Hindawi
Journal of Mathematics
Volume 2023, Article ID 9874714, 1 page
https://doi.org/10.1155/2023/9874714

Retraction

Retracted: International Chinese Education Expert System Based on Artificial Intelligence and Machine Learning Algorithms

Journal of Mathematics

Received 10 October 2023; Accepted 10 October 2023; Published 11 October 2023

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] L. Shen and F. Latif, "International Chinese Education Expert System Based on Artificial Intelligence and Machine Learning Algorithms," *Journal of Mathematics*, vol. 2022, Article ID 2160289, 12 pages, 2022.

Hindawi
Journal of Mathematics
Volume 2022, Article ID 2160289, 12 pages
https://doi.org/10.1155/2022/2160289

Research Article

International Chinese Education Expert System Based on Artificial Intelligence and Machine Learning Algorithms

Lin Shen[1] and Faiza Latif[2]

[1]*College of Foreign Languages, Guizhou University, Guiyang 550025, China*
[2]*Department of Business, University of Central Punjab Lahore, Lahore, Pakistan*

Correspondence should be addressed to Faiza Latif; faiza_latif@ucp.edu.pk

Received 9 April 2022; Revised 16 May 2022; Accepted 24 May 2022; Published 18 July 2022

Academic Editor: Naeem Jan

This study builds an international Chinese education expert system based on artificial intelligence and machine learning algorithms, introduces interval intuition fuzzy sets to express expert evaluation information, and uses the entropy weight method to determine the weight of evaluation attributes in order to improve the effect of international Chinese teaching and learning. The group utility value, personal regret value, and comprehensive evaluation value of each system are then calculated in this study. At the same time, this study introduces the degree of closeness and satisfaction to improve the decision-making process and finally determines the optimal solution. In addition, this study constructs an intelligent system based on the improved algorithm. The research shows that the international Chinese education expert system based on artificial intelligence and machine learning algorithm proposed in this study has a very good effect.

1. Introduction

Compared with physical spaces such as traditional classrooms and multimedia classrooms, online Chinese learning spaces have unique environmental metaphors. Moreover, cyberspace stores a large number of Chinese learning resources such as pictures, texts, audio, and video, and is a treasure trove of knowledge for Chinese learners. The creation of a network resource database allows for the integration of multiple dispersed resources, making it easier for individuals to search and analyze them. There are no limits and uniform time schedules in the online Chinese learning environment. All Chinese learners may use the internet to study Chinese at any time and from any location, and they can choose their own material and learning techniques. Furthermore, the online Chinese learning environment offers Chinese students a free, autonomous, resource-integrated, and convenient Chinese learning environment.

The interactive function of the online Chinese learning space is a distinctive feature that is different from the traditional Chinese learning space. Students can send requests to the platform system according to their own needs, and the system can feed back the corresponding information and related module content after retrieval. In the process of human-computer interaction, online Chinese learning can effectively improve students' autonomy and self-control, enabling Chinese learners to participate and control the Chinese learning process independently. The online Chinese learning space can break through the limitations of time and space, making it possible for flipped classrooms and cross-regional collaborative Chinese learning. On the one hand, online Chinese learning can break through the time limit, and the construction of online classrooms makes teaching activities not limited to classroom time. Teachers turn the course content into videos for students to watch Chinese learning at any time, breaking away from traditional classroom teaching and time constraints. On the other hand, online Chinese learning can break through space constraints. Through real-time transmission technology, different schools can form teaching alliances, integrate their own high-quality teaching resources, provide the best-quality teaching content to all students in the alliance, and maximize the utilization of high-quality teaching resources.

Space resources include various forms of multimedia materials, courseware, texts, and other materials that require learners to browse independently. The learner's way of learning is acceptance learning, and the way of knowledge construction is individual construction. The live teaching space relies on real-time video tools and voice communication software to achieve real-time dialogue, which is the reproduction of real classrooms in cyberspace. Learners and teachers communicate, leave messages, vote, etc., through the interactive area of the screen. The learning method is acceptance learning, and the knowledge construction method is group construction [1]. In the learning community space, learners or teachers and students can interact and communicate, and any account subject can post or leave messages, comments, and likes independently. The learning method is discovery learning, and the knowledge construction method is group construction. In the role-playing space, learners or teachers select virtual characters representing their own images according to the role settings. Moreover, they complete tasks through autonomous exploration, group cooperation, or teacher-student cooperation in a virtual situation. The learning method is discovery learning, and the knowledge construction method may be individual construction or group construction [2]. The course service space relies on the course platform to provide course selection, teaching, learning support services, etc. The learning method is acceptance learning, and the knowledge construction method may be individual construction or group construction [3].

In order to improve the effect of international Chinese teaching and learning, this study constructs an international Chinese education expert system based on artificial intelligence and machine learning algorithms to improve the intelligent development effect of international Chinese education.

2. Related Work

Online learning theory research covers computer science, psychology, communication, education, and other disciplines and related interdisciplinary subjects, with multiple theoretical backgrounds. Literature [4] believes that online learning is the product of the combination of education and network technology, and the process of online learning is the process of knowledge increment, transmission, exchange, and generation, emphasizing the active construction of learners and the interaction of the learning process, widely recognized and widely used in academia. Literature [5] believes that online learning can help learners to independently control the learning content, progress, and time, and rely on the learner's own experience to achieve learning goals. Scholars in the field of educational technology pay attention to the technical support means related to online learning, including learning system design, software development, and application [6]. Literature [7] proposes the definition of online learning, and points out that the four key elements of online learning are teachers, learners, courses, and technology, which is an earlier and more complete analysis of online learning in China. The technical research related to online learning mainly covers the design and support services of learning system components and platforms. The research in the field of application focuses on the teaching mode, teaching strategy, and teaching application of online learning, and the literature [8] studies the design process of the contextual experience course. At present, the evaluation system and management research of online learning are relatively small, and it rarely involves the funds, market operation, and management of the online learning system. Research trends in the field of online learning are increasingly focused on how to enable learners to experience personalized learning and deep learning, and how to sustain learners' interest in learning. The application of virtual technology and artificial intelligence technology will change the form of learning places, bring a new interactive participation experience, and improve the convenience of teacher-student interaction and student-student interaction [9].

The macrolevel study seeks to build the digital and ecological environments of online learning, and give a fundamental framework guide for the system [10]. The digital and ecological environments for e-learning are carefully designed in literature [11]. The research at the mesolevel is rather large and in-depth, based on the number of papers published, and the research hotspot is the design, development, and effective communication techniques of external learning websites and platforms. The two publications on the building of network teaching platforms heavily rely on literature [12]. This study analyzes the learners' needs for the construction of learning network teaching platforms and the specific application strategies of social interaction in language teaching platforms. The construction of the teaching platform provides a literature. Literature [13] proposed the conceptual model, structure, and function of the remote visual external teaching platform. The visual teaching platform focuses on interactivity and the analysis of learners' needs. Research at the microlevel mainly focuses on online learning behavior, learning strategies, and the compilation of teaching courseware [14]. Literature [15] proposes a dual-class teaching model that combines real classrooms and virtual classrooms based on cloud platforms, and points out that the dual-class teaching mode is helpful to improve the practical problems of insufficient teaching hours in real classrooms, low level of participatory learning, and resource sharing.

Literature [16] constructed the basic framework of "everyone in cyberspace" and pointed out that the development of technical specifications can ensure the effective implementation of the framework. Literature [17] summarizes the general design principles of online learning spaces and focuses on analyzing the value demands of individual learning spaces. Literature [18] discusses the developmental goals and value positioning of the online learning space platform in detail, and summarizes the construction strategy of the online learning space platform. Literature [19] summarizes the network learning space into five types and proposes the enlightenment of the classification to the practice field.

3. Expert Data Processing System Based on Machine Learning and Artificial Intelligence

In order to describe the ambiguity of information, a language-intuitive fuzzy set, which reflects people's uncertainty preference, is proposed.

Definition 1. We set $X = \{x_1, x_2, x_3\}$ as a nonempty universe and define an intuitionistic fuzzy set A on any element in the following form:

$$A = \left\{\left(x, \mu_A(x)^0, \nu_A(x)^0\right) | x \in X\right\}. \tag{1}$$

Definition 2. We call $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ the hesitation degree of the x element in A, which represents the uncertainty degree of whether x belongs to the set A or not. Obviously, there is $0 \leq \pi_A(x) \leq 1$.

Due to the complexity and uncertainty of the decision-making environment, it is difficult for experts to express the values of $\mu_A(x)^0$ and $\pi_A(x)$ with exact real numbers in the actual scoring, but it is more suitable to express them in the form of interval numbers. For this reason, the membership degree and nonmembership degree of the intuitionistic fuzzy set can be improved to the interval number, so that it becomes the interval intuitionistic fuzzy set.

As an information expression, fuzzy numbers can reflect the fuzziness of decision-making information. Compared with the previous intuitionistic fuzzy set, the interval intuitionistic fuzzy set expresses the membership degree and nonmembership degree of the intuitionistic fuzzy set as interval values, so as to better show the psychological hesitation state of decision-makers. Atanassovl et al. extended the intuitionistic fuzzy set and proposed the definition of interval intuitionistic fuzzy set.

Definition 3. x is set to be a nonempty set, and the interval intuitionistic fuzzy set A is expressed as follows:

$$A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}. \tag{2}$$

Among them, there is $\mu_A(x) \subseteq [0,1], \nu_A(x) \subseteq [0,1]$, and the condition $\sup\mu_A(x) + \sup\mu_A(x) \leq 1$ is satisfied. $u(x)$ is the membership function of A, and $\nu(x)$ is the nonmembership function of A. The upper and lower bounds of $u_a(x)$ are denoted as $u_t(x)$ and $p(x)$, respectively, and the upper and lower bounds of $\nu_a(x)$ are denoted as $\nu_A(x)$, respectively. Formula (2) can also be expressed as follows:

$$A = \left\{x, \left(\left[\mu_A^L(x), \mu_A^R(x)\right]\right), \left[\nu_A^L(x), \nu_A^R(x)\right] | x \in X\right\}. \tag{3}$$

Then, the hesitation degree of A is expressed as follows:

$$\begin{aligned} \pi_A(x) &= 1 - \mu_A(x) - \nu_A(x) \\ &= \left[1 - \nu_A^R(x) - \mu_A^R(x), 1 - \mu_A^L(x) - \nu_A^L(x)\right]. \end{aligned} \tag{4}$$

For the convenience of description, the interval intuitionistic fuzzy number is denoted as $\alpha = (\mu_\alpha, \nu_\alpha) = ([\mu_\alpha^L, \mu_\alpha^R], [\nu_\alpha^L, \nu_\alpha^R])$, and the hesitation degree of α is denoted as $\pi_\alpha(x) = [\pi_\alpha^L, \pi_\alpha^R]$. Among them, there is $\mu_\alpha \subseteq [0,1], \nu_\alpha \subseteq [0,1], \mu_\alpha^R + \nu_\alpha^R \leq 1$.

Definition 4. We set a set of interval intuitionistic fuzzy numbers. IIFWA is an interval intuitionistic fuzzy weighted operator, and the formula is as follows:

$$\mathrm{IIFWA}_\omega(r_1, r_2, \ldots, r_z) = \left(\left[1 - \prod_{j=1}^{n} \prod n\left(1 - \mu_j^L\right)^{\omega_j}, 1 - \prod_{j=1}^{n}\left(1 - \mu_j^R\right)^{\omega_j}\right], \left[\prod_{j=1}^{n}\left(\mu_j^L\right)^{\omega_j}, \prod_{j=1}^{n}\left(\mu_j^R\right)^{\omega_j}\right]\right). \tag{5}$$

The Euclidean distance between the two can be used to represent the difference between the two interval intuitionistic fuzzy numbers, which is similar to calculating the distance between the two intuitionistic fuzzy numbers.

$$d(\gamma_{ab}, \gamma_{c\,d}) = \sqrt{\frac{1}{4}\left[\left(\mu_{ab}^L - \mu_{c\,d}^L\right)^2 + \left(\mu_{ab}^R - \mu_{c\,d}^R\right)^2 + \left(\nu_{ab}^L - \nu_{c\,d}^L\right)^2 + \left(\nu_{ab}^R - \nu_{c\,d}^R\right)^2\right]}. \tag{6}$$

For any two real numbers m, n[0,1], the Einstein product is represented by $T(m,n)$, and the Einstein sum is represented by $S(m,n)$. Einstein's algorithm is as follows:

$$\begin{aligned} T(m,n) &= \frac{mn}{1 + (1-m)(1-n)}, \\ S(m,n) &= \frac{m+n}{1+mn}. \end{aligned} \tag{7}$$

We set the sum of interval intuitionistic fuzzy sets as $B=\{(x,\mu_B(x),\nu_B(x))|x\in X\}$ and $A=\{(x,\mu_A(x),\nu_A(x))|x\in X\}$. Based on the Einstein algorithm given by formula (7), Wang et al. proposed the following interval intuitionistic fuzzy set algorithm as follows:

$$\begin{aligned}
&(1) A^c=\{\{(x,\nu_A(x),\mu_A(x))|x\in X\}\},\\
&(2) A\oplus B=\left\{\left[S\left(\left[\mu_A^L(x),\mu_A^L(x)\right]\right),S\left[\nu_A^R(x),\nu_A^R(x)\right]\right],T\left(\left[\nu_A^L(x),\nu_B^L(x)\right]\right),T\left[\nu_A^R(x),\nu_B^R(x)\right]\right\}\\
&=\left\{\left[\frac{\mu_A^L(x)+\mu_B^L(x)}{1+\mu_A^L(x)\mu_B^L(x)},\frac{\mu_A^R(x)+\mu_B^R(x)}{1+\mu_A^R(x)\mu_B^R(x)}\right],\left[\frac{\nu_A^L(x),\nu_B^L(x)}{1+\left(1-\nu_A^L(x)\right)\left(1-\nu_B^L(x)\right)}\right],\frac{\nu_A^R(x),\nu_B^R(x)}{1+\left(1-\nu_A^R(x)\right)\left(1-\nu_B^R(x)\right)}\right\},\\
&(3) A\otimes B=\left\{\left[T\left(\left[\mu_A^L(x),\mu_A^L(x)\right]\right),T\left[\nu_A^R(x),\nu_A^R(x)\right]\right],S\left(\left[\nu_A^L(x),\nu_B^L(x)\right]\right),S\left[\nu_A^R(x),\nu_B^R(x)\right]\right\}\\
&=\left\{\left[\frac{\mu_A^R(x)+\mu_B^R(x)}{1+\left(1-\mu_A^R(x)\right)\left(1-\mu_B^R(x)\right)},\frac{\mu_A^R(x),\mu_B^R(x)}{1+\left(1-\mu_A^R(x)\right)\left(1-\mu_B^R(x)\right)}\right],\left[\frac{\nu_A^L(x)+\nu_B^L(x)}{1+\nu_A^L(x)\nu_B^L(x)},\frac{\nu_A^R(x)+\nu_B^R(x)}{1+\nu_A^R(x)\nu_B^R(x)}\right]\right\},\\
&(4) A^\epsilon=\left\{\left[\frac{2\left(\mu_A^L(x)\right)^\epsilon}{\left(2-\mu_A^L(x)\right)^\epsilon+\left(\mu_A^L(x)\right)^\epsilon},\frac{2\left(\mu_A^R(x)\right)^\epsilon}{\left(2-\mu_A^R(x)\right)^\epsilon+\left(\mu_A^R(x)\right)^\epsilon}\right],\right.\\
&\left.\cdot\left[\frac{\left(1+\nu_A^R(x)\right)^\epsilon-\left(1-\nu_A^R(x)\right)^\epsilon}{\left(1+\nu_A^L(x)\right)^\epsilon+\left(1-\nu_A^L(x)\right)^\epsilon},\frac{\left(1+\nu_A^R(x)\right)^\epsilon-\left(1-\nu_A^R(x)\right)^\epsilon}{\left(1+\nu_A^R(x)\right)^\epsilon+\left(1-\nu_A^R(x)\right)^\epsilon}\right]\right\},\quad \epsilon>0.
\end{aligned}\tag{8}$$

Among them, A^C represents the complement of A.

For any $A=\{(x,\mu_A(x),\nu_A(x))|x\in X\}$ and $B=\{(x,\mu_B(x),\nu_B(x))|x\in X\}$, the mapping is as follows:

(1) $\mu_A^L(x)=\mu_A^R(x)=0$, $\mu_A^L(x)=\mu_A^R(x)=1,\nu_A^L(x)=\nu_A^R(x)=0$;

(2) $E(A)=1$ holds if and only if $[\mu_A^L(x),\mu_A^R(x)]=[\nu_A^L(x),\nu_A^R(x)]$;

(3) $E(A)=E(A^C)$, and there is $A^C=\{(x,\mu_A(x),\nu_A(x))|x\in X\}$;

(4) If there is $\nu_x\in X$, when there is $u_n(x)\geq v$: (x), and there is $u_a(x)\geq u_s(x)$ and $\nu_a(x)\leq \nu_g(x)$ or when there is $4=(X)\leq \nu_s(x)$, and there is $u_g(x)\leq u_z(x)$ and $\nu_a(x)\geq V$: (x), then there is $E(A)\leq E(B)$. Then, $E(A)$ is the interval intuitionistic fuzzy entropy.

The interval intuitionistic fuzzy entropy $E(A)$ can be defined as follows:

$$E_A=\frac{1}{n}\sum\frac{4-\left[\left|\mu_A^L(x_i)-\nu_A^L(x_i)\right|+\left|\mu_A^u(x_i)-\nu_A^u(x_i)\right|\right]^2+\left[\pi_A^L(x_i)-\pi_A^v(x_i)\right]^2}{8}.\tag{9}$$

It can be seen from formula (9) that the entropy formula not only includes the interval membership degree and interval nonmembership degree, but also includes the interval hesitation degree, which makes the information of interval intuition fuzzy entropy more complete. Thus, formula (9) completely contains the entropy information of interval intuitionistic fuzzy sets.

A typical multiattribute decision-making approach is the simple linear weighting method. When using the SWA approach, it is important to remember that the decision-maker must standardize the decision matrix such that all signs are positive. Because of its easy decision-making processes, the SWA approach is often utilized for dealing with multiattribute decision-making situations. The basic steps of this method include the following points:

(a) First, the attribute weights of the alternatives are determined, and the weight vectors of several attributes are set as follows:

$$\omega=(\omega_1,\omega_2,\ldots,\omega_n)^T.\tag{10}$$

(b) The standard matrix $X=(x_{ij})_{n\times m}$ is obtained, and m is the number of alternatives.

(c) The linear weighted average value of each alternative is obtained, as shown by the following formula:

$$\mu_j = \sum\nolimits_{j=1}^{m} \omega_j x_{ij}, \quad 1, 2, \ldots, n. \tag{11}$$

(d) The linear weighted average is calculated by formula (11), and the optimal solution is selected according to the principle of u maximization, which is shown by the following formula:

$$U\left(P^{*}\right) = \max_{1\leq i\leq n} \sum\nolimits_{j=1}^{m} \omega_j x_{ij}. \tag{12}$$

As a common and simple decision-making method, the AHP has been widely studied and applied by various scholars. This approach is distinguished by the use of numbers to indicate the connection between the influencing elements, and it is used to evaluate decision-making possibilities, method plans, and so on. The concept is to arrange the things to be approximately examined according to their advantages and disadvantages before evaluating and selecting them one by one in the order of sorting. The issue is then separated into three layers: the goal layer, criteria layer, and indication layer. The upper-level factors have a dominant effect on the lower-level factors, and at the same time, it can divide multiple research objects into multiple factors. For simple system properties, the two are compared in pairs. After the comparison, the importance of the relevant indicators is obtained, so as to rank the alternatives, and provide a theoretical basis for decision-makers from the perspective of qualitative and quantitative conversion. The calculation sequence is shown in Figure 1.

Because the AHP decomposes the decision-making problem into the multilevel target level, criterion level, and index level. Therefore, its weight determination principle is to simulate the logical relationship of the human brain, with great human subjectivity. It cannot make use of existing data, cannot convince people, and goes against the idea of objective science.

We set $F: R^n \longrightarrow R$, and there is the following:

$$F_w\left(x_1, x_2, \ldots, x_n\right) = \sum\nolimits_{j=1}^{n} \omega_j y_j. \tag{13}$$

Among them, $\omega = (\omega_1, \omega_2, \ldots, \omega_n)^T$ and F are related to each other, and ω_j satisfies the following conditions. Among them, there is $\sum_{j=1}^{n} \omega_j = 1\,(j \in N), 0 \leq \omega_j \leq 1$.

The ordered weighted average method is based on the range of the index weight given by the decision-maker and uses the linear programming method to establish a mathematical model to obtain an index weight. Compared with the analytic hierarchy process, the ordered weighted average method has obvious advantages in objective science. However, its operation process is more complicated, and it still retains the limitation of a simple linear weighting method for decision-making of complex problems.

We assume a decision problem with m alternatives and n attributes. Among them, the evaluation value of the scheme the TOPSIS method is calculated as follows:

Step 1. The decision matrix $R = (r_{ij})_{n\times m}$ is standardized and transformed to obtain a standardized decision matrix:

$$F = \left(f_{ij}\right)_{n\times m}, f_{ij} = \frac{r_{ij}}{\sqrt{\sum_{i=1}^{m}\left(r_{ij}\right)^2}}, \quad i = 1, 2 \ldots, m; j = 1, 2, \ldots, n. \tag{14}$$

Step 2. The following formula is adopted for the decision matrix $Y = (y_{ij}) m \times n$.

$$y_{ij} = \omega_j \times f_{ij}, \quad i = 1, 2, \ldots, m, j = 1, 2, \ldots, n. \tag{15}$$

Among them, $\omega_j = (j = 1, 2, \ldots, n)$ is the weight of attribute c_j.

Step 3. The positive-ideal solution y^+ and the negative-ideal solution y of the scheme are calculated.

Among them, for the benefit index, there is the following:

$$\begin{aligned} y_i^{+} &= \max_{1\leq i\leq m}\left\{y_{ij}\right\},\\ y_i^{-} &= \min_{1\leq i\leq m}\left\{y_{ij}\right\}. \end{aligned} \tag{16}$$

Second, for cost metrics, there is the following:

$$\begin{aligned} y_i^{+} &= \min_{1\leq i\leq m}\left\{y_{ij}\right\},\\ y_i^{-} &= \max_{1\leq i\leq m}\left\{y_{ij}\right\}. \end{aligned} \tag{17}$$

Step 4. The distances from scheme $A_i (i = 1, 2, \ldots, m)$ to the positive-ideal solution and the negative-ideal solution are calculated.

$$\begin{aligned} d_i^{+} &= \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^{+}\right)^2}, \quad i = 1, 2, \ldots, m,\\ d_i^{-} &= \sqrt{\sum_{j=1}^{n}\left(y_{ij} - y_j^{-}\right)^2}, \quad i = 1, 2, \ldots, m. \end{aligned} \tag{18}$$

Step 5. The approximation coefficient of scheme A_i $(i = 1, 2, \ldots, m)$ and the positive-ideal solution is calculated.

$$T_i = \frac{di^{-}}{di^{+} + di^{-}}, \quad i = 1, 2, \ldots, m. \tag{19}$$

Step 6. According to the value of the closeness coefficient T_i $(i = 1, 2, \ldots, m)$, the alternatives are sorted from large to small, so as to select the scheme. The larger the program is, the better the program is.

In recent years, the multiattribute decision-making approach based on fuzzy theory has become a hotspot for study in decision-making methods. Numerous researchers have been experimenting with and developing the VIKOR multiattribute decision-making approach, which is extensively utilized in many domains. VIKOR has an advantage over the TOPSIS in that it can modify the effect of group utility value and individual regret value on program ranking. It compensates for TOPSIS' impact on solution ordering, which solely examines the distance between alternatives and positive- and negative-ideal solutions.

Step 1. The positive- and negative-ideal solutions Y^+ and Y^+ of each scheme in the alternative scheme are calculated, which is the same as the TOPSIS method.

Step 2. The group utility value s_i and the individual regret value R_i of each alternative are calculated by the following formula:

$$S_i = \sum_{j=1}^{n} \omega_j \frac{\left(f^+ - f_{ij}\right)}{\left(f^+ - f_j^-\right)}, \quad 1 \le i \le m,$$
$$R_i = \max_j \omega_j \frac{\left(f^+ - f_{ij}\right)}{\left(f^+ - f_j^-\right)}, \quad 1 \le i \le m. \tag{20}$$

In the formula, ω_j represents the weight of the indicator.

Step 3. The following formula is used to calculate the degree of proximity between each scheme and the ideal solution, that is, the comprehensive evaluation value Q_i.

$$Q_i = x \frac{\left(s^+ - s_{ij}\right)}{\left(s^+ - s_j^-\right)} + (1 - x) \frac{\left(R^+ - R_{ij}\right)}{\left(R^+ - R_j^-\right)}. \tag{21}$$

Among them, when x is greater than 0.5, the group utility value has a greater impact on the outcome of the program. When x is less than 0.5, the personal regret value has a greater impact on the program results. When x is equal to 0.5, the group utility value and the individual regret value have an equal impact on the program outcome. For problems in real life, we generally set $x = 0.5$ to achieve a more reasonable purpose.

Step 4. According to the calculated three evaluation values S_t, R, and Q, the multiple attribute sequence of the alternatives is performed. At the same time, the most compromised solution is selected according to the following two conditions. When the two conditions are satisfied at the same time, the compromise solution that needs to be arranged according to the value of Q is the best solution. The smaller the Q, the better the solution [20].

Condition 1. The acceptable advantage is $Q(A^2) - Q(A^1) \ge (1/(m-1))A$.

Condition 2. Acceptable stability in the decision-making process is as follows: when sorted according to S and R, the stability requirement is met when A is still ranked first.

3.1. The Comprehensive Fuzzy Decision Matrix Is Calculated. We set $U_k\,(k = 1, 2, \ldots, l)$ as the kth expert, and the expert weight $\lambda_k\,(0 \le k \le 1)$ through the subjective weighting method satisfies $\sum_{k=1}^{1} \lambda_k = 1, \lambda_k \ge 0$. The attribute evaluation value is an interval intuitionistic fuzzy number. We set $A = \{A_i, A_2, \ldots, A_m\}$ as the scheme set and $C = \{C, c, \ldots, C\}$ as the attribute set. $D = \left\{D, D_2, \ldots, D_g\right\}$ (k represents k decision-makers or k time periods) represents a set of group decision matrices. Then, D_x (the k^{th} decision matrix in the group decision matrix) is the decision matrix about the solution set A on the attribute set c as follows:

$$D_k = \begin{bmatrix} \gamma_{11}^k & \gamma_{12}^k & \cdots & \gamma_{1n}^k \\ \gamma_{21}^k & \gamma_{22}^k & \cdots & \gamma_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{m1}^k & \gamma_{m2}^k & \cdots & \gamma_{mn}^k \end{bmatrix}. \tag{22}$$

Among them, $\gamma_{ij}^k = ([\mu_{ij}^{kL}, \mu_{ij}^{kR}], [v_{ij}^{kL}, v_{ij}^{kR}])$ $(i = 1, 2, \ldots, m;\ j = 1, 2, \ldots, n)$ is the interval intuition fuzzy representation of the attribute C of the k^{th} decision-maker on scheme A.

The expert weight is used as a weighting factor; formula (22) is used to collect the evaluation value matrix of each attribute of each decision-making expert about the scheme; and the synthetic fuzzy decision matrix is obtained as follows:

$$D = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{m1} & \gamma_{m2} & \cdots & \gamma_{mn} \end{bmatrix}. \tag{23}$$

The positive- and negative-ideal schemes A^+ and A^- can be directly obtained from the comprehensive fuzzy decision matrix.

$$A^+ = \left(r_{ij}^+\right) = \max_{i=1} r_{ij} = \left(\left[\max_{i=1} \mu_{ij}^L, \max_{i=1} \mu_{ij}^R\right], \left[\max_{i=1} v_{ij}^L, \max_{i=1} v_{ij}^R\right]\right),$$
$$A^- = \left(r_{ij}^-\right) = \min_{i=1} r_{ij} = \left(\left[\min_{i=1} \mu_{ij}^L, \min_{i=1} \mu_{ij}^R\right], \left[\min_{i=1} v_{ij}^L, \min_{i=1} v_{ij}^R\right]\right). \tag{24}$$

The entropy weight method is objective, scientific, and accurate. Moreover, it does not require decision-makers to provide subjective evaluation information of weights and can directly use the collected data to obtain more objective attribute weights. Based on the analysis of interval intuitionistic fuzzy theory, this study chooses the entropy weight

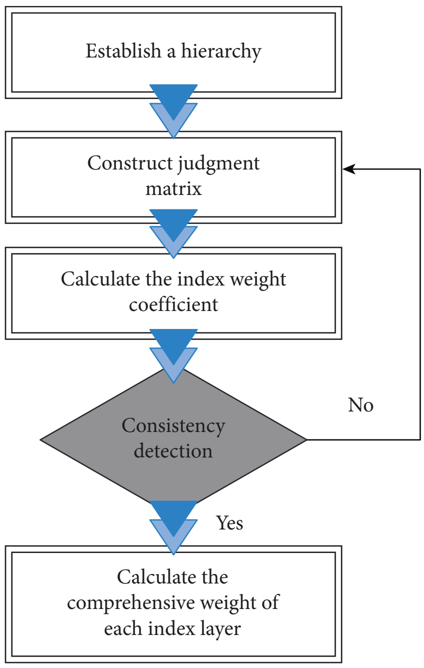

Figure 1: AHP calculation sequence.

method with strong objectivity to determine the attribute weight. It can eliminate the influence of subjectivity on weights to a certain extent, and make the analysis process objective and fair. The weight o of each attribute can be obtained as follows:

$$\omega_i = \frac{1 - e_i}{\sum_{p=1}^{n} \left(1 - e_p\right)}, \quad i = 1, 2, \ldots, m. \tag{25}$$

3.2. Proximity T_{ij} and Satisfaction φ_{ij} Are Calculated. To avoid that when the distance between the alternatives and the positive- and negative-ideal schemes is used to determine the pros and cons of the schemes, several alternatives and the positive-ideal scheme have the same distance value, making it impossible to sort case, and several alternatives and the positive-ideal scheme have the same distance value. Here, the following definitions of closeness and satisfaction are introduced according to the concepts related to the VIKOR method, and the distance formula of formula (6) is used to solve the following:

$$T_{ij} = \frac{d\left(r_{ij}^{-}, r_{ij}\right)}{\left(d\left(r_{ij}^{+}, r_{ij}\right) + d\left(r_{j}^{-}, r_{ij}\right)\right)}, \quad 1 \le i \le m. \tag{26}$$

Typically, T_i is between 0 and 1. The closeness of the decision experts to the evaluation value of the plan and the ideal point of the group evaluation is expanded into a group closeness matrix as follows:

$$T = \begin{bmatrix} T_{11} & T_{12} & \cdots & T_{1n} \\ T_{21} & T_{22} & \cdots & T_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ T_{m1} & T_{m2} & \cdots & T_{mn} \end{bmatrix}. \tag{27}$$

According to the decision satisfaction function, the threshold for measuring the decision satisfaction is set for the transformation of the closeness matrix. The decision satisfaction function is defined as follows:

$$\varphi_{ij} = \begin{cases} 1, & T_i > 0.5, \\ 0, & \text{other}. \end{cases} \tag{28}$$

According to formula (28), the group closeness matrix T is converted into a 0-1 matrix, and the group satisfaction matrix p is obtained as follows:

$$\varphi_{ij} = \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{m1} & \varphi_{m2} & \cdots & \varphi_{mn} \end{bmatrix}. \tag{29}$$

According to the group satisfaction matrix op, the ratio of the number of elements 1 in the matrix to the number of matrix elements is calculated, that is, the group satisfaction.

The indicator GSI is as follows:

$$\mathrm{GSI} = \frac{1}{mn}\left(\sum_{i}^{m}\sum_{j}^{n}\varphi_{ij}\right). \tag{30}$$

When the decision-making group satisfaction index GSI meets the set group satisfaction threshold GSIO (GSI ≥ GSIO), the group decision-making activities can proceed.

3.3. Group Utility Value S and Individual Regret Value R_t Are Calculated. Interval intuitionistic fuzzy set Definition 4 is combined with formula (6), which can be transformed into the following:

$$\begin{aligned} S_i &= \sum_{j=1}^{n} \omega_j \frac{d\left(r_j^{+}, r_{ij}\right)}{d\left(r_j^{+}, r_j^{-}\right)}, \quad 1 \le i \le m, \\ R_i &= \max_{j} \omega_j \frac{d\left(r_j^{+}, r_{ij}\right)}{d\left(r_j^{+}, r_j^{-}\right)}, \quad 1 \le i \le m. \end{aligned} \tag{31}$$

3.4. The Comprehensive Evaluation Value Q_i Is Calculated.

$$Q_i = x\frac{\left(s_i - s^{-}\right)}{\left(s^{+}, s^{-}\right)} + (1 - x)\frac{d\left(R^{+} - R_{ij}\right)}{d\left(R^{+} - R_j^{-}\right)}, \tag{32}$$

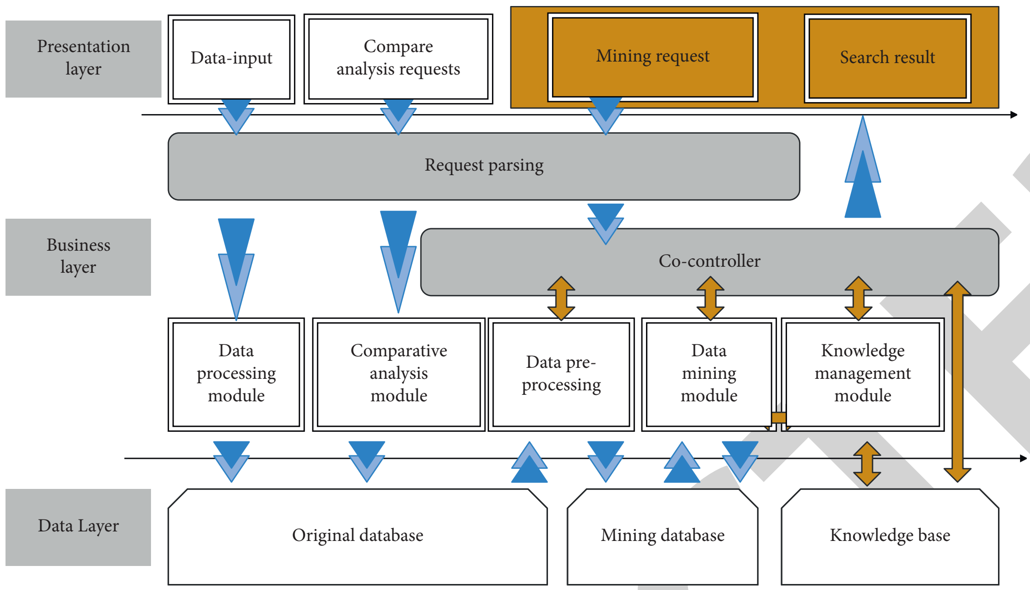

Figure 2: The three-layer structure of the international Chinese education expert system.

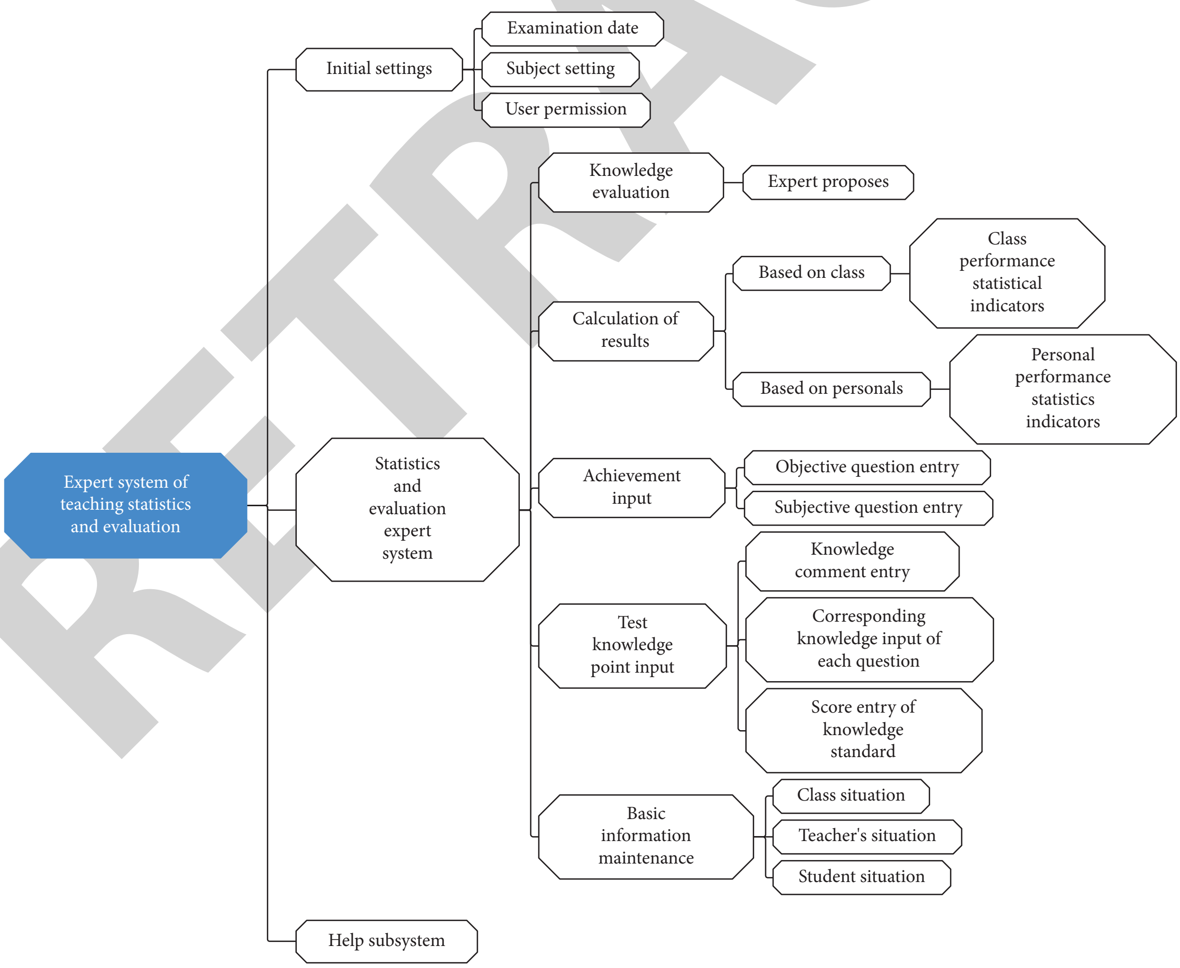

Figure 3: Exploded view of system function modules.

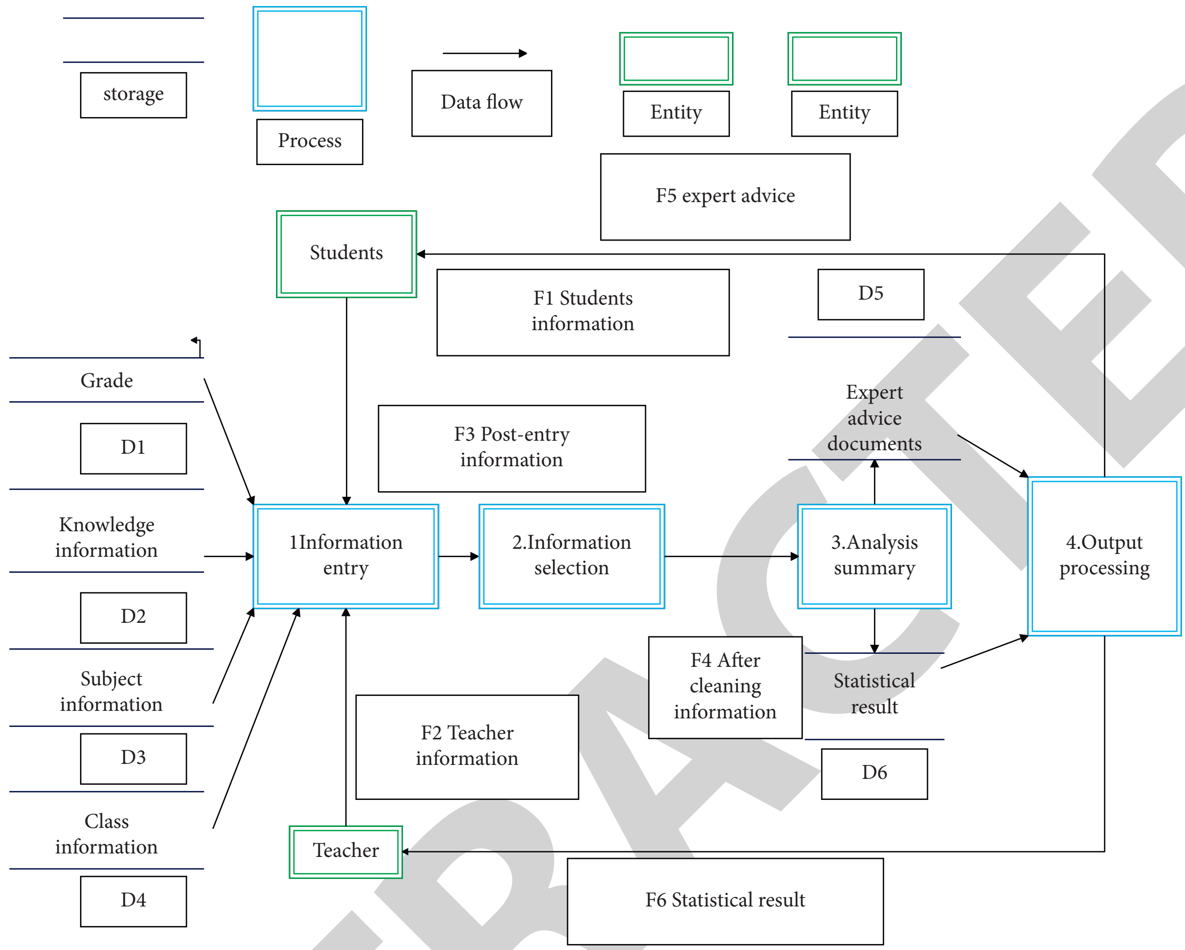

Figure 4: Top-level data-flow diagram.

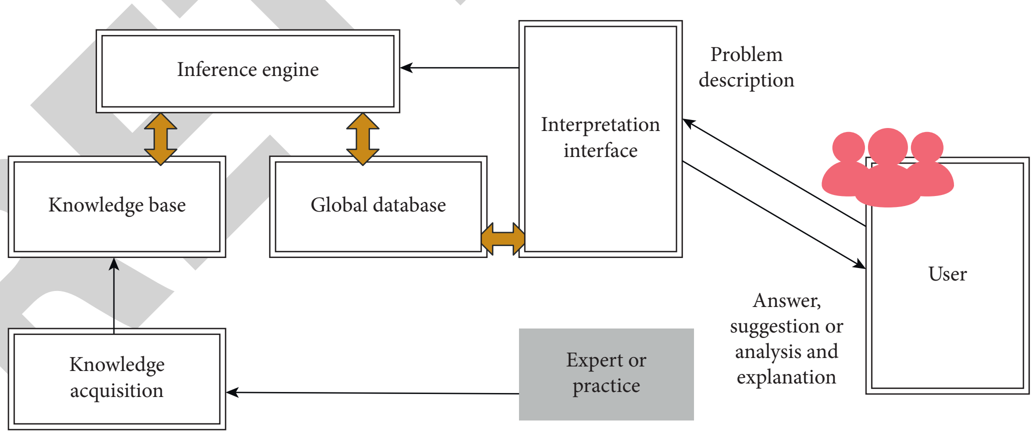

Figure 5: General structure of the international Chinese education expert system.

where x is a compromise coefficient, which reflects the subjective preference of decision-makers. When there is $x > 0.5$, it means that the decision-makers formulate strategies according to the opinions of the majority, that is, in a way that maximizes the group benefit. When there is $x < 0.5$, it means that it formulates a strategy based on the objection, that is, in a way that minimizes the weight of individual regrets. When there is $x = 0.5$, it means that both group

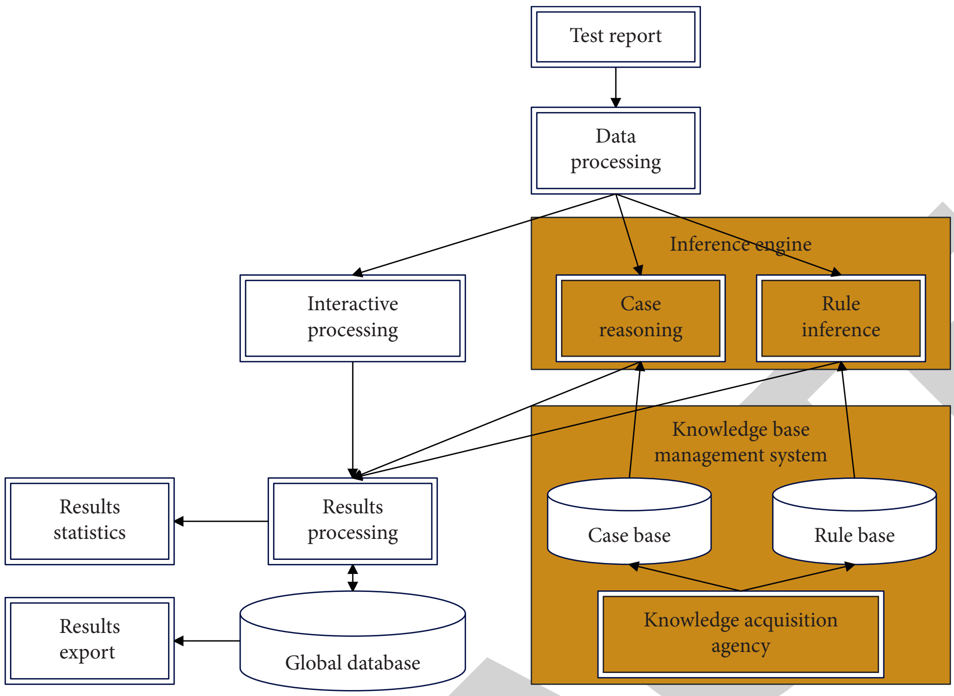

Figure 6: Overall model diagram of the international Chinese education expert system.

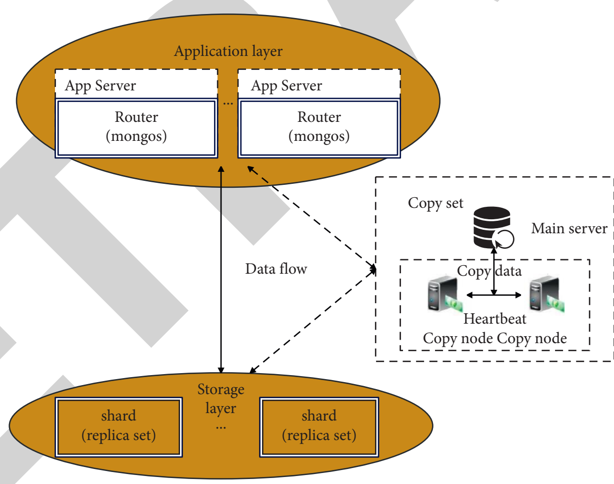

Figure 7: Cluster architecture diagram.

benefit and individual regret are considered, and strategies are formulated according to the equilibrium situation. Usually, $x = 0.5$ is taken.

4. International Chinese Education Expert System Based on Artificial Intelligence and Machine Learning Algorithms

The overall system architecture diagram is as shown in Figure 2.

On the basis of subsystem division, the corresponding subsystems are further decomposed into functional modules with clear meaning and single function, so as to obtain the functional module decomposition diagram of the system, as shown in Figure 3.

The data-flow analysis method is adopted to obtain the business process and the business and data connection from the description, and the analysis result is represented by a data-flow diagram (data-flow diagram, DFD), as shown in Figure 4.

The structure of the international Chinese education expert system includes a knowledge base, an inference engine, a comprehensive database, a human-machine interface, an interpreter, and a knowledge acquisition program, as shown in Figure 5.

On the basis of the core model design of the system, the overall model design of the system needs to be completed. In

Table 1: Chinese teaching effect of international Chinese education expert system based on artificial intelligence and machine learning algorithm.

Number	Teaching effect	Number	Teaching effect	Number	Teaching effect
1	81.16	25	87.75	49	84.67
2	85.39	26	77.03	50	83.19
3	79.26	27	88.30	51	81.50
4	78.36	28	82.83	52	89.37
5	80.12	29	85.04	53	84.87
6	81.66	30	79.97	54	83.43
7	82.68	31	86.90	55	85.77
8	88.11	32	83.16	56	88.60
9	81.71	33	85.09	57	83.69
10	78.72	34	79.07	58	89.69
11	77.70	35	84.17	59	87.35
12	82.05	36	80.61	60	81.87
13	87.69	37	88.90	61	82.02
14	89.33	38	83.75	62	83.27
15	77.32	39	88.04	63	85.77
16	77.59	40	86.15	64	89.67
17	82.65	41	84.09	65	85.25
18	89.10	42	88.11	66	87.56
19	81.77	43	84.38	67	86.31
20	88.58	44	87.31	68	84.94
21	77.19	45	81.65	69	79.72
22	84.03	46	79.36	70	79.80
23	83.21	47	87.14	71	82.29
24	86.65	48	89.74	72	85.03

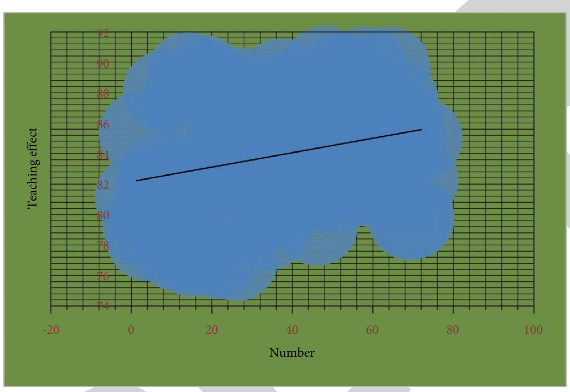

Figure 8: Chinese teaching clustering in the international Chinese education expert system based on artificial intelligence and machine learning algorithms.

addition to the design of the knowledge base and inference engine, the key modules included in the system are data processing, knowledge acquisition, comprehensive database management, and report import and export. Figure 6 is the overall model diagram of the system.

MongoDB has been extensively addressed in the structural design as a core data management tool for big data processing to assure data availability and consistency, parallel efficiency of data processing, and scalability of enormous data storage. The sharded cluster design following MongoDB 3.0 is seen in Figure 7. MongoDB created the replica set and sharded cluster functionalities to address the issues of big data volumes, high expansion, high performance, high availability, and a flexible data model. The replica set selects the master server using the bully method, ensuring the cluster's high availability. The main server stores metadata information, and the application layer interacts with the main server to obtain the storage address of the slice server where the data actually exist and then interacts with the slice storage layer to access data. In order to ensure high performance under large concurrency, the primary and secondary nodes of the replica set adopt a read-write separation strategy. Slice storage is to divide and expand collections horizontally, and perform distributed storage according to the data copy strategy. Moreover, MongoDB supports big data basic storage platforms such as HDFS and S3.

On the basis of the above research, the effect of the international Chinese education expert system based on artificial intelligence and machine learning algorithm is verified; the Chinese teaching effect is calculated; and the results shown in Table 1 and Figure 8 are obtained.

It can be seen from the above research that the international Chinese education expert system based on artificial intelligence and machine learning algorithm proposed in this study has a very good effect.

5. Conclusions

There are also some drawbacks in the online Chinese learning space, which adversely affect the effect of independent Chinese learning and Chinese learning experience. Online Chinese learning space resources have a large capacity and various forms. Because Chinese students must explore, evaluate, and compare many materials, they set higher standards for Chinese learning capacity and media literacy. Simultaneously, the absence of connection and emotional experience in the process of autonomous Chinese learning in cyberspace makes it easy to feel alone and lonely. Online Chinese students must organize their own Chinese learning approach. In Chinese learning, a lack of instructor monitoring and direction will quickly lead to slackness and inefficiency. This study builds an international Chinese education expert system based on artificial intelligence and machine learning algorithms in order to increase the effectiveness of international Chinese teaching and learning. The research results show that the international Chinese education expert system based on artificial intelligence and machine-learning algorithm proposed in this study has a very good effect.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. Keating and I. Nourbakhsh, "Teaching artificial intelligence and humanity," *Communications of the ACM*, vol. 61, no. 2, pp. 29–32, 2018.

[2] K. Kim and Y. Park, "A development and application of the teaching and learning model of artificial intelligence education for elementary students," *Journal of The Korean Association of Information Education*, vol. 21, no. 1, pp. 139–149, 2017.

[3] F. Kong, "Application of artificial intelligence in modern art teaching," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 15, no. 13, p. 238, 2020.

[4] X. Li, "The construction of intelligent English teaching model based on artificial intelligence," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 12, no. 12, p. 35, 2017.

[5] J. R. Mianroodi, N. H Siboni, and D. Raabe, "Teaching solid mechanics to artificial intelligence—a fast solver for heterogeneous materials," *NPJ Computational Materials*, vol. 7, no. 1, p. 99, 2021.

[6] M. Pantic, R. Zwitserloot, and R. Grootjans, "Teaching introductory artificial intelligence using a simple agent framework," *IEEE Transactions on Education*, vol. 48, no. 3, pp. 382–390, 2005.

[7] C. Yang, S. Huan, and Y. Yang, "A practical teaching mode for colleges supported by artificial intelligence," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 15, no. 17, p. 195, 2020.

[8] S. C. H. Yang, W. K. Vong, R. B. Sojitra, T. Folke, and P. Shafto, "Mitigating belief projection in explainable artificial intelligence via Bayesian teaching," *Scientific Reports*, vol. 11, no. 1, p. 9863, 2021.

[9] S. Zou, "Designing and practice of a college English teaching platform based on artificial intelligence," *Journal of Computational and Theoretical Nanoscience*, vol. 14, no. 1, pp. 104–108, 2017.

[10] Y. Lee, "An analysis of the influence of block-type programming language-based artificial intelligence education on the learner's attitude in artificial intelligence," *Journal of The Korean Association of Information Education*, vol. 23, no. 2, pp. 189–196, 2019.

[11] J. M. Alonso, "Teaching explainable artificial intelligence to high school students," *International Journal of Computational Intelligence Systems*, vol. 13, no. 1, p. 974, 2020.

[12] R. Yang, "Artificial intelligence-based strategies for improving the teaching effect of art major courses in colleges," *International Journal of Emerging Technologies in Learning (IJET)*, vol. 15, no. 22, p. 146, 2020.

[13] P. Ribeiro, H. Simões, and M. Ferreira, "Teaching artificial intelligence and logic programming in a competitive environment," *Informatics in Education*, vol. 8, no. 1, pp. 85–100, 2009.

[14] V. Rampton, M. Mittelman, and J. Goldhahn, "Implications of artificial intelligence for medical education," *The Lancet Digital Health*, vol. 2, no. 3, pp. e111–e112, 2020.

[15] Q. Zhou, "Reforms in teaching the course of introduction to artificial intelligence," *Solid State Technology*, vol. 64, no. 2, pp. 6331–6335, 2021.

[16] K. I. M. Haejoong and L. E. E. Sangmin, "Do less teaching, do more coaching: toward critical thinking for ethical applications of artificial intelligence," *Journal of Learning and Teaching in Digital Age*, vol. 6, no. 2, pp. 97–100, 2021.

[17] P. H. Lin, A. Wooders, J. T. Y. Wang, and W. M. Yuan, "Artificial intelligence, the missing piece of online education?" *IEEE Engineering Management Review*, vol. 46, no. 3, pp. 25–28, 2018.

[18] C. Guan, J. Mou, and Z. Jiang, "Artificial intelligence innovation in education: a twenty-year data-driven historical analysis," *International Journal of Innovation Studies*, vol. 4, no. 4, pp. 134–147, 2020.

[19] D. Ni, "THE Application of artificial intelligence technology in international Chinese language teaching," *Chinese Journal of Social Science and Management*, vol. 5, no. 1, pp. 101–112, 2021.

[20] J. Xianzhu, "Design of pedagogy course information sharing system based on wireless sensor network," *Security and Communication Networks*, vol. 2022, Article ID 7040441, 12 pages, 2022.