Expert Systems with Applications 38 (2011) 6480–6485

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Data mining for adaptive learning in a TESL-based e-learning system

Ya-huei Wang [a,b,*], Hung-Chang Liao [c,b]

[a] Department of Applied Foreign Languages, Chung Shan Medical University, Taiwan
[b] Department of Medical Education, Chung Shan Medical University Hospital, No. 110, Sec. 1, Jian-Koa N. Road, Taichung 402, Taiwan
[c] Department of Health Services Administration, Chung Shan Medical University, Taiwan

ARTICLE INFO

Keywords:
Adaptive learning
Data mining
Neural network
e-Learning system

ABSTRACT

This study proposes an **A**daptive **L**earning in Teaching English as a Second Language (**TESL**) for **e-learning system** (AL-TESL-e-learning system) that considers various student characteristics. This study explores the learning performance of various students using a data mining technique, an artificial neural network (ANN), as the core of AL-TESL-e-learning system. Three different levels of teaching content for vocabulary, grammar, and reading were set for adaptive learning in the AL-TESL-e-learning system. Finally, this study explores the feasibility of the proposed AL-TESL-e-learning system by comparing the results of the regular online course control group with the AL-TESL-e-learning system adaptive learning experiment group. Statistical results show that the experiment group had better learning performance than the control group; that is, the AL-TESL-e-learning system was better than a regular online course in improving student learning performance.

1. Introduction

In the conventional learning institutions of Taiwan, English teachers present the same content to all students regardless of the individual student's gender or learning characteristics. In other words, English courses are based on "static" learning material, not "dynamic" learning material (Romero, Ventura, Delgado, & Bra, 2007). This is because of the enormous costs universities must pay for education materials in Taiwan, which make it impossible to design personalized learning environments to accommodate the learning needs of individual students. In this type of learning system, if students wish to maximize their learning outcomes, they must adapt to the course content, as the course content cannot be adapted to accommodate *their* individual needs and preferences.

However, adaptive learning for individual students has recently become popular in the educational field. An adaptive learning system is a system developed to accommodate a variety of individual needs and differences. To improve student interaction and learning outcomes, several researchers have recently examined ways to develop adaptive learning for use in different courses (Arlow & Neustadt, 2001; Constantine, 2001; Gibbons, Nelson, & Richards, 2001; Larman, 2001). When educational costs are considered, e-learning is an attractive contemporary approach to achieving the goal of adaptive learning. Chen, Liu, and Chang (2006) presented a personalized web-based instruction system, based on modified item response theory, which performs personalized curriculum sequencing while simultaneously considering course difficulty and learner abilities. This approach uses the concept of learning pathways to help students learn more effectively. In addition, Chen, Hsieh, and Hsu (2007) discovered the association rules of common learning misconceptions using the testing item responses of various learner profiles for web-based learning diagnosis, and applied these association rules to promote learning performance. Tseng, Su, Hwang, Tsai, and Tsai (2008) proposed an adaptive learning system based on a modular framework that segments and transforms teaching materials into modular learning objects. Using this approach, a teacher can dynamically compose the course content according to the profiles and portfolios of individual students. Hsu (2008a) proposed a recommender teaching and learning system to help identify and address student problems and weaknesses in the English language learning process.

The data mining technique is indispensable in developing an e-learning system. Huang, Huang, and Chen (2007) used computerized adaptive testing of individual learner requirements to develop a summative examination and assessment analysis and construct a personalized e-learning system based on a genetic algorithm data mining technique. Hsu (2008b) used content-based analysis, collaborative filtering, and data mining techniques—including an association rules algorithm—to analyze students reading data and select appropriate lessons for each student. Sun, Cheng, Lin, and Wang (2008) proposed a grouping method based on data mining to establish effective groups. Their method helps teachers improve group leaning performance in e-learning. Chen and Hsu (2007) proposed a novel data mining technique consisting of tree-like

* Corresponding author at: Department of Applied Foreign Languages, Chung Shan Medical University, Taiwan.
E-mail address: huncliao@ms43.hinet.net (Y.-h. Wang).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.11.098

patterns that integrated a pair of items into a novel e-learning platform using their cause and effect relationships.

Based on the results of the studies above, this paper presents an adaptive leaning system that accommodates individual student needs and differences in the field of Teaching English as a Second Language (TESL). A data mining technique was used to construct the proposed e-learning system. Specifically, this paper adopts a 4-*step* approach based on an artificial neural network (ANN) core data mining technique to develop an **A**daptive **L**earning in **TESL** for **e-learning system** (AL-TESL-e-learning system). A back-propagation (BP) algorithm selected from the ANNs was used for the supervised cluster classification of student characteristics and learning performances. Different levels of teaching content for vocabulary, grammar, and reading were then set for different students with different combinations of characteristics. Finally, a control group in a regular online course and an experimental group enrolled in the AL-TESL-e-learning system were compared in the pre-test and post-test to validate the feasibility of the AL-TESL-e-learning system. The following section discusses the concept of ANNs and how to use the BP algorithm. Section 3 introduces the sample material to further verify the AL-TELS-e-learning system. Section 4 describes the 4-*step* approach for developing the AL-TELS-e-learning system. The experimental results in Section 5 confirm the proposed AL-TELS-e-learning system. Section 6 presents a summary of the paper's findings and contribution to the literature.

2. ANNs model

ANNs are composed of processing elements (nodes or neurons) and their connections. The nodes are interconnected layer-wise among themselves. Each node in each successive layer receives the inner product of synaptic weights with the outputs of the nodes in the previous layer. The operation of single node is shown in Fig. 1. ANNs have been shown to be effective for addressing complex nonlinear problems. The two types of learning networks are supervised and unsupervised respectively. For a supervised learning network, a set of training input vectors with a corresponding set of target vectors is trained to adjust weights in the ANN. For an unsupervised learning network, a set of input vectors is proposed; however, no target vectors are specified. In this study, a supervised learning network was thought to be more suitable for the classification problem. Several well-known supervised learning ANNs are the BP algorithm, learning vector quantization, and counter propagation network. The BP algorithm is used most extensively and can provide better solutions for many applications (Dayhoff, 1990; Lippmann, 1987). Therefore, the BP algorithm was selected for the current study.

A BP algorithm consists of three or more layers, including an input layer, one or more hidden layers, and an output layer. Fig. 2 illustrates a basic BP algorithm with three layers. The BP algorithm learning works on a gradient-descent algorithm (Funahashi, 1989). The BP algorithm initially receives the input vector and directly passes it into the hidden layer(s). Each element of the hidden layer(s) is used to calculate an activation value by summing up

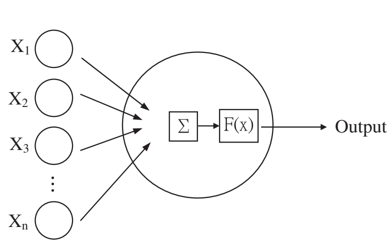

Fig. 1. Node operation.

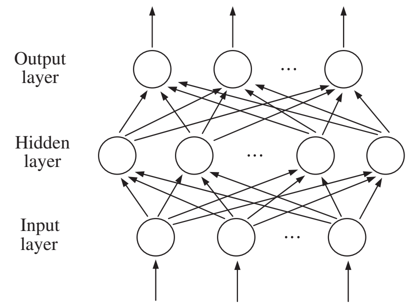

Fig. 2. A BP neural network.

the weighted input, and the sum of the weighted input will be transformed into an activity level by using a transfer function. Each element of the output layer is then used to calculate an activation value by summing up the weighted inputs attributed to the hidden layer. Next, a transfer function is used to calculate the network output. The actual network output is then compared with the target value. The BP algorithm refers to the propagation of errors of nodes from the output layer to nodes in the hidden layer(s). These errors are used to update the network weights. The amount of weights to be added to or subtracted from the previous weight is governed by the delta rule. After the knowledge representation is determined, the BP algorithm will be trained to attempt the classification behavior. The number of hidden layers and the number of nodes in each hidden layer are determined during the training phase. In this study, a fully connected feed-forward neural network was used, and its network parameters and stopping criterion were set.

To be able to attempt the classification behavior, a learning rule is used in the BP algorithm. In the case of a multi-layer perception, this rule should also be able to adapt the weights of all connections in order to model a nonlinear function. The learning rule used most frequently for this purpose is the BP rule. It acts through the following two steps. First, the generalized difference $D_i^*(t)$ is calculated by

$$D_i^*(t) = (A_i^*(t) - A_i(t)) * A_i(t) * (1 - A_i(t)), \tag{1}$$

where $A_i^*(t)$ is the desired activation of output unit i, and $A_i(t)$ is the generated activation of this unit. In order to obtain the generalized difference $D_i^*(t)$, the calculated difference $(A_i^*(t) - A_i(t))$ is multiplied by the simplified derivative of the activation function $A_i(t) * (1 - A_i(t))$. Second, the generalized differences of the units in the output layer are propagated back through the weighted connections to the units of the hidden layer(s). The generalized difference collected from a hidden unit is multiplied by the simplified derivative of the unit's activation function in order to obtain the generalized difference of the hidden unit

$$D_j^*(t) = \sum_{i=1}^{n} (W_{ij}(t) * D_i^*(t)) * A_j(t) * (1 - A_j(t)). \tag{2}$$

Using the generalized difference $D_i^*(t)$, the weights are adjusted by

$$W_{ij}(t+1) = W_{ij}(t) + C * D_i^*(t) * A_j(t). \tag{3}$$

The adaptation size of the weight $W_{ij}(t)$ of the connection used to send information from unit j to unit i is influenced by the existing weight $W_{ij}(t)$, the learning rate C, the generalized difference $D_i^*(t)$, and the actual activation $A_j(t)$ of unit j. To reduce the probability of weight change oscillation, a weight momentum term is added to adjust the weight. The weight momentum term is constructed by the previous adjustment of the weight $D * W_{ij}(t)$ and a constant value B, so

$$W_{ij}(t+1) = W_{ij}(t) + C * D_i^*(t) * A_j(t) + B * D * W_{ij}(t). \tag{4}$$

If more hidden layers are implemented, the BP rule will use the generalized differences of the hidden units of the BP algorithm to get the hidden units of the hidden layer closer to the input layer. To test the network, test set data are assigned to the network, and then the output is evaluated. The network should be able to interpolate and, possibly, extrapolate.

In this study, through the above-mentioned principles for constructing a BP model, the researchers collected training and testing patterns by randomly selecting data from the sample to correlate the presence of students' characteristics with learning performances of reading, grammar, and vocabulary to develop a BP model that could obtain underlying relationships. The BP model can be constructed without requiring any assumptions concerning the functional form of the relationship among students' characteristics with the learning performances of reading, grammar, and vocabulary. The developed BP model can classify the behaviors of all possible combinations of students' characteristics. Then, all students' characteristics combinations in the developed classification model will be presented and the estimated learning performances would be computed.

3. Experimental sample

This section introduces the experimental sample used in this study. A total of 70 freshmen at a university in central Taiwan were selected as the experimental sample. These students had studied English for at least 6 years since junior high school. The regular online English course lasted for 12 weeks, 3 h a week. In the first week, the 70 freshmen were asked to take an English entry test and to fill out a questionnaire gathering information about gender (male and female), personality type (introverted, mildly introverted, neutral, mildly extroverted, and extroverted), and anxiety level (low, moderate, and high anxiety). The English entry test assessed questions on vocabulary, grammar, and reading.

This study also revised and translated the Foreign Language Classroom Anxiety Scale (FLCAS) developed by Horwitz, Horwitz, and Cope (1986) to measure the anxiety levels of the students participating in the study. Horwitz et al.'s FLCAS has been used to measure three components of student language anxiety—communication apprehension, test anxiety, and fear of negative evaluation—in learning a foreign language in the classroom. The FLCAS has 33 items and is scored on a 5-point Likert scale, ranging from "completely agree" to "completely disagree." Possible scores based on this scale range from 33 to 165 (Horwitz et al., 1986). Based on Bekleyen's classification (2004), students with scores between 33 and 66 are classified as low anxiety students. The students with scores between 67 and 132 were identified as moderate anxiety students. Students with scores between 133 and 165 are regarded as high anxiety students. After the pilot study, the reliability coefficient of the FLCAS was 0.937 for the 70 students tested.

This study also adapted the extroversion scale (ES) from the Eyesenck Personality Inventory (1964). This extroversion scale measures the student personality types using 24 items based on a 5-point Likert scale, which ranges from 5 (strongly agree) to 1 (strongly disagree). Possible scores of the ES range from 24 to 120. Some items on the questionnaire were negative statements and hence scored in reverse. Following Ganschow and Sparks' grouping model (1996), this study grouped the students into introverted, mildly introverted, neutral, mildly extroverted, and extroverted groups according to the scores obtained from the ES scale. The mean of questionnaire scores for the 70 students was 78.56, and the standard deviation was 9.14. Students whose scores lay between one standard deviation above the mean and one standard deviation below the mean (scores ranging from 70 to 87) were categorized as having a neutral personality. Students whose scores lay between one and two standard deviations above the mean were identified as mildly extroverted (scores ranging from 88 to 96). Students scoring two or more standard deviations above the mean were identified as extroverted students (scores ranging from 97 to 120). Students who scored between one and two standard deviations below the mean were identified as mildly introverted (scores ranging from 61 to 69). Students scoring two or more standard deviations below the mean were identified as introverted students (scores ranging from 24 to 60). After the pilot study, the reliability coefficient of the extroversion scale was 0.948 for the 70 students tested.

The English teaching content was divided into 3 levels – level 1 (basic), level 2 (intermediate), and level 3 (high intermediate). Each of these three levels included different vocabulary, grammar, and reading components. After 12 weeks of instruction, an exit test was administered to determine the students' learning outcomes for vocabulary, grammar, and reading. The final score for each student's learning performance was computed by $\frac{\text{final test score} - \text{entry test score}}{\text{entry test score}}$ for vocabulary, grammar, and reading.

4. The 4-*step* approach

Using the experimental sample to obtain data, this study applied a 4-*step* approach to identify the relationship between the combination of each student's characteristics and learning performance in vocabulary, grammar, and reading to form the core approach of the proposed AL-TESL-e-learning system. The 4-*step* approach is as follows:

Step 1. Identify the relationship between student characteristics and learning performance.

Defining the knowledge representation, network parameters, and stopping criterion of a BP model is crucial to obtaining the best classification. Knowledge representation defines the relationship between student characteristics and learning performance in the areas of reading, grammar, and vocabulary. The number of input nodes is equal to the number of student characteristics. This study uses three student characteristics: gender, personality type, and anxiety level. The input values for these characteristics are coded as the following:

Gender: male = 1, female = 2
Personality type: introverted = 1, mildly introverted = 2, neutral = 3, mildly extroverted = 4, and extroverted = 5
Anxiety level: high anxiety = 1, moderate anxiety = 2, and low anxiety = 3

The number of output nodes is also three (vocabulary, grammar, and reading); these output values represent the learning performance levels. To help the trained network achieve convergence and stable classification behavior, iterations were limited to 100,000, the momentum was set to 0.12, and the learning rate was set to dynamically auto-adjust from 0.001 to 0.3. These settings enabled rapid, effective learning and stable behavior, as evidenced by the mildly varying values of the root mean square error (RMSE), which is the stopping criterion in the training and testing processes. Table 1 lists various BP models, showing that model **3-5-3** (input nodes–hidden nodes–output nodes) was selected because it produced the lowest RMSE for both training and testing.

Step 2. Obtain the learning performance levels of all combinations of different characteristics.

To obtain the relationship between different combinations of student characteristics and learning performance levels for vocab-

Table 1
BP mode options for this study.

BP model	RMSE	
	Training	Testing
3-2-3	0.01303	0.01165
3-3-3	0.01290	0.01147
3-4-3	0.01259	0.01123
3-5-3	**0.01226**	**0.01099**
3-6-3	0.01243	0.01102
3-7-3	0.01286	0.01119
3-8-3	0.01308	0.01150

BP model: input nodes-hidden nodes-output nodes.

ulary, grammar, and reading, the total number of student characteristics ($2 * 5 * 3 = 30$) can be inputted into the BP model **3-5-3** to obtain the learning performance. Interestingly, no students identified themselves as extroverted, and no students belonged to the low anxiety group. It could be that Taiwanese students are so shy that in class they like to sit quietly in rows and passively copy down whatever the teacher tells them (Rendon, 2005). Students' foreign language learning anxiety could result from academic over-competitiveness in Taiwan, which emphasizes the importance of school entrance examinations. When learning environments foster competitiveness, students have the desire to outperform their classmates to win their teachers' praise. Hence, students experience a higher level of language learning anxiety. An overemphasis on entrance examinations also leads to a competitive learning environment that increases student language learning anxiety (Oxford, 1999; Scarcella & Oxford, 1992). In addition, East Asian students have high expectations of their academic performance, partially originating from students themselves and partially originating from their family and culture (Butterfield, 1986; Dyal & Chan, 1985; Mizokawa & Ryckman, 1990; Oropeza, Fitzgibbon, & Baron, 1991). They tend to exert tremendous effort to get the highest possible scores. Compared to Western students, East Asian students experience much higher levels of anxiety before, during, and after a test (Butterfield, 1986; Mizokawa & Ryckman, 1990). Therefore, this study excluded the values of low anxiety and extroverted, and input a total number of 16 ($2 * 4 * 2$) student characteristic combinations to obtain the learning performance levels.

Step 3. Set α^--cut, and α^+-cut for the different learning performance levels.

The α^--cut, and α^+-cut were set to evaluate the learning performance of different students. In other words, if the student exhibits learning performance lower than α^--cut, the student must learn in level 1, and if the student has a learning performance higher than α^+-cut, the student can advance to level 3. Otherwise, if the student's learning performance is between α^--cut and α^+-cut, the student remains in level 2. In this study, an expert panel composed of five English teachers was asked to determine the different α^--cut and α^+-cut in vocabulary, grammar, and reading. After panel discussion, which found that Taiwanese students have been trained to be good at answering questions about reading comprehension, the α^--cut and α^+-cut for reading were set at 0.2 and 0.5. However, English and Chinese differ from each other in phonological and morphological structures. Compared to the reading test, the vocabulary test it is more difficult for Taiwanese students. This is because they must make and remember the connection between the word meaning, or signified, and the word form, or signifier. Thus, the α^--cut and α^+-cut for vocabulary were set at 0.2 and 0.45. As for English grammar, Taiwanese students have difficulty developing a knowledge of English grammar and syntax due to the different sentence structures and patterns of Mandarin Chinese and English. Hence, the α^--cut and α^+-cut for grammar were set at 0.2 and 0.4.

Table 2
The combination of characteristics for using teaching content.

Gender	Personality type	Anxiety level	The level of teaching content		
			Vocabulary	Grammar	Reading
1	1	1	I	II	II
1	1	2	II	I	III
1	2	1	I	III	I
1	2	2	II	I	II
1	3	1	II	III	I
1	3	2	III	I	III
1	4	1	II	III	I
1	4	2	II	II	III
2	1	1	III	III	I
2	1	2	III	III	II
2	2	1	II	II	I
2	2	2	III	II	II
2	3	1	I	II	I
2	3	2	III	I	II
2	4	1	II	I	I
2	4	2	II	I	I

Step 4. Determine the teaching content of different levels in the AL-TESL-e-learning system for different combinations of student characteristics.

Based on panel discussion, this study adopted the teaching material of the First Choice/Smart Choice series by Wilson and Healy (2007a, 2007b). First Choice/Smart Choice series are multi-level and multi-skill courses for young adult learners seeking to improve their English proficiency. To make the English-learning process enjoyable and effective, the series not only includes sound classroom methodology, but also offers personalization opportunities. Table 2 shows the results of all different combinations of student characteristics and the levels of teaching content.

5. Empirical experiment

After completing the 4-*step* approach, this study established the AL-TESL-e-learning system. In addition, to confirm that the proposed system is feasible and effective, this study conducted a pilot study on 70 freshmen. After the pilot study, another 72 students were randomly assigned to the experimental group or the control group by flipping a coin. Each group consisted of 36 students. The control group adopted a regular online course. Because the mean scores of the pre-test fell into the intermediate level, or Level 2, the control group used the intermediate level of teaching material for vocabulary, grammar, and reading. The experimental group, which adopted the AL-TESL-e-learning system, used online courses and teaching materials tailored to their characteristic combinations. Further, when students in the experimental group thought that they had mastered their current level, they could request taking the individual level approval test. After passing the level approval test, these students were placed in the suitable level to proceed with their personalized learning path for optimal learning performance.

In addition, to test and verify the homogeneity between the control group and the experimental group, both the control group and the experimental group took an English pre-test covering vocabulary, grammar, and reading. This test included 60 multiple-choice questions for the vocabulary section and another 60 questions for the grammar section, with 20 lower level (Level 1) questions, 20 higher level (Level 3) questions, and 20 intermediate level (Level 2) questions. Each question counted for one point, with a total of 60 points for the vocabulary section and 60 points for the grammar section. The reading section consisted of five articles and 25 multiple-choice questions, with eight lower level (Level 1) questions, eight higher level (Level 3) questions, and nine intermediate level (Level 2) questions. Each question counted for two points, for a total of 50 points. The vocabulary pre-test showed that the mean (*M*) and standard deviation (*S.D*) of the experimental group was 35.69 and 7.08, respectively. For the control group, *M* was 36.71 and *S.D* was 8.90. The independent sample *t*-test between these two groups was $t = -0.528$ and the p-value = 0.599, indicating that there was no significant difference between these two groups in the vocabulary section. In the grammar section, the experimental group had an *M* of 32.69 and a *S.D* of 2.05; the control group's *M* was 32.21 and *S.D* was 2.93. The *t*-test result ($t = 0.811$; p-value = 0.420) showed no significant difference between the two groups in the grammar section. In the reading section, the experimental group's *M* was 25.00 and *S.D* was 6.23; the control group's *M* was 24.82 and *S.D* was 7.66. The *t*-test result ($t = 0.106$; p-value = 0.916) indicated no significant difference between the two groups in the reading section.

To evaluate student learning performance after 16 weeks of the e-learning course, students from both groups were compared in the post-test. The post-test covered vocabulary, grammar, and reading sections using the same test style as the pre-test, with items and articles randomly assigned and extracted from different level databases. The post-test results indicated that for vocabulary, the experimental group's *M* was 44.95 and *S.D* was 3.58, while the control group's *M* was 40.74 and *S.D* was 6.55. The *t*-test result showed a significant difference ($t = 3.311$, p-value = $0.002 < 0.01$) between the two groups in the vocabulary section. In the grammar section, the experimental group's *M* was 40.92 and *S.D* was 2.93, while the control group's *M* was 36.59 and *S.D* was 2.11. The *t*-test result showed a significant difference ($t = 7.125$, p-value = $0.000 < 0.01$) between the two groups in the grammar section. In the reading section, the experimental group's *M* was 37.89 and *S.D* was 6.57, while the control group's *M* was 31.09 and *S.D* was 7.85. The *t*-test result showed a significant difference ($t = 3.939$, p-value = $0.000 < 0.01$) between the two groups in the reading section. These results demonstrated that in the vocabulary, grammar, and reading section of the post-test, the mean scores of the experimental group were significantly higher than the mean scores of the control group. In other words, the AL-TESL-e-learning system is better than the regular on-line course. Fig. 3 shows the means of the pre-test and post-test for different sections. Clearly, the sequence of the improvement slope from high to low is reading > vocabulary > grammar.

As mentioned above, English and Chinese have different phonological and morphological structures. Therefore, it is difficult for Taiwanese students to remember the connection between word meanings, or the signified, with the word form, or the signifier. This is because the combination of the signified and the signifier is random, making it difficult for students to make a connection between them. Nevertheless, Taiwan's school entrance exam system requires extensive reading and vocabulary test-taking strategies, such as understanding the main idea and details, using details to make inferences, using word parts or context clues—definition clues, series clues, synonym clues, antonym clues, and experience clues, etc.—to make a logical guess about the meaning of a new word and to comprehend the reading article (Wang, Tsen, & Liao, 2009). If students can follow the adaptive online reading and vocabulary courses in the AL-TESL-e-learning system, they can master the reading comprehension strategies and vocabulary memorization techniques and enhance their learning performance.

However, an overemphasis on entrance examinations also has some negative effects on students' English learning in that students are forced to memorize grammatical rules and coach testing skills related to various types of tests (Young & Chu, 1993). Focusing on grammar and translating exercises (Butler, 2005), Taiwanese students may be good at memorizing the rules, but have few opportunities to apply these grammatical rules in their writing. This may explain their inability to use English confidently. Without substantial practice and steady improvement, students cannot easily improve their grammar abilities.

6. Conclusion

This study proposes an AL-TESL-e-learning system that optimizes student learning outcomes by considering different student characteristics. Based on students' gender, personality types, and anxiety levels, the proposed system sets different levels of teaching content for vocabulary, grammar, and reading for students with different characteristic combinations. This allows students to learn with a personalized adaptive learning. This study explores the learning performance of various types of students using a data mining technique, ANN, as the core of AL-TESL-e-learning system. A BP algorithm selected from the ANNs was used for the supervised cluster classification of student characteristics and learning performances. After using the experimental sample to derive relative data, this study applied a 4-*step* approach to construct the relationship between the combination of each student's characteristics and their learning performances on the vocabulary, grammar, and reading. This 4-*step* approach includes constructing the relationship between student characteristics and learning performance, obtaining the learning performance of all combinations of different characteristics, setting α^--cut, and α^+-cut for the different learning performance levels, and setting different levels of teaching content in the AL-TESL-e-learning system for different student characteristics combinations. This 4-*step* approach to identifying the relation-

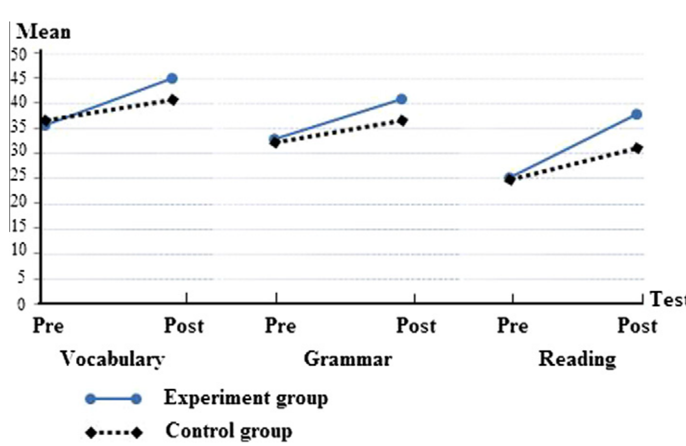

Fig. 3. The results for pre-test and post-test.

ship between student characteristics and learning performance forms the core of this AL-TESL-e-learning system. This study also verifies the feasibility and performance of the AL-TESL-e-learning system using a control group and an experimental group. Statistical results showed that the experimental group had better learning performance than the control group in terms of vocabulary, grammar, and reading.

In traditional TESL education, teachers present the same content to all students, without taking each student' learning differences into consideration. The enormous cost that universities must pay for education material in Taiwan prohibits the developments of an adaptive learning system to meet each student's needs. Hence, students cannot be motivated in the traditional learning system because the teaching–learning flow is static instead of dynamic or interactive (Romero et al., 2007). To motivate students to learn, TESL teachers should adapt the course content and difficulty level to their students' abilities, and develop an adaptive e-learning system in which different learning paths accommodate the needs and differences of each student (Arlow & Neustadt, 2001; Chen et al., 2006; Constantine, 2001; Larman, 2001).

This paper proposes an AL-TESL-e-learning system, an adaptive leaning system, to accommodate individual student needs and differences in the field of TESL. Further research may apply the AL-TESL-e-learning system to non-ESL e-courses, disadvantaged students, or continuing education.

References

Arlow, J., & Neustadt, I. (2001). *UML and unified process: Practical object-oriented analysis and design*. Boston: Addison Wesley.

Bekleyen, N. (2004). The influence of teachers and peers on foreign language classroom anxiety, A.Ü.TÖMER Dil Dergisi, vol. 123, (pp. 49–66). <http://www.tomer.ankara.edu.tr/dildergileri/123/49-66.pdf> Accessed 20.08.08.

Butler, Y. G. (2005). Comparative perspectives towards communicative activities among elementary school teachers in South Korea, Japan and Taiwan. *Language Teaching Research, 9*(4), 423–446.

Butterfield, F. (1986). Why Asians are going to the head of the class. *New York Sunday Times, August, 3*, 18–23.

Chen, C. M., Hsieh, Y. L., & Hsu, S. H. (2007). Mining learner profile utilizing association rule for web-based learning diagnosis. *Expert Systems with Applications, 33*, 6–22.

Chen, T. S., & Hsu, S. C. (2007). Mining frequent tree-like patterns in large datasets. *Data & Knowledge Engineering, 62*, 65–83.

Chen, C. M., Liu, C. Y., & Chang, M. H. (2006). Personalized curriculum sequencing utilizing modified item response theory for web-based instruction. *Expert Systems with Applications, 30*, 378–396.

Constantine, L. (2001). *The people ware papers: Notes in the human side of software*. New Jersey: Prentice Hall.

Dayhoff, J. E. (1990). *Neural network architecture*. New York: Van Nostrand Reinhold.

Dyal, J. A., & Chan, C. (1985). Stress and distress: A study of Hong Kong Chinese and Euro–Canadian students. *Journal of Cross-Cultural Psychology, 16*, 447–466.

Eysenck, H. J., & Eysenck, S. B. G. (1964). *Manual for the Eysenck personality inventory*. London: Hodder & Stoughton.

Funahashi, K. (1989). On the approximate realization of continuous mappings by neural networks. *Neural Networks, 2*, 183–192.

Ganschow, L., & Sparks, R. (1996). Anxiety about foreign language learning among high school women. *Modern Language Journal, 80*, 199–212.

Gibbons, A. S., Nelson, J., & Richards, R. (2001). In D. A. Wiley (Ed.), *The nature and origin of instructional objects, in the Instructional use of learning objects*. Bloomington: Association for educational communications and technology.

Horwitz, E. K., Horwitz, M., & Cope, J. A. (1986). Foreign language classroom anxiety. *Modern Language Journal, 70*, 125–132.

Hsu, M. H. (2008a). Proposing an ESL recommender teaching and learning system. *Expert Systems with Applications, 34*, 2102–2110.

Hsu, M. H. (2008b). A personalized English learning recommender system for ESL students. *Expert Systems with Applications, 34*, 683–688.

Huang, M. J., Huang, H. S., & Chen, M. Y. (2007). Constructing a personalized e-learning system based on genetic algorithm and case-based reasoning approach. *Expert Systems with Applications, 33*, 551–564.

Larman, C. (2001). *Applying UML and patterns: An introduction to object-oriented analysis and design the unified process*. Englewood Cliffs, NJ: Prentice Hall.

Lippmann, R. P. (1987). An introduction to computing with neural nets. *IEEE ASSP Magazine*, 4–12.

Mizokawa, D., & Ryckman, D. B. (1990). Attribution of academic success and failure: A comparison of six Asian-American ethnic groups. *Journal of Cross-Cultural Psychology, 4*, 434–451.

Oropeza, B. A., Fitzgibbon, M., & Baron, A. (1991). Managing mental health issues of foreign college students. *Journal of Counseling and Development, 69*, 280–284.

Oxford, R. L. (1999). Anxiety and the language learner: New insights. In J. Arnold (Ed.), *Affect in language learning* (pp. 58–67). UK: Cambridge University Press.

Rendon, L. (2005). Realizing a transformed pedagogical dreamfield: Recasting agreements for teaching and learning. *Spirituality in Higher Education, 2*(1), 1–13.

Romero, C., Ventura, S., Delgado, J. A., & Bra, P. D. (2007). Personalized links recommendation based on data mining in adaptive educational hypermedia systems. In E. Duval, R. Klamma, & M. Wolpers (Eds.), *Creating new learning experiences on a global scale (Proceedings 2nd European Conference on Technology Enhanced Learning, EC-TEL 2007, Crete, Greece, 17-20 September, 2007). Lecture Notes in Computer Science* (Vol. 4753, pp. 292–306). Crete, Greece: Springer.

Scarcella, R. C., & Oxford, R. L. (1992). *The tapestry of language learning: The individual in the communicative classroom*. Boston: Heinle & Heinle.

Sun, P. C., Cheng, H. K., Lin, T. C., & Wang, F. S. (2008). A design to promote group learning in e-learning: Experiences from the field. *Computers & Education, 20*, 661–677.

Tseng, S. S., Su, J. M., Hwang, G. J., Tsai, C. C., & Tsai, C. J. (2008). An object-oriented course framework for developing adaptive learning systems. *Educational Technology & Society, 11*(2), 171–191.

Wang, Y., Tsen, M., & Liao, H. (2009). Data mining for adaptive learning sequence in English language instruction. *Expert Systems with Applications, 36*, 7681–7686.

Wilson, K., & Healy, T. (2007a). *First choice*. Oxford: Oxford University Press.

Wilson, K., & Healy, T. (2007b). *Smart choice*. Oxford: Oxford University Press.

Young, R. L., & Chu, J. W. C. (1993). Balancing the English teaching process in Taiwan. In *The 10th conference on English teaching and learning in the R.O.C.* (pp. 221–230). Taipei: Crane.