



Formative Assessment Methods of English Language Application Competence Based on Consistency Evaluation

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Abstract: In order to improve the evaluation effect of English language application ability, this paper analyzes the consistency evaluation method, and combines the fuzzy clustering method to improve the algorithm to improve the effective processing and recognition of English language application data. Moreover, this paper effectively reorganizes multiple kernel functions, promotes the fuzzy consistency method to exert better overall performance, and can find the best cluster labels and kernel functions. The weight of the function is constantly changing, and it has strong resistance to change, which is suitable for the needs of English language application ability assessment. In addition, this paper constructs an intelligent consistency evaluation model. The experimental research results show that the consistency evaluation method of English language application ability based on consistency evaluation can play a good role in the evaluation of English language application ability.

Keywords: consistency evaluation; English language; application ability; formative evaluation

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1 INTRODUCTION

Globalization has become the most important theme in today's society, and communication and exchanges have also become the main means of promoting globalization. As the most widely used international language at present, the importance of English has been further enhanced, and China's basic education has also paid considerable attention to English teaching. Due to the importance of English, English teaching has even started from the kindergarten teaching stage under the impetus of the mentality of looking forward to the child. English learning tasks and English learning pressure have become the most concerned and troubled learning topics of current Chinese students. In the stage of university education, English teaching has been separated from the task of English performance testing in exam-oriented education, but has become to improve college students' English application ability and cultivate comprehensive application talents that are in line with social needs. However, under the overall influence of the current university

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education model, college English teaching is more inclined to deal with the English training of the college English test, but it ignores its important role as an expansion of English ability.

The reform of English teaching in higher education has been going on for a period of time, but the results have been minimal. The reason is that the implementation of English teaching reform cannot be guaranteed. The new curriculum reform has increased the teaching share of English extracurricular reading and English listening and speaking skills. The core of curriculum education is also focused on English culture education and English environment training. However, due to the insufficient construction of multimedia teaching environment in many schools, this training model cannot be implemented [4]. Now, we need to change the preaching-style teaching in large classes in the past, and try diversified teaching models such as English interest groups and English team building. At the same time, it is necessary to give special lectures on the importance of English application ability in job search and workplace application, correct the cognitive misunderstanding of college students for the cultivation of English application ability, and regain the enthusiasm of college students for English learning [7]. In addition, in the assessment methods of English teaching, it is necessary to adopt a diversified assessment mode that combines examinations and ability demonstrations, pay attention to English listening and speaking skills, encourage students to participate in English expression competitions, performances, and public welfare activities, and increase the school's organizational investment in such activities [9].

In the process of cultivating English communicative competence, teachers should play an important role in preaching and solving puzzles in the first classroom. The classroom must be a venue for language skills training. Teachers should regularly organize students to conduct English debates and English speeches together. Various forms of practical activities, such as competitions and English sketch contests, will improve students' language communication skills and English skills to a greater extent. Second, we must pay attention to the cultivation of English professional ability; the teaching mode can try to use various methods such as the development of team project learning, the construction of training bases, and thematic outreach training activities to improve students' English application ability. Improving to provide a strong foundation to truly ensure that students can learn more solid English use skills while learning the basics of English, paving the way for them to enter the society smoothly, and providing them with future jobs in the English industry Strong vitality. Third, for the cultivation of English certificate ability, the most important thing is to continuously innovate and reform the teaching model with the help of English skills analysis and extracurricular learning.

According to the needs of English language and English proficiency evaluation, this paper combines the consistency evaluation method to construct an intelligent evaluation system to evaluate and analyze the modern English language application ability to improve the language application ability in modern college English teaching.

2 RELATED WORK

Scholars at home and abroad have developed a keen interest in fuzzy theory. There are many researches on the effectiveness of fuzzy clustering. So far, domestic and foreign scholars have proposed many fuzzy clustering effectiveness indicators. Based on the fuzzy theory he created, Professor Zade once proposed a separation index to judge the effectiveness of fuzzy clustering, but in subsequent applications, he found that the discrimination method was not ideal [4]. Literature [13] proposed an improved division coefficient sum, which overcomes this monotonic trend. However, these effectiveness indicators are only related to fuzzy membership, and not closely related to the geometric structure of the data. Consider the characteristics of the data structure itself. Literature [20] proposed a new validity function year from the perspective of compactness and separation, and proposed a new validity index based on the geometric structure of the data set. This method is based on the compactness and separation As the effectiveness index.

Literature [6] defines a new effectiveness index. The best classification number obtained by this method is more accurate, but the actual operation of this indicator is more complicated and time-consuming. Literature [1] introduced a penalty function to avoid the tendency of monotonous decrease when the number of clusters is close to the number of data points. Literature [3] believes that if a fuzzy partition is dense, then the effectiveness index should have a low index value. Literature [21] proposed an index of clustering effectiveness. In fact, this index also takes the degree of compactness within clusters and the degree of separation between clusters as the main measurement standards. Although this method solves the problems in some indicators, the indicator is based on the calculation of cluster centers, and does not consider the overall cluster shape of the data. It has defects in the measurement of data sets with multiple geometric structures. Literature [17] started to study the validity index of fuzzy clustering from two factors of input cluster number and fuzzy weighting factor, and proposed a new validity index. A penalty function is added to the numerator and denominator to prevent the index function value from tending to infinity when the fuzzy weighting factor m tends to infinity. Literature [14] proposed a new clustering validity index, which overcomes the monotonous decreasing trend of the entire index function. Literature [15] combines the compactness of traditional indicators with the improved overlap, and proposes a new structured effectiveness indicator. In fact, this index uses three parts: compactness, separation and overlap to describe the effectiveness of fuzzy clustering. This method can make correct judgments for situations such as overlap between classes, multiple outliers, and dispersion. Literature [2] proposed a new fuzzy clustering effectiveness index, based on the degree of separation and compactness, constructed a new fuzzy clustering effectiveness index. Literature [18] proposed a new degree of separation, which is obtained by calculating the distance of the fuzzy set. The distance is measured by similarity. This degree of separation can overcome the shortcomings of traditional separation degree that only considering the clustering centers between clusters MN cannot measure multiple structure data sets. Literature [11] links the fuzzy clustering evaluation method with the decision tree classification algorithm, and proposes a fuzzy clustering effectiveness evaluation method based on the information entropy theory decision tree algorithm, and applies this method to customer loyalty classification in the securities industry In the model. The results show that this method can significantly improve the effect of clustering, and the clustering results are more interpretable and practical. Literature [5] comprehensively considered the clarity, compactness, and separation of the data set division results, and constructed a new index of fuzzy clustering effectiveness, which also considered the fuzzy division of the data set and the geometry of the data set itself. feature. Simulation experiments are carried out on artificial data sets and real data sets, and the results show that this indicator can accurately measure whether the fuzzy division is clear or not, and the misjudgment rate is relatively low. Literature [16] gave a new definition to the degree of separation, and proposed a new fuzzy clustering validity index, and through theoretical proof and experimental analysis, the reliability of this index was proved.

3 RESEARCH ON FUZZY C MEAN VALUE AND ITS IMPROVED ALGORITHM

The FCM algorithm is a widely used algorithm in the field of fuzzy clustering, and it is also fully studied based on the objective function algorithm. Although the FCM algorithm is classic, it also has shortcomings, such as slow convergence and poor anti-noise performance. In response to these problems, continuously improved fuzzy clustering algorithms have gradually emerged.

The FCM (Fuzzy C-Means Clustering Algorithm) algorithm mainly optimizes the objective function and obtains the optimal objective function value to cluster images or data samples. The data set $X = \{x_1, x_2, \dots, x_n\}$ is divided into categories c . The FCM clustering algorithm achieves data

classification by minimizing the membership matrix and the objective function of the clustering center. The objective function is as follows [19]:

$$J_{\text{FCM}} = \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m d_{ij}^2 \quad (3.1)$$

m represents the weighted type index, d_{ij} represents the distance between the j -th point and the i -th cluster center, and u_{ij} represents the membership matrix. The iteration formula is as follows:

$$u_{ij} = \frac{1}{\sum_{s=1}^c \left(\frac{d_{ij}}{d_{sj}} \right)^{\frac{2}{m-1}}} \quad (3.2)$$

v_i represents the i -th cluster center, and its iterative formula is as follows:

$$v_i = \frac{\sum_{j=1}^n u_{ij}^m x_j}{\sum_{j=1}^n u_{ij}^m} \quad (3.3)$$

However, when the FCM algorithm clusters the data set, it does not take into account the information of the spatial distribution of the data set, so the results obtained are not very ideal.

The function expression of the PCM algorithm is as follows:

$$J_{\text{pcm}} = \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m d^2(x_j, v_i) + \sum_{i=1}^c r_i \sum_{j=1}^n (1 - u_{ij})^m \quad (3.4)$$

Among them, u_{ij} represents the membership value of the j -th sample point x_j to the i -th cluster center v_i , and $d(x_j, v_i)$ represents the Euclidean distance between the j -th sample point and the i -th cluster center. m takes a value of [1.5, 2.5], usually 2, r_j is the penalty factor, which can be expressed as [10]:

$$r_i = \frac{\sum_{j=1}^n u_{ij}^m d(x_j, v_i)}{\sum_{j=1}^n u_{ij}^m} \quad \text{among } > 0 \quad (3.5)$$

Normally, when $k=1$ is taken, the calculation method of membership is as follows:

$$u_{ij} = \frac{1}{1 + \left[\frac{d^2(x_j, v_i)}{r_i} \right]^{\frac{1}{m-1}}} \quad (3.6)$$

The clustering process of the PCM algorithm is as follows:

Step1: The algorithm randomly initializes the cluster center v_i and the membership matrix u , sets the interval value ε and the fuzzy weighting index m , and the maximum number of iterations max_item;

Step2: The algorithm updates the membership matrix u_{ij} and cluster centers v_i according to the iterative formula;

Step3: According to the objective function J value, the algorithm compares the two adjacent objective function values, and adds 1 to the number of iterations. If $|J_t - J_{t+1}| < \varepsilon$, the algorithm stops iterating;

Step4: If the number of iterations $t > \text{max_item}$, the algorithm stops running, otherwise the algorithm returns to Step2. As we mentioned in the above content, the possibility clustering algorithm is prone to the problem of coincident classes.

The MKFC algorithm combines the fuzzy C-means clustering algorithm and the possibility fuzzy clustering algorithm. The MKFC algorithm has both the concept of membership and the concept of typical values. The degree of membership is the degree of membership of a data point to a certain class, and the degree of membership matrix contains the degree of membership of all points to all classes. The typical value is the membership value of a data point to a certain class. The difference is that the latter may not satisfy the constraint condition of the membership degree, and the concept of multi-core is introduced at the same time. The MKFC algorithm aims to obtain multiple calculation results at the same time, such as combined weight values, membership degrees, and cluster centers. In practical applications, it is more complicated to directly find the clustering center, so it is generally possible to find the combined weight value and the value of the clustering center first, and finally find the membership value.

The MKFC objective function is as follows [12]:

$$J_{mbc} = \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m D_{ij}^2 \quad (3.7)$$

When the weight and the degree of membership are fixed, by introducing the function λ , we can get the following expression:

$$J_{\lambda}(u, v) = \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m D_{ij}^2 + \lambda \left(\sum_{j=1}^n u_{ij} - 1 \right) \quad (3.8)$$

Through derivation, the functional expression of membership degree u_{ij} is as follows:

$$u_{ij} = \left(\frac{-\lambda}{m} \right)^{\frac{1}{m-1}} \frac{1}{D_{ij}^{\frac{2}{m-1}}} \quad (3.9)$$

Through derivation, the cluster center formula is obtained as:

$$v_i = \frac{\sum_{j=1}^n u_{ij}^m \varphi(x_j)}{\sum_{j=1}^n u_{ij}^m} \quad (3.10)$$

When the membership value is fixed, the objective function can be expressed by weight:

$$J(w) = \sum_{k=1}^M \beta_k w_k^2 \quad (3.11)$$

$$w_1 + w_2 + \dots + w_m = 1 \quad w_k \geq 0 \quad (3.12)$$

The expression of the coefficient β_k :

$$\beta_k = \sum_{i=1}^N \sum_{c=1}^c u_{ic}^m \alpha_{ick} \quad (3.13)$$

Finally, the expression of the weight w_k is obtained:

$$w_k = \frac{\frac{1}{\beta_k}}{\frac{1}{\beta_1} + \frac{1}{\beta_2} + \dots + \frac{1}{\beta_M}} \quad (3.14)$$

The multi-core fuzzy clustering algorithm exerts the effectiveness of the fuzzy clustering algorithm, fully shows the effect of multi-core, and its role in actual production is also very obvious.

At present, there are many algorithms with their own characteristics. Among these algorithms, the FCM algorithm and the improved algorithm based on the FCM algorithm have the most complete system. This type of algorithm is supported by very good mathematical theory, and has also achieved good results in many applications, but there are still some problems with this type of algorithm.

(1) FCM and its improved algorithm belong to the division algorithm. As long as an initial value is given as the classification number, regardless of the type of the data set, the final classification number is this initial value, not the actual classification of the data set. This is an unreasonable way. It makes the existing FCM-type algorithms not analyze the agglomeration of the data set, but rather rigidly impose a certain membership relationship on the data. Therefore, such clustering results are difficult to interpret.

(2) FCM and its improved algorithm need to set a number of classifications in advance. Without knowing the prior knowledge of the data set, the initial value of unsupervised clustering will have no theoretical basis. On the other hand, the clustering results need to be evaluated for validity, including the verification of the optimal number of classifications and the clustering result set. Because many data sets do not have any prior knowledge and only perform data mining when needed, this feature of this type of algorithm severely limits its application in real life.

(3) FCM-type algorithms generally can only achieve better results in compactness within clusters, better separation between clusters, or clustering subsets of stars. For data sets with irregular structure, FCM algorithm and its improved algorithm can not get ideal results.

The multi-core function is to recombine two or more kernel functions that meet the Mercer condition to enhance its generalization ability and learning ability. Its expression is as follows:

$$k(x_i, x_j) = \sum_{k=1}^k \beta_k k_k(x_i, x_j), \quad \beta_k \geq 0 \quad (3.15)$$

Because the FCM algorithm's membership degree of 1 makes it particularly sensitive to outliers and noise points, in the algorithm of this paper, the original membership degree and the constraint condition of 1 are relaxed, and a typical value is introduced to represent the membership value. Moreover, this paper designs a fuzzy clustering algorithm with a double-variable weighted kernel, and at the same time introduces penalty factors to optimize the experimental results, which further improves the feasibility and correctness of the clustering algorithm. As the number of iterations continues to increase, the experimental results will further tend to the best clustering results. The objective function is as follows:

$$J = \sum_{i=1}^c \sum_{j=1}^n (u_{ij} + t_{ij})^m D_{ij}^2 + \sum_{i=1}^c r_i \sum_{j=1}^n (\partial_i - t_{ij})^n \quad (3.16)$$

Among them, c represents the classification number of the data set, and n represents the total

number of samples of the data set to be classified. u_{ij} represents that the value m of the j th data point belonging to the i th class is between $[1.5, 2.5]$, usually 2. For the value of m , there is no specific formula or authoritative judgment. In fact, from a mathematical point of view, the value of m is meaningless and not necessary. However, the fuzzy algorithm proposed in this paper

introduces the concept of m in order to better distinguish between hard clusters. t_{ij} represents the typical value of the j -th data point belonging to the i -th category, also called the possibility of

membership value, and its meaning is similar to u_{ij} . r_i represents the penalty factor. We assign

an overall weighted value ∂_i to each sample, which indicates the degree of contribution to the clustering. For noise points and outliers that are irrelevant to the clustering process, the impact of

these points is greatly reduced. ϕ is a non-linear mapping function, $\phi: R^L \rightarrow H, x \rightarrow \phi(x)$,

$x \in R^L$ is a data point in the low-dimensional space, and H is the high-dimensional feature space

processed by the kernel function. The set of samples is $x = \{x_1, x_2 \dots x_n\}$, and the expression of

∂_j is as follows:

$$\partial_j = \sum_{k=1}^n \exp(-9 \|x_j - x_k\|^2) \quad (3.17)$$

Among them, 9 is a constant and a positive number, $\|x_j - x_k\|$ represents the Euclidean distance between two data points, and the size of the sample weight is related to the distance between all samples. If outliers or noise points are relatively far away, the weight value will naturally be small, and the impact on clustering will be small. The mapping method is shown in the following Figure 1.

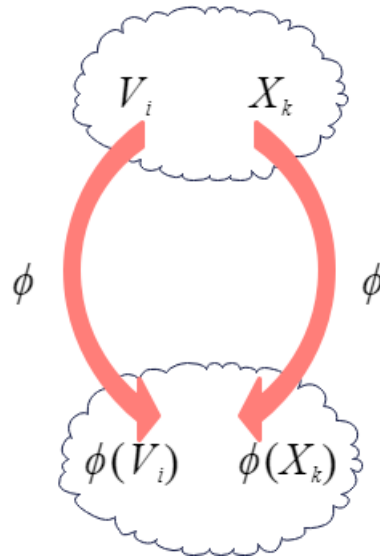


Figure 1: Schematic diagram of mapping.

In the feature space, the cluster centers can be calculated according to the prior PCM algorithm, or can be obtained by obtaining the partial integral of the objective function. The objective formula that it satisfies is as follows:

$$\phi(\hat{v}_i) = \frac{\sum_{j=1}^n (u_{ij} + t_{ij})^m \phi(x_j)}{\sum_{j=1}^n (u_{ij} + t_{ij})^m} \quad (3.18)$$

By taking the partial integral of J_2 and using mathematical formulas to derive, we can get the fuzzy membership value u_{ij} that we want. The value of the degree of membership satisfies the

formula $\sum_{i=1}^c \sum_{j=1}^n u_{ij} = n$ and the typical value t_{ij} , and the target formulas are as follows:

$$u_{ij} = \frac{1}{\sum_{s=1}^c \left[\frac{\sum_{i=1}^L [1-k(x_j, \hat{v}_i)]}{\sum_{i=1}^L [1-k(x_j, \hat{v}_s)]} \right]^{\frac{1}{m-1}}} \quad (3.19)$$

and

$$t_{ij} = \frac{1}{1 + \left\{ \frac{2b \sum_{l=1}^L [1-k(x_j, \hat{v}_l)] \frac{1}{n-1}}{\sigma^2} \right\} \frac{1}{\eta-1}} \quad (3.20)$$

r_i is the punishment factor, and its expression is as follows:

$$r_i = k \frac{\sum_{j=1}^n u_{ij}^m d(x_j, v_i)}{\sum_{j=1}^n u_{ij}^m}, \text{ among } k > 0 \quad (3.21)$$

If the function $k: X \times X \rightarrow R$ is a positive definite kernel, if and only if k is positive definite and satisfies the equation:

$$\sum_{i=1}^n \sum_{j=1}^n c_i c_j k(x_i, x_j) \geq 0 \quad (3.22)$$

for and any $n \geq 2$ holds, where $c_r \in R, r = 1, \dots, n$. At the same time, the Mercer kernel can be expressed as an inner product, as shown below:

$$k(x_i, x_j) = \langle \Phi(x_i), \Phi(x_j) \rangle \quad (3.23)$$

Among them, Φ represents the high-dimensional feature space mapped to: $X \rightarrow H$ is the mapping from the initial low-dimensional input space R^s to the high-dimensional feature space H .

We calculate the distance D_{ij} in the feature space through the kernelization distance. The kernel space is expressed by Euclidean distance, which is the Euclidean distance of the kernel function. Its representation is fundamentally different from ordinary space, and it reflects the distance between the data point in the kernel space and the cluster center based on the kernel.

The formula for D_{ij} is as follows:

$$D_{ij} = \left(\phi(x_j) - \phi(\hat{v}_i) \right)^T \left(\phi(x_j) - \phi(\hat{v}_i) \right) = k(x_j, x_j) - 2k(x_j, \hat{v}_i) + k(\hat{v}_i, \hat{v}_i) \quad (3.24)$$

In order to represent the Gaussian function between the j-th sample and the i-th cluster center, we use \hat{v}_i to represent the cluster center in the high-dimensional space, and the specific expression formula is as follows:

$$k(x_j, \hat{v}_i) = \phi(x_j)\phi(\hat{v}_i) = \frac{\phi(x_j)\phi(x_i)\sum_{j=1}^N(u_{ij}+t_{ij})^m}{\sum_{j=1}^N(u_{ij}+t_{ij})^m} = \frac{k(x_i, x_j)\sum_{j=1}^N(u_{ij}+t_{ij})^m}{\sum_{j=1}^N(u_{ij}+t_{ij})^m} \quad (3.25)$$

The distance function from the \hat{v}_i -th cluster center to itself is represented by a Gaussian function as shown below:

$$k(\hat{v}_i, \hat{v}_i) = \phi(\hat{v}_i)\phi(\hat{v}_i) = \frac{\phi(x_i)\phi(x_i)\sum_{j=1}^N(u_{ij}+t_{ij})^m\sum_{j=1}^N(u_{ij}+t_{ij})^m}{\sum_{j=1}^N(u_{ij}+t_{ij})^m\sum_{j=1}^N(u_{ij}+t_{ij})^m} = \frac{k(x_i, x_i)\sum_{j=1}^N(u_{ij}+t_{ij})^m\sum_{j=1}^N(u_{ij}+t_{ij})^m}{\sum_{j=1}^N(u_{ij}+t_{ij})^m\sum_{j=1}^N(u_{ij}+t_{ij})^m} \quad (3.26)$$

The expression formula of the multi-core-based clustering algorithm in the core space is:

$k_l(x_i, x_j) = \phi_l(x_i)^T \phi_l(x_j)$. The clustering in the feature space uses the mapping relationship ϕ to map each data set to the feature space. Here, the Gaussian kernel function is used:

$$k_l(x_i, x_i) = \exp\left(-\|x_i - x_i\|^2 / \sigma\right) \quad (3.27)$$

A function can be used as a kernel function if it satisfies the Mercer condition. The Mercer condition is as follows: there is a kernel function $k(x, y) = \langle \Phi(x), \Phi(y) \rangle$, and any square product function

$f(x)$ has $\int_{x \times x} k(x, z)f(x)f(z)dx dz \geq 0$. In order to determine that the result of the objective

function based on multi-core still satisfies Mercer's condition, we assume that a parameter ϕ' , and ϕ' satisfies

$$\phi' = \sum_{l=1}^L w_l \phi_l(x) \quad \text{and} \quad w_l \geq 0 \quad \dots \quad (3.28)$$

After introducing the weight index, the distance function is as follows:

$$D_{ij}^2 = \sum_{l=1}^L W_l^2 k_l(x_i, x_i) - 2 \sum_{j=1}^n \sum_{l=1}^L w_l^2 k_l(x_i, v_j) + \sum_{j=1}^n \sum_{l=1}^L w_l^2 k_l(v_j, v_j) \quad (3.29)$$

When the degree of membership is fixed, we simplify the formula as follows:

$$\theta_l = \sum_{i=1}^c \sum_{j=1}^n k_l(\phi(x_i), \phi(x_i)) - 2\phi(x_i) \frac{\sum_{l=1}^L (u_{ij} + t_{ij})^m \phi(x_{il})}{\sum_{l=1}^L (u_{ij} + t_{ij})^m} + \left(\frac{\sum_{l=1}^L (u_{ij} + t_{ij})^m \phi(x_{il})}{\sum_{l=1}^L (u_{ij} + t_{ij})^m} \right)^2 \quad (3.30)$$

After simplification, we get:

$$J(w) = \sum_{l=1}^L \sum_{i=1}^c \sum_{j=1}^n (u_{ij} + t_{ij})^m \theta_l w_l^2 + \sigma^2 \sum_{i=1}^c \sum_{j=1}^n (\partial_i - t_{ij})^\eta \quad (3.31)$$

At the same time, the weight function must meet the following conditions and restrictions:

$$\phi(x_i) = w_1 \phi(x_1) + w_2 \phi(x_2) + w_3 \phi(x_3) + \dots + w_l \phi(x_l) \quad \text{and} \quad w_1 + w_2 + w_3 + \dots + w_l = 1 \quad (3.32)$$

The expression of the converted J_λ is

$$J_\lambda(w, \lambda) = \sum_{l=1}^L \sum_{i=1}^c \sum_{j=1}^n (u_{ij} + t_{ij})^m \theta_l w_l^2 + \sigma^2 \sum_{i=1}^c \sum_{j=1}^n (\partial_i - t_{ij})^\eta - 2\lambda \left(\sum_{k=1}^c w_k - 1 \right) \quad (3.33)$$

The partial integral of the weight w_k is expressed as follows:

$$\frac{\partial J_\lambda}{\partial w_k} = 2 \sum_{i=1}^c \sum_{j=1}^n \sum_{l=1}^L (u_{ij} + t_{ij})^m \theta_l w_l - 2\lambda = 0 \quad (3.34)$$

Because $\sum_{l=1}^L w_l = 1$ and $H = (au_{ij}^m + bt_{ij}^\eta)$, the original formula can be expressed as:

$$\sum_{l=1}^L w_l = \left(\frac{1}{\theta_1 H} + \frac{1}{\theta_2 H} + \dots + \frac{1}{\theta_m H} \right) \lambda = 1 \quad (3.35)$$

Therefore, the expression formula of λ is as follows:

$$\lambda = \frac{1}{\frac{1}{\theta_1 H} + \frac{1}{\theta_2 H} + \dots + \frac{1}{\theta_m H}} \quad (3.36)$$

The calculation formula for weight is as follows:

$$w_l = \frac{\frac{1}{\theta_L H}}{\frac{1}{\theta_1 H} + \frac{1}{\theta_2 H} + \dots + \frac{1}{\theta_L H}} \quad 0 < \sum_{j=1}^n u_{ij}^p \leq n \quad (3.37)$$

The above successfully introduces dynamic weights to represent data changes. The detailed process of the fuzzy clustering algorithm for the possibility of multi-core is shown above. At the same time, the membership degree of the function and the weight of the kernel function must be non-negative, and u_{ij} is the value of the j-th point belonging to the i-th possible cluster center and satisfies $0 < u_{ij} < 1$.

4 CONSISTENCY EVALUATION METHOD OF ENGLISH LANGUAGE APPLICATION ABILITY BASED ON CONSISTENCY EVALUATION

The developed system is mainly used by students for oral English learning and for final exams, so the user group is fixed. Moreover, the system is mainly used in the local area network of teaching and research offices, and it is also concentrated in terms of geographical location. In addition, the CS architecture has a narrow application area, and it is usually used in local area networks and requires fixed user groups and other shortcomings that will not affect us. At the same time, it can make full use of the advantages of the CS architecture. After comparing the advantages and disadvantages of the two architectures and the actual usage, the system chose the client server (ClientServer) architecture. In the CS architecture, the system is divided into three parts: the presentation layer, the function layer and the data layer according to functions, which are placed on the same or different hardware platforms. The three-layer CS structure diagram is shown in Figure 2.

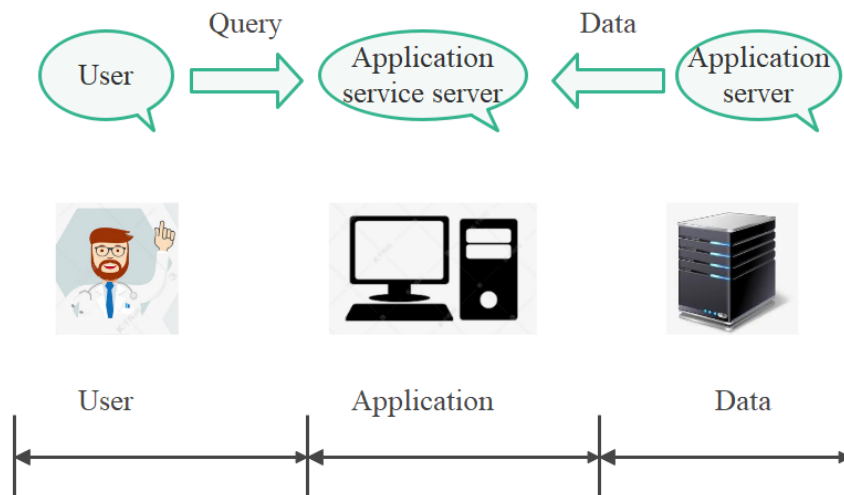


Figure 2: Schematic diagram of three-tier C/S architecture.

The functional structure of the system is divided into three main subsystems, namely the question bank management subsystem, the examination management subsystem, and the marking subsystem, and each subsystem can be divided into several modules. The specific functional structure is shown in Figure 3:

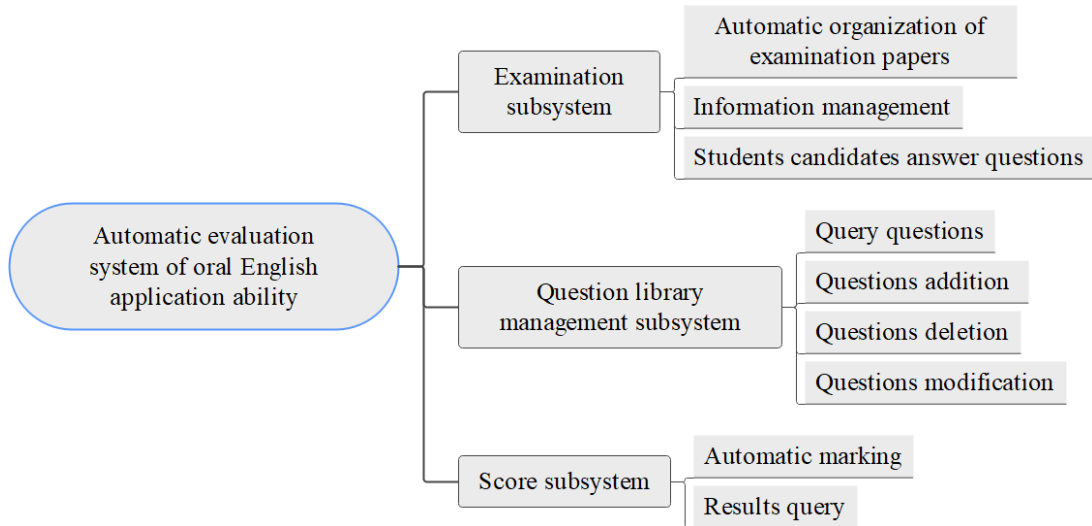


Figure 3: System function structure diagram.

Open coding is the basis and prerequisite for the ability to apply English language. It is mainly based on the concept as a unit to systematically decompose the original data, understand the attributes of related concepts, and classify them. Specifically, the main operating steps of open coding are shown in Figure 4.

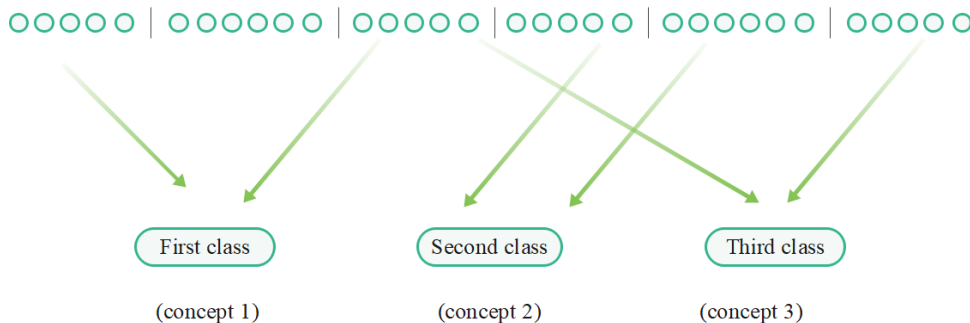


Figure 4: The process of open coding.

Based on the basic assumptions of English language application ability evaluation, this paper constructs a basic model of English language application ability evaluation, as shown in Figure 5. Through the analysis and analysis of consistency evaluation, the hypothesis of the previous assessment model of students' oral communication ability can be verified, and an optimized assessment model of students' oral communication ability can be obtained, as shown in Figure 6.

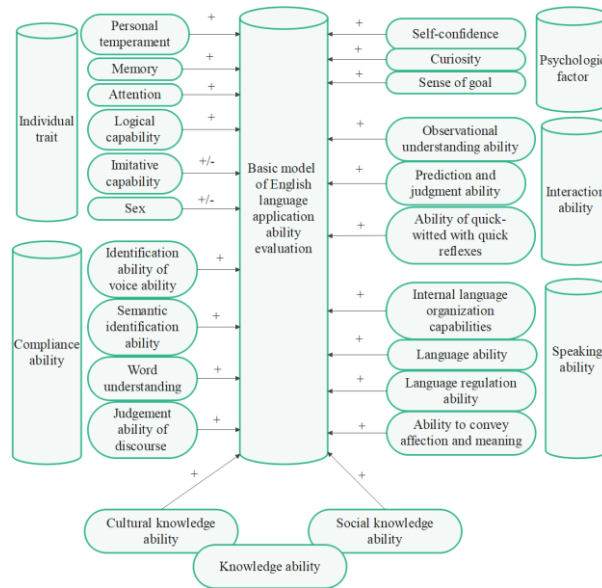


Figure 5: The basic model of English language application ability evaluation.

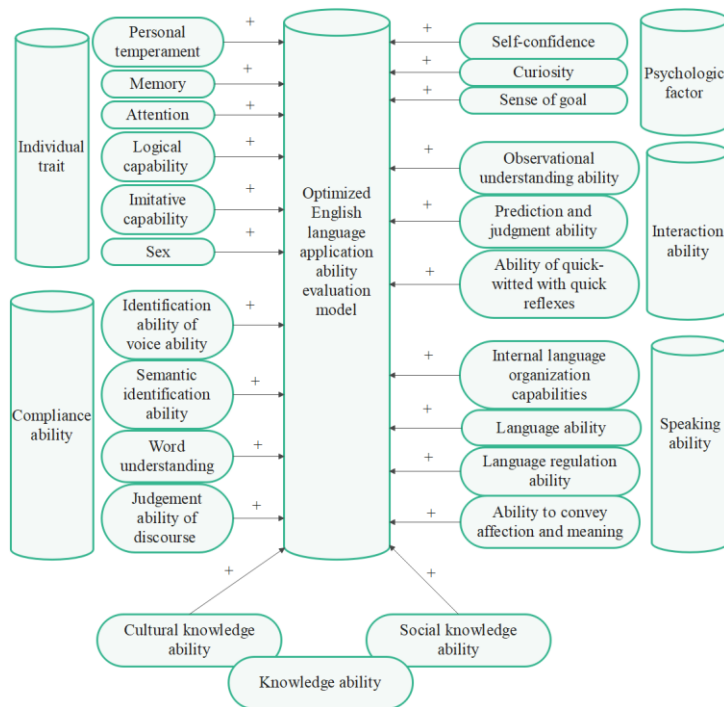


Figure 6: The optimized English language application ability evaluation model.

After hypothesis testing and consistency analysis of the model, the English language application ability evaluation system is finally obtained, as shown in Figure 7.

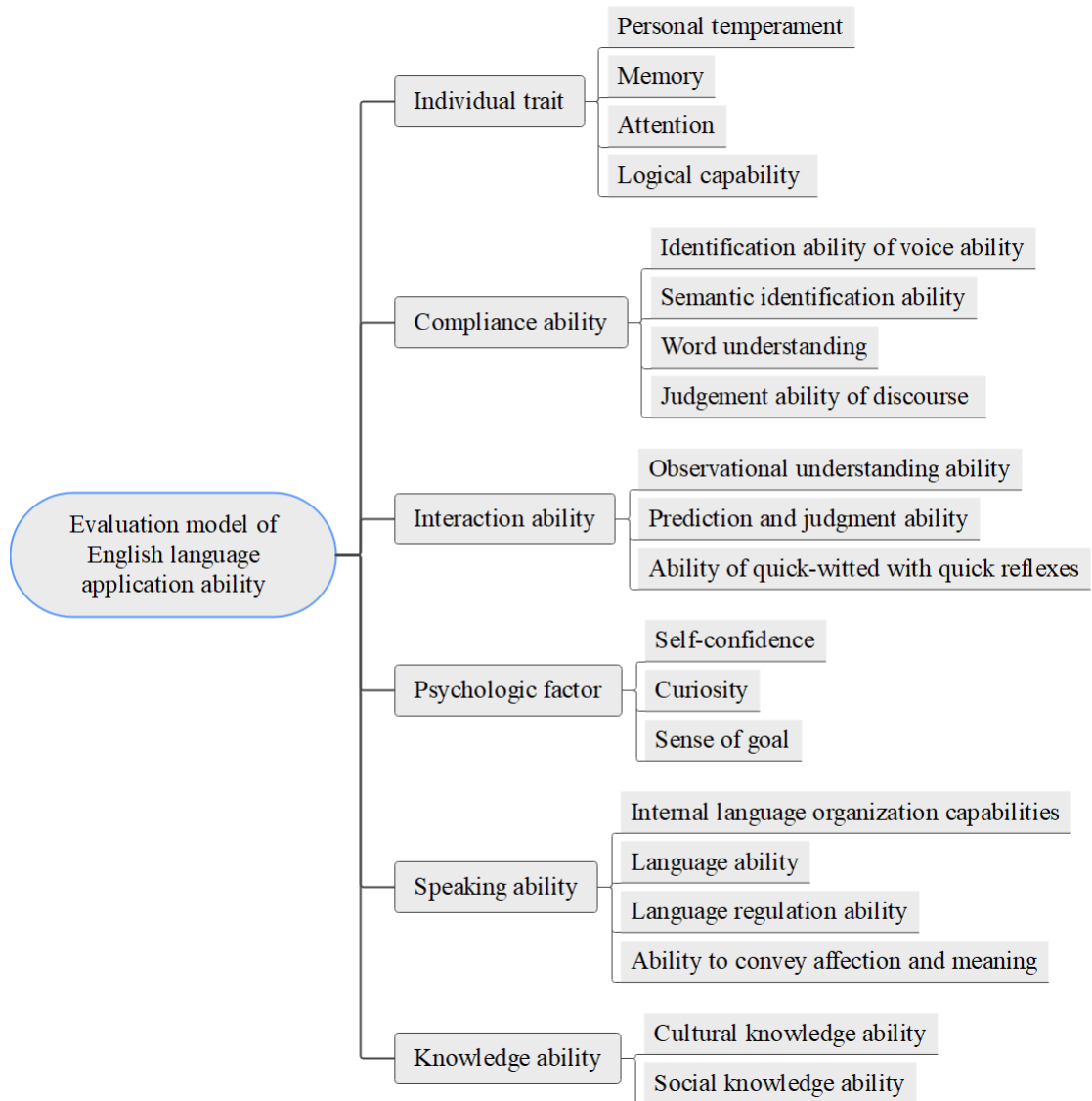


Figure 7: English language application ability evaluation system.

The fault state recognition of transformer based on language model is a classification problem. According to the manifestation of the subsequent parts, the reasoning method and the processing method of the classification decision, we divide the classification method based on fuzzy logic into two strategies: the fuzzy controller strategy and the fuzzy classifier strategy. The follow-up part of the fuzzy model adopting the fuzzy classifier takes the form of a type

label or a type fuzzy set, that is to say, the follow-up part describes the degree to which the input vector pattern belongs to a certain class or this class under the rule. The output of the entire model is various membership degrees. In order to obtain the precise type, the maximum value or threshold function is generally added when using the fuzzy model as a fuzzy classifier to obtain the type number in the input vector mode. The classification of fuzzy controller is shown in Figure 8.

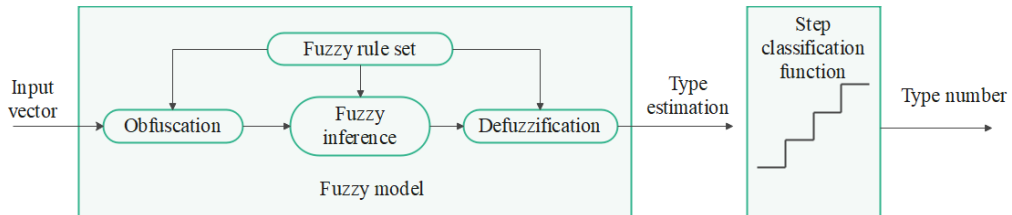


Figure 8: Classification of fuzzy controllers.

After obtaining the above formative evaluation method of English language application ability based on consistency evaluation, the reliability of the fuzzy consistency evaluation method proposed in this paper is evaluated, and its reliability effect is counted. In this paper, a large amount of speech data is used for training and processing, and the evaluation results are shown in Table 1 and Figure 9.

| <i>NUM</i> | <i>Reliability analysis</i> | <i>NUM</i> | <i>Reliability analysis</i> |
|------------|-----------------------------|------------|-----------------------------|
| 1 | 89.36 | 16 | 81.60 |
| 2 | 87.11 | 17 | 87.01 |
| 3 | 88.92 | 18 | 82.04 |
| 4 | 86.35 | 19 | 92.58 |
| 5 | 89.03 | 20 | 81.85 |
| 6 | 91.42 | 21 | 86.97 |
| 7 | 86.42 | 22 | 90.90 |
| 8 | 89.06 | 23 | 92.62 |
| 9 | 84.29 | 24 | 81.13 |
| 10 | 91.77 | 25 | 84.35 |
| 11 | 92.01 | 26 | 84.21 |
| 12 | 92.20 | 27 | 89.09 |
| 13 | 81.22 | 28 | 89.09 |
| 14 | 89.94 | 29 | 92.90 |
| 15 | 85.71 | 30 | 81.85 |

Table 1: Reliability score of fuzzy consistency evaluation method.

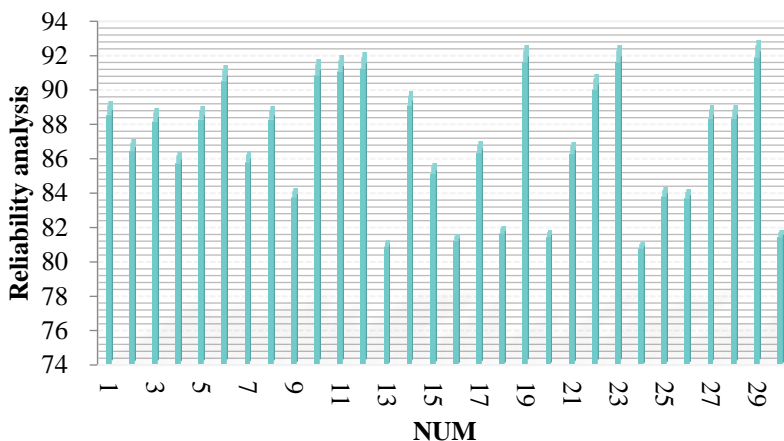


Figure 9: Statistical diagram of the reliability of the fuzzy consistency evaluation method

From the above research, we can see that the fuzzy consistency evaluation method proposed in this paper has high reliability and can play an important role in the formative evaluation of English language and English ability. On this basis, this paper verifies the practical effect of the consistency evaluation method of English language application ability based on consistency evaluation, and the results are shown in Table 2 and Figure 10. Table 2 The effect of the formative evaluation method of English language application ability based on

| NUM | Evaluation effect | NUM | Evaluation effect |
|-----|-------------------|-----|-------------------|
| 1 | 91.58 | 16 | 90.91 |
| 2 | 93.53 | 17 | 89.18 |
| 3 | 90.89 | 18 | 91.17 |
| 4 | 92.95 | 19 | 88.52 |
| 5 | 88.83 | 20 | 93.53 |
| 6 | 88.32 | 21 | 93.30 |
| 7 | 92.57 | 22 | 89.81 |
| 8 | 91.75 | 23 | 89.55 |
| 9 | 91.11 | 24 | 90.16 |
| 10 | 92.47 | 25 | 93.99 |
| 11 | 91.51 | 26 | 90.51 |
| 12 | 89.37 | 27 | 89.35 |
| 13 | 93.00 | 28 | 91.07 |
| 14 | 90.59 | 29 | 92.43 |
| 15 | 93.53 | 30 | 92.12 |

Table 2: The effect of the formative evaluation method of English language application ability based on.

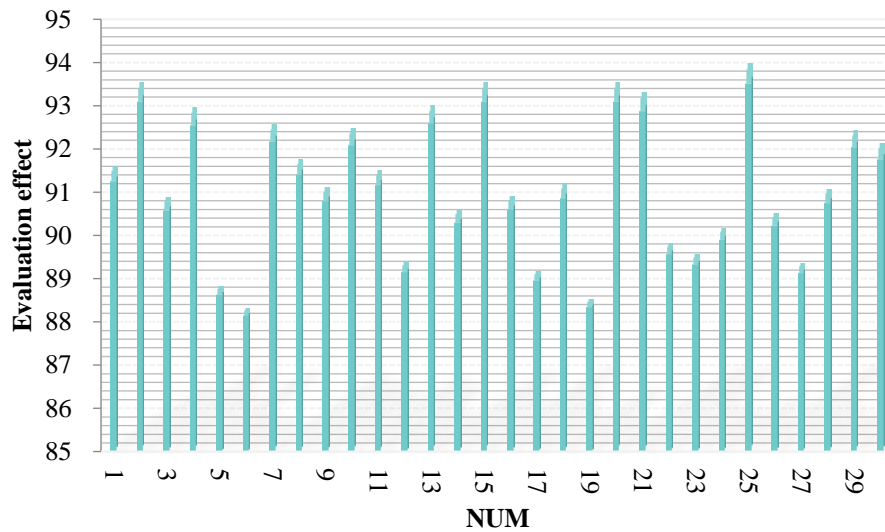


Figure 10: Statistical diagram of consistency evaluation methods of English language application ability based on consistency evaluation.

From the above research, it can be seen that the consistency evaluation method of English language application ability based on consistency evaluation can play a good role in the evaluation of English language application ability.

5 CONCLUSION

The improvement of English teaching mode should be based on students' actual English application ability, and actively explore good teaching methods and methods that can improve students' English application ability. The improvement of English application ability requires students to acquire it through a lot of practice and active learning. Therefore, a good English teaching model should rely on the important power of information technology to promote English learning in the direction of modernization and individualization without being affected by time and space. At the same time, it is necessary to break the traditional teacher-led singular classroom teaching model, and create more opportunities for students to participate in classroom learning. According to the requirements of English language and English proficiency evaluation, this article combines the consistency evaluation method to construct an intelligent evaluation system to evaluate and analyze the modern English language application ability to improve the language application ability in modern college English teaching. Through experimental analysis, it can be known that the consistency evaluation method of English language application ability based on consistency evaluation can play a good role in the evaluation of English language application ability.

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