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Personalized Learning Path Construction in Chinese Education Based on Fuzzy Logic Reasoning

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Abstract Traditional Chinese language teaching methods are difficult to meet students' individualized needs, while fuzzy logic inference technology can accurately assess learners' characteristics, provide targeted learning resources, and effectively improve learning outcomes. In this study, fuzzy logic inference technology is used to establish a fuzzy control rule system to predict learners' performance by taking four dimensions, namely, average daily online learning time, average daily vocabulary growth, average answering time, and total vocabulary mastered, as input variables, and then matching Chinese vocabulary learning resources of corresponding difficulty. The experiment selects 60 Chinese majors in a university as the research subjects, randomly divided into the experimental group and the control group of 30 people each, and verified through a 9-month teaching experiment. The results showed that the experimental group using the personalized learning path based on fuzzy logic reasoning was significantly better than the control group with traditional teaching methods after the teaching intervention (P=0.003<0.05). The within-group comparison analysis showed that the students' Chinese test scores before and after the intervention in the experimental group exhibited significant differences, while the control group did not produce significant changes. Through the application of fuzzy set construction and fuzzy relationship matrix, this study successfully applies fuzzy logic reasoning technology to the field of Chinese language education, which confirms the effectiveness of this method in enhancing learning effects and provides new technical support and practical reference for personalized teaching in Chinese language education.

Index Terms fuzzy logic reasoning, Chinese language education, personalized learning, learning path, fuzzy set, fuzzy relationship matrix

I. Introduction

Chinese language and culture are the treasures of China's ancient civilization. As China's economic strength and cultural influence continue to grow, Chinese language education has taken an important place in China and internationally. At the same time, Chinese language education is also facing some problems and challenges that need to be solved and improved at an early stage. First of all, whether it is international Chinese education or Chinese education within China, due to economic development, local policies and other factors, there are significant differences in the time when Chinese education has been carried out in different regions, which leads to the widening of the differences in Chinese language fundamentals among students [1]-[3]. Secondly, it is necessary to combine with the actual requirements of the current situation to achieve multi-dimensional competence cultivation in addition to the basic language skills, and to promote the personalized development of students [4], [5]. Finally, in teaching practice, many teachers are not able to use teaching methods flexibly, develop a reasonable teaching process in combination with the specific conditions of students, and are difficult to take into full consideration of students' psychological characteristics and learning patterns, and lack of real-time response to students' cognitive changes, which is, to a certain extent, not conducive to the development of Chinese language education [6], [7]. And it has been shown in several studies that personalized teaching is one of the most important methods to improve learning effects [8]-[10].

The basic principle of fuzzy logic reasoning is to utilize the fuzzy set's affiliation function to operate and derive the fuzzy set through the rules of fuzzy logic, and finally get the fuzzy conclusion. In the event of decision analysis, it can deal with uncertainty and ambiguity in decision problems, and help decision makers make accurate decisions through fuzzy modeling and fuzzy reasoning on decision factors, which can provide a new paradigm for the realization of personalized learning [11], [12].

With the continuous development of education informatization, personalized learning has become an important trend in modern education. The traditional Chinese language education model often adopts uniform teaching content and progress, which is difficult to meet the individualized needs of different learners and leads to uneven learning results. Chinese language education, as an important part of language learning, has a direct impact on the development of learners' language ability. Research shows that learners show different cognitive styles, learning interests and learning abilities in the learning process, and these different factors determine the necessity of personalized learning paths. The construction of personalized learning paths in Chinese language education not only needs to take into account the individual differences of learners, but also needs to dynamically adjust the learning content and difficulty according to the actual situation of the learners, so as to achieve the accurate matching of learning resources. In recent years, with the wide application of artificial intelligence technology in the field of education, the learning path construction method based on fuzzy logic reasoning has gradually attracted attention. Fuzzy logic reasoning can deal with uncertain information and establish fuzzy inference rules by fuzzy processing of learner characteristics, thus realizing accurate assessment of learner ability and personalized recommendation. Compared with the traditional explicit mathematical model, fuzzy logic reasoning is more suitable for dealing with the vagueness and uncertainty problems existing in the education field, providing new technical support for the construction of personalized learning paths. At present, fuzzy logic reasoning has achieved certain results in personalized teaching in mathematics, English and other disciplines, but relatively little research has been conducted on its application in the field of Chinese education. As a language with rich cultural connotations and linguistic characteristics, the learning process of Chinese is complex and variable, which requires more accurate support of personalized learning paths. Therefore, exploring the personalized learning path construction method of Chinese education based on fuzzy logic reasoning is of great significance to enhance the effect of Chinese education.

In this study, fuzzy logic reasoning is applied to the construction of personalized learning paths in Chinese education. Through the analysis of four dimensions: average daily online learning time, average daily vocabulary growth, average answering time, and the total amount of vocabulary mastered by the learner, a fuzzy control rule system is established to predict the learner's level of learning ability, and accordingly, Chinese vocabulary learning resources of matching difficulty are pushed. The study first collects learners' learning data, carries out outlier processing and data smoothing, and determines the affiliation function of each dimensional variable; then constructs a fuzzy relationship matrix based on fuzzy statistical methods, and establishes fuzzy control rules; finally, through the de-fuzzying process, we obtain the predicted learners' scores, and match the learning resources with the corresponding difficulty. In order to verify the effectiveness of the method, this study selects 60 Chinese majors in a university as the research object, and compares the effect difference between the personalized learning path using fuzzy logic reasoning and the traditional teaching method through a 9-month teaching experiment, so as to provide practical reference for the personalized teaching of Chinese education.

II. Exploring personalized learning paths in Chinese language education

II. A. Fuzzy Logic Reasoning

The so-called fuzzy inference model is a kind of “pragmatic” model that uses fuzzy knowledge and fuzzy information to reason by fuzzy logic. It is a kind of uncertainty reasoning model that “expands” the traditional deterministic reasoning in terms of uncertainty knowledge expression and logical operations [13]. In many ways, it is a better model for simulating the human reasoning process, especially in the construction of personalized learning paths in Chinese education, which has a good application prospect.

II. A. 1) Definition of fuzzy sets

A fuzzy set is generally represented by the corresponding affiliation function, and the significance of the affiliation function usually exists in a particular practice situation [14], [15]. Usually the shape of the affiliation function is arbitrary, but mostly appears in triangular or trapezoidal shape, at present there are many ways to determine the affiliation function, the fuzzy statistical method is a method that is more similar to the idea of probability statistics, and the process of determining it also corresponds to randomized trials in probability statistics, and its four elements are:

(1) The thesis domain X.

(2) A fixed element x_0 in the thesis X for which the degree of affiliation is to be determined.

(3) A mutable subset A of the thesis domain X, which serves as a reflection of the plasticity boundaries of the fuzzy set, from which a judgment is obtained as to whether or not x_0 in each trial conforms to the fuzzy concept inscribed by the fuzzy set.

(4) Conditional set B, which constrains the variation of sub-set A.

The basic principle of the fuzzy statistical method is to clearly determine whether x_0 belongs to subset A through each experiment, and each time the subset A can be changed, based on several such experiments, the membership frequency of x_0 for the fuzzy set is the quotient of the number of trials belonging to the subset A and the total number of trials, and with the increase of the number of trials, the membership frequency will tend to be stable, and this stable membership frequency is called membership. This is the process of determining the membership degree of an element of set X. Based on the membership function of the entire set, set X should first be divided into several small groups, and then the membership degree of the midpoint of each group is taken as an approximate value for the membership degree of the entire group. This results in an approximate membership function. If the groups are small enough, it can lead to a membership function that is close to the theoretical level. This is the process of determining the membership function in fuzzy statistics.

Fuzzy statistical method (two-phase fuzzy statistics) is based on the concept of the domain is divided into two opposing fuzzy sets on the basis of a method of determination, but the concept of the domain may also be divided into three or more opposing fuzzy sets, so at this point in order to determine the affiliation function needs to be used in multi-phase fuzzy statistical methods, trichotomous method is one of the representatives of this method, the specific realization of the process can be referred to the relevant books. In addition to mathematical methods, sometimes you can also determine the general shape of the affiliation function based on practical experience, in order to enable the reader to have a more intuitive understanding of the affiliation function, the following and Figure 1 lists several commonly used affiliation function.

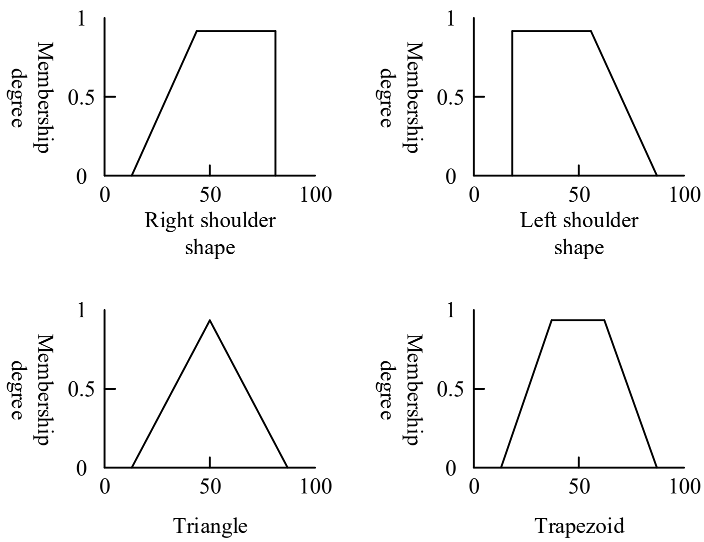


Figure 1: Common Membership Functions

II. A. 2) Correlation operations on fuzzy sets

The intersection operation of a fuzzy set is similar to the and operation of an ordinary set, for any element in a given domain, the degree of affiliation of the fuzzy set obtained by the intersection operation of the element with respect to two fuzzy sets is the minimum of the degree of affiliation of the element with respect to those two fuzzy sets. Assuming the existence of two fuzzy sets A and B on an argument domain, the formula for calculating the fuzzy set affiliation of an element with respect to their intersection operation is as follows:

$$F_{A\cap B}(x)=\min\{F_A(x),F_B(x)\} \tag{1}$$

Similarly the ensemble element of a fuzzy set is similar to the or operation between ordinary sets, for any element in a given domain, the degree of affiliation of the new fuzzy set of the element with respect to the two fuzzy sets on the domain by the ensemble operation is obtained by obtaining the maximum value of the degree of affiliation of the element in the two fuzzy sets obtained. Assuming the existence of two fuzzy sets A and B on the domain, the formula for calculating the affiliation of an element with respect to the fuzzy set derived from their ensemble operation is as follows:

$$F_{A\cup B}(x)=\max\{F_A(x),F_B(x)\} \tag{2}$$

The complement operation of a fuzzy set is a monadic algorithm for fuzzy sets, and the degree of affiliation of a modal set obtained by complement operation for any element on a given thesis domain with respect to a fuzzy set on that domain is obtained by subtracting 1 from the degree of affiliation of that element with respect to that fuzzy set on the thesis city. Assuming that there exists a fuzzy set A on a given theoretical domain, the formula for the degree of affiliation of a fuzzy set obtained by complementary set operation of an element with respect to the fuzzy set A is as follows:

$$F_A(x)^{'} = 1 - F_A(x) \tag{3}$$

Restricting terms can be seen as unary operators on a certain fuzzy set within a domain, used to modify fuzzy sets in that domain. Common restricting terms we often use include "very" and "fairly." Generally, when a fuzzy set in a domain is modified by the restricting term "very," the membership degree of the modified fuzzy set is the square of the membership degree of the fuzzy set before modification, leading to a corresponding reduction in the membership degree of the modified fuzzy set. Suppose there is a fuzzy set A within a domain; then the calculation formula for the membership degree of fuzzy set A modified by the restricting term "very" is as follows:

$$F_{wy(A)} = (F_A(x))^2 \tag{4}$$

If the fuzzy set on the domain is modified by the restriction “fairly”, then the affiliation of the fuzzy set after modification is the structure of the square root of the affiliation of the fuzzy set before modification, and the affiliation of the fuzzy set after modification is enlarged accordingly. Assuming that there exists a fuzzy set A on a domain, the formula for solving the degree of affiliation of the fuzzy set A after it is modified by the “fairly” restriction is as follows:

$$F_{FAIRLY(A)} = \sqrt{F_A(x)} \tag{5}$$

II. A. 3) Basic patterns of fuzzy reasoning

There are various modes of fuzzy inference, and in expert systems, the commonly used basic modes are the synthetic inference mode based on fuzzy (causal) relations. Let X and Y be two basic theory domains, if there exists some kind of fuzzy (causal) relationship $R \subseteq X \times Y$ between X and Y, then fuzzy reasoning can be carried out accordingly. The model is:

(MP) Major premise: There is a relation $R(R \subseteq X \times Y)$ between X and Y.

Minor premise: X is A.

Conclusion: Y is B = A∘R.

(MT) Major premise: There is a relationship between X and Y $R(R \subseteq X \times Y)$.

Minor premise: Y is B.

Conclusion: X is A = B∘R-1.

Where: R^{-1} is the inverse relation of R derived from R and “∘” denotes the fuzzy synthesis operation.

II. A. 4) Practical methods for direct construction of fuzzy relationship matrices

Constructing a fuzzy relation R is the key to realize fuzzy inference. Constructing a fuzzy relation R can be derived from known rules based on certain implication rules, or a statistically significant fuzzy relation can be directly generalized based on statistical samples. In Chinese education personalized learning paths, it may be more common to construct fuzzy relations for fuzzy inference directly based on empirical or observational statistics. Part of this approach is essentially the same as traditional statistical regression analysis. They both aim to generalize statistically significant laws based on statistical samples, with the difference that generalizing fuzzy relationships often employs fuzzy statistical induction, which reduces the requirement for statistical samples, i.e., statistical data can be fuzzy or approximate, and their values can be either point values or set values. The fuzzy relationships thus summarized are essentially approximate and contain some uncertainty. As a result, the results inferred from this model often only give a result with uncertainty, and further processing is often required.

Consider the case of binary relations first, let X and Y be two related theories, and let X be the independent variable theory, Y be the dependent variable theory, when X, Y is is a finite discrete theory, i.e., set:

$$X = \{x_1, x_2, \cdots, x_m\} \tag{6}$$

$$Y = \{y_1, y_2, \cdots, y_n\} \tag{7}$$

Then the relation R between X and Y can be expressed by a matrix. That is, the ordering:

$$R(X \times Y) = \left[R_{ij}\right]_{m \times n} \tag{8}$$

where R_{ij} expresses the relationship between x_i and y_j. When this relationship is a fuzzy relationship, i.e., if R_{ij} is a fuzzy number or a fuzzy affiliation function, the above equation is the fuzzy relationship matrix.

The main engineering methods for the direct construction of fuzzy relationship matrices are as follows:

(1) Statistical regression methods in the form of hypothesized distributions.
(2) Probability and set-value statistical methods.
(3) The fuzzy information method with information diffusion modeling.

The fuzzy relationship matrix constructed with the method of assuming the form of distribution is convenient and easy to use, but assuming the form of distribution is often a very difficult step. Sometimes exploring the form of the distribution itself is necessary to determine the nature of the problem and is unknown. Therefore, it is often not feasible to hope that a reasonable form of the affiliation function can be assumed for every statistical analysis. The way out of this step lies in finding a method of constructing fuzzy relationship matrices directly from the original observations without the need for artificial assumptions, and the set-value statistics method is one of them.

Fuzzy relational matrices constructed by assuming the form of the distribution are convenient and easy to use, but assuming the form of the distribution is often a difficult step. Sometimes exploring the form of the distribution is itself necessary to determine the nature of the problem and is unknown. Therefore, it is often not feasible to hope that a reasonable form of the affiliation function can be assumed for every statistical analysis. The way out to avoid this step lies in finding a way to construct fuzzy relationship matrices directly from the original observation data without artificial assumptions, and the set-value statistics method is one of them. When X and Y can be divided into small intervals, or only the dispersion of X or Y is some small intervals, the calculation of the histogram is often simple and effective. Fixing a variable and calculating the percentage number of observations of another related variable falling into each small interval, the fuzzy relationship between two variables can be initially obtained. In summary, the fuzzy relationship matrix in this system is constructed using fuzzy relationships for fuzzy inference based directly on experience, observed statistics and mechanistic analysis. Among them, the main methods for constructing fuzzy relationships for observed statistics in engineering are probability and set-value statistics.

II. B.Learning paths based on fuzzy logic reasoning

The core concept of personalized learning path based on fuzzy logic in Chinese education is to push personalized learning resources according to the learner's original cognitive structure, learning interests, learning preferences, and other factors, and guide the navigation learning path, so that the learner can complete his/her own learning tasks according to the local conditions, improve the efficiency of learning, achieve the learning goals, and obtain the joy of learning. The main framework is to predict the learning ability of learners through the analysis of their learning characteristics, and then recommend English vocabulary of appropriate difficulty according to the level of their learning ability in order to achieve the purpose of self-adaptation and personalization. The score is full of 100 points, and the grade is divided into 5 levels, while the difficulty level of Chinese writing is also divided into 5 difficulty levels according to certain criteria, which are matched to the corresponding learning ability level and recommended to the corresponding learners. The test scores of the students are predicted based on the learners' on-daily average learning time, average daily vocabulary growth, average answering time, and the total number of vocabulary mastered to assess the learners' learning ability and match the Chinese vocabulary of the corresponding difficulty level. After input items, fuzzification, fuzzy inference, de-fuzzification, and finally the output is obtained.

II. B. 1) Fuzzification of input terms

Based on the principle of fuzzy statistics, fuzzy sets of four dimensional variables were obtained and their respective affiliation functions were determined. Online learning duration reflects the learners' commitment to word memorization, which is divided into three fuzzy sets, short (S), medium (M), and long (L) in terms of daily average volume, with a thesis domain of [0, 240] (minutes). Vocabulary growth determines the efficiency of learners' word memorization, which is divided into 4 fuzzy sets of low (L), medium (M), high (H), and extra-high (EH) in terms of daily average volume, with a thesis domain of [0, 150] (pieces). The average answer time represents the learner's proficiency in mastering the content, in terms of the average number of questions, and is categorized into 3 fuzzy sets, Short (S), Medium (M), and Long (L), with a thesis domain of [0, 120] (seconds). The total number of vocabulary words mastered, on the other hand, specifies how much control students have over the overall vocabulary of the high school exams, and is categorized into 4 fuzzy sets of low (L), medium (M), high (H), and extra-high (EH), with a thesis domain of [0, 5600] (pcs). As for the result set, for more possible improvement of accuracy, the author categorized the output variable student achievement into 5 levels: low (L), lower (RL), medium (M), higher (RH), and high (H), with the thesis domain of [0, 200] (points). The affiliation functions for the four input volume dimensions as well as the output volume scores are shown in Figures 2 through 6.

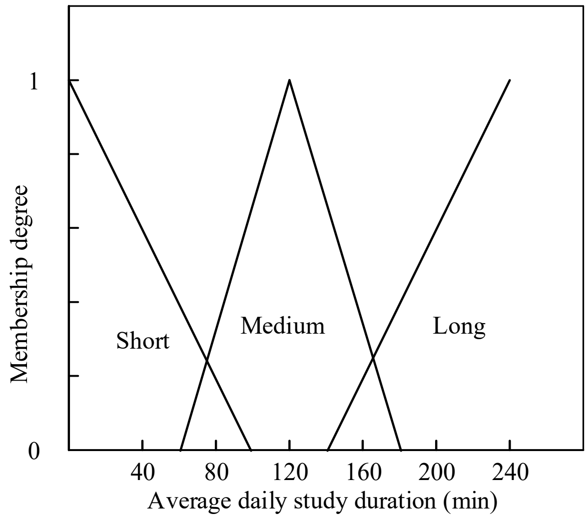


Figure 2: Membership function of average daily online learning duration

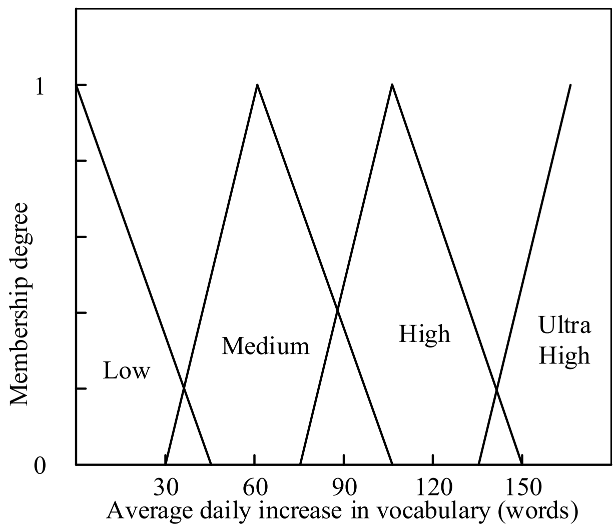


Figure 3: The average daily increase in vocabulary belongs to the degree function

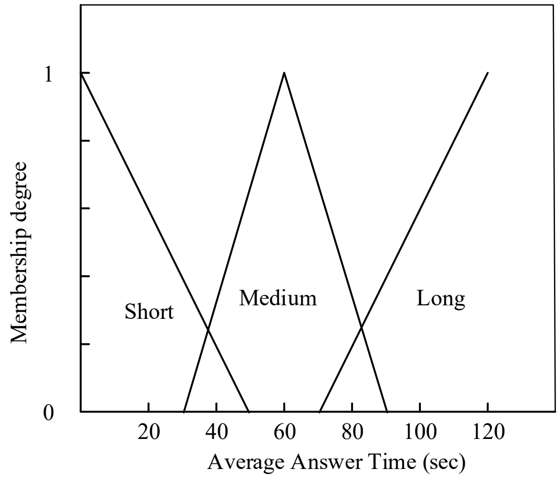


Figure 4: Membership function of average answering time.

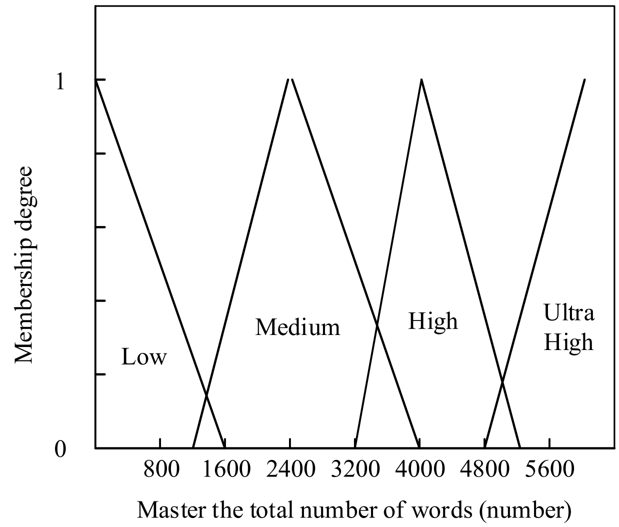


Figure 5: Mastering the total number of words belongs to the degree function

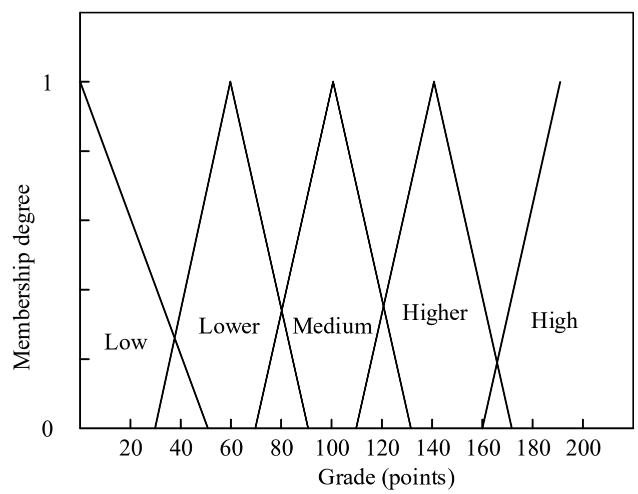


Figure 6: Grades belong to the degree function

II. B. 2) Establishment and reasoning of fuzzy control rules

The adoption of fuzzy control rules has a guiding role for the whole experimental research and determines the scientificity and accuracy of the research results. The establishment of rules is often based on a large amount of data analysis and mining, to find out the commonalities, discard the differences, and encompass all possibilities. The author selected the three experimental classes (120 students in total) in which the pre-test data will be collected as the output classes of the fuzzy control rules to measure the other classes.

Each specific student in the class corresponds to a specific fuzzy control rule as an element that makes up the overall rule. For example, Student A, if the average daily online learning time is long (L), the average daily vocabulary growth is super high (EH), the average answering time is short (S), and the total amount of vocabulary mastered is super high (EH), his grade is high (H), which is described in fuzzy language as IF the average daily online learning time is long AND the average daily vocabulary growth is super high AND the average answering time is short AND the total amount of vocabulary mastered is super high, THEN the The achievement is high.

Since the relationship between the input quantities is an “and” relationship, the intersection relationship is adopted for the combined consideration of the dimensions, and the minimum value (min) is taken to represent the weight of the rule. Therefore, the weight of the i rule generated by the i learner can be expressed as follows:

$$w_i = \mu_{dti} \cap \mu_{dni} \cap \mu_{ati} \cap \mu_{ni} \tag{9}$$

where μ_{dni} denotes the maximum value of the average daily online learning hours affiliation for the i th student, μ_{ati} denotes the maximum value of the average daily vocabulary growth affiliation for the i th student, μ_{ati}

denotes the maximum value of the average question answering time affiliation, μ_{tmi} denotes the maximum value of the total mastered vocabulary affiliation, and the so-called maximum value is taken. For example, in the online learning time affiliation function, when the horizontal axis time is 80 minutes, its corresponding "short" region affiliation is about 0.365, and corresponds to the "medium" region affiliation is about 0.117, taking into account that the higher the affiliation possibility Considering that the higher the probability of affiliation, the larger value of 0.357 was retained and 0.142 was discarded, while the average daily study duration of 45 minutes was also included in the "short" region (S).

II. B. 3) Defuzzification and Outputs

The processing of data in the defuzzification stage is to transform a series of parametric variables obtained in the inference stage into a clear quantity as an output. The process of defuzzification of personalized learning paths in Chinese education is to transform four input quantities, namely, the average daily length of online learning time, the average daily vocabulary growth, the average answering time, and the total number of vocabulary words mastered, into a predicted student performance, and this performance score is also the output quantity required. The full score of the simulation test in the system is 100 points, in order to get more accurate output results, as much as possible, the results will be subdivided and modularized, here the author divided the score into five segments, each segment corresponding to the total score (low: 0~40, lower: 40~50, medium: 50~60, higher: 60~70, high: 70~100).

Based on the weights of each rule obtained in the fuzzy inference stage, and the grades corresponding to the rules, the predicted grade of this learner can be expressed as $score=\frac{\sum_{i=1}^{n}(w_i+s_i)}{\sum_{i=1}^{n}w_i}$. Where i is the first rule, w_i is the weight of the rule, and s_i is the grade score matched by the rule.

Finally, according to the grade band that the score is in, we go to the vocabulary database to find words of the corresponding difficulty level to push to the learners. Of course, in order to match the learners' dynamically changing vocabulary ability, the learners' Chinese ability will be reassessed every day to ensure the reasonableness of the resource push.

III. Empirical analysis of personalized pathways in Chinese language education

III. A. Analysis of learning path construction based on fuzzy logic

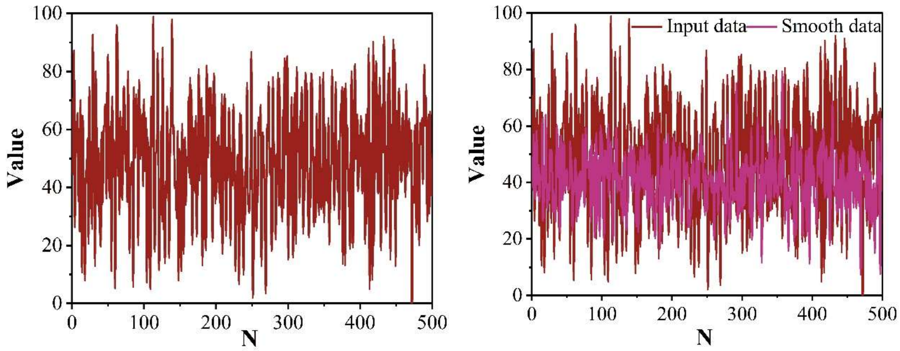
III. A. 1) Sample data collection

The sample data mainly came from Chinese majors in a university, and the sample was recruited through the organization of summer public welfare training. In order to ensure the scientificity and usefulness of the model construction, the subsequent teaching experiment samples were also experimented by Chinese majors. The Chinese learning platform used was a Chinese learning platform, which is a learning platform that can respond to students' learning in the background. The final data used in the study were the average daily online learning time, average daily vocabulary growth, average question answering time, and total vocabulary mastered in the Chinese vocabulary platform, and a total of 500 sample data were collected for model training and testing.

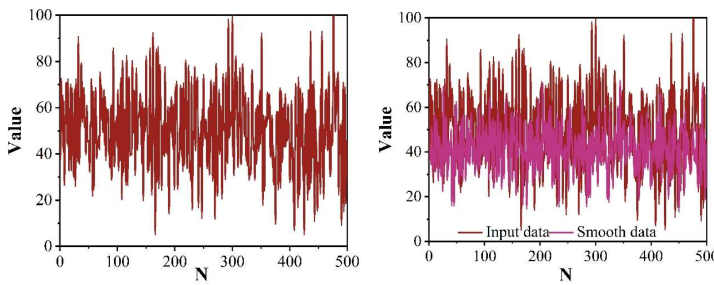
III. A. 2) Sample data pre-processing

(1) Outliers and Smoothing

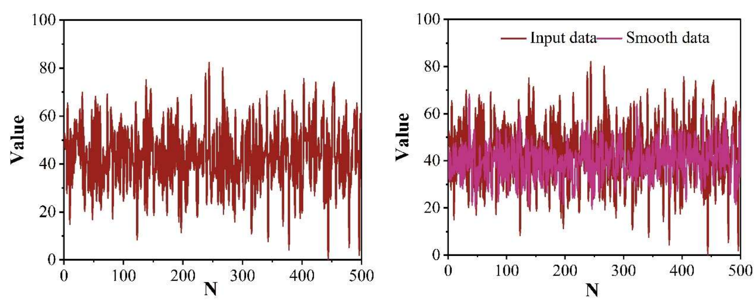
Pre-processing of the collected sample data is necessary before starting the analysis. Due to the complexity and different formats of the collected data sources, there may be noise and missing values in the raw data due to manual errors or technical problems, and since the algorithms cannot run with incomplete or noisy data, data preprocessing is very important in order to improve the robustness of the model to achieve high-quality prediction and evaluation functions. Data preprocessing is performed in three main areas: missing value processing, outlier detection and processing, and data smoothing. Missing value is the most likely problem of raw data collection, once the system or machine collecting data is stuck or stops working for some reasons, it is the cause of data loss, and currently the main use of discard, replacement, interpolation and extrapolation are indeed data processing. Outliers are data that are greater than twice the standard deviation of the mean of the data set and are considered outliers. Outlier data detection and data processing with replacement can be performed by using the 3σ principle of normal distribution or drawing box plots. The purpose of data smoothing is to reduce the data noise and make the calculation of the model more accurate. The data collected in this study have been pre-controlled for missing values, so the study focuses on preprocessing the sample data to resolve outliers and reduce data noise. A comparison of the preprocessed data is shown in Figure 7, where (a) to (d) are the average daily length of online learning time, the average daily vocabulary growth, the average answer time, and the total amount of vocabulary mastered, respectively. The picture on the left shows the original data distribution graph, and the magenta line in the right graph shown by the burgundy line is the data situation after outlier processing and data smoothing. The outlier processing here uses spline interpolation to fill in the outliers, using the median in the data to define the outliers, and the threshold factor is set at 2.945, which is a method that uses smooth curves to interpolate the data, and enables the data to have a better stabilizing line and smoothness. The smoothing method developed for smoothing the data was to move the median, defining the smoothing factor as 0.242.



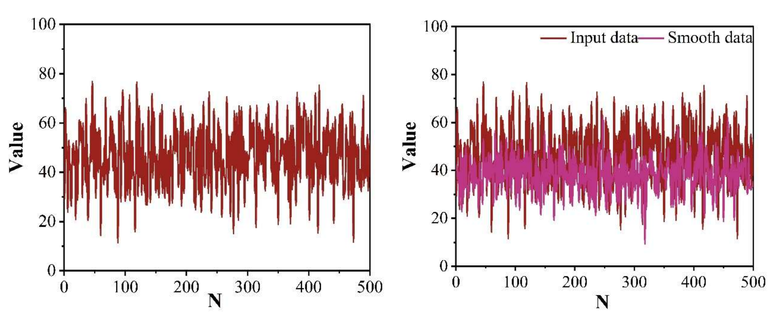
(a)The average daily online learning time is long



(b)Average daily vocabulary growth



(c)Average answering time



(d)Master the total vocabulary

Figure 7: The comparison of the preprocessed data is shown in the figure

(2) Normalization Processing

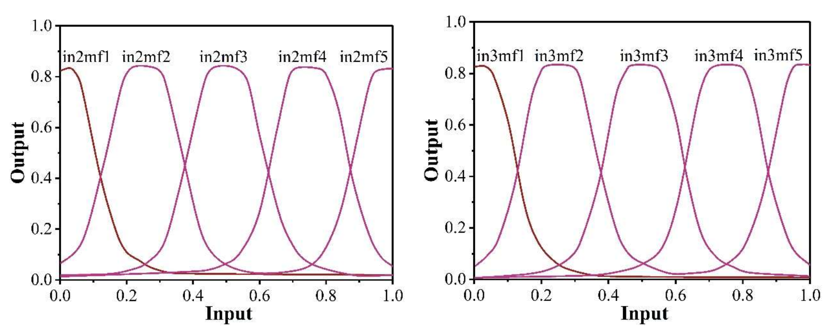
In order to input the collected data into the fuzzy logic inference model, the data must be normalized to eliminate redundant and inconsistent dependent data and to protect the data. Assuming that there is an attribute A, let $\min A$ and $\max A$, this study adopts the basic normalized data processing method, and then maps each value x on the interval $[0,1]$ to A by min-max normalization, to obtain x' which is the normalized data, based on the input variables positive or negative correlation with the output variable, the formula used is as follows:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

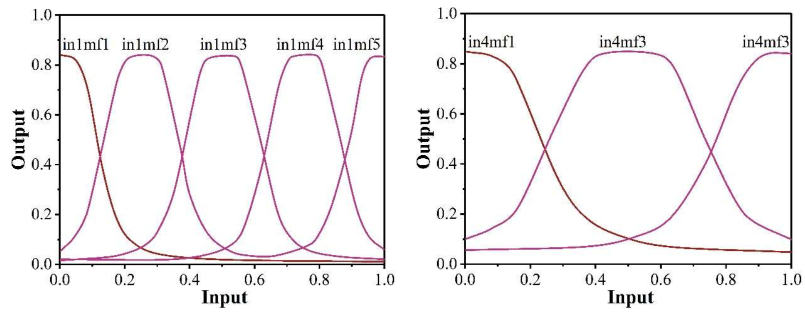
The commonly used ratio of training and testing samples is 8:2, and the total sample data has been data randomized in advance, so here the first 400 sample data are used as training samples and the remaining 100 data are used as testing samples.

III. A. 3) Analysis of results

Four main aspects will be considered: number of affiliation functions, type of affiliation functions, training options (training data samples and number of training sessions) and overfitting. The study will analyze the personalized learning path based on fuzzy logic reasoning in Chinese education from these four aspects. First of all, the selection and determination of the affiliation function, after the sample data are processed, the affiliation function and fuzzy rules can be determined, generally the initial number of fuzzy combinations is generally an odd number, 3, 5 or 7, in principle, the finer the set is divided into prediction and evaluation accuracy, but the increase in the number of entries of the affiliation function and fuzzy rules will increase the smoothness and sensitivity of the operation of the ANFIS system. Based on the graph of variables obtained from data preprocessing and previous experience, this study finally set the initial affiliation functions of average daily online learning time (X1), average daily vocabulary growth (X2), average answering time (X3) as five fuzzy sets, and the initial affiliation function of total vocabulary mastery (X4) as three fuzzy sets. Then the graphs of the affiliation functions of the initial four variables are shown in Fig. 8, where (a)~(d) are X1~X4, respectively. in the graphs, inxmf1, inxmf2, inxmf3, and inxmf4 are the linguistic values of each input linguistic variable, and the linguistic values of inxmf4 are denoted by less/low (L), medium (M), and more/high (H), inxmf1, The linguistic values of inxmf2 and inxmf3 are denoted by very low (NB), low (NS), medium (O), high (PS), and very high (PB), with the horizontal axis denoting the normalized data values in the range of [0,1], and the vertical axis denoting the degrees of affiliation in the range of [0,1], each of which is a clock-type affiliation function. The output personalized learning path is high if the inputs X1=high, X2=high, X3=high, and X4=low. This can be expressed as a personalized Chinese learning path that can be developed to fit the student's needs based on the average daily length of online learning time, average daily vocabulary growth, average question answering time, and total amount of vocabulary mastered.



(a)X1 (b)X2



(c)X3 (d)X4

Figure 8: Input the initial membership function of the variable

III. B. Path application analysis

III. B. 1) Research Subject Setting

The object of this study is the Chinese majors of a university, a total of 60 students, and the ratio of men to women is close to 1:1, taking a random distribution, the research object is divided into experimental group and control group, the number of each group is 30, the experimental group adopts the personalized learning path based on fuzzy logic reasoning in Chinese education, while the control group adopts the traditional Chinese education path.

III. B. 2) Steps for teaching experiments

The Chinese education semester in colleges and universities starts from the beginning of March every year, and the first half of the semester lasts 5 months from the beginning of March to the middle of August, and the second half of the semester lasts 5 months from the beginning of September to the end of January of the following year, which is a total of 5 months, and the total number of months in an academic year is 10 months, but because colleges and universities have a lot of vacations, the class time is roughly about 9 months after subtracting the usual vacations. During this period, the schedule of Chinese language lessons for both experimental and control group classes was one lesson per week, one lesson of 60 minutes, and the total number of academic hours in one academic year was 10 months, 40 hours, and 2400 minutes. The main experimental steps are as follows:

(1) Understand the situation of students, teachers, teaching materials and schools, so as to provide favorable guidance for the conduct of the teaching experiment.

(2) According to the observation, most of the students were at about the same level, showing that they could follow the reading in class better, but their attention span was shorter, and they could memorize about 70% of the pinyin, vocabulary and sentence patterns they had learned. Individual students were more outstanding, showing that they were active in class, fluent in pinyin spelling, and could remember most of the vocabulary and sentence patterns they had learned.

(3) In the lessons, the teachers used two different teaching paths for the selected research subjects according to the content of the Chinese textbook.

(4) During the 9-month teaching experiment, because the school is not allowed to give students a separate examination other than the one organized by the school. Therefore, this experiment tested students in Chinese at the end of the first semester and at the end of the second semester respectively, and collected the scores of the two tests, processed them with SPSS software, and analyzed them according to the processing results so as to draw conclusions.

III. B. 3) Testing tools

The school stipulates that a student's regular and final grades are 2:8 for a total of 100 points, i.e., 20 points for the regular grade and 80 points for the final grade, and that the final exams are to be in the form of multiple-choice questions, with three options for each question. In addition to stipulating the form and percentage of the exam, the school gives more freedom to the teachers of the class, and the teachers of each subject make their own questions, mainly based on what they have learned in class. Since this experiment mainly focuses on language blocks, the assessment of phonetics and Chinese characters will be included in the usual assessment score by the author. The usual assessment score consists of five parts: 4 points for completing the exercise book, 4 points for daily performance, 4 points for completing the dialogues, 4 points for recognizing pinyin, and 4 points for writing Chinese characters. Except for students who had to take a leave of absence, they would come to Chinese class whenever they were at school, so daily attendance was not included in the usual assessment score. The final exam consisted of 80 multiple-choice questions. After two semesters of the teaching experiment, the results of the two tests were collected and the author numbered the students numerically. The pre-test scores and post-test scores of the experimental and control groups were imported into SPSS software, and the scores of the experimental and control groups were professionally analyzed using statistical methods.

III. B. 4) Pre-intervention comparative analysis

The Chinese scores of the students before the intervention were processed and imported into the SPSS software and analyzed using the independent samples t-test, and the results of the pre-intervention comparative analysis are shown in Fig. 9, where EG and CG denote the experimental group and the control group, respectively. The data performance in the figure shows that there is no significant difference between the students in the experimental group and the control group before the teaching experiment intervention ($P=0.104>0.05$), which indicates that there is no homogeneous difference in the samples selected for this study, which is in line with the requirements of the study, and the follow-up research can be further carried out.

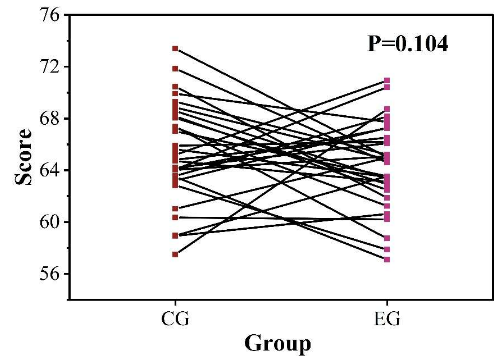


Figure 9: Comparative analysis results before intervention

III. B. 5) Comparative post-intervention analysis

After a period of teaching experiment intervention, the Chinese test scores of the students in the experimental group and the control group were compared and analyzed after the intervention, and the results of the post-intervention comparative analysis are shown in Figure 10. Based on the P-values in the table, it can be seen that there is a significant difference between the Chinese test scores of the students in the experimental group and the control group after the intervention of the teaching experiment ($P=0.003<0.05$). It can be concluded that the personalized learning path of Chinese education based on fuzzy logic reasoning has a more significant effect on the improvement of students' performance than the traditional Chinese education path.

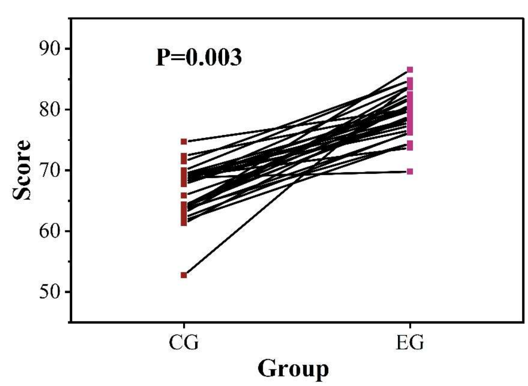
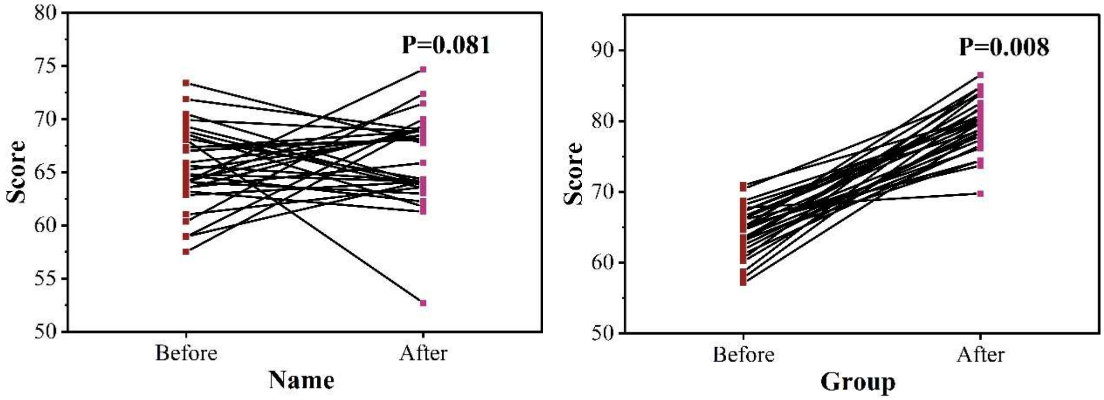


Figure 10: The results were compared and analyzed after the intervention

III. B. 6) Comparative analysis within groups

After exploring the intergroup comparative analysis, the next in-depth exploration of the experimental group and the control group within the group differences, so that the results of this paper are more convincing, the intragroup comparative analysis is shown in Figure 11, in which (a) ~ (b) are the control group, the experimental group, respectively. The data show that students' Chinese test scores before and after the intervention in the experimental group show significant differences, on the contrary, there is no significant difference in the control group, which fully verifies the practical application effect of the personalized learning path in Chinese education in this paper.



(a)Control group (b)Experimental group

Figure 11: Intra-group comparative analysis

IV. Conclusion

This study constructed a personalized learning path model for Chinese education based on fuzzy logic reasoning, and verified the effectiveness of the model through teaching experiments. The results of the study show that the personalized learning path based on fuzzy logic reasoning can significantly improve the effect of Chinese learning, which is reflected in the following aspects:

The fuzzy logic reasoning technique can effectively deal with the uncertainty information in Chinese education. Through the fuzzification of four dimensional variables, namely, average daily online learning time, average daily vocabulary growth, average answering time and total vocabulary mastered, an affiliation function reflecting the learner's ability characteristics is established, which provides a theoretical basis for personalized recommendation.

The results of the teaching experiment confirmed the effectiveness of the method. There was no significant difference between the experimental group and the control group before the intervention ($P=0.104>0.05$), and after 9 months of teaching experiments, the experimental group using the personalized learning path of fuzzy logic reasoning and the control group using the traditional teaching method produced a significant difference in Chinese test scores ($P=0.003<0.05$). The within-group comparison analysis showed that the test scores of students in the experimental group before and after the intervention showed significant differences, while the control group did not produce significant changes, which fully verified the practical application effect of the personalized learning path of fuzzy logic reasoning.

The fuzzy control rule system established in the study can dynamically assess learners' learning ability and push Chinese vocabulary learning resources with matching difficulty, realizing accurate matching of learning resources. By analyzing 500 pieces of sample data, the form of the affiliation function suitable for Chinese language education is determined, in which the affiliation function for the average daily length of online learning time, the average daily vocabulary growth and the average answering time are set as 5 fuzzy sets, and the affiliation function for the total amount of mastered vocabulary is set as 3 fuzzy sets, which effectively improves the prediction accuracy of the model.

Overall, this study successfully applies fuzzy logic reasoning technology to the construction of personalized learning paths in Chinese education, proposes a new teaching method for Chinese education, and provides new technical support and practical reference for improving the effectiveness of Chinese education. Future research can further optimize the fuzzy control rules, expand the range of experimental samples, and explore the application effect of this method in different learning stages.

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