 3(a) illustrates that the outputs 0.75 and 0.7 are obtained by the mentioned two fuzzy rules MF_1 and MF_2, respectively.

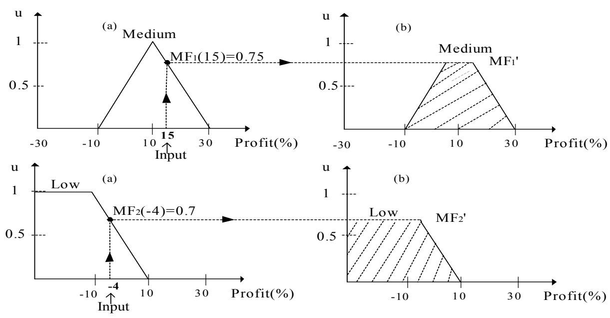

Figure 3. (a) Fuzzy matching step (b) inference step

(b) inference step

After the fuzzy matching step, we will calculate the rule’s conclusion based on its matching degree. Figure 3(b) using the clipping method, the matching degree 0.75 and 0.7 suppress the membership functions MF_1 and MF_2 into MF_1’ and MF_2’.

(c) combination step

The step combines the conclusion inferred by all fuzzy rules into a final conclusion. This is illustrated in Figure 4(a) for combining two fuzzy conclusions MF_1’ and MF_2’using the clipping method.

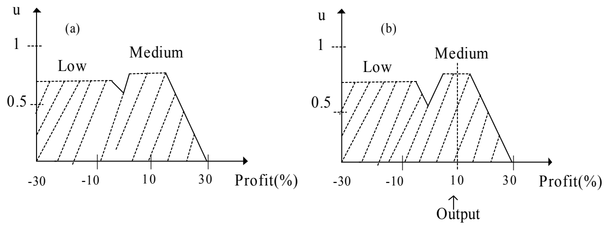

Figure 4. (a) Combining fuzzy conclusions inferred by the clipping method (b) the result of MOM defuzzification.

(d) defuzzification step

For the reason that we need a crisp output, an additional step is used to convert a fuzzy conclusion into a crisp one. This step is called defuzzification. The Mean of Maximum (MOM) method is used to calculate the average of all variable values with maximum membership degrees. Figure 4(b) shows the result of applying MOM defuzzification to a combined fuzzy conclusion. The value of final conclusion is 10%; that is, the final profit is 10%. Therefore, in this example, the final promoted price is C(1+10%).

With the proposed price strategy, we have three opportunities for promotion discount.

(1) general discount : The cross-selling and up-selling products will obtain the price discount based on the strategies above.
(2) purchased quantity discount : The new, best-selling, worst-selling, seasonal or festival products in general promotion will obtain the price discount when the purchased quantity is greater than or equal to a decision-maker specified minimum quantity threshold.
(3) purchased total amount discount : The customer will obtain the price discount when the purchased total amount is greater than or equal to a decision-maker specified minimum total amount threshold.

2.3 Promotion pattern model

In this stage, we propose a promotion pattern model which is illustrated in Figure 5. It utilizes data mining techniques and cross analysis to carry out the promotion strategies, as discussed in Section 2.2, from product, customer, and transaction databases. The purpose is to assist the business in discovering appropriate promotion patterns.

For the easy management and analysis consideration, all the products are classified into several categories in advance. For example, suppose that there are fifteen products, and all products are classified into five classes A, B, C, D, and E. The outcome is listed in Table 4. The product with Item_ID '1' is classified into the class 'A.'

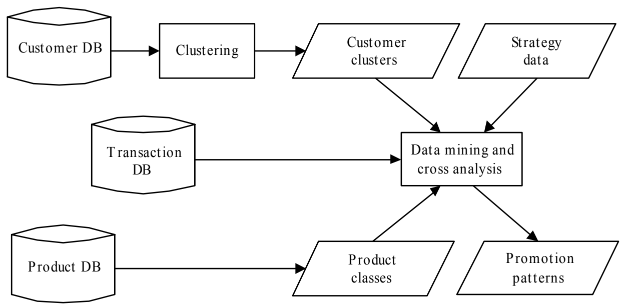

Figure 5. Promotion pattern model

Table 4. Product classes

Item_ID	Class	Brand	Price	Cost	Status
1	A	IBM	$740	$643	-
2	A	ACER	$1,250	$937	-
3	A	ACER	$1,567	$1,160	New
4	B	TWINHEAD	$2,293	$1,700	-
5	B	IBM	$1,829	$1,460	-
6	C	EPSON	$83	$67	-
7	C	HP	$153	$127	-
8	C	HP	$223	$157	New
9	D	EPSON	$183	$153	-
10	D	HP	$110	$100	-
11	D	HP	$170	$143	-
12	E	LEMEL	$87	$70	-
13	E	PLEXTOR	$100	$83	-
14	E	PLEXTOR	$200	$153	New
15	E	RITEX	$0.33	$0.30	-

2.3.1 data mining for customer database

Market segmentation divides a larger market into submarkets based upon different needs or product preferences. Clustering analysis is one of the most frequently used method for segmenting a market.

(1) clustering

All products were classified into five classes earlier. However, we don't know the exact number of customer categories. Hence, clustering technique becomes the choice. Here, we will utilize the automatically clustering feature of Adaptive Resonance Theory Network (ART) to cluster customers. It uses customers' demographic and behavior to segment customers. In other words, all the customers who are in the same cluster have the similar demographic and behavior.

ART is an unsupervised learning network developed by Carpenter and Grossberg [1]. It is capable of determining the number of clusters through progressive adaptation.

(a) ART allows a training example to modify an existing cluster only if the cluster is sufficiently close to the example; otherwise a new cluster is formed to handle the example.

(b) ART can determine when a new cluster should be formed by using a "Vigilance parameter" as a threshold of similarity between patterns and clusters.

For example, there are five customers data shown in Table 5. Since the inputs of ART should be binary values, we must design the corresponding values for the inputs of the example in advance. Here, some discretization techniques [4] are used to divide customers' attributes Income, Age, and Total amount into the intervals labeled as Low, Medium, and High. Take attribute Income as an example. The Low interval is defined below 1000, and can be coded as "00." The Medium interval is defined between 1000 and 1700, and can be coded as "01." The High interval is defined above 1700, and can be coded as "11." Similarly, attributes Age and Total amount are discretizated and encoded in the same way as in Table 6.

Table 5. The customers data

Customer_ID	Name	Income	Age	Sex	Total amount
111	Sam	1,800	35	M	400
122	Mary	8,00	22	F	2,000
123	Annie	1,300	27	F	1,200
113	David	1,900	52	M	500
133	Jacky	1,400	55	M	1,500

Table 6. Discretizating and encoding attributes as an ART input

Attribute	Range / Code		
Income	<1,000	1,000-1,700	>1,700
	00	01	11
Age	<30	30-50	>50
	00	01	11
Sex	M	F	
	1	0	
Total amount	<300	300-1,000	>1,000
	00	01	11

According to the discretiaztion and encoding method, five vectors corresponding to the five customers' data shown in Table 5 can be obtained as follows.

Attribute sets = {Income, Age, Sex, Total amount}
Sam = {11, 01, 1, 01}
Mary = {00, 00, 0, 11}
Annie = {01, 00, 0, 11}
David = {11, 11, 1, 01}
Jacky = {01, 11, 1, 11}

(2) customer clusters

Set the Vigilance parameter as 0.5, three clusters can be generated by ART. Mary and Annie belong to the first cluster, Sam and David belong to the second cluster, and the third cluster contains Jacky. Table 7 displays the cluster label and the corresponding customer ids. For example, the customer numbered 113 belongs to the cluster label of A.

Table 7. Clusters of customers

Cluster	Customer ID
A	{111, 113}
B	{122, 123}
C	{133}

2.3.2 data mining and cross analysis for transaction database

The above section discussed that the business divides customers into several different clusters based on a clustering technique. Therefore, we can take that as a basis to provide different promotions for different clusters. In this section, we will progress towards the data analysis of transaction database by data mining and cross analysis in order to find out different promotion fitting for the different clusters.

(1) data mining

Here, we will utilize association rule mining and sequential pattern mining respectively. Then we discover association products and sequential products which are purchased together and purchased in sequence respectively.

(a) association mining

It can be found that what kinds of products are purchased at the same time through association rules mining. In the paper, an association mining method [9] is used to find out the affinity of products purchased together from the transaction data of all customers. At the same time, the association mining method can also be applied to each customer cluster and individual customer to extract the purchasing patterns for each customer cluster and each individual customer.

Consider the transaction database in Table 8. Assume that the minimum support is 4. The association products {2, 7} and {13, 15} are obtained for all customers. That means that all the customers tend to buy items 2 and 7 together or buy items 13 and 15 together. From Table 8, customer 113 belongs to customer cluster A. By association mining on customer cluster "A," we discovered that the customers of this cluster tend to buy items 13 and 15 together. Similarly, applying association mining to each individual customer (say customer 113), we found that the customer loved to buy items 13 and 15 together as well. All the association product patterns for three customer categories (all customers, customer cluster and individual customer) in this example are shown in Table 9.

(b) sequential pattern mining

It can be found that what kinds of products are purchased after buying some item through sequential patterns mining. In the paper, sequential pattern mining methods [9] are used to find out the products frequently purchased in sequence over time from the transaction data of all customers. At the same time, the sequential pattern methods can also be applied to each customer cluster and individual customer to extract all the sequential purchase patterns.

Table 8. Transaction data

TID	Itemset	Customer ID	Cluster
1	{2,7,11}	111	A
2	{9,10,12}	111	A
3	{2,5,7}	112	A
4	{7,13,15}	113	A
5	{4,10,13,15}	113	A
6	{3,13}	121	B
7	{2,5,7}	122	B
8	{1,8,12,13}	122	B
9	{2,13,15}	123	B
10	{15}	123	B
11	{2,7}	131	C
12	{12}	131	C
13	{2,4,9}	132	C
14	{10,13}	132	C
15	{2,7,11,14}	133	C

Table 9. Association product patterns for three customer categories

All customers	{2,7}{13,15}
Customer cluster A	{13,15}
Individual customer (Customer 113)	{13,15}

Consider the transaction database in Table 8. Assume that the minimum support is 2. The sequential product patterns {2, 12} and {7, 12} are obtained for all customers. That means that all the customers have a trend to buy item 12 after buying item 2 and to buy item 12 after buying item 7. From Table 8, customer 113 belongs to customer cluster A. Similarly, by sequential pattern mining on customer cluster A, we found that the customers of this cluster tend to buy item 10 after buying item 7. All the sequential product patterns are shown in Table 10.

Table 10. Sequential product patterns for three customer categories

All customers	{2,12}{7,12}
Customer cluster A	{7,10}
Individual customer (Customer 113)	-

(2) cross analysis

We will utilize the cross analysis for best and worst selling and up-selling strategy. The best-selling and worst-selling products can be found based on the statistical analysis. The upgraded products can be found with up- selling strategy.

(a) statistical analysis

For each product class, cross analysis can be firstly carried out on the product data (as shown in Table 4) and transaction data (as shown in Table 8) of each kind of customer category for acquiring the best-selling (e.g., the ratio of sales volume is more than 50%) and worst-selling (e.g., the ratio of sales volume is 0%) products.

Here, cross analysis will not be carried out on the products with the status labeled as "new" because no sufficient transaction data can be analyzed for those new products.

(b) up-selling strategy

A technique is applied to the association, sequential, and best-selling products for increasing sales of each customer category. For example, an item set {2, 7} is an association product pattern mined for the category of all customers. Up-selling analysis is firstly applied to item 2 which belongs to product class A. Then, item 3 will be obtained for up-selling because items 2 and 3 belong to the same class A and have the same characteristic.

Table 11. Best-selling and worst-selling of all product classes for all customers, customer cluster A and customer 113

Product class	All customers		Customer cluster A		Individual customer (Customer 113)	
	Best selling	Worst selling	Best selling	Worst selling	Best selling	Worst selling
A	{2}	-	{2}	{1} {3}	-	-
B	{4} {5}	-	{4} {5}	-	{4}	-
C	{7}	{6}	{7}	{6}	{7}	-
D	{10}	-	{10}	-	{10}	-
E	-	-	-	-	{13} {15}	-

Here, we use attribute "brand" as the characteristic of up-selling case. In the proposed up-selling strategy, we can consider combined items for up-selling if an up-selling item is combined to other items belonging to an extracted association product pattern. Therefore, the item set {3, 7} is also an up-selling product. All up-selling products are listed in Table 12 for each kind of customer categories.

2.4 Personalized promotion products proposed

The proposed system will generate many promotion products such as those in Table 12, and we regard them as candidate promotion products. However, not all the candidate products should be offered for promotion. Some evaluation should be done for ordering all of the candidate promotion products. In this paper, WSM (Weighted Sum Model) is used for ranking. WSM is a multi-criteria decision making method.[12] Figure 6 illustrates the model of personalized promotion products proposed.

2.4.1 promotion patterns

Promotion patterns are discovered from product, customer, and transaction databases with data mining techniques. Table 12 shows the promotion products.

Table 12. Promotion all product classes for all customers, customer cluster A, and customer 113

All customers	Association products	{2,7} {13,15}	Up-selling products	{3} {3,7} {8} {2,8} {3,8} {14} {14,15}
	Sequential products	{2,12} {7,12}		{3} {3,12} {8} {8,12}
	Best-selling products	{2}		{3}
		{4}		-
		{5}		-
		{7}		{8}
		{10}		{11}
	Worst-selling products	{6}		
Customer cluster A	Association products	{13,15}	Up-selling products	{14} {14,15}
	Sequential products	{7,10}		{8} {11} {8,10} {7,11} {8,11}
	Best-selling products	{2}		{3}
		{4}		-
		{5}		-
		{7}		-
		{10}		{11}
	Worst-selling products	{6}		
Individual customer (Customer 113)	Association products	{13,15}	Up-selling products	{14} {14,15}
	Sequential products	-		-
	Best-selling products	{4}		-
		{7}		-
		{10}		{11}
		{13}		{14}
		{15}		-
	Worst-selling products	-		

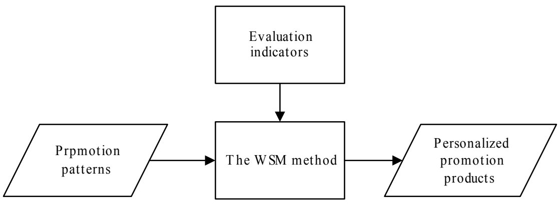

Figure 6. The model of personalized promotion products proposed

2.4.2 evaluation indicators

To evaluate the candidate products, we propose three evaluation indicators which are profit, customer satisfaction, and success indicators. All these indicator values should be first normalized by scaling its values to a small specified range, such as 0.0 to 1.0.

(a) profit indicator

Making money is the primary goal for the businesses. Therefore, they hope the promotion products with high profit should have a high priority when the products are promoted. For this reason, the profit should be included as an evaluation indicator.

(b) customer satisfaction indicator

Along with the customer relationship management (CRM) becoming more and more important recently, the customer satisfaction must be subsumed. The manner for evaluating customer satisfaction is to ask the customer whether they are satisfied with the promoted manners, including the product bundling, product price, and so on. The customer will be asked to carry out an evaluation after purchasing is made. The evaluation score is obtained as a feedback from the customer for measuring the effectiveness of each promotion product.

(c) success ratio indicator

This indicator is used to estimate the acceptance ratio of promotion. The success ratio is defined as follows.

Success ratio = the number of promotions accepted / the number of promotions proposed

2.4.3 the WSM method

We will calculate the score of each candidate promotion product by utilizing the WSM method to rank them and obviate those products with low scores. If there are m candidate promotion products and n indicators, then the WSM score of each product can be calculated as follows [12]:

$$A_{WSM-score} = \max_{i} \sum_{j=1}^{n} a_{ij} w_j \text{ , for } i = 1, 2, \ldots, m, \quad (1)$$

where a_{ij} is the *j-th* actual indicator value of the *i-th* candidate promotion product and w_j is the importance of the *j-th* indicator.

We assume the weights of the three indicators are 0.2, 0.5, and 0.3, respectively. After applying the WSM method, the WSM score are showed in Table 13.

2.4.4 personalized promotion products

After all the WSM scores for candidate promotion products, a filtering process follows.

Take the products in Table 13 and assume 0.5 is the filtering threshold. Finally, the final ranking of price discount promotion products is : {11} > {14} > {8, 10} = {10} > {5} > {3, 7} > {2, 8} = {2} > {2, 7} > {7}; that is,

Table 13. Each indicator score and final score of candidate promotion products

Candidate promotion products		Profit indicator	Customer satisfy indicator	Success ratio indicator	Final score
General discount products	{2,7}	0.27	0.5	0.7	0.51
	{13,15}	0.15	0.5	0.7	0.49
	{3}	0.35	0.5	0.3	0.41
	{8}	0.4	0.2	0.8	0.42
	{3,7}	0.28	0.5	0.8	0.55
	{2,8}	0.37	0.5	0.7	0.53
	{3,8}	0.38	0.4	0.5	0.43
	{14}	0.3	0.8	0.7	0.67
	{14,15}	0.2	0.5	0.4	0.41
	{2,12}	0.27	0.4	0.5	0.40
	{7,12}	0.2	0.3	0.7	0.40
	{3,12}	0.28	0.2	0.1	0.19
	{8,12}	0.3	0.2	0.2	0.22
	{11}	0.18	0.9	0.9	0.76
	{7,10}	0.15	0.3	0.6	0.36
	{8,10}	0.25	0.8	0.7	0.66
	{7,11}	0.19	0.5	0.4	0.41
	{8,11}	0.29	0.1	0.5	0.26
Purchased quantity discount	{2}	0.33	0.5	0.7	0.53
	{4}	0.35	0.4	0.3	0.36
	{5}	0.25	0.7	0.6	0.58
	{7}	0.2	0.5	0.7	0.50
	{10}	0.1	0.8	0.8	0.66
	{6}	0.2	0.2	0.8	0.38
	{13}	0.2	0.5	0.3	0.38
	{15}	0.1	0.5	0.7	0.48

customer 113 will obtain the price discount when he purchases the above products. He will obtain the general discount when he purchases general discount products; moreover, customer 113 will also obtain the purchased quantity discount when his purchase quantity is greater than or equal to a decision-maker's specified minimum quantity threshold.

2.5 On-Line transaction model

Whenever a customer logons to the proposed system, the on-line transaction model is provided, illustrated as in Figure 7. In the model, the system responses immediately to a legal customer when he is in one of the three user statuses: "enter system," "select a product," and "shell out." The response draws forth the corresponding responsive strategy according to which status the customer is.

Finally, when a customer quits the system, it will update related database and record the promoted result for calculating success ratio as a basis to enhance the proposed on-line personalized promotion's effectiveness.

3. Conclusions and Future Work

In this paper, we mentioned that the development of Internet has shortened the distance between business and customers. However, it is a bigger challenge that business will face because there are more competitors in Internet than in traditional market, and the customers' loyalty is so low that it is a difficult problem for a business to attract and retain customers. Traditional mass marketing is no longer suitable; the business must change to one-to-one marketing so as to provide personalized promotion products for each customer.

Hence, in this paper, different promotion products are proposed for different customers. We present a decision support system to assist business intelligently developing on-line promotion products suitable for each customer. The main concept of the system is that business can utilize data mining techniques to find out effective promotion products based on marketing strategies, pricing strategies, and customers' purchasing behaviors, where customers may refer to all customers, customer clusters, or an individual customer. Best promotion products are

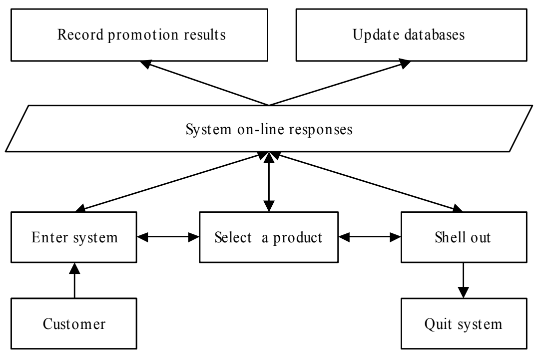

Figure 7. On-line transaction model

Table 14. On-line responsive strategies

Customer status	System on-line responsive strategies
Enter system	· Select personalized promotion products
Select a product	· Select associated products · Select discount data for the amount
Shell out	· Select discount data for the total

developed after all candidate promotion products are evaluated in terms of multiple criteria. It can increase customer satisfaction and loyalty and finally achieve the goal of strengthening business competitiveness. The system consists of four components: (1) marketing strategies, (2) promotion pattern model, (3) personalized promotion products, and (4) on-line transaction model.

In the future, we shall develop this decision support system and experiment on it in real world to achieve the goal of supporting e-business. In addition, it involves many kinds of techniques in our research. We will continue to devote to the improvement of the techniques later in order to shorten system's response time and then promote its effectiveness.

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