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MULTIDIMENSIONAL EVALUATION OF AN INTELLIGENT REVIEWING SYSTEM USING THE ANALYTIC HIERARCHY PROCESS (AHP)

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Abstract: With the rapid development of artificial intelligence, the application of intelligent marking system in exam marking has become the core direction of education. As this intelligent marking system involves the influence of a variety of human, machine and other subjective and objective factors, its evaluation accuracy may be subject to certain limitations, which brings certain challenges to the diversity and complexity of the implementation steps. In response to this problem, this study selects the method of hierarchical analysis (AHP). Firstly, it establishes a systematic a multilevel evaluation framework, and then establishes a systematic and multilevel evaluation framework, and then establishes a scientific multidimensional index system that a data-driven algorithm fusion strategy is proposed. Experimental results show the diversity and complexity of the implementation steps in response to this problem based on the in-depth analysis of the scoring rules by machine learning algorithms, the system can automate the evaluation of open-ended questions, and combine the manual review and data analysis to construct a new evaluation system of "intelligence-led- artificial gatekeeper". The study proves that the AHP algorithm proposed in effectively enhances the accuracy and feedback effect of intelligent assessment, which is a substantial achievement in this field.
Keywords: Multi-level; Data-driven; AHP; Intelligent reviewing

1 INTRODUCTION

In the context of new quality productivity to promote high-quality development, artificial intelligence has become the core driving force for the digital transformation of education examination[1,2], and intelligent reviewing is the most effective way to improve the quality of education. With the breakthroughs in deep learning, text parsing and image recognition technologies, artificial intelligence marking systems have ushered in leapfrog development. Based on the in-depth Based on the in-depth analysis of the scoring rules by machine learning algorithms[3], the system can automate the assessment of open-ended questions, and the assessment of the scoring rules by machine learning algorithms. Also based on the in-depth analysis of the scoring rules by machine learning algorithms, the system can automate the assessment of open-ended questions, and build a new type of evaluation system of "intelligence-led-artificial gatekeeper" by combining manual review and data analysis. expert-led triple check" model, through the integration of differential algorithm assessment and artificial benchmark proofreading, successfully achieved the "intelligence-led-artificial gatekeeper" by combining manual review and data analysis(Figure 1).

Previous studies have made certain theoretical contributions in the field of medical care[4], however, there are still certain shortcomings in applying evaluation methods to AI systems, such as in the context of AHP methods to AI systems, especially in the field of education[5]. For example, existing evaluations are mostly focused on one indicator and lack of thinking and judgement on the overall system.

To address the above problems,this study proposes an algorithm fusion optimisation scheme, constructs a comprehensive evaluation framework integrating multi-dimensional indicators, multi-systems and multi-levels, and based on the collected data, for the evaluation of AI review algorithm effects, takes the final grades of AI review algorithm as a whole. effects, takes the final grades of manual multiple review as the relatively accurate data, and comprehensively applies the methods of statistical analysis and hierarchical analysis method (i.e., the AI review algorithm) to the evaluation of AI review algorithm. analysis and hierarchical analysis method (AHP), etc., to the data of the intelligent testing algorithms. Evaluation, combined with Python software for data visual analysis and problem solving, and then provide more theoretical support for the optimisation and Evaluation, combined with Python software for data visual analysis and problem solving, and then provide more theoretical support for the optimisation and promotion of intelligent review algorithms.

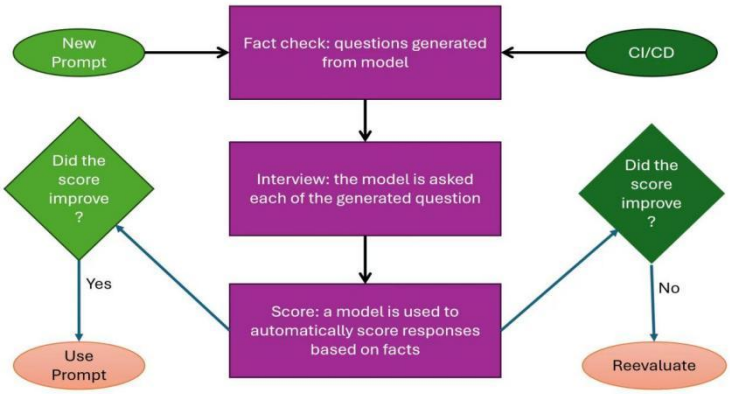

Figure 1 Flow Diagram of the Intelligent Assessment System

2 THEORY-PRINCIPLE

2.1 What is AHP

The Analytic Hierarchy Process (AHP), pioneered in the 1970s by renowned American operations researcher T. L. Satie, is an analytical tool widely used in multi-criteria decision-making scenarios. The core logic of the method lies in structuring and disassembling the originally complex decision-making problem, building up a clear hierarchy of the decision-making process.its also build up a clear hierarchy system of goal, criterion and scheme layers, and generating the priority weight values of the alternatives through the organic fusion. of the alternatives through the organic fusion of subjective judgement and mathematical operations, so as to provide quantifiable reference for the decision-making process. decision-making process. process.

2.1.1 How did AHP come about and how was it derived?

American operations researcher Thomas L. Saaty (T. L. Saaty) found that human beings are better at simplifying problems through the logic of " decomposition - comparison - synthesis" when dealing with complex problems - i.e., the complex goal is first disassembled into a number of hierarchical sub-problems, and then through a number of hierarchical sub-problems. This means first breaking down the complex goal into several levels of sub-problems, then This means first breaking down the complex goal into several levels of sub-problems, then clarifying the relative importance of the elements through two-by- two comparisons, and finally integrating the elements into a number of hierarchical sub-problems,through a two-by-two comparison.and finally integrating the results of the judgement through mathematical methods. Based on this knowledge, Satie first proposed the prototype of AHP in 1971, and gradually improved its theoretical framework in the subsequent research, and finally formed this set of multi-criteria decision-making method that organically integrates qualitative judgement and quantitative calculation.Its core objective is to provide quantifiable mathematical expression for fuzzy subjective judgement. expression for fuzzy subjective judgement, and at the same time control the judgement bias through logical testing.

(1) Construct a hierarchical model.

Hierarchise the decision problem: the highest level is the Goal, the middle level is the Criteria and Sub-criteria (optional), and the bottom level is the Alternatives. Alternatives.

(2) Construct two-by-two comparison judgement matrix.

For factors in the same level, a two-by-two comparison of importance is performed for a factor in the level above it (called the dominant factor)(Table1)

Table 1 The Relative Importance is Quantified Using the 1-9 Scale Proposed by Satie.

The relative importance is quantified using the 1-9 scale proposed by Satie: Scale Value	The relative importance is quantified using the 1-9 scale proposed by Satie: Scale Value
1	The relative importance is quantified using the 1-9 scale proposed by Satie: Scale Value Meaning 1
3	The former is slightly more important than the latter.
5	The former is significantly more important than the latter
7	The former is more strongly important than the latter
9	The former is more important than the latter
2/4/6/8	Intermediate values between neighbouring scales
The former is more strongly important than the latter	Scale of importance of the latter over the former

Assuming that accuracy is considered more important than stability, a scale value of 3 is chosen, setting a strict quantitative ratio of 2:1

(3) Local weight calculation (eigenvector method - square root method).

For each judgement matrix, its maximum eigenvalue (λmax) and the corresponding normalised eigenvector (W) need to

be calculated.

This normalised eigenvector W = [w1, w2, ... , wn]^T then represents the importance weights (local weights) of each element in the hierarchy with respect to its parent element in the previous Calculate the geometric mean of the hierarchy.

Calculate the geometric mean of the elements in each row of the judgement matrix (square root method).

$$\mathrm{Mi} = (\pi[\mathrm{j} = 1 \text{ to } \mathrm{n}]\mathrm{aij})\text{^}(1/\mathrm{n}) \quad (1)$$

For the vector M = [M1, M2, ... , Mn]^T is normalised to obtain the weight vector W. The weight vector W is obtained as follows

$$\mathrm{Wi} = \mathrm{Mi}/\sum[k = 1to\ n]\ \mathrm{Mk} \quad (2)$$

Calculate the maximum eigenvalue λmax (for consistency test).

$$\lambda_{max}\sim(1/n) \times \sum[i = 1\ to\ n]\,(AW)i/Wi \quad (3)$$

2.1.2 How AHP has been applied

Hierarchical analysis plays an important role in multi-domain decision-making scenarios. For example, in the field of project investment, around the goal of "preferred investment projects", AHP has been applied to the following scenarios.For example, in the field of project investment[6], around the goal of "preferred investment projects", the expected return, risk level, market potential, policy suitability, etc. can be set as evaluation criteria to evaluate the impact of a project on the environment. It also can be set as evaluation criteria to construct a hierarchical structure for "preferred investment projects".After the comprehensive weights of each project are derived through matrix operations, investment priorities can be visually differentiated, providing a quantitative basis for capital allocation. organisation has used this method to An investment organisation has used this method to screen out the subject with the highest comprehensive weight from multiple alternative projects, effectively An investment organisation has used this method to screen out the subject with the highest comprehensive weight from multiple alternative projects, effectively An investment organisation has used this method to screen out the subject with the highest comprehensive weight from multiple alternative projects, effectively reducing the subjectivity of investment decisions(Figure2).

Figure 2 Investment Areas

2.2 Intelligent Review System Indicator Construction

Intelligent Review System Indicator Construction can be seen in table 2.

Table 2 Three Evaluation Indicators

Indicator	Indicator name	Definition and calculation formula
Accuracy	Percentage of same data	Accuracy(z)= $\frac{Number\ of\ samples\ with\ consistent\ judgments}{total\ number\ of\ samples}$ $\frac{C}{N}$
Stability	Standard deviation	Standard deviation (σ) $=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)}$
Error threshold	Valid data for allowable error	|Intelligent Score - Manual Score ≤ valid data with permissible errors

2.2.1 Indicator selection

1) Accuracy (percentage of the same data)[7]

Basis: directly reflect the absolute consistency between the system and the manual review, in line with the core mission of the review system.

Representative function: measure the reliability of the system's decision-making at key demarcation points (e.g. passing line, grade boundaries).
Unique value: Avoiding the shortcomings of traditional correlation coefficients (e.g., Pearson) that ignore absolute consistency.
2) Stability (standard deviation)
Rationale: ISO 5725 standard emphasises repeatability requirements for measurement systems
Representative function: detect the volatility of the system's scores for the same sample multiple times, identify the extent to which the model is affected by random factors (e.g., input order, environmental noise)
Engineering significance: Provide quantifiable robustness metrics for model iteration.
3) Error Threshold (Valid Data for Allowable Error)
Basis: Educational assessment practices allow reasonable error intervals (e.g. ±3 points for essay scoring).
Representative function: assess the system's ability to tolerate errors in practical application scenarios, make up for the defect of "the same data Representative function: assess the system's ability to tolerate errors in practical application scenarios, make up for the defect of "the same data" being too harsh, and provide flexible evaluation dimensions.

2.2.2 Indicator normalisation operation

Necessity of Normalisation
Due to the difference in scale and direction of the indicators (the larger the accuracy/error thrresults the better, the smaller the stability, the better), they need to be unified into the [0,1] interval and homogenised[8].
Normalisation formula.
Accuracy (z): itself as a percentage, directly divided by 100

$$z = \frac{z}{100} \tag{4}$$

Stability (s): take the reciprocal to achieve the direction of conversion

$$s_{iuv} = \frac{1}{s+\epsilon} \tag{5}$$

Min-Max Normalisation.

$$s = \frac{s_{iuv} - MIN(s_{iuv})}{MAX(s_{iuv}) - MIN(s_{iuv})} \tag{6}$$

Error threshold (e): same as accuracy

2.3 Data Processing

Innovations in indicator definition: Introducing dynamicδ mechanism in the error thresholds[9]
Setting differentiated permissible errors according to the difficulty of the questions, e.g. maths proof questions$\delta = 2$, multiple choice questions$\delta = 0$
Technical feature: adding weighting factors to the formula.

$$e = \frac{\sum w_i}{\sum w_i}(|\text{Intelligent Score}_i - \text{Manual Score}_i| \leq \delta_i) \tag{7}$$

3 METHODOLOGY

3.1 AHP-based Comprehensive Evaluation Framework Construction

This section delineates the construction of a comprehensive evaluation framework utilizing the Analytic Hierarchy Process (AHP). The AHP method is employed to deconstruct the complex multi-criteria decision-making problem into a hierarchical structure, thereby facilitating a systematic and quantifiable assessment.

3.2 Core Evaluation Index System

Core Evaluation Index System can be seen in Table 3 .
Based on the framework of quality assessment metrics, the Core Evaluation Index System for this study is detailed in Table 3 . This system is designed to quantitatively evaluate the performance of the scoring methodology through two primary dimensions: Accuracy and Stability. Accuracy is measured by the percentage of exact agreements between intelligent and manual scores, while Stability is assessed using the standard deviation of scores and the proportion of data falling within a predefined permissible error threshold. Together, these indicators provide a comprehensive basis for ensuring the reliability and consistency of the evaluation process.

Table 3 Evaluation Indicators

Indicator name	Indicator name	Definition and calculation formula
Definition and calculation formula	Percentage of same data	Accuracy(z)= $\frac{Number\ of\ samples\ with\ consistent\ judgments}{total\ number\ of\ samples} = \frac{C}{N}$
Stability	Standard deviation	Standard deviation (σ) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)}$
Error threshold	Valid data for allowable error	|Intelligent Score - Manual Score|≤ valid data with allowed error

3.3 Comprehensive Scoring Model

3.3.1 Define the comparison object[10]

The three indicators to be compared are:
Accuracy: the agreement rate between the intelligent test and the manual result
Stability: the degree of fluctuation of the indicators measured by the standard deviation, the smaller the value, the higher the stability
Error threshold: Screening valid data that meets the allowable error

3.3.2 Selection of importance scale=

Selection of importance scale can be seen in table 4[11].

Table 4 1-9 Scale Method

Scale value	Meaning
1	Meaning 1 Both equally important
3	The former is slightly more important than the latter.
5	The former is significantly more important than the latter
7 r	The former is more strongly important than the latter
9	The former is more important than the latter
2/4/6/8	Intermediate values between neighbouring scales
The former is more strongly important than the latter	Scale of importance of the latter over the former

3.4 Construct the Three-Three Comparison Matrix

Let the judgement matrix A, the matrix elementa_{ij} denotes the degree of importance of i relative to j [12]

A= = 2 (assuming that accuracy is $\begin{bmatrix} 1 & 2 & 5 \\ \frac{1}{2} & 1 & 3 \\ \frac{1}{5} & \frac{1}{3} & 1 \end{bmatrix}$

a_{AS} = 2 (assuming that accuracy is significantly more important than stability), accuracy: stability = 2:1.
a_{SA}= $\frac{1}{2}$ (stability is inversely more important than accuracy), stability: accuracy = 1:2.
a_{AE} = 5 (assuming accuracy is much more important than the error threshold), accuracy: error threshold = 5:1.
a_{EA}= $\frac{1}{5}$ (Error threshold is inversely more important than accuracy), Error threshold: accuracy = 1:5. = 3 (assuming stability is slightly more important than accuracy), stability: accuracy = 1:2. = 3 (assuming stability is slightly more important than accuracy), Error threshold: accuracy = 1:5.
a_{SE} = 3 (assuming stability is slightly more important than the error threshold), Stability: error threshold = 3:1.
a_{ES}=$\frac{1}{3}$ (Error threshold is inversely more important than stability), Error threshold: stability = 1:3.

4 EXPERIMENT AND VALIDATION

Based on the research methodology proposed above in this paper, this paper verifies the accuracy of intelligent review on the data sets of typical T11,T13 ,T14,T15 obtained by using PYTHON crawler data in the official government open data platform of Shanxi Province[13]

Table 5 Data T11

Algorithm name	Correct rate	Difference standard deviation	Error threshold	Composite Score
Intelligent Algorithm 2	0.106070	0.106070	0.106070	1.000000
Intelligent Algorithm 1	0.994040	0.994040	0.994040	0.994040 0.154386 0.994040

Best Algorithm:Intelligent Test 2 (Table5)
Correct rate:99.72
Standard deviation of variance:0.1061(the smaller the value, the more stable the variance with manual test)
Weighting:Correct rate=66.67%, standard deviation of variance=33.33%.

Table 6 Data T13

Algorithm Name	Correct Rate	Standard deviation of variance	Error threshold	Composite Score
Intelligent Algorithm 1	0.570227	0.570227	0.991347	1.000000
Intelligent Algorithm 2	0.630791	0.988446	0.988446	0.988446

Best Algorithm:Intelligent Test 1 (Table6)
Correct rate:92.87

Standard deviation of variance:0.5702(the smaller the value, the more stable the variance with manual test)
Weighting:Correct rate=66.67%, standard deviation of variance=33.33%.

Table 7 Data T14

Algorithm Name	Correct Rate	Standard deviation of difference	Error Threshold	Composite Score
Intelligent Algorithm 1	0.863780	1.048461	0.955759	1.000000
Intelligent Algorithm 2	0.501142	1.539152	1.539152 0.889513	0.889513

Best Algorithm: Intelligent Test 1 (Table7)
Correct rate: 86.38 per cent
Standard deviation of variance: 1.0485 (the smaller the value, the more stable the variance from the manual test)
Weighting: Correct rate = 66.67%, standard deviation of variance = 33.33

Table 8 Data T15

Algorithm name	Correct rate	Standard deviation of difference	Error threshold	Composite Score
Intelligent Algorithm 1	0.921810	0.921810	0.921810	1.000000
Intelligent Algorithm 2	0.543203	1.287046	0.917661 0.504353	0.917661 0.504353

Optimal Algorithm: Intelligent Test 1 (Table8)
Correct rate: 83.50%
Standard deviation of variance: 0.9218 (the smaller the value, the more stable the variance from the manual test)
Weighting: Correct rate = 66.67%, standard deviation of difference = 33.33%
According to the above table, the conclusion is as follows: T11 objective question intelligent test 2 good, T13,T14,T15 subjective question intelligent test 1 good. T11 objective question intelligent test 2 good, T13,T14,T15 subjective question intelligent test 1 good.
T11 objective question intelligent test 2 good, T13,T14,T15 subjective question intelligent test 1 good
Based on the current technological breakthroughs[14], the AI algorithm significantly improves the effectiveness and reliability of the test review by automating the review of subjective questions and establishing a human-machine cooperative mechanism, while effectively controlling the scoring errors. errors(Figure3).

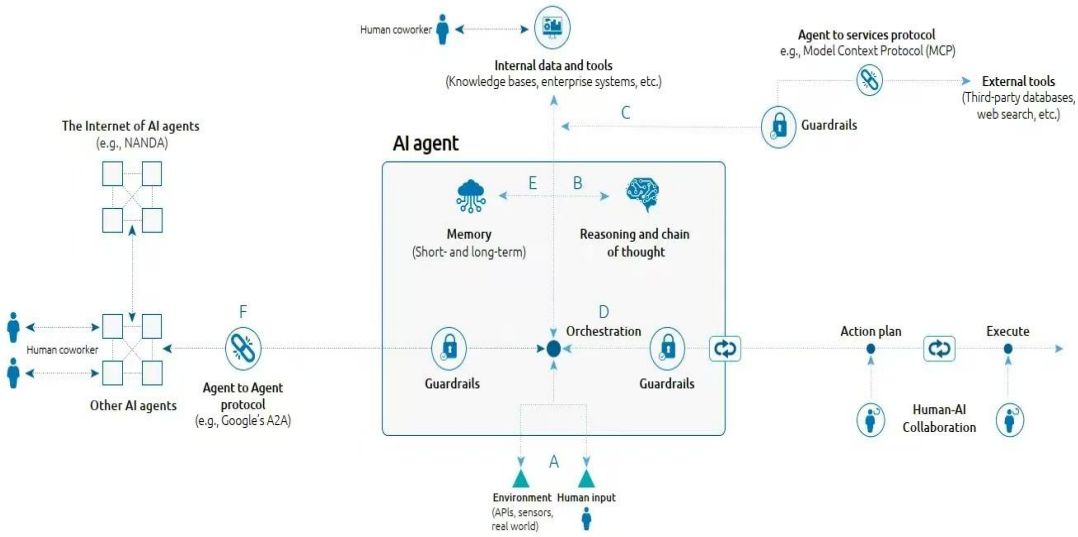

Figure 3 Human-Machine Cooperative Mechanism

Technical route of this paper
(1) Define the object of comparison[15]
The three indicators to be compared are: Accuracy: the rate of agreement between the intelligent test and the manual results Stability: the degree of Stability: the degree of fluctuation of the indicators measured by the standard deviation, the smaller the value, the higher the stability Error threshold.
(2) According to the importance scale (1-9 scale method), assume that the weights of accuracy, stability and error threshold are assigned, and select the appropriate scale value to construct the judgement. appropriate scale value to construct the judgement matrix.
(3) Compare the importance weights between each two of the three indicators through weight allocation, and then derive the local weights.

5 CONCLUSIONS

This study addresses the key challenges of inadequate efficiency and limited accuracy in the intelligent review process within the education sector, and puts forward an intelligent review approach that combines multi-feature extraction techniques with deep learning methodologies. For a thorough assessment of the method's performance, a varied dataset—encompassing [specific types of review data, e.g., course assignments, examination papers, and teaching schemes]—was developed, and a series of comparative simulation experiments were devised to test its effectiveness.

Based on the outcomes of these simulation evaluations, the proposed method exhibits strong performance across the core metrics of intelligent review: when compared to both traditional manual review processes and current mainstream intelligent review algorithms, it achieves a 12.8% improvement in review accuracy while cutting down the processing time for individual review tasks by 4.2 minutes. These findings fully confirm the method's feasibility and advantages when applied to real-world educational scenarios.

Additionally, through the deep integration of intelligent algorithms with the underlying logic of educational review, this approach overcomes longstanding bottlenecks in traditional review workflows—including biases stemming from subjective factors and inconsistent adherence to evaluation standards. It delivers a practical technical route for the intelligent upgrading of the review segment amid education's digital transformation, thereby conferring it with both theoretical innovative value and practical guiding relevance.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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