

# Promotive Effect of Psychological Intervention on English Vocabulary Teaching Based on Hybrid Collaborative Recommender Technology

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Baodi Chen <sup>(✉)</sup>, Jierong Wu  
North China Electric Power University; Baoding, China  
chenbaodisweo@136.com

**Abstract**—Psychological changes will often play a huge influence on the teaching effects in the English vocabulary learning and teaching process. To further explore the relationship of psychological regulation with English vocabulary teaching, the hybrid collaborative recommender technology may be underlying to propose a hybrid algorithm for studying how the English vocabulary teaching effect is subjected to the psychological emotion factors as parameters added in the original similarity calculation method in the psychological regulation environment where the emotion is the core of study. In the end, the paper conducts the questionnaire survey among 300 students. Test data show that positive emotion acts as the catalyst of the English vocabulary teaching effect, having basically reached the expected goal of study.

**Keywords**—Collaborative recommender, similarity, emotional factor, English vocabulary teaching, questionnaire

## 1 Introduction

It is common knowledge that people who have accepted English education generally learn from ABC of vocabulary to the phrases and syntax, and further to entry to all-wave training for listening, speaking, reading and writing skills. The vocabulary is rather important for learning the whole English system, so it plays the most fundamental and core role in English teaching process [1]. In the actual hands-on teaching, it will take much time and efforts for teachers to help students learn vocabulary in various ways, but there is no good effect in lexical cognition and mastery. In essence, it may be attributed to the changes in students' psychological regulation that plays a significant role in the vocabulary teaching process involved of teachers and students [2]. Statistically, when the students hold negative emotions, it is tormenting and futile for them to learn English vocabulary. Instead, when the students are highly emotional and optimistic, the English vocabulary learning will get relaxed and cheerful and yield immediate results. In this sense, the psychological regulation has a far-reaching significance in future study of English vocabulary.

A flood of literature show that collaborative recommender technology affords good results in the study of English vocabulary teaching. Its core idea is to calculate and analyze the similarities of indicators such as content, method and psychology. There are major algorithms including the Collaborative Filtering (CF), Contents-Based Filtering (CBF), the Principal Elemental Analysis, and Knowledge Discovery [3-5], which only involve the "hardware" indicators such as knowledge and content for calculating the similarity of factors, but lack of deliberation of "software" indicators such as psychology and emotion. For this purpose, the paper attempts to facilitate the English vocabulary teaching by merging the emotional factors into simulation calculation of traditional collaborative recommender algorithm.

To further discuss the relationship between psychological regulation and English vocabulary teaching, the paper simulates what roles the psychological regulation of students plays in learning English vocabulary based on the collaborative recommender technology. With the emotional influence in psychological regulation as the core, the hybrid collaborative recommender algorithm that incorporates the emotion factors is hereby built to calculate the catalytic relationship between the two. In the end, a questionnaire survey is conducted among 300 students [6-8] in the trial phase to test how well the students master the English vocabulary in different emotional states. Test data show that the catalyst for English vocabulary learning is possible as long as positive and optimistic emotion exist, basically reaching the intended purpose of study.

## **2 Basis for Collaborative Recommender**

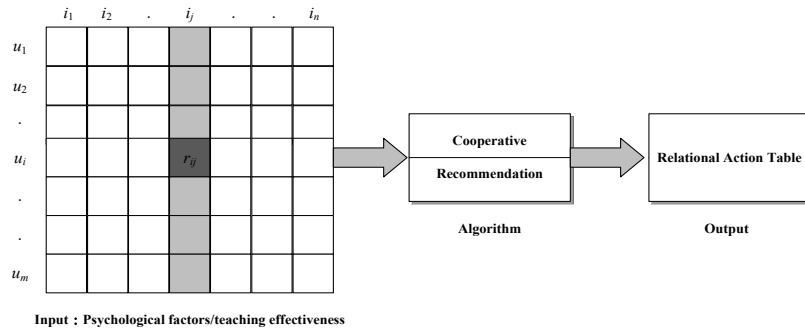
### **2.1 Algorithm process**

The collaborative filtering algorithm makes incessant classification against the psychological factors of students, and then sorts and calculates the English vocabulary teaching effects. In the establishment of the relational model, the classic collaborative recommender algorithm is used to simulate  $u$  and  $i$ , and eventually reveal the interaction between the two. The process the model algorithm simulates the relationship of the psychological regulation factors with the English vocabulary teaching effects is shown in Figure 1 [9].

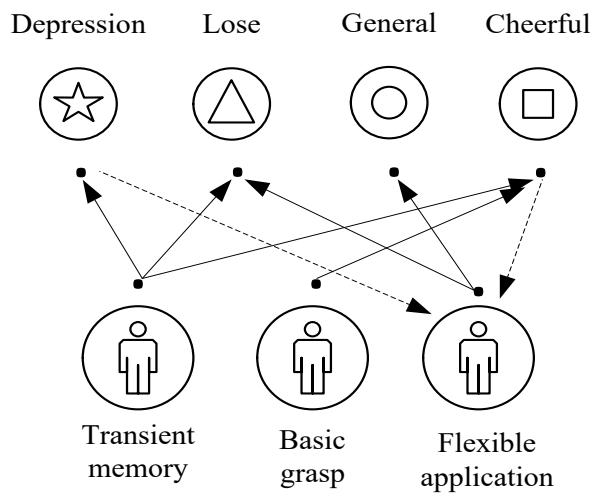
As shown in Figure 1, the set of psychological factors and the set of English vocabulary teaching effects constitute a matrix, where the line represents the psychological factors, and the columns represent the teaching effects;  $m$  and  $n$  are the numbers of psychological factors and teaching effects, respectively. Then, can represent the value of the teaching effect that psychological factors play.

In the collation of matrix factors, psychological factors such as depression, lose, general, and cheerful can be available; the standards of teaching effects of English vocabulary such as transient memory, basic grasp, and flexible application are measured. Then, the factors in the matrix are calculated using the hybrid collaborative recommender algorithm, in conjunction with the similarities of the psychological factors and the teaching effects. The relationship between the two is compared accord-

ing to the calculated similarities (as shown in Figure 2) to analyze which factors will play a positive role. At last, the relational action table is output.



**Fig. 1.** Process of collaborative recommendation algorithms



**Fig. 2.** Relationship between psychological factors and teaching effectiveness

In the hybrid collaborative recommender algorithm, the core function is to calculate the similarity of the core function factors in the algorithm commonly by the recursive evolution of the cosine similarity, adjusted cosine similarity, Pearson similarity, and adjusted Pearson similarity, laying the foundation for the implementation of the algorithm.

## 2.2 Document content

In the psychological factors-teaching effects matrix  $S$ , the interaction  $r_{ij}$  of the two is regarded as the vector of the  $n$ -dimensional vector space. The cosine angle between the vectors can evaluate the similarity between the two, that, the smaller the angle, the

higher the similarity [10]. Therefore, the definition of cosine similarity can be followed to calculate the similarity between psychological factors:

$$sim(u, v) = \cos(\vec{u}, \vec{v}) = \frac{\vec{u} \cdot \vec{v}}{\|\vec{u}\|_2 \times \|\vec{v}\|_2} = \frac{\sum_{i \in G_{uv}} r_{ui} \cdot r_{vi}}{\sqrt{\sum_{i \in G_{uv}} r_{ui}^2} \sqrt{\sum_{i \in G_{uv}} r_{vi}^2}} \quad (1)$$

where,  $G_{uv}$  is a set of items in which the psychological factors  $u$  and  $v$  function together, i.e.  $G_{uv} = \{i | i \in G_u, i \in G_v\}$ .

In calculating cosine similarity, the influencing factors between the psychological factors are not involved. Therefore, the mean value of the psychological factors is subtracted from the calculated cosine similarity to reduce the influence between the factors themselves. The adjusted cosine similarity definition is followed to calculate the similarity between psychological factors:

$$sim(u, v) = \cos(\vec{u}, \vec{v}) = \frac{\sum_{i \in G_{uv}} (r_{ui} - \bar{r}_u) \cdot (r_{vi} - \bar{r}_v)}{\sqrt{\sum_{i \in G_{uv}} (r_{ui} - \bar{r}_u)^2} \sqrt{\sum_{i \in G_{uv}} (r_{vi} - \bar{r}_v)^2}} \quad (2)$$

where,  $\bar{r}_u$  and  $\bar{r}_v$  represent the mean values of the sets  $G_u$  and  $G_v$  of respective teaching effects that psychological factors  $u$  and  $v$  play, that is,  $\bar{r} = \frac{1}{|G_u|} \sum_{i \in G_u} r_{ui}$  and  $\bar{r}_v = \frac{1}{|G_v|} \sum_{i \in G_v} r_{vi}$ , where  $|G_u|$  and  $|G_v|$  are the numbers of sets of the psychological factors  $u$  and  $v$ , respectively.

The degree of linear correlation between the two variables can also be expressed in terms of Pearson similarity as a mathematical formula:

$$sim(u, v) = \frac{\sum_{i \in G_{uv}} (r_{ui} - \bar{r}_{u/v}) \cdot (r_{vi} - \bar{r}_{v/u})}{\sqrt{\sum_{i \in G_{uv}} (r_{ui} - \bar{r}_{u/v})^2} \sqrt{\sum_{i \in G_{uv}} (r_{vi} - \bar{r}_{v/u})^2}} \quad (3)$$

where,  $\bar{r}_{u/v}$  and  $\bar{r}_{v/u}$  represent the mean values of the functions that psychological factors  $u$  and  $v$  play on the common English vocabulary teaching set  $G_{uv}$ , respectively. The two values can be analogous to the cosine similarity and expressed as  $\bar{r}_{u/v} = \frac{1}{G_{uv}} \sum_{i \in G_{uv}} r_{ui}$  and  $\bar{r}_{v/u} = \frac{1}{G_{uv}} \sum_{i \in G_{uv}} r_{vi}$ .

Similar to the adjusted cosine similarity, a statistic of English vocabulary teaching effect that the psychological factors play can be subtracted from the function factors, in order to reduce the influence between the psychological factors themselves, expressed by the mathematical formula:

$$sim(u, v) = \frac{\sum_{i \in G_{uv}} (r_{ui} - \bar{r}) \cdot (r_{vi} - \bar{r})}{\sqrt{\sum_{i \in G_{uv}} (r_{ui} - \bar{r})^2} \sqrt{\sum_{i \in G_{uv}} (r_{vi} - \bar{r})^2}} \quad (4)$$

Where,  $\bar{r}$  represents the mean value of functions in the recommender algorithm.

With the similarity calculation, the degree of correlation between psychological factors can be available. Then the alienation between their similarities should be considered. Assume the calculated similarity between psychological factors is regarded as weight of individual function, then the calculation method for interaction between the two can be available:

$$P_{ui} = \frac{\sum_{v \in G_i} sim(u,i)r_{vi}}{\sum_{v \in G_i} sim(u,i)} \quad (5)$$

For the calculation function available from (5), the individualized conditions of the psychological factors should also be included, so it follows that individualized influence between psychological factors can be reduced by subtracting the mean value of functions of similarities as a weight, so that the prediction method can be improved as:

$$P_{ui} = \bar{r}_u + \frac{\sum_{v \in G_i} sim(u,i)(r_{vi} - \bar{r}_v)}{\sum_{v \in G_i} sim(u,i)} \quad (6)$$

### 2.3 Algorithm analysis

Collaborative recommender algorithm will get the upper hand of unstructured businesses such as music, shopping, books, etc. It can quickly finish the pickup and classification of samples, no need to interpret and classify commodities, books and music factors in a procedural manner. Then, there are strong subjective factors in the analysis of the psychological regulation factors, so that it is unlikely to make the choice of the psychological factors, etc. As a result, cold boot and the sparsity in the algorithm have not been well improved, while in the process of collaborative filtering algorithm, it is required to traverse the whole database to calculate the similarity between psychological factors or English vocabulary teaching effects, greatly reducing the efficiency of the algorithm.

When performing similarity calculation in the collaborative filtering algorithm, all sets  $I_i$  of the teaching effects in the database are usually processed on an equal "status". It only allows for the increase and decrease in the number of statistics, but lacks of deliberation on the influence of students' emotions on English vocabulary learning since the different emotions of students can have obvious subjective tendencies in learning English vocabulary. When calculating the similarity of English vocabulary teaching effects, emotional factors should be included [11].

To solve problems mentioned above and respond to the challenge of cold boot and sparsity in the recommender system, this paper proposes the hybrid collaborative recommender algorithm based on the similarity of emotional factors.

### 3 Hybrid Collaborative Recommender Algorithm Based on Emotion Factors

#### 3.1 Defined emotion factors

Three sets  $U = \{u_1, u_2 \dots u_m\}$ ,  $I = \{i_1, i_2 \dots i_n\}$ ,  $R = \{r_{11}, r_{12} \dots r_{ij} \dots i_{mn}\}$  respectively for psychological factors, teaching effects and the interactions between the two constitute a new data set  $(u, i, r_{ui})$ , which represents that the action of the psychological factor  $u$  on the English vocabulary teaching effect  $i$  is  $r_{ui}$ . Given the important influence of the emotion factors, the emotional factor  $t$  is added based on the original three factors  $(u, i, r_{ui})$  to form a new data set  $(u, i, r_{ui}, t)$ , which suggests that the action of the psychological factor  $u$  on the English vocabulary learning effect  $i$  in the  $t$ -type emotion is  $r_{ui}^t$ .

The set of different English vocabulary teaching effects is also be classified based on the emotion factors. From the set  $U_i$  of English vocabulary teaching effects with the psychological factors  $u$ , the set  $U_{i/T_c}$  in the emotion segment  $T_c$  is extracted, then the data set  $U_{i/T_c}$  included in the emotion  $T_c$  is the focus. If any teaching effect  $i \in U_i$  and  $i \in U_{i/T_c}$  are true, the psychological factors play a positive action on the teaching effect  $i$  in  $T_c$ , which should be focused [12].

After the emotion factors are added, the weight  $W_{uj}$  is referenced when calculating the similarity between psychological factors - English vocabulary teaching effect. It may be defined as:

$$W_{uj} = \frac{\sum_{k \in G_{u/T_c}} S_{jk}}{\sum_{k \in G_u} S_{jk}} \quad (7)$$

$W_{uj}$  represents the weight of similarity of action that the psychological element  $u$  plays on the English vocabulary teaching effect  $j$ , where

$$S_{jk} = \begin{cases} sim(j, k) & \text{when } j \neq k \\ 1 & \text{when } j = k \end{cases}$$

It is known from the above formula that the higher the occupancy rate of the teaching effect in  $U_{i/T_c}$  under the influence of psychological factors, the greater the weight of the teaching effect under the emotion factor. It is required to assign a higher weight to the similarity of the teaching effect in  $T_c$ , otherwise, this weight assigned will be lower.

#### 3.2 Similarity calculation based on emotion factor

In the hybrid collaborative recommender algorithm, the similarity calculation should be performed on the psychological factors and English vocabulary teaching effects based on the emotional factors. On the basis of adjusted Pearson similarity, the

similarity weight  $W_{uj}$  between psychological factors - English vocabulary teaching effects are added to further correct the results of the calculated action table.

Similarity calculation of emotional factors based on psychological factors: assuming that psychological factors  $u$  and  $v$  affect the teaching effect  $i$ , then when calculating the similarity between  $u$  and  $v$  for teaching effect  $i$ , it is necessary to increase the weighting coefficient to improve the calculation of the action table. The function can be expressed as:

$$P_{ui} = \bar{r}_u + \frac{\sum_{v \in G_i} sim(u, v)(r_{vi} - \bar{r}_v)}{\sum_{v \in G_i} sim(u, v) \cdot W_{vi}} \quad (8)$$

The similarity calculation of emotional factors based on the English vocabulary teaching effect: assume the English vocabulary teaching effects  $i$  and  $j$  have an influence under the psychological factor  $u$ , then when calculating the similarity  $sim(i, j)$  between  $i$  and  $j$  on the psychological factor  $u$ , it is required to increase the weight coefficient  $W_{uj}$  to improve the functions in the relational action table, expressed as:

$$P_{ui} = \bar{r}_i + \frac{\sum_{j \in G_u} sim(i, j) \cdot W_{uj} \cdot (r_{ui} - \bar{r}_j)}{\sum_{j \in G_u} sim(i, j) \cdot W_{ui}} \quad (9)$$

It is known from Formulas (8) and (9) that under the action of emotion factors on the English vocabulary teaching, the set of teaching effects under the influence of emotion  $T_c$  as psychological factor will gradually expand to approach all data sets, i.e.  $G_{u/T_c} \approx G_u$ , then psychology factor-English vocabulary teaching effects similarity weight is 1, and the weights of each psychological factor and teaching effect are all 1 [13]. Therefore, whether the psychological factors or the teaching effects are underlying, the functions in relational action table will more objectively reflect the effect produced by emotional factors, while alleviating the problem of cold boot and sparsity to a certain extent.

### 3.3 Algorithm implementation

The hybrid collaborative recommender algorithm based on the similarity of emotional factors can be implemented by the following procedures:

- Input psychological factors - English vocabulary teaching effects relationship matrix  $S$ , and calculate the similarity  $sim(u, v)$  of psychological factors according to Formula (4);
- Add the emotional factor  $t$  to the original three factors  $(u, i, r_{ui})$  to form a new four-factor array  $(u, i, r_{ui}, t)$  with the sets of psychological factors-English vocabulary teaching effects;
- Analyze the set  $G_u$  of teaching effects under the influence of psychological factor  $u$  and the set  $G_{u/T_w}$  of teaching effects under the influence of emotional factor  $T_c$ ;

- Calculate the psychological factors – English vocabulary teaching effects weight  $W_{uj}$  according to Formula (7);
- Calculate the function  $P_{ui}$  of the psychological factor  $u$  on the English vocabulary teaching  $i$  according to Formula (9).

After the calculation of the hybrid collaborative recommender algorithm based on the similarity of the emotional factors, we can objectively evaluate the influence of psychological factor  $u$  based on the derived result  $P_{ui}$ . The higher the value  $P_{ui}$ , the better the English vocabulary teaching effect.

## 4 Questionnaire Survey and Analysis of Results

### 4.1 Preparation for survey

The respondents were randomly chosen from freshmen at the RUC (Renmin University of China). There are objective choice and subjective essay questions in the questionnaires, so designed to examine whether students can master the English vocabulary in the depression, lose, general and cheerful moods, judge them in accordance with the transient memory, basic grasp and flexible application standards. Based on the design principle of the questionnaire survey, for the purpose of protecting the individual privacy, this test is conducted in an anonymous and irresponsible mode, with an aim to objectively analyze how the English vocabulary teaching effect is subject to the psychological regulation [14].

In this test, Root Mean Square Error (RMSE) is used to evaluate the collaborative filtering algorithm based on the cosine, Pearson similarities and the similarity of emotion factors. The RMSE mainly compares the different results under the variables in the questionnaires, thereby reach the conclusion. The greater the value of RMSE, the better the teaching effect.

$$RMES = \sqrt{\frac{1}{|Tes|} \sum_{(u,i,r_{ui})} (r_{ui} - P_{ui})^2} \quad (10)$$

Where  $|Tes|$  represents the data set of statistical results in the questionnaire, where,  $r_{ui}$  is the rating score;  $P_{ui}$  is the correction value.

The questionnaire survey lasts for one week. It takes 30 min extracurricular time to conduct a questionnaire survey among 300 students in the student activity room. A total of 300 questionnaires are distributed, and collected successfully. Based on them, data aggregation and results analysis are further made.

### 4.2 Analysis of survey results

The objective and subjective questions in the questionnaires are marked respectively based on the hundred-mark system to analyze and judge whether students master the English vocabulary under different emotional influences. Based on the 300 ques-



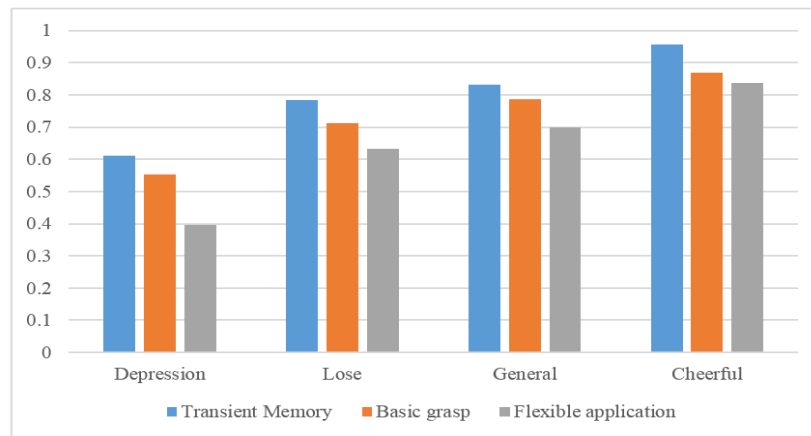
tionnaires collected, the mean value of student's scores under each type of factor is taken as test data. The statistical results are shown in Table 1.

**Table 1.** Questionnaire statistical result table

	Transient Memory		Basic grasp		Flexible application	
Depression	61.1	64.2	55.3	61. 8	39.5	41.3
Lose	78.4	73.3	71.1	69.5	63.2	63.9
General	83.1	80.9	78.7	70.4	69.8	65.5
Cheerful	95.6	90.8	86.9	84.2	83.8	81.4

As learned from the statistical results, when students are cheerful, the teaching effect are better whether in terms of transient memory, basic grasp, or flexible application of vocabulary; when students are depressed and fatigue, the whole teaching effect of English vocabulary seems to be poor; when the students' moods rise and fall, the English vocabulary teaching effect also shows ups and downs. Therefore, positive and optimistic mood has played a positive role in English vocabulary teaching. The RMSE standard can be used to further analyze statistical data of this survey questionnaires to further provide evidence for this view [15].

The RMSE takes 0~1, that is, the greater the value, the better the English vocabulary teaching effect; otherwise it is worse. The RMSE values in the questionnaires are estimated according to the four psychological factors, i.e. depression, lose, general and cheerful emotions. The calculated results are shown in Figure 3.



**Fig. 3.** RMSE value of questionnaire statistical results

Based on the statistically calculated RMSE values, it is known that the RMSEs of objective and subjective questions are all greater than 0.8 under the psychological regulation of cheerful emotion, but higher than 0.6 only in transient memory under the psychological influence of depression, and even less than 0.4 in flexible application. It is thus obvious that different psychological factors have greatly influenced the English vocabulary teaching effects, further demonstrating the conclusion.

## 5 Conclusion

The English vocabulary learning occupies important status in the whole English education system, while in this process, the influence of psychological factors is also one of basic factors that should not be ignored. Here, the collaborative recommender algorithm is underlying to simulate and calculate the similarities of psychological factors and English vocabulary teaching effects, discuss the relationship between the two. It is also proposed to use the emotional factor parameter as the fourth element in the hybrid collaborative recommender algorithm, where, the focus is on the weight assignment calculation for the similarity under the influence of emotional factors. Lastly, the objective and fair questionnaire survey was conducted among 300 students. Data analysis was made based on the questionnaire statistics. It is proved that the positive and optimistic psychological factors can well facilitate the English vocabulary teaching practice, achieving the intended purpose of the study.

## 6 Acknowledgement

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## 8 Authors

**Baodi Chen** has graduated from North China Electric Power University with the major of English Language and Literature. She is a college English instructor and has done some scientific researches in her field. She has published more than five papers, some of which are retrieving articles and some of which are kernel articles. Besides, she has participated in the compilation of a professional textbook for college. What's more, she has hosted and participated in seven provincial and school-level scientific research projects.

**Jierong Wu** has graduated from Hebei University with English major. She has lectured in college and published four papers and participated in the compilation of a professional textbook for college. She participated and hosted in one provincial and school-level scientific research topics.

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