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Constructing Repurchase Intention Prediction Model Based on PWOM/NWOM Effect and Service Recovery Considerations by Using BPNN Technique

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Abstract: When customers do not feel satisfaction because the service was not delivered well as the customer's expectation, the service failures occur. And the same time, the customer's complains will be happened along with the service failure. How to effectively rectify a service delivery failure via a service recovery will be an important consideration during the competitive and dynamic environment. And, if customers are satisfied with the complaints handling, consumers' repurchase intention and WOM effect may be kept or enhanced, especial for positive WOM (PWOM) and Negative WOM (NWOM). Besides, how to address the possible non-linear correlation among service failure, service recovery, repurchase intention and PWOM/NWOM effect will be an important consideration to managers' decision-making. In this study, a modeling approach by using back propagation neural networks (BPNN) technique is proposed to achieve such non-linear modeling. Besides, an illustrative example owing to LOHAS restaurant industry at Taiwan is applied to demonstrate the rationality and feasibility of the proposed approach.

Keywords: Service Failures/Service Recovery, PWOM/NWOM, Repurchase, Backpropagation Neural Networks (BPNN)

INTRODUCTION

As we known, meeting customers' expectations and needs had been regarded as the basic requirement for most enterprises. A good customer's service should create a value proposition to exceed consumers' expectations. When the service was not delivered well as the customer's original plan or expectation, service failure will arises. Generally, most enterprises will make more efforts to intend to handle with those possible service failures. Service recovery became an important activity for most enterprises to handle the cutomers' service failures. Although customer service and service recovery are inseparable, they can be regarded as two sides of a coin for most enterprises [1]. The importance of developing a mutually beneficial ongoing buyer-seller relationship has been emphasized in relating studies [2-5]. When service is not delivered as consumer's expectations, the negative disconfirmation will prompt dissatisfied customers to exhibit multiple options, namely exit, voice, and loyalty [6]. Complaints can offer service providers' chances to rectify the problems and complaints may positively influence subsequent consumer behavior [7,8]. The previous study had observed that if customers are satisfied with the complaints handling, dissatisfaction can be reduced and the probability of repurchase may be increased. Furthermore, Tax et al. also mentioned the effective complaint handling may have a dramatic impact on customer retention rate, deflect the spread of negative word-of-mouth (NWOM), and improve profitability [9]. Understanding the impact of each dimension of justice on post-complaint evaluations should allow enterprise's manager to develop more effective and cost-efficient methods of resolving conflicts. Then, higher levels of customer retention as well as higher profits can also be achieved [10]. Service recovery can help enterprises developing a long-term relationship with consumers. The customer satisfaction and re-purchase intention can be enhanced or improved via taking the necessary and optimum service recovery and the evaluation of positive WOM (PWOM) and NWOM. Such process can be viewed as a learning model from the viewpoint of system. And, it denoted a dynamic characteristic during the competitive environment. From those previous relating studies, we can recognize that a possible relationship among the service failure, service recovery and satisfaction, re-purchase intention and WOM effect may exist [11-13]. Hence, how to model the correlation between service failures, the evaluation of PWOM/NWOM and the service recovery, and how to model the complicate correlations among the service failures, the service recovery, the evaluation of PWOM/NWOM and the consumers' repurchase intention other worthy issue to be addressed, especially for the possible non-linear correlation consideration. Restated, it will be an important core action for the construction of the service dynamic learning model. Such model will aid the managers making the necessary decision about their service management during the dynamic and competitive environment.

LITERATURE REVIEW

Service failure

Almost enterprises should aim to offer zero defects service, but some service failures are inevitable. When the service was not delivered well as the customer's original plan or expectation, service failure will arises. And then, the customer's complains will be also happened along with the service failures. Bitner et al.[14] had used the critical incident technique to identify a service failure classification model which has been widely adopted by other researchers [15-17]. Understanding the type of service failure that has occurred can be reviewed as an important activity to choose an appropriate recovery strategy and to develop future policies. When service failures arise from employee actions and personnel behavior, the appropriate service recovery might be the focus on to those first-line managers.

Service recovery

Service failures can be defined as any service related mishaps or problems that occur during a consumer's experience with an organization. How to effectively respond to those service failures will be an important consideration. This response is often referred to as service recovery and is defined as the process by which an organization attempts to rectify a service delivery failure [18] Past studies [15, 17, 19-20] had suggested that effort of an organization's service recovery can either reinforce customer relationships. In contrast to a poor recovery, Goodwin & Ross [21] had suggested that a proper service recovery can restore levels of satisfaction and promote referrals for future purchases. A superior service recovery effort may induce a paradoxical scenario, whereby consumers will rate the failing organization higher after the service recovery than they rated the organization prior to the failure [17]. Goodwin and Ross [21] also claimed that satisfaction levels after complaint-handling (secondary satisfaction) can prove to be higher than previous levels of satisfaction. Their research further suggests that effective complaint-handling can lead to stronger customer loyalty [22]. Kelley *et al*. [17] had also suggested that organizations should make every attempt to recover from a service failure, as an effective recovery will maintain customer loyalty despite the type of failure. In their study, customer retention exceeded 70% for those customers that perceived effective recovery efforts. Another study reported that customers who experienced a service failure told nine or ten individuals about their poor service experience, whereas satisfied customers only told four or five individuals about their satisfactory experience. Therefore, an effective recovery process may lead to PWOM, or at least diminish the NWOM typically associated with poor recovery efforts [8, 10]. Such advantages of effective service recovery efforts display the importance they can play in satisfying current customers. From this viewpoint, it seems reasonable to propose that the manner in which a firm recovers from service failure could become a sustainable competitive advantage in the marketplace.

PWOM/NWOM

Word of mouth (WOM) may be NWOM or PWOM. Evidence that negative information has more impact on attitude or belief than positive information has been presented by Anderson [23], Arndt [24], Fiske[25], Mittal, Ross and Baldasare [26] and Mizerski [27]. There is less evidence on the impact of negative information on behaviour but Fiske [25] showed that it had more effect on attention time than positive information and Arndt showed more effect of NWOM than PWOM on brand purchase. Arndt's research involved a new brand in a frequently purchased food category; he found that NWOM reduced sales of the food product more than twice as much as PWOM increased the sales of the product. Ahluwalia [28] has questioned the strong effect of NWOM on brand decisions. Alhuwalia's method is to measure the attitudinal changes of people exposed to positive and negative information under experimental conditions. Herr et al. [29] and Laczniak et al. [30] also use attitudinal measures in their experiments. Such experiments show how information is processed but do not tell us whether these processes have an effect on choice behaviour in everyday settings.

Backpropagation neural networks (BPNN)

A neural network is known as a computational algorithm which consists of a number of simple, highly interconnected processing elements (PE) [31]. It had been employed into many applications [32-40], especially for the modeling issue about non-linear relationship between input and output for a complicate system. The perceptron, backpropagation neural network (BPNN), learning vector quantization (LVQ), counter propagation network (CPN) has regarded as the conventional supervised learning neural models [36, 37, 38]. Basically, a BPNN consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. The backpropagation learning algorithm employs a gradient- or steepest-heuristic [33] that enables a network to self organize in such ways that improve its performance over time. In training this type of network, an input pattern is presented and the network adjusts the set of weights in all the connecting links such that the desired output is obtained at the output node. The output generated by the network is compared to the known target value. If there is no difference, no learning takes place. If a difference exists, the resulting error term is propagated back through the network, using a gradient- or steepest-descent heuristic to minimize the error term by adjusting the connection weights. The overall training process for the network using the gradient descent technique can be referred to the relating literatures [31, 33].

THE PROPOSED APPROACH

Goodwin & Ross (1992) had mentioned that the negative reactions or responses frequently represented since service failures occurring for the possible service contact point. Those negative reactions or responses will lead most consumers to have the corresponded complain. Basically, the enterprises can choose the corresponding service recoveries to those complains of the service failures. At the same time, the evaluation for the service recoveries will be also affected by the effect of PWOM and NWOM. Finally, the customer's repurchase evaluation can be predicted by using those factors including the PWOM/NWOM, the evaluation of service recoveries. A non-linear relationship will significantly exist among those complicated structure. Hence, the BPNN which have the capabilities of parallel computation and fault tolerance will be applied into resolving such non-linear modeling problems. Figure 1 is the architecture of the proposed service prediction model based on service recovery consideration by using BPNN modeling technique. The detailed construction procedure will be given as follows:

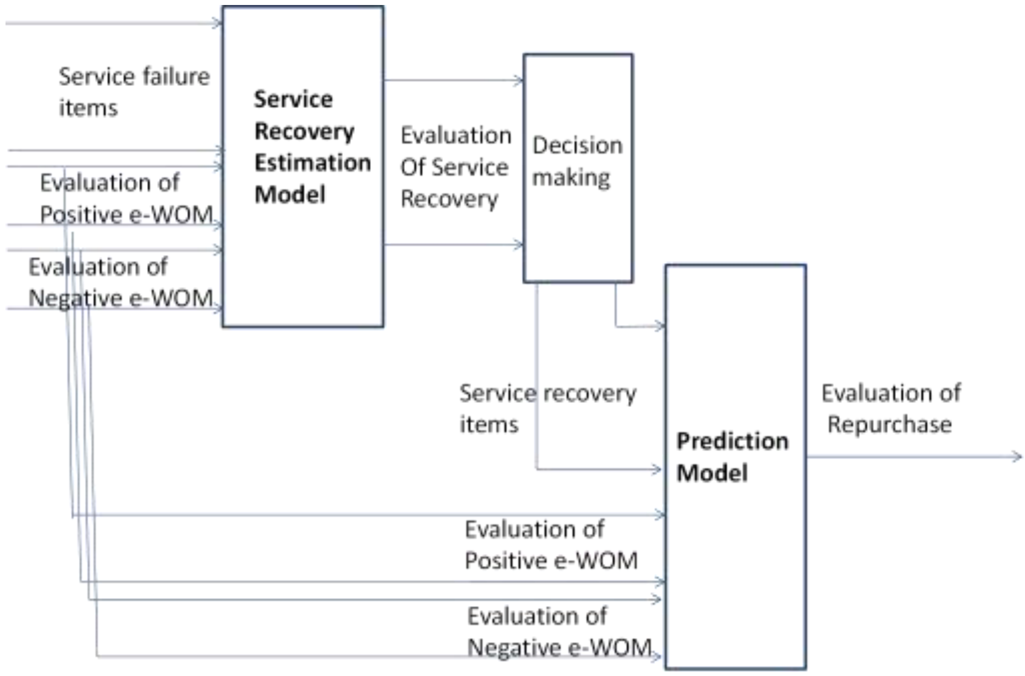

Fig-1:The architecture diagram for the proposed model.

Step 1. Collect the data via an on-line questionnaire platform.

Four primary parts will be designed in the questionnaire including (1) the item of service failure, (2) the evaluation of service recovery, (3) the evaluation of satisfactory, (4) the evaluation of repurchase, (5) the evaluation of PWOM and NWOM effect. Herein, the signal of service failure will be designed as yes/no (i.e. yes is set as "1" and no is set as "0"), the evaluation of service recovery, the evaluation of satisfactory, the evaluation of repurchase and the evaluation of positive and negative WOM effect will be designed as a Likert five scale (i.e., the larger value denote a higher expectation or higher evaluation).

Step 2. Constructing the predicted model of service recovery.

1-1 Randomly take around one-fourth from the experimental data or historical data to form the testing set of BPNN. The remaining parts of the experimental data forms the training set of BPNN.
1-2 The item of service failure, the evaluation of PWOM, the evaluation NWOM/the evaluation of service recovery will be taken as the input/output of the first BPNN. Those signals can obtain from the questionnaire platform.
1-3 Test several different architectures (e.g., the number of PEs in the input layer-the hidden layer-output layer, the learning rate, the learning rule, the momentum, etc) of BPNN by using the training set and testing set chosen in Step-1-1. The root mean square error (RMSE) [31] of the training and testing data for each architecture can be utilized as the criterion in determining the best BPNN architecture. A pre-determined training epoch can

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be regarded as the stopping criteria of training process [31]. The best architecture can simultaneously minimize the RMSEs of the training set and testing set in Step 1-1.

1-4 Combine the training set and testing set chosen in Step 1-1 into a final training set. Restated, assign all historical manufacturing data as the training set. Retrain the best BPNN chosen from Step 1-3 until the best BPNN's architecture reaches the pre-determined training epoch.

Step 3. Constructing the repurchase prediction model.

2-1 It is the same as Step 1-1.

2-2 The actual of service recovery, the evaluation of PWOM and NWOM/the evaluation of repurchase will be set as the input/output of the second BPNN. Herein, those signals can also obtain from the questionnaire platform.

2-3 It is the same as Step 1-3.

2-4 It is the same as Step 1-4.

ILLUSTRATIVE EXAMPLE

In order to verify the rationality and feasibility of proposed model, we take an illustrative example owing to the restaurant industry at Taiwan to demonstrate it. In this study, a LOHAS restaurant trade union would like to design a web-based recommending platform to aid the first-line managers enhancing their service quality, especially for the possible information about the evaluation of service recovery, the evaluation of repurchase intention and the evaluation of PWOM and NWOM. Hence, a project team including several senior managers in restaurant union and ICT programmers was assigned. The detailed procedure of model construction will be described well as follows:

Step 1. The data were collected via an on-line questionnaire platform from 2011/10 to 2013/09. The signals of service failure (herein, six primary service failure will be defined and it is denoted as "1/0" with respect to "happened/not happened"), the evaluation of service recovery, the evaluation of repurchase, the evaluation of PWOM (via three items) and NWOM (via three items) based on Likert's five scale in restaurant can be collected. About one hundred and eighty-five respondents with possible service failures had fulfilled the on-line questionnaire. But, thirty records are judged as ineffective data with some missing information. Finally, one hundred and fifty-five data will be kept to the subsequent analysis. Screening out the collected respondents' information, the age range is about 24~60 years old, the income range is about NT 30000~100000 for one month, the ratio of man/women is about 73/82, all respondents are from Taiwan and six LOHAS restaurants are included in this database.

Step 2. In order to construct the service recovery estimation model, the six signals of service failure items (SFi, i= 1, …, 6; "SFi=1" will denote the service failure to be happened and "SFi=0" will denote the service failure to be not happened), three evaluations of PWOM and three evaluations of NWOM and the five evaluation of service recovery items will be taken as the inputs/outputs of the first BPNN model. Herein, the learning rule is set as delta-bar-delta rule, earning rate is set as 0.1, the momentum is set as 0.8, the learning epochs are set as 10000 according to the previous random trails. Next, the root of mean square error (RMSE) of training and testing will be regarded as the criteria to determine the optimum BPNN architecture (with the minimum training and testing RMSE values), i.e. the number of PEs in the hidden layer. Forty respondents are randomly selected as the testing samples. It will lead the ratio of testing samples/training samples to be close to ¼ [31, 37,38]. Depending on different architectures of BPNN, the optimum architecture with the minimum training RMSE value and testing RMSE value at the same time can be determined as 12-15-5 in Figure 2.

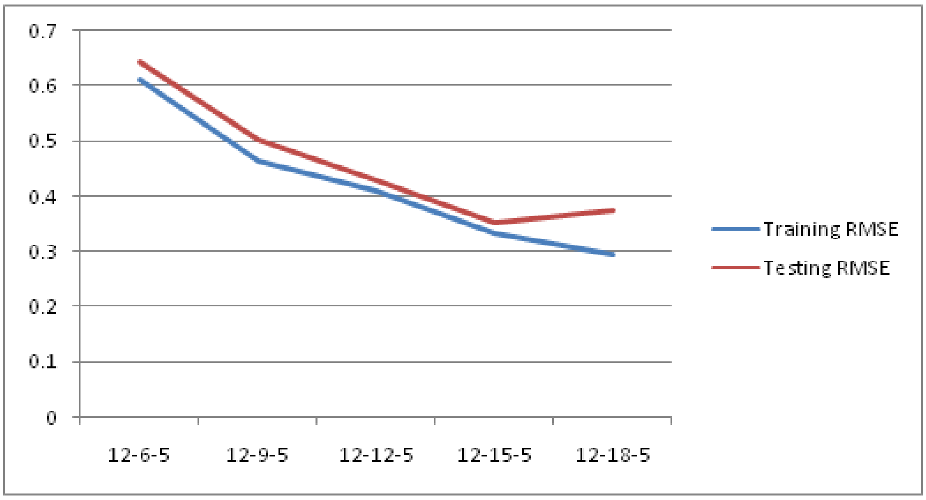

Fig-2: The comparison diagram of the training/testing RMSE for the estimation model.

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Then, the repurchase prediction model is also constructed by taking the five signals of service recovery items, the three evaluations of PWOM and three evaluations of NWOM and the evaluation of repurchase will be taken as the inputs/output of prediction model. Next, the learning rule is also set as delta-bar-delta rule, learning rate is set as 0.1, the momentum is set as 0.8, the learning epochs are set as 10000 according to the previous random trails. Next, the root of mean square error (RMSE) of training and testing will be also regarded as the criteria to determine the optimum BPNN architecture (with the minimum training and testing RMSE values), i.e. the number of PEs in the hidden layer. Fifty-seven respondents are randomly selected as the testing samples. It will lead the ratio of testing samples/training samples to be close to 1/4. Depending on different architectures of BPNN, the optimum architecture with the minimum training RMSE and testing RMSE can be determined as 11-8-1 in Figure 3.

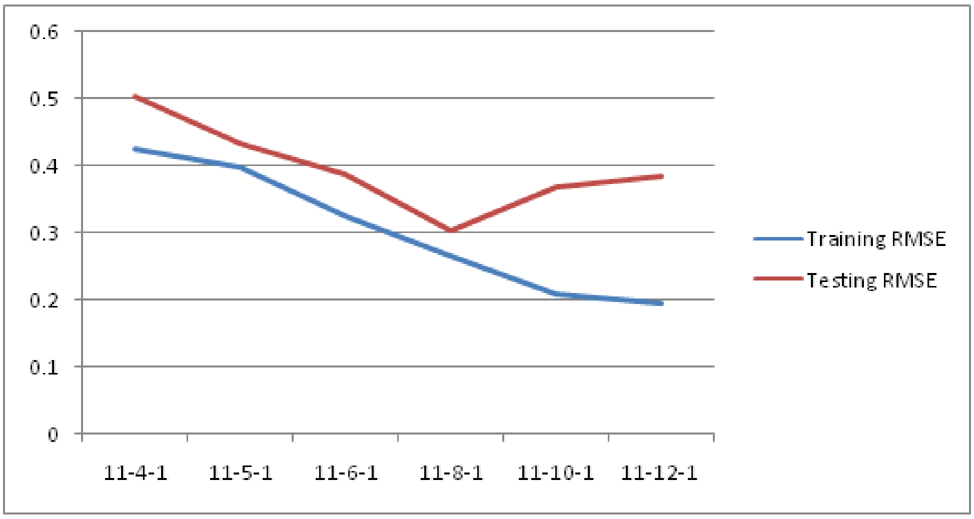

Fig-3: The comparison diagram of the training/testing RMSE for the prediction model.

After constructing the repurchase prediction model, an innovative web service is provided to those LOHAS restaurant group. The first-line mangers in LOHAS restaurants can login the platform to obtain the recommending information about the customers with service failure. For example, one manager login the platform at due to that one member made a complaint about the service failure for waiter service and the attitude of employee (the five item, it is defined as SF5) in his restaurant. At the same time, the manager can obtain the information about the PWOM and NWOM during the past records via on-line questionnaire platform. That is, the manager can input the signal of service failure and the average evaluations of PWOM and NWOM (SF1, SF2, SF3, SF4, SF5, SF6, PWOM1, PWOM2, PWOM3, NWOM1, NWOM2, NWOM3) = (0, 0, 0, 0, 1, 0, 3.6, 3.2, 4, 2, 3, 2) into the estimation model, the expected evaluation of service recovery can obtain (ESR1, ESR2, ESR3, ESR4, ESR5) = (3.48, 2.32, 2.03, 2.26, 4.35). From the obtained results, we can sort the evaluation score to screen out the possible service recovery, i.e. the possible service recovery for such case can be chosen as ESR5→ESR1→ESR2→ESR4→ESR3. Then, the manager can choose the suitable service recovery according to the obtained sorting result. Basically, the larger score will denote the higher expectation for such service failure. The score of ESR5 and ESR1 significantly exceed 3, hence, the ESR5 and ESR1 can be set as the recommended service recovery. Next, the manager can input the obtained information (PWOM1, PWOM2, PWOM3, NWOM1, NWOM2, NWOM3, ESR1, ESR2, ESR3, ESR4, ESR5) = (3.65, 3.48, 2.32, 2.03, 2.26, 4.35, 1, 0, 0, 0, 1) into the prediction model. The predicted satisfaction and the predicted repurchase can be then computed as 4.25. According to the obtained result, the expected evaluation of repurchase significantly exceeds 3. At the same time, the platform automatically sends a short message and an e-mail to the member. The member can evaluate the repurchase evaluation after manager's service recoveries to his service failure and it was denoted as 4. The obtained score of repurchase intention is significantly closed to the predicted satisfaction 4.25, the customer's evaluation of repurchase can be improved via taking the necessary recovery activity.

CONCLUDING REMARKS

To the possible service failures at service contact point during the customer-centric competitive environment, most consumers will lead to complains. The enterprises will choose service recovery to those failures. The satisfaction, repurchase intention of consumers will be significantly affected by the choice of service recoveries, the effect of PWOM and NWOM. If the enterprise's manager chooses an optimum or suitable service recovery and the repurchase of consumers can be kept or enhanced. The repurchase intention may be reduced when enterprise's manager chooses an unsuitable service recovery. The complaints handling (or service recovery) can be viewed as the second marketing activity for enterprises. How to effectively and efficiently choose the service recovery will be an important work to those managers. Restated, if the managers can obtain the recommended possibility for service recoveries, it will aid managers into making their decision about complaints handling. Including those characteristics into the model will be the first purpose of this study. Two contributions to management implication can be summarized as follows:

(1) The complicate non-linear correlations among service failures, service recovery, repurchase and PWOM/NWOM effect will be modeled well. Managers can apply it into obtaining the estimation about service recovery and the estimation about consumer's repurchase intentions. That is, a learning characteristic during competitive environment can be mentioned.

(2) The retraining capability of BPNN will lead those managers to dynamically adjust the BPNN architecture depend on their real requirements. Because the records will be gradually increased, managers can update and remodel BPNN to be a robust architecture depending on their real requirements. That is, a dynamic characteristic during competitive environment can be mentioned.

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