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Telecare Adoption Model Based on Artificial Neural Networks

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1. Introduction

Telecare will become a trend in the twenty-first century (Haux, 2006; Miller, 2007). With respect to telecare, evaluation studies are few in number. Furthermore, few studies were carried out using nonlinear structural models (such as the nonlinear neural network model) to explore the users' adoption. Therefore, the purpose of this study is to utilize the healthcare information adoption model (HIAM) that it is created first time by Huang (2010), and use it to establish telecare adoption by artificial neural networks (ANNs).
According to the healthcare information adoption model (HIAM) Huang, 2010), the research structure underlying this study is shown in Fig. 1.

H1. An individual's attitude toward using (ATT) and behavioral intention to use (BI) with respect to telecare are found to be positively associated.

H2a. Perceived ease of use (PEOU) has a direct effect on the ATT of telecare.

H2b. PEOU has a direct effect on PUB (perceived usefulness and benefits).

H3. The stronger the perceived usefulness and benefits (PUB) of telecare, the stronger is the ATT of telecare.

H4. The stronger the perceived disease threatens (PDT) (which includes perceived susceptibility and perceived severity), the stronger is the ATT of telecare.

H5. The stronger is the perceived barriers of taking action (PBTA) of telecare, the weaker is the ATT of telecare.

H6. The stronger the cues to action (CUES), the stronger is the ATT of telecare.

H6a. The stronger the external cues to action (ECUE), the stronger is the ATT of telecare.

H6b. The stronger the internal cues to action (ICUE), the stronger is the ATT of telecare.

2. Research methodology

2.1 Data collection

This study used face-to-face interview to collect senior citizens aged over 60 years, who lived in a village in Taiwan. A total of 295 valid copies of a questionnaire were obtained with males accounting for 57% of the respondents. Most of them were age groups of 60–69 (amounting to 58%). In terms of the educational level, 49% of the subjects had completed primary schools, and the average monthly income ranged between NT$20,000 and NT$50,000 (amounting to 71%) (US$1 ≈ NT$31.61).

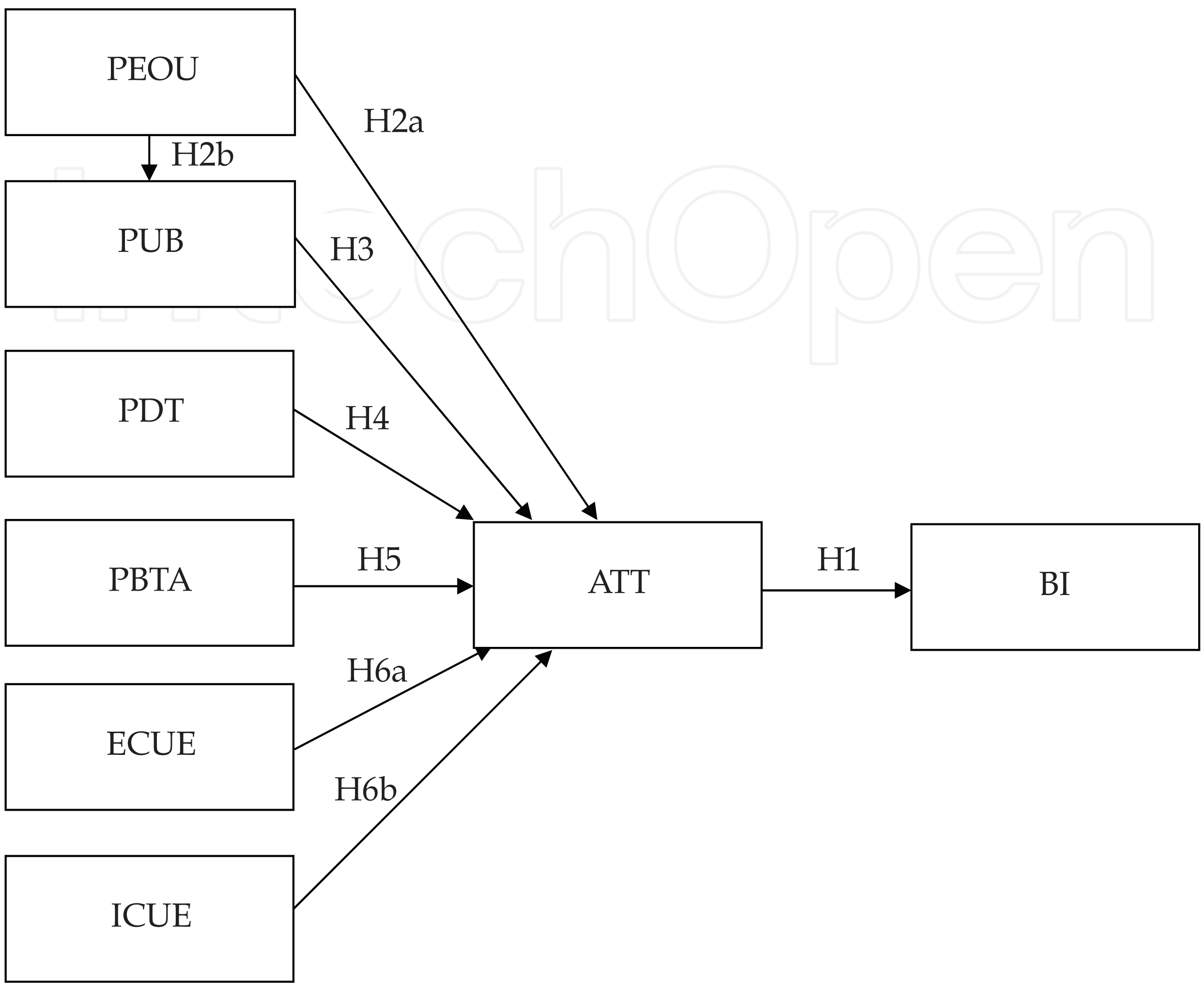

Fig. 1. Research structure. Note: perceived ease of use (PEOU), perceived usefulness and benefits (PUB), perceived disease threat (PDT), perceived barriers of taking action (PBTA), external cues to action (ECUE), internal cues to action (ICUE), attitude toward using (ATT), behavioral intention to use (BI).

2.2 Measures of the constructs

This study is based on the definition as well as on the constructs related to TAM (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) and HBM (Rosenstock, 1966; Rosenstock, 1974). The healthcare information adoption model (HIAM) includes eight constructs: perceived ease of use (PEOU), perceived usefulness and benefits (PUB), perceived disease threatens (PDT), perceived barriers of taking action (PBTA), external cues to action (ECUE), internal cues to action (ICUE), attitude toward using (ATT), and behavioral intention to use (BI). The operationalization and sources of measurement items in this study are shown in Table 1. All evaluation items employ a five-point Likert-type scale for measurement, where 1, 2, 3, 4, and 5 indicate “strongly disagree,” “disagree,” “fair,” “agree,” and “strongly agree,” respectively.

2.3 Reliability and validity analysis

The internal consistency was assessed by using Cronbach's alpha. The alpha coefficients of all the seven constructs were higher than the benchmark of 0.6, as suggested by Bagozzi and Yi (1988). This demonstrated the reliability of each construct. Besides, the questionnaires of this study have considerable content validity (refer to Table 1).

Categories	Measure
Perceived ease of use (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989)	
PEOU1	I find that using telecare is simple.
PEOU2	I find that telecare is easy to learn.
PEOU3	I find that telecare is easily understandable and clear.
PEOU4	Overall, I find that using telecare is convenient.
Perceived usefulness and benefits (Davis, 1989; Davis, Bagozzi, & Warshaw, 1989; Rosenstock, 1966; Rosenstock, 1974)	
PUB1	I find that using telecare is helpful in monitoring health.
PUB2	I find that using telecare makes me safer in my daily life.
PUB3	Telecare can enhance my level of convenience in accessing medical care service.
PUB4	Telecare can enhance the quality of my life.
PUB5	Overall, I find telecare highly useful.
Perceived disease threat (Rosenstock, 1966; Rosenstock, 1974)	
PDT1	I find that I can fall ill easier than others.
PDT2	I find that I can suffer from high blood pressure, diabetes, heart disease and other chronic diseases in the future.
PDT3	I find that my health is deteriorating.
PDT4	I find that I can suffer from high blood pressure, diabetes, heart disease, and other chronic diseases in the future and could be forced to change my previous way of life.
Perceived barriers of taking action (Rosenstock, 1966; Rosenstock, 1974)	
PBTA1	For me, the cost of telecare is a very heavy burden to bear.
PBTA2	I am concerned that telecare is not adequately secure

Categories	Measure
	and that it might lead to the leak or abuse of my personal information.
PBTA3	I am concerned that telecare would violate my privacy.
PBTA4	I am concerned that the accuracy and reliability of the instruments of telecare are not high enough.
PBTA5	I am concerned that I might forget to use the telecare.
PBTA6	I am concerned that I might be too busy to use the telecare equipment.
External cues to action (Rosenstock, 1966; Rosenstock, 1974)	
ECUE1	Relatives encourage and support me to use telecare.
ECUE2	Friends encourage and support me to use telecare.
ECUE3	Medical care personnel encourage and support me to use telecare.
ECUE4	Media endorses the use of telecare.
ECUE5	I have always obtained health-related information from TV, newspapers, and other media.
ECUE6	I have always obtained health-related information from the Internet.
Internal cues to action (Rosenstock, 1966; Rosenstock, 1974)	
ICUE	How many times did you fall sick in the last three months?
Attitude toward using (Taylor & Todd, 1995)	
ATT1	I like using telecare.
ATT2	Overall, I consider telecare to be just right.
ATT3	In my old age, using telecare would be ideal.
Behavioral intention to use (Taylor & Todd, 1995)	
BI1	Overall, I am highly willing to use telecare.
BI2	If necessary, I would use telecare often.
BI3	In my old age, I am willing to use telecare.
BI4	In my old age, I would use telecare often.

Table 1. Measuring items used in this study

2.4 Data analysis methods

2.4.1 Research framework of the Artificial Neural Network (ANN)

Of the various Artificial Neural Network (ANN) models, the Back-Propagation Network (BPN) is the simplest model and the easiest to understand. The feed-forward neural network (FFNN) has a general architecture, as shown in Fig. 2 (Kumar, 2007). The development procedure of ANN can be divided into two processes: learning process, and recalling process. A large number of examples are required in both processes as the input data, in order for the ANN operation to complete at each process. During the learning process, the errors of trained examples with targets are used to adjust the weights of ANN by various efficient learning algorithms. The weights are updated after processing all examples. The final weights are adjusted to meet the minimization of errors we desired. Then, the trained weights are stored in the network after learning is completed. In the second process, testing examples are used to verify the validity of the network. Furthermore, neural network is utilized in case study to infer the results.

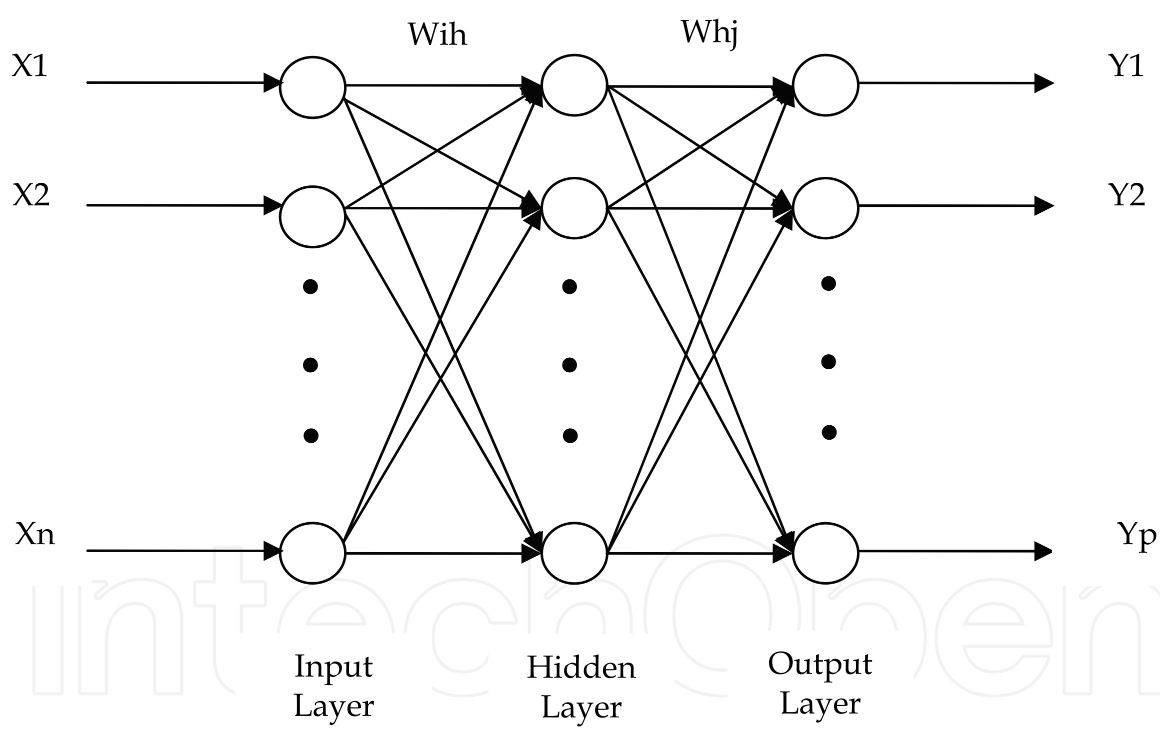

Fig. 2. Feed-forward neural network with n inputs and p outputs

This study adopted three ANN frameworks that use a single hidden layer. They are shown in Figs. 3~5, and Back-Propagation Network (BPN) was used to adjust the network connection weights. The parameters of three ANNs are summarized in Tables 2~4. In Fig. 3, PEOU, PUB, PDT, PBTA, ECUE, and ICUE are input layers, ATT is the output layer. In Fig. 4, PEOU is the input layer, and PUB is the output layer. In Fig. 5, ATT is the input layer, and BI is the output layer.

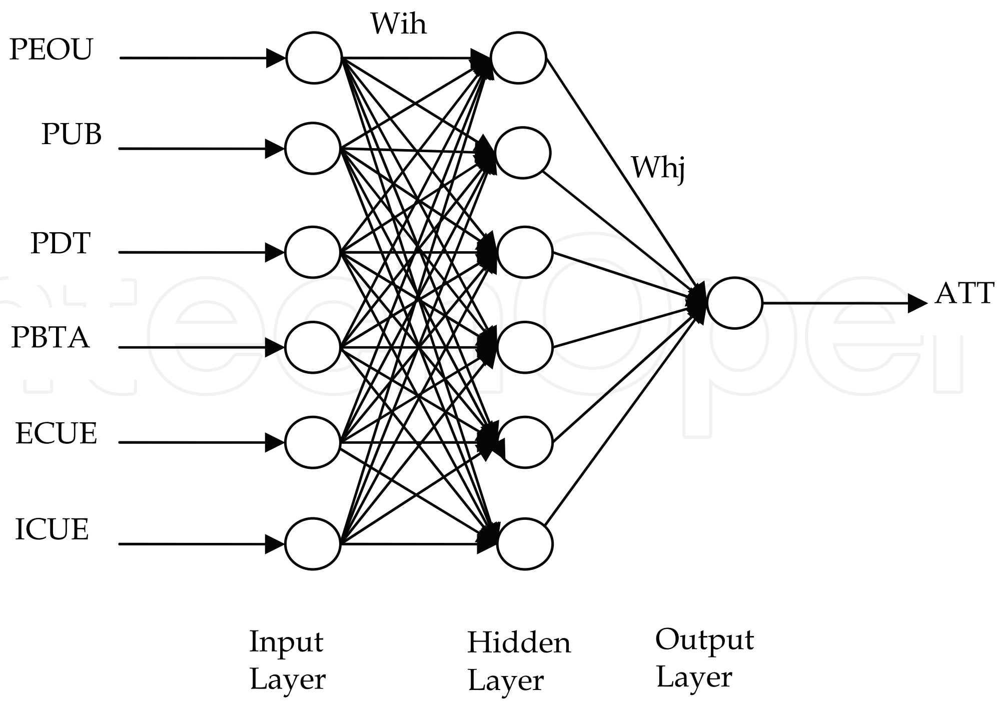

Fig. 3. ANN research framework diagram (A). Note: perceived ease of use (PEOU), perceived usefulness and benefits (PUB), perceived disease threat (PDT), perceived barriers of taking action (PBTA), external cues to action (ECUE), internal cues to action (ICUE), attitude toward using (ATT).

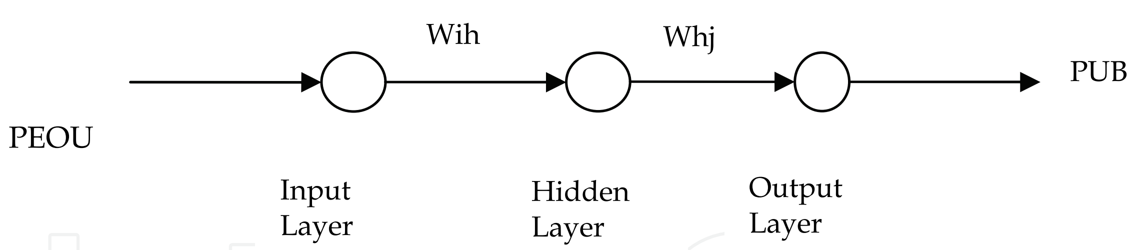

Fig. 4. ANN research framework diagram (B). Note: perceived ease of use (PEOU), perceived usefulness and benefits (PUB).

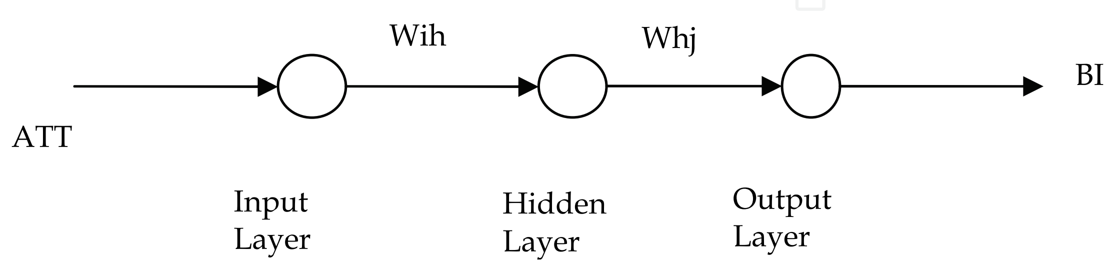

Fig. 5. ANN research framework diagram (C). Note: attitude toward using (ATT), behavioral intention to use (BI).

	Input		Hidden		Output
Number of neurons	6		6		1
Signal function	linear		sigmoidal		linear
Neuron index range	i=0,…., 5		h=0,…,5		j=0
Weights (including bias)		→ Wih →		→ Whj →	

Table 2. The parameter for ANN research framework diagram (A)

	Input		Hidden		Output
Number of neurons	1		1		1
Signal function	linear		sigmoidal		linear
Neuron index range	i=0		h=0		j=0
Weights (including bias)		→ Wih →		→ Whj →	

Table 3. The parameter for ANN research framework diagram (B)

	Input		Hidden		Output
Number of neurons	1		1		1
Signal function	linear		sigmoidal		linear
Neuron index range	i=0		h=0		j=0
Weights (including bias)		→ Wih →		→ Whj →	

Table 4. The parameter for ANN research framework diagram (C)

2.4.2 Data analysis steps

In this study, we constructed, performed training on and tested the ANN model with Matlab Neural Netowork Toolbox.

Step 1. Normalize all data into [0, 1], including PEOU, PUB, PDT, PBTA, ECUE, ICUE, ATT, and BI.

Step 2. The trained algorithm of the Levenberg-Marquardt backpropagation (Hagan and Menhaj, 1994) is used to adjust the weight with MSE (Mean Square Error).

Step 3. Randomly choose the initial weights.

Step 4. Proceed with the ANN model training, 2/3 of the total samples (196 samples) are chosen as training examples. Each training session for all 196 data is deemed as an epoch. Parameters are updated during this period to obtain the optimal ANN models.

Step 5. The final optimal ANN model is acquired after completing the training. Tests (a) and (b) are employed to examine the stability and reliability of the ANN; tests (c) and (d) are employed to estimate the effect of individual input variables on output variables.

a. Input the 196 samples which have been used in training to obtain the 196 estimated output values. The errors between the estimated and raw data are shown in Fig. 6. The statistical result of errors, including mean, standard deviation (S.D.), and Root of Mean Square (RMS) are shown in Table 5.

b. Input the remaining 1/3 of the samples (99 samples), which have not been used in training to obtain the 99 estimated output values. The errors between the estimated and raw data are shown in Fig. 6. The statistical result of errors, including mean, standard deviation (S.D.), and Root of Mean Square (RMS) are shown in Table 5.

c. Take the dependence of ATT on PEOU as an example, the correlation with ATT could be obtained by setting PEOU to 1 and other input variables to zero. Thus, the test vector of input is [1 0 0 0 0]. Similarly, the correlation between all input variables and output variables could be acquired (Table 5).

d. Besides test (c), there is another approach to identify the effect of one input variable on output variables, and it is by fixing other input variables to zero. Thus, continuous discrete input is used with one input variable increasing from 0 to 1 at 0.01 steps. Similarly, the correlation between all input variables and output variables could be acquired. The results are presented in Figs. 7~9. Therefore, the dependence of all output variables on input variables can be identified.

3. Results

Table 5 shows the dependence of ATT on PEOU, PUB, PDT, PBTA, ECUE, and ICUE. As presented in the ANN research framework diagram (A) of Fig. 3, the error mean (S.D) and Root of Mean Square (RMS) for the training examples are 0.1304 (0.0793) and 0.1525, respectively; the error mean (S.D) and Root of Mean Square (RMS) for the testing examples are 0.1282 (0.0722) and 0.1468, respectively. As to the dependence of PEOU on PUB, as presented in the ANN research framework diagram (B) of Fig. 4, the error mean (S.D) and Root of Mean Square (RMS) for the training examples are 0.1035 (0.0962) and 0.1411, respectively; the error mean (S.D) and Root of Mean Square (RMS) for the testing examples are 0.0475 (0.0438) and 0.0643, respectively. As to the dependence of ATT on BI, as presented in the ANN research framework diagram (C) of Fig. 5, the error mean (S.D) and Root of Mean Square (RMS) for the training examples are 0.1091 (0.0847) and 0.1380, respectively; the error mean (S.D) and Root of Mean Square (RMS) for the testing examples are 0.1211 (0.0948) and 0.1532, respectively. As shown, the errors are acceptable. Furthermore, it could also be inferred from Fig. 6 that the errors for the training and testing examples in both ANN research framework diagram (A), (B) and (C) are acceptable. And, it is means that the model of ANN constructed in this study is stable and reliable.

Path	Correlation	Train error		Test error	
		Mean (S.D.)	RMS	Mean (S.D.)	RMS
PEOU → ATT PUB → ATT PDT → ATT PBTA → ATT ECUE → ATT ICUE → ATT	0.1571 0.2606 0.4319 -0.0119 Minimum Minimum	0.1304 (0.0793)	0.1525	0.1282 (0.0722)	0.1468
PEOU → PUB	0.9867	0.1035 (0.0962)	0.1411	0.0475 (0.0438)	0.0643
ATT → BI	0.9628	0.1091 (0.0847)	0.1380	0.1211 (0.0948)	0.1532

Table 5. Analysis results of the ANN model.

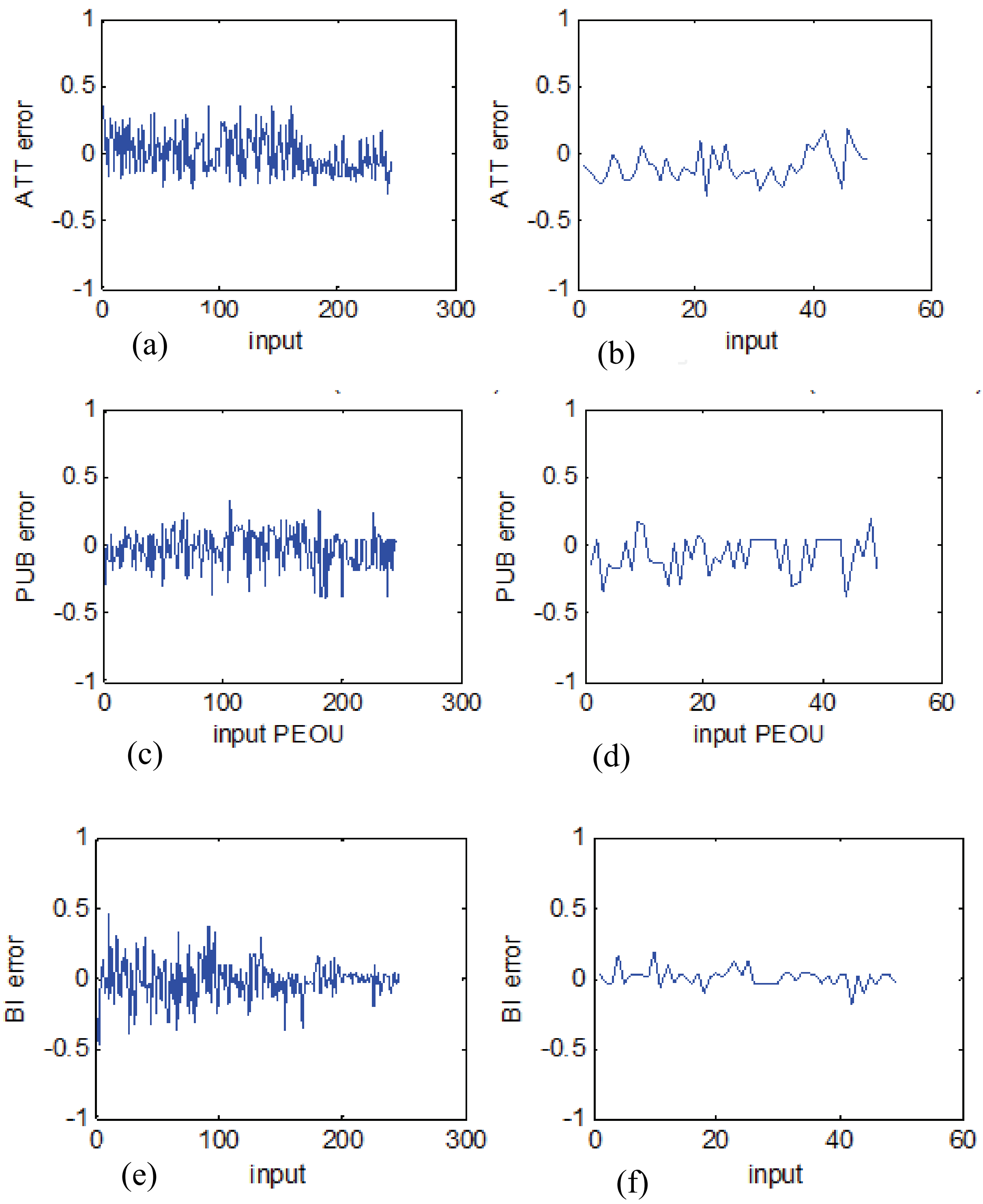

Fig. 6. Errors of the training and testing examples in both ANN research framework diagram (A), (B) and (C). Note: (a) Errors of the training examples in ANN research framework diagram (A), (b) Errors of the testing examples in ANN research framework diagram (A), (c) Errors of the training examples in ANN research framework diagram (B), (d) Errors of the testing examples in ANN research framework diagram (B), (e) Errors of the training examples in ANN research framework diagram (C), (f) Errors of the testing examples in ANN research framework diagram (C).

As shown in Fig. 7, ATT varies positively with BI and thus H1 is supported. As shown in Fig. 8, PEOU varies positively with PUB and thus H2b is supported. As shown in Fig. 9, PEOU, PUB, PDT and ECUE have a significantly positive effect on ATT, and thus H2a, H3, H4, and H6a are supported. PBTA has a significantly negative effect on ATT which indicates that H5 is also supported. However, ICUE has no significant effect on ATT which leads to the rejection of H6b.
The correlation coefficients in Table 5 showed that, among the effects of PEOU, PUB, PDT, PBTA, ECUE and ICUE on ATT, that of PDT is the most significant (with a correlation coefficient 0.4319) and positive; followed by PUB and PEOU (with a correlation coefficient of 0.2606 and 0.1571, respectively) which are also positive. The following is the effect of PBTA (with a correlation coefficient of -0.0119) on ATT, which is negative. However, ATT does not vary significantly with ECUE and ICUE.

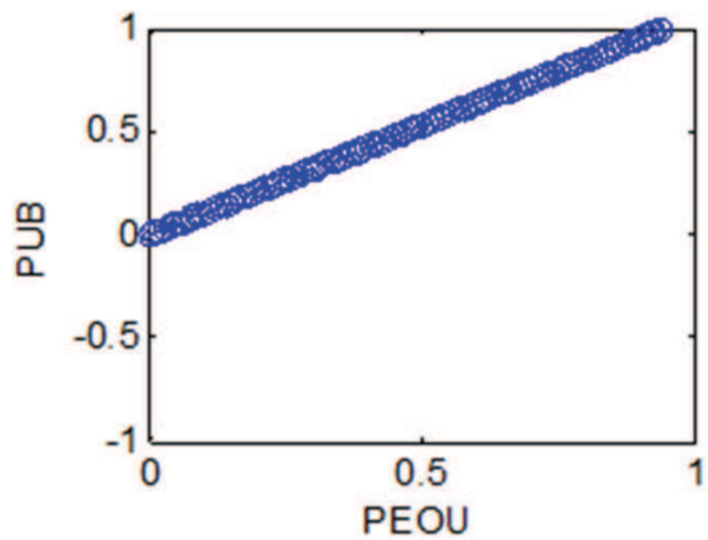

Fig. 7. Effects of ATT on BI. Note: attitude toward using (ATT), behavioral intention to use (BI).

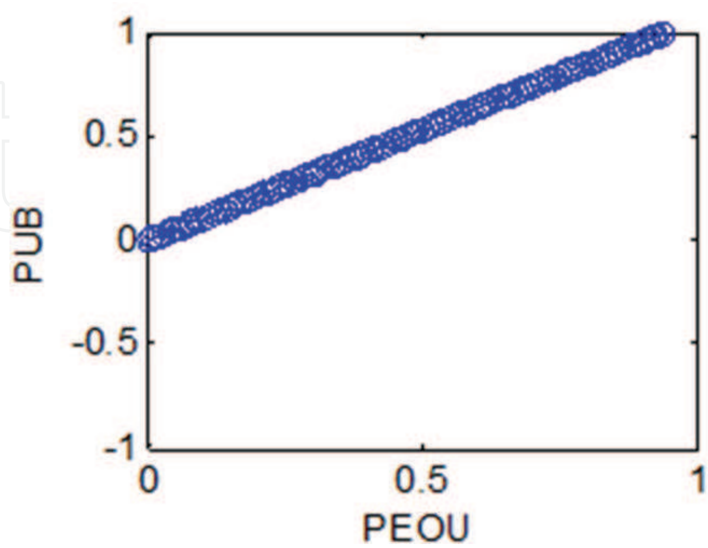

Fig. 8. Effects of PEOU on PUB. Note: perceived ease of use (PEOU), perceived usefulness and benefits (PUB).

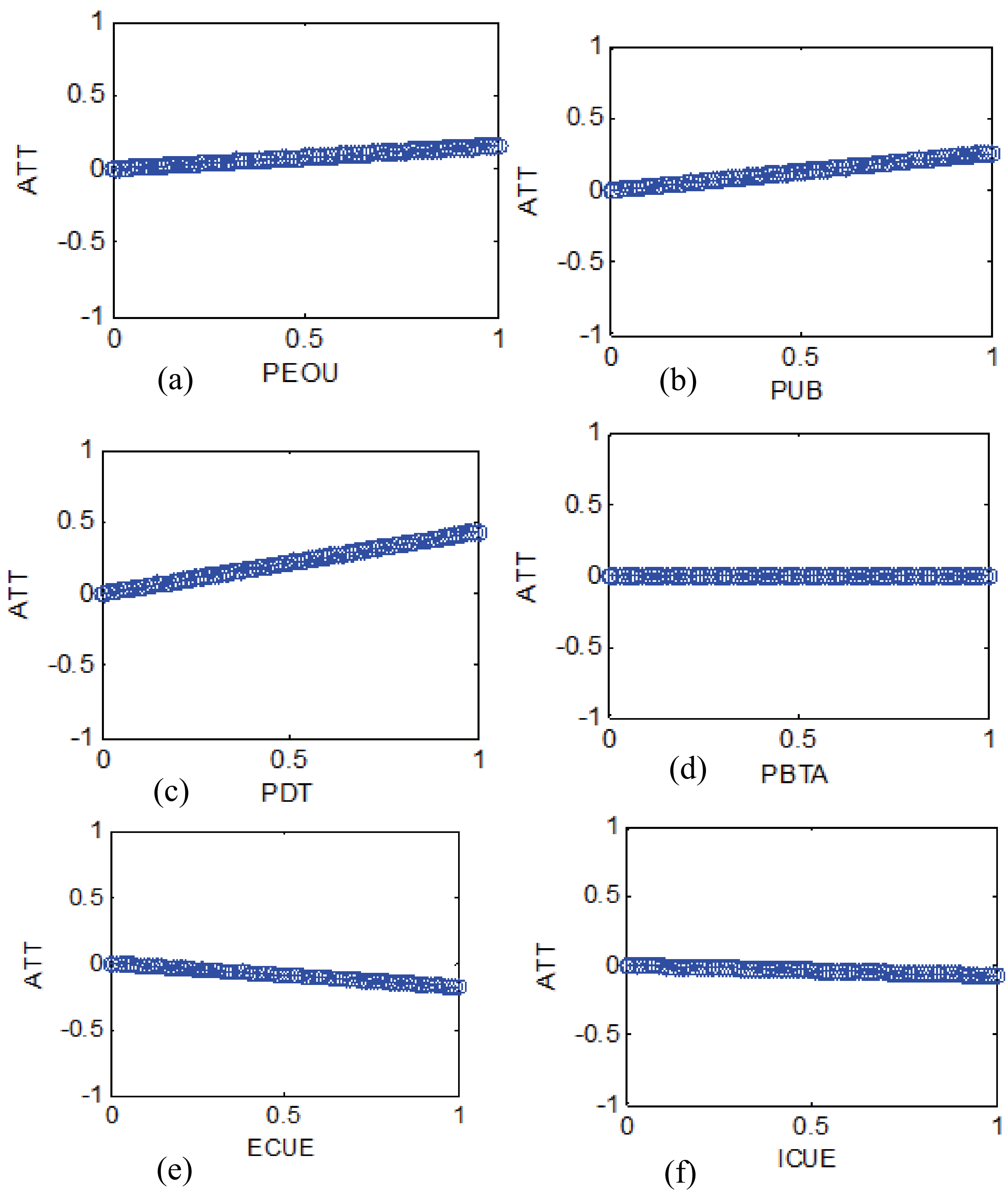

Fig. 9. Effects of PEOU, PUB, PDT, PBTA, ECUE and ICUE on ATT. (a) Effects of PEOU on ATT, (b) Effects of PUB on ATT, (c) Effects of PDT on ATT, (d) Effects of PBTA on ATT, (e) Effects of ECUE on ATT, (f) Effects of ICUE on ATT. Note: perceived ease of use (PEOU), perceived usefulness and benefits (PUB), perceived disease threat (PDT), perceived barriers of taking action (PBTA), external cues to action (ECUE), internal cues to action (ICUE), attitude toward using (ATT).

4. Conclusions

The results indicated that it is feasible to construct a model with ANN, and identify telecare adoption model by using ANN based on the healthcare information adoption model (HIAM) that is created first time by Huang (2010). The finding may offers significant reference for subsequent studies. Besides, the most effective way to enhance the adoption of telecare is to improve the perceived disease threat (PDT) for potential users.

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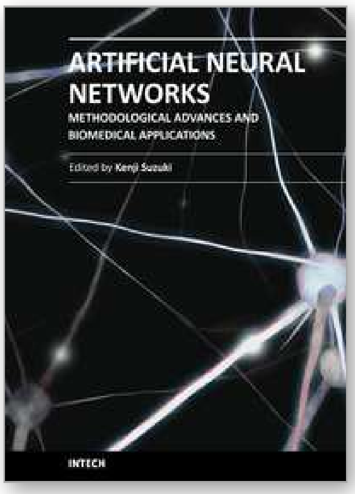

Artificial Neural Networks - Methodological Advances and Biomedical Applications
Edited by Prof. Kenji Suzuki

ISBN 978-953-307-243-2
Hard cover, 362 pages
Publisher InTech
Published online 11, April, 2011
Published in print edition April, 2011

Artificial neural networks may probably be the single most successful technology in the last two decades which has been widely used in a large variety of applications in various areas. The purpose of this book is to provide recent advances of artificial neural networks in biomedical applications. The book begins with fundamentals of artificial neural networks, which cover an introduction, design, and optimization. Advanced architectures for biomedical applications, which offer improved performance and desirable properties, follow. Parts continue with biological applications such as gene, plant biology, and stem cell, medical applications such as skin diseases, sclerosis, anesthesia, and physiotherapy, and clinical and other applications such as clinical outcome, telecare, and pre-med student failure prediction. Thus, this book will be a fundamental source of recent advances and applications of artificial neural networks in biomedical areas. The target audience includes professors and students in engineering and medical schools, researchers and engineers in biomedical industries, medical doctors, and healthcare professionals.