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Flow Prediction Model in English Intercultural Learning Based on BP Algorithm

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Abstract

In recent years, the emotions in English learning have been studied. To investigate the flow experience in the intercultural learning in English as a Foreign Language (EFL) class, a questionnaire survey was conducted with 460 students in one vocational college and 450 valid questionnaires were collected. The SmartPSL was utilized for data analysis to determine the moderating effects of flow experience and core input vectors were selected for the Backpropagation Neural Network (BPNN) model. After constructing a flow prediction model for English intercultural learning and validating the predictive results, the study showed that learners were able to enter a flow state and the predictive outcomes were relatively accurate. Based on the results, the study has been highlighted the significance of flow experience in intercultural English learning. It also offers a flow prediction model, which assists teacher to assess students' active emotion in English learning and to enhance the teaching quality in intercultural teaching.

Keywords: flow experience, intercultural english learning, vocational education, backpropagation neural network

1. Introduction

Intercultural competence (IC) has diverse definitions, with the most widely accepted one being that intercultural competence is the ability to interact effectively and appropriately with individuals from diverse linguistic and cultural backgrounds (Byram, 1997; Deardorff, 2006). It encompasses the capacity to communicate effectively and appropriately in intercultural contexts, based on intercultural knowledge, skills and attitudes. This concept primarily comprises three elements: intercultural context, effectiveness and appropriateness. With the ongoing advancement of internationalization, IC has become increasingly vital, serving as an essential skill for effective intercultural interaction (Peng et al., 2020). Many scholars have proposed models of intercultural competence (IC), with some of the most influential being Byram's and Deardorff's models. The most influential one is Byram's model of IC, consisting of attitudes, knowledge, skills of interpreting and relating, skills of discovery and interaction, and critical cultural awareness (Byram, 1997). Another influential model is the Pyramid Model of IC (Deardorff, 2009) which centers on attitudes and emphasizes the development of knowledge and skills and the transformation from internal outcomes to external outcomes. Drawing on these theoretical models, more practical models have emerged, such as the interacting processes of intercultural pedagogy (Liddicoat & Scarino, 2013) and the model of language and cultural learning development (Shaules, 2016), which have promoted the practice of intercultural language teaching.

However, the researchers have ignored the students' emotions in English intercultural learning. Additionally, there is a noticeable gap in research concerning the application of flow theory in intercultural teaching. This study aims to construct a Backpropagation Neural Network (BPNN) prediction model to predict the flow experience in intercultural reading and provide teachers with useful and feasible tools for dynamically monitoring the flow states and learning outcomes.

2. Theoretical Framework

2.1 Intercultural Teaching Models of EFL Teaching

The intercultural teaching model in our study integrates Byram's (1997) and Deardorff's (2009) models of IC and

Liddicoat and Scarino's (2013) interacting processes of intercultural pedagogy. The goal is to construct a model aimed at cultivating Chinese EFL learners' IC and the ability to express their native culture in English (as illustrated in Figure 1).

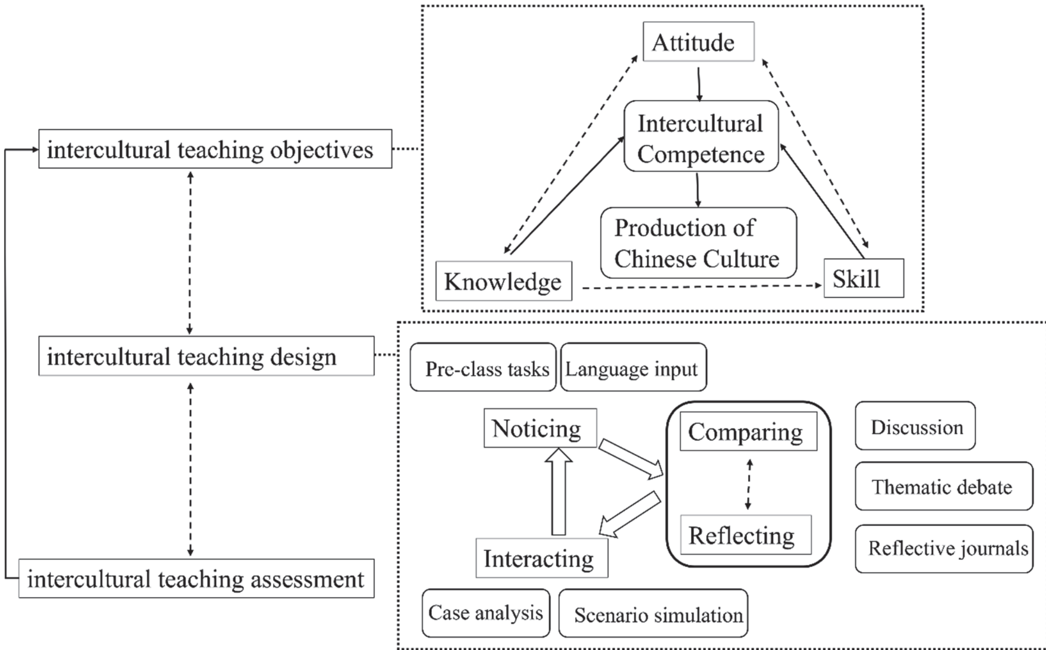

Figure 1. Intercultural teaching model for EFL learners

The four interrelated processes of noticing, comparing, reflecting and interacting in intercultural teaching (Liddicoat & Scarino, 2013) form the foundation of our teaching model, as they provide practical teaching guidance for teachers in EFL class. Each process in the model is associated with specific teaching activities. For instance, through pre-class assignments, language input, etc., learners can notice the cultural similarities and differences of Chinese and Western cultures, which helps them understand the connection between language and culture, stimulates their interest and encourages active participation. Then we set the three components, namely attitude, knowledge and skill, as both our teaching objectives and teaching assessments. In addition to enhancing learners' IC, this model places a strong emphasis on developing the ability to express the native culture in English.

2.2 Core Factors of Flow Antecedents and Consequences in Intercultural Teaching

Flow, also referred to as the flow experience or optimal experience, is characterized by a high degree of concentration and immersion. It represents an extreme state of pleasure that individuals reach when they are completely engaged in an activity (Csikszentmihalyi, 1990). Csikszentmihalyi (1990) put forward nine components of flow: challenge-skill balance, clear goals, immediate feedback, concentration on the task at hand, sense of control, merging of action and awareness, distortion of sense of time, loss of self-consciousness and autotelic experience. Many studies have constructed conceptual models of flow, dividing the flow process into flow antecedents, flow experience and flow outcomes (Barthelmäs & Keller, 2021). Flow antecedents refer to the pre-existing factors or conditions that can trigger the flow experience, such as challenge-skill balance, clear goals and timely feedback. Flow consequences refer to various outcomes brought about by the flow experience, such as satisfaction and learning performance.

Egbert (2003) was the first to introduce the flow theory into foreign language teaching. This model comprehensively considered multiple factors such as learner motivation, task difficulty and feedback, aiming to clearly illustrate how the flow state influences the final learning effectiveness in language learning. Then many scholars have conducted fundamental research on flow in English teaching (Shin, 2006). These basic studies provide a theoretical framework for the construction of conceptual framework of flow experience in the study. Based on all the researches mentioned above and the intercultural teaching model for EFL learners (Figure 1), we define the core factors of flow antecedents as clear goals, timely feedback, challenge-skill balance, noticing, comparing, reflecting and interacting and define the core factors of flow consequences as intercultural knowledge, skill and attitude (Figure 2).

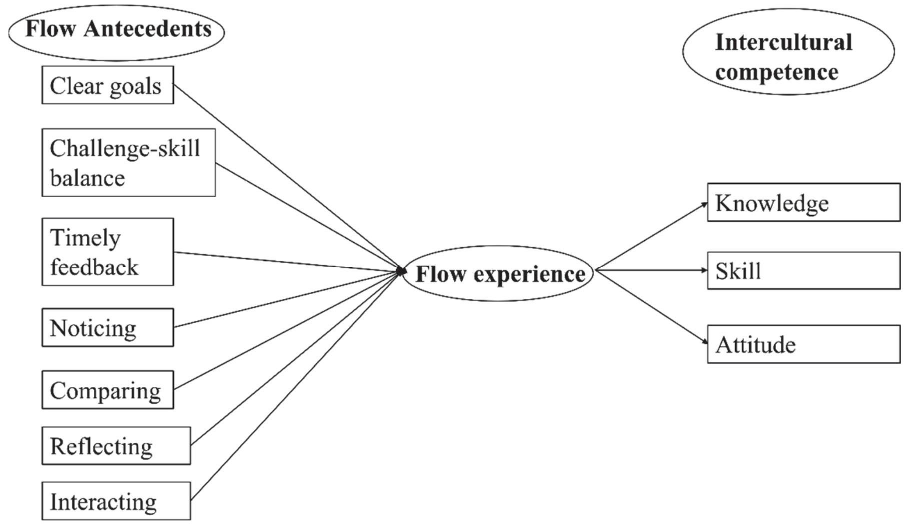

Figure 2. Predefined model of flow in intercultural teaching

3. The Construction of BPNN Prediction Model

Back propagation neural network (BPNN), known for its multilayer feedforward architecture, plays a pivotal role in various applications such as function approximation, classification and pattern recognition. The BP neural network algorithm fundamentally aims to minimize error. Through extensive training on numerous samples, it typically makes use of the gradient descent method to minimize the error, ultimately converging to the minimum point. On any closed interval, a continuous function can be mapped from *n*-dimensions to *m*-dimensions through an infinite approximation process using a BPNN with a hidden layer (Zaffar et al., 2022). It consists of interconnected layers: an input layer, one or more hidden layers, and an output layer. Each layer consists of neurons, analogous to the biological neurons in the human brain. The input layer receives stimulation, which is then transmitted to the hidden layer(s) through weighted connections. Subsequently, the hidden layer processes the information and forwards it to the output layer based on the established neuron weights. The output layer compares the predicted results with the desired outputs, initiating error correction if necessary.

The number of neurons in the input layer is determined by the number of features in the input data. Similarly, the number of neurons in the output layer is the number of variables in the output data. The neurons in the hidden layer compute a weighted sum of inputs from the previous layer, along with a bias term. This weighted sum is then passed through an activation function (such as sigmoid) to produce the output of the hidden layer neurons. To increase the accuracy of the result, the proper number of hidden layer neurons needs to be selected. In our study, the neurons are selected by the equation:

$$\mathrm{p} = \sqrt{m+n} + a \tag{1}$$

which is commonly used and where m is the number of neurons in the input layer, and n is the number of neurons in the output layer. The constant *a* is selected between 1 and 10, which is needed to determine by several calculation (Zhang et al., 2022).

3.1 Determination of Input and Output Vectors

Feature selection is needed before using the BPNN model to predict the target (Zhang et al., 2022). Our study needs to do the flow antecedents selection because the primary goal of our study is to promote intercultural competence. By identifying the most core influencing factors that trigger flow experience, the accuracy of flow prediction can be improved to ensure the value of the flow prediction model.

First, a questionnaire survey was conducted (Li et al., 2019; Wang & Huang, 2022; Huang, 2021) to connect the data of (1) flow antecedents: challenge-skill balance (3 items), clear goals (3 items), timely feedback (3 items), noticing (3 items), comparing (3 items), reflection (3 items) and interacting (3 items), (2) flow experience (14 items) and (3) flow consequences: knowledge (6 items), skill (6 items) and attitude (7 items). A 5-point Likert-type scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used and the learners need to choose to show the extent of agreement to each statement. Then 460 vocational freshmen who took the course in College

English completed the questionnaires and 450 valid questionnaires were collected. The Alpha coefficients of the variables range from .834 to .933, which confirm the reliability of the questionnaire.

Second, a structural model was measured by adopting the SmartPSL to determine the moderating effects of flow experience, thus completing the selection of vectors. Some indices were then assessed to examine the fit of the structural model. The factor loadings of all variables are greater than 0.7 and there is no cross-loading, indicating that the variables can effectively reflect their corresponding observed scalars. The R^2 of the model ranges from 0.617 to 0.739, suggesting that the model has a strong explanatory power. The AVE of all variables is greater than 0.5, indicating that the correlation of the items of each construct is relatively high and has reached the evaluation criteria for convergent validity. Through the analysis of the Q^2 value, the values of flow experience (0.511), knowledge (0.413), skill (0.469) and attitude (0.385) indicate that the model has a strong predictive correlation.

Regarding the effects of antecedents, it was found that challenge-skill balance (β = 0.295, p =.000), noticing (β = 0.120, p =.02), comparing (β = 0.128, p =.007), reflecting (β = 0.148, p =.000) and interacting (β = 0.431, p =.000) have positively influenced flow experience. However, no significant relationship was found between clear goals and flow experience (β = 0.026, p =.507), timely feedback and flow experience (β = 0.087, p =.098). Regarding the effects of flow experience, knowledge (β = 0.786, p =.000), skill (β = 0.812, p =.000) and attitude (β = 0.750, p =.000) were all positively influenced by experience. The structural model was shown in figure 3.

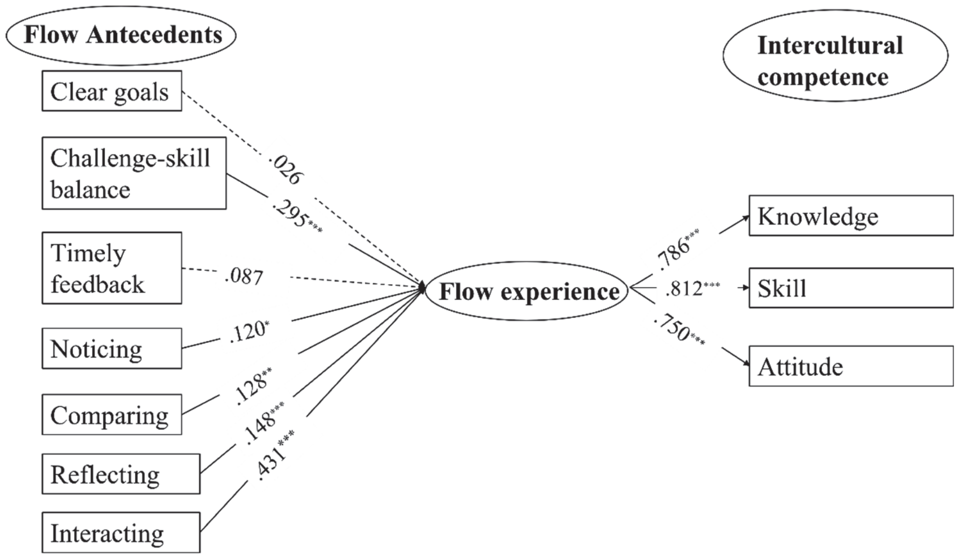

Figure 3. The structural model

Note: *p<.05, **p<.01, ***p<.001.→ Significant path;- - -►Nonsignificant path.

Finally, the input and output vectors need to be determined. We retained challenge-skill balance, noticing, comparing, reflecting and interacting as the input vectors and flow experience as output vector. Clear goals and timely feedback may have a certain degree of information overlap with other variables. For example, timely feedback may also be included in processes such as interacting and noticing. Removing them can reduce redundant information in the model, making the model more concise and efficient. It is possible to focus more on these key factors, enabling the model's prediction of flow experience to better reflect the core influencing mechanism and improve the interpretability of the model.

3.2 The Experiment

The experiments were conducted on a computer with Intel CORE i7 and 32G available main memory. Neural Net Fitting in Deep Learning Toolbox of MATLAB were used for the algorithms implementation process to train the BP neural network prediction models. The data was automatically divided into two parts, the training set (70%) and the test set (30%).

3.2.1 The Construction of Flow Prediction Model Based on BPNN

Five relevant variables, namely challenge-skill balance, noticing, comparing, reflecting, and interacting are for the input layer (m = 5). One variable, the flow experience, is for the output layer (n = 1). After trial calculations, the number of neurons for the hidden layer was set to 8 according to the Equation (1). The best validation performance is 0.032603 at the 9th epoch, indicating that the model performs best at this epoch (Figure 4).

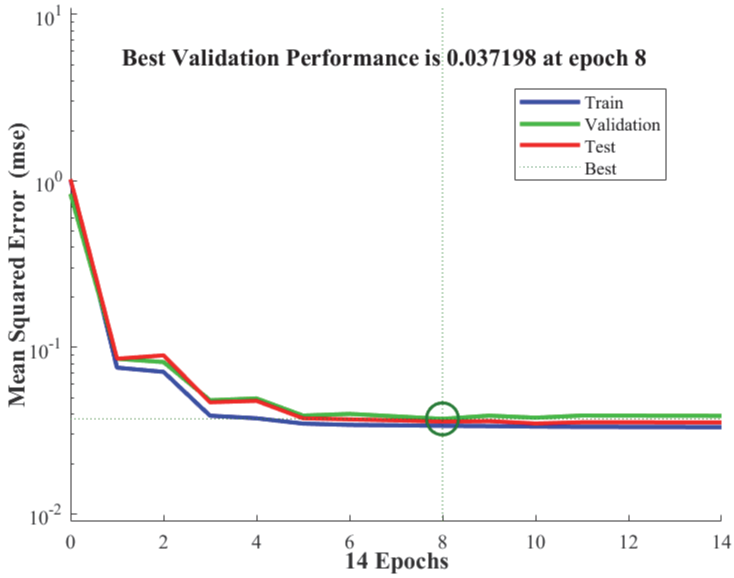

Figure 4. Mean squared error of the BP neural network

According to Figure 5, the correlation coefficient for the training dataset is 0.89335, for the validation dataset is 0.92771, for the test dataset is 0.93614 and for all the combined data is 0.90459. The higher correlation coefficients indicate a better fit between the output and the target values and a strong linear correlation between the output values and the predicted values.

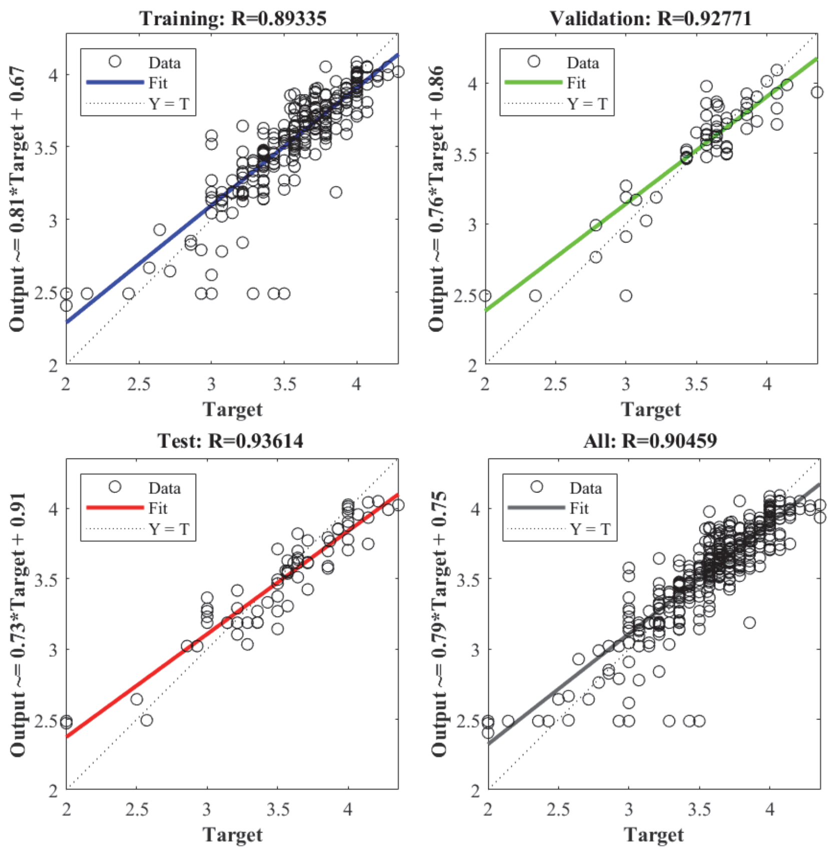

Figure 5. Regression fittings

3.2.2 The Predictive Results

Thirty students were randomly selected and their flow experiences were predicted to verify the accuracy and effectiveness of flow prediction model. The data of five factors (challenge-skill balance, noticing, comparing, reflecting, and interacting) were input into MATLAB and the sim function was used to predict the flow experiences. The predicted values ranged from 2.488 to 3.991. The maximum absolute error was 0.295. The Mean Squared Error (MSE) analysis and the Mean Absolute Error (MAE) analysis were conducted on the 30 prediction error results, because MAE and MSE are commonly used indicators for measuring the error between the predicted values and the true values. The smaller these two values are, the better the prediction performance of the model is. The Equations are shown as follows.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i^{pred} - y_i^{true})^2 \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i^{pred} - y_i^{true}| \quad (3)$$

The result showed that the MAE value was 0.2055 (MAE < 0.5) and the MSE value was 0.0679 (MSE < 0.1), indicating that the prediction model demonstrates high accuracy and effectively approximates the true values.

4. Discussion and Conclusion

The learners have entered the flow states, as the mean score of the flow experience was 3.550, surpassing the 3.0 threshold (Egert, 2003). Other variables in our study ranged from 3.023 to 3.054. For the flow antecedents, the challenge-skill balance (M = 3.554) scored the highest, suggesting that having an appropriate match between challenge and skill is the most crucial factor. When the learners perceive that the tasks they are engaged in are neither too easy nor too difficult, they are more likely to enter a state of flow. That implies that teachers have provided proper tasks in intercultural teaching. For the flow consequences, skill scored the highest, indicating that intercultural skill can be efficiently cultivated in class learning.

Our empirical research has shown that the errors between the output values and the actual values for two BP neural network prediction models were within an acceptable range, although the deviations for a few individual students' results were slightly larger. Some learners might have provided less accurate responses due to various reasons, such as scoring almost all items with a rating of two. This suggests that teachers should pay special attention to learners who consistently give low scores and investigate whether their lack of engagement stems from a complete disinterest in learning English or other underlying factors. The BPNN prediction model enables teachers to observe scores across different dimensions for each learner. This insight allows teachers to better understand the diverse needs of their learners, facilitating personalized instructions and tailored guidance to support individual learning trajectories.

Therefore, teachers need to carefully design tasks according to the students' actual skill levels in future intercultural teaching. Learners can prepare themselves better if they are required to do some pre-class assignments and encouraged to notice the cultural similarities and differences of Chinese and Western cultures. Then learners can not only stimulate their own interest but also deeply realize the connection between language and culture. When learners complete tasks, positive feedback should be given to affirm their efforts and achievements, which can enhance students' learning motivation. Students can also be more actively involved in intercultural learning by interactive tasks, continuously improving their intercultural skills and entering the flow state more frequently. The flow prediction model provided by this study helps teachers detect the psychological states of the learners, facilitating proper teaching guidance in EFL teaching.

Disclosure Statement

The author declares no conflict of interest.

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