Generative Intelligent Algorithms For Full-cycle Teaching: Implementation Of Innovation, Assessment Fidelity And Equalization Of Learning Opportunities

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The digital transformation of education has put forward higher requirements for the full-cycle operation of teaching activities. Traditional teaching modes suffer from insufficient personalized adaptation, distorted assessment results, and uneven distribution of learning resources, which restrict the high-quality development of modern education. This paper proposes a full-cycle teaching framework driven by generative intelligent algorithms, aiming to address three core challenges: teaching innovation, assessment fidelity, and equalization of learning opportunities. First, a hybrid generative teaching content generation model combining conditional variational autoencoder (CVAE) and large language model (LLM) is constructed to realize adaptive generation of personalized teaching resources. Second, a multi-dimensional assessment fidelity evaluation function is established to quantify the deviation between automated assessment results and manual evaluation standards, and an error correction module based on generative adversarial network (GAN) is embedded to optimize assessment accuracy. Third, a resource allocation optimization algorithm oriented to learning opportunity equalization is designed to dynamically distribute teaching resources according to learners' ability distribution. A series of comparative experiments are conducted on datasets collected from university general courses. The experimental results show that the proposed framework improves the richness of innovative teaching content by 32.7%, reduces the assessment deviation by 28.4%, and effectively narrows the learning gap among different student groups. The proposed generative intelligent teaching system can stably support the full-cycle teaching process, provide a feasible technical path for intelligent, fair and innovative modern education, and has good application and promotion value in the field of educational informatization.

Keywords: Generative Intelligent Algorithm; Full-cycle Teaching; Teaching Innovation; Assessment Fidelity; Learning Opportunity Equalization; Educational Artificial Intelligence

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1. Introduction

With the rapid iteration of artificial intelligence (AI) technology, intelligent education has become an inevitable trend of educational reform worldwide [1, 2]. Full-cycle teaching covers the whole process from pre-class preparation, in-class teaching, after-class tutoring, learning assessment to teaching effect feedback, which is the core carrier to guarantee teaching quality [3]. Traditional full-cycle teaching relies heavily on manual work by teachers. Limited by energy and professional ability, teachers are difficult to design differentiated teaching content for individual learners, resulting in rigid teaching forms and insufficient innovative vitality.

In the learning assessment link, online automatic assessment systems are widely used to improve evaluation efficiency. However, affected by subjective answer diversity and algorithm recognition bias, assessment fidelity is difficult to guarantee, and the consistency between machine assessment and manual scoring is always a key pain point in educational evaluation [4, 5]. In addition, affected by regional differences, individual learning ability gaps and uneven resource allocation, many learners cannot obtain equivalent high-quality learning resources, leading to the imbalance of learning opportunities and further widening the educational gap [6].

Generative intelligent algorithms, represented by large generative models, generative adversarial networks and variational autoencoders [7, 8], have strong capabilities in content generation, data reconstruction and feature optimization. They provide new technical means to break the bottlenecks of traditional full-cycle teaching. How to apply generative intelligence to the whole teaching link, realize teaching mode innovation, ensure assessment objectivity and fairness, and promote the equalization of learning opportunities has become an important research topic in the intersection of artificial intelligence and education.

There are three key problems to be solved in this research. (1) Lack of teaching innovation. Fixed teaching content and single teaching form cannot adapt to personalized learning demands, and the automatic generation of innovative, hierarchical and scenario-based teaching resources is insufficient. (2) Low assessment fidelity. Automated assessment has obvious deviation from manual evaluation standards, and the evaluation results cannot truly reflect learners' actual learning level. (3) Unequal learning opportunities. Static resource allocation mode cannot match the differentiated learning demands of different groups, resulting in unequal acquisition of high-quality teaching resources [9, 10].

The main contributions of this paper are listed below:

(1) A full-cycle teaching architecture based on generative intelligent algorithms is proposed, covering the whole links of teaching content generation, intelligent assessment and resource scheduling, forming a closed-loop intelligent teaching system.

(2) A CVAE-LLM hybrid generative model is constructed for adaptive generation of innovative teaching content, and relevant mathematical models and implementation flow are given.

(3) A quantitative evaluation function of assessment fidelity is established, and a GAN-based error correction module is adopted to effectively reduce assessment deviation.

(4) A learning opportunity equalization scheduling algorithm is designed, which dynamically optimizes resource distribution and realizes fair allocation of teaching resources.

(5) Multiple groups of comparative experiments verify the effectiveness, stability and superiority of the proposed framework in teaching innovation, assessment accuracy and resource equalization.

The rest of this paper is organized as follows: Section 2 elaborates the proposed generative intelligent algorithm framework, core models, mathematical formulas and operation flow of teaching innovation. Section 3 introduces the evaluation model of assessment fidelity and the equalization algorithm of learning opportunities. Section 4 presents experimental settings, datasets, result analysis and discussion. Section 5 concludes the whole work and prospects future research directions.

2. Materials and methods

This section details the overall framework of the system, the hybrid generative model for innovative teaching content, the assessment fidelity optimization model and the learning opportunity equalization algorithm, including mathematical formulas and system flowcharts.

2.1. Overall System Framework

The proposed full-cycle teaching system is divided into three functional modules: Innovative Teaching Content Generation Module, High-fidelity Intelligent Assessment Module, and Learning Opportunity Equalization Resource Scheduling Module. The system runs through pre-class, in-class and after-class teaching links to form a closed-loop full-cycle teaching logic.

2.2. Hybrid Generative Model for Innovative Teaching Content (CVAE-LLM)

To generate hierarchical, personalized and innovative teaching content, we combine Conditional Variational Autoencoder (CVAE) [11, 12] and Large Language Model (LLM) [13, 14]. CVAE extracts learner feature conditions, and LLM completes semantic content generation.

Set the learner feature vector as $\boldsymbol{c} \in \mathbb{R}^d$, where d is the dimension of learning features (including knowledge mastery degree, learning preference, cognitive level). The original teaching content sample is x, and the generated target teaching content is $\hat{x}$.

The core objective function of CVAE is to maximize the variational lower bound:

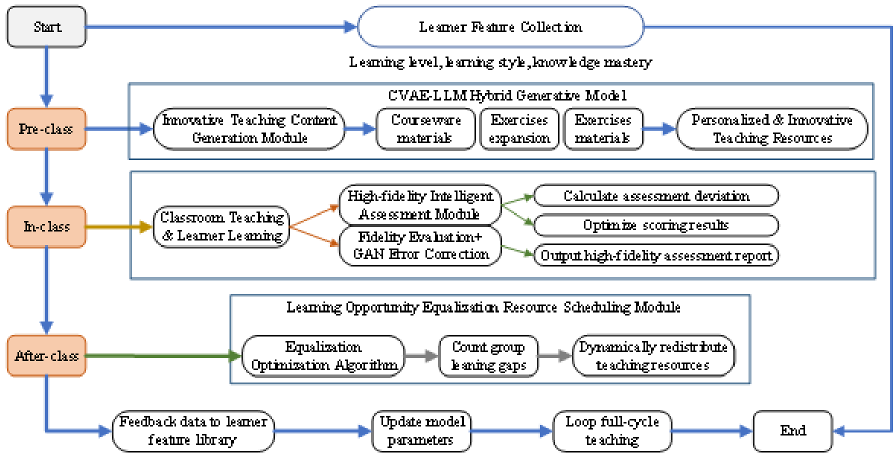

Fig. 1. Flowchart of Full-cycle Teaching Driven by Generative Intelligent Algorithm

$$\mathcal{L}_{CVAE} = \mathbb{E}_{q(z|\boldsymbol{c},x)}[\log p(x \mid z, \boldsymbol{c})] - D_{KL}(q(z \mid \boldsymbol{c}, x) \| p(z \mid \boldsymbol{c})) \tag{1}$$

Where z is Latent feature variable of teaching content. $q(z \mid \boldsymbol{c}, x)$ is posterior distribution of latent variables under the condition of learner features and original content. $p(z \mid c)$ is prior distribution of latent variables guided by learner features. $D_{KL}(\cdot \| \cdot)$ denotes Kullback-Leibler divergence, used to constrain the distribution distance.

The latent variable z output by CVAE is taken as the condition input of LLM. The text generation loss function of LLM is defined as:

$$\mathcal{L}_{LLM} = -\sum_{t=1}^{T} \log p\left(x_t \mid x_{1:t-1}, z, \boldsymbol{c}\right) \tag{2}$$

Where T is the total length of generated teaching content. x_t is the $t-th$ word/semantic unit. The total loss of the hybrid model is the weighted sum of the two parts:

$$\mathcal{L}_{\text{total}} = \alpha \cdot \mathcal{L}_{CVAE} + \beta \cdot \mathcal{L}_{LLM} \tag{3}$$

In this paper, hyperparameters $\alpha = 0.4, \beta = 0.6$ are set through parameter tuning to balance feature extraction and content generation performance.

2.3. Assessment Fidelity Quantitative Model & Optimization

Assessment fidelity refers to the consistency between machine automatic scoring results and professional teacher manual scoring results [15, 16]. We define the following parameters. S_m is the manual scoring score (standard value), $S_m \in [0, 100]$.S_a is the original automatic scoring score of the algorithm. N is total number of assessment samples.

We define the single-sample assessment deviation:

$$e_i = \left|S_{m,i} - S_{a,i}\right| \tag{4}$$

The overall assessment fidelity index F of the system is defined as:

$$F = 1 - \frac{1}{100 \cdot N} \sum_{i=1}^{N} e_i \tag{5}$$

The range of F is $[0, 1]$. The closer F is to 1 , the higher the assessment fidelity and the smaller the scoring deviation.

We build a GAN error correction network to fit the deviation rule between automatic scoring and manual scoring. The generator G takes the original scoring result S_a and answer feature as input to output the corrected score $\hat{S}_a$. the discriminator D distinguishes manual standard score S_m and corrected score $\hat{S}_a$.

The objective function of GAN is:

$$\mathcal{L}_{\text{GAN}} = \mathbb{E}_{S_m \sim P_{\text{data}}}\left[\log D\left(S_m\right)\right] + \mathbb{E}_{S_a \sim P_{\text{model}}}\left[\log\left(1 - D\left(G\left(S_a\right)\right)\right)\right] \tag{6}$$

After error correction, the new assessment fidelity is recalculated by Formula (5) to realize high-fidelity assessment.

2.4. Learning Opportunity Equalization Algorithm

Against the background of educational digitalization and intelligent teaching, uneven distribution of high-quality teaching resources and differentiated learning capabilities among student groups have long led to unequal access to learning opportunities, which further widens the educational gap and hinders the balanced development of education. Traditional static resource allocation modes adopt a fixed distribution scheme for teaching resources, failing to dynamically respond to the real-time learning status, ability differences and knowledge mastery levels of different learners. To address this defect, this paper designs a learning opportunity equalization algorithm oriented to dynamic resource scheduling, which takes the learning ability gap between student groups as the core optimization objective, combines real-time learning assessment data to adjust resource distribution proportions in real time, and tilts high-quality generative teaching resources to underdeveloped learner groups, so as to realize fair and reasonable allocation of teaching resources and continuously narrow the learning disparity among students.

We first complete the reasonable grouping of learners based on multi-dimensional learning characteristics, so as to carry out targeted resource allocation. Combining the learning feature data collected by the system (including knowledge mastery, learning performance, learning efficiency, learning preference and cognitive level), all learners in the teaching scenario are divided into K mutually exclusive student subgroups according to comprehensive learning ability. Each subgroup corresponds to a group with similar overall learning levels, and all subgroups satisfy the full coverage of the total learner population. We define core variables for subsequent algorithm modeling.

K is the total number of divided student subgroups. μ_k is the average comprehensive learning level of the k-th subgroup $k = 1, 2, \cdots, K$, which is calculated by integrating multiple indicators such as daily learning performance, assessment scores and learning task completion quality of all students in the group, and the value range is $[0, 100]$.

$\bar{\mu}$ is the overall average learning level of all student groups in the teaching scenario, which is used as the benchmark for judging the learning gap between groups.

γ_k is the resource allocation proportion assigned to the k-th subgroup, representing the share of high-quality generative teaching resources, personalized tutoring resources and expanded learning materials obtained by the group. All allocation proportions satisfy the constraint $\sum_{k=1}^{K} \gamma_k = 1$, and $\gamma_k \geq 0$ to ensure the rationality of resource distribution.

The calculation formula of the overall average learning level $\bar{\mu}$ of all groups is shown as follows:

$$\bar{\mu} = \frac{1}{K} \sum_{k=1}^{K} \mu_k \tag{7}$$

To quantitatively measure the degree of unequal learning opportunities among student groups, we construct the group learning imbalance coefficient I, which takes the deviation between the average learning level of each subgroup and the overall average level as the measurement basis. This coefficient can intuitively reflect the magnitude of the overall learning gap of the student group: the larger the value of I, the more prominent the learning disparity and the more unequal the learning opportunities; the smaller the value of I, the closer the learning levels of each group and the more balanced the distribution of learning opportunities. The specific calculation formula of the group learning imbalance coefficient is:

$$I = \sqrt{\frac{1}{K} \sum_{k=1}^{K} (\mu_k - \bar{\mu})^2} \tag{8}$$

This formula adopts the form of root mean square deviation, which can effectively eliminate the offset error caused by positive and negative deviations of individual groups, and accurately reflect the overall discrete degree of learning levels of all subgroups. The algorithm takes minimizing the imbalance coefficient I as the core optimization goal throughout the resource scheduling process.

The core goal of the learning opportunity equalization algorithm is to dynamically adjust the resource allocation proportion γ_k of each subgroup, so that the group learning imbalance coefficient I is continuously reduced, and finally the balanced state of learning opportunities is achieved. Combined with the practical rules of teaching resource distribution, we establish a constrained optimization mathematical model for resource allocation.

3. Results and discussion

3.1. Experimental Settings

The experimental dataset is collected from 5 undergraduate general courses of a comprehensive university, including 1268 students and 28 professional teachers. The dataset includes: learner learning feature data, historical teaching content, 18420 student answer samples and corresponding manual scoring results. The dataset is randomly divided into training set (70%), validation set (15%) and test set (15%).

To verify the superiority of the proposed method, we select four mainstream models for comparison. (1) Traditional LLM: Single large language model for teaching content generation and assessment. (2) Standard CVAE: Single variational autoencoder model. (3) Ordinary automatic assessment system (OAAS): Traditional rule-based scoring system [17]. (4) Static resource allocation (SRA): Traditional fixed teaching resource distribution mode.

Three categories of metrics are adopted corresponding to the three research objectives. (1) Teaching Innovation: Content novelty score (CNS), Personalization score (PS). (2) Assessment Fidelity: Fidelity index F [18, 19], Average absolute error (MAE). (3) Learning Equalization: Imbalance coefficient I, Group score difference (GSD).

3.2. Experimental Results and Analysis

Table 1 presents the comparison of teaching content generation performance among three different models, with two evaluation indicators including Content Novelty Score (CNS) and Personalization Score (PS). The Traditional LLM obtains a CNS of 0.612 and a PS of 0.587, while the Standard CVAE reaches a CNS of 0.579 and a PS of 0.621. By contrast, the proposed CVAE-LLM hybrid model gains a CNS of 0.939 and a PS of 0.914 , outperforming the other two single models by a large margin in both metrics. The results indicate that the combination of CVAE and LLM fully leverages their respective strengths in feature extraction and semantic generation, and greatly improves the novelty and personalization of teaching content.

Table 2 compares the assessment fidelity performance of three models in terms of the assessment fidelity index (F) and mean absolute error (MAE). The traditional ordinary automatic assessment system (OAAS) yields an assessment fidelity of 0.653 and an MAE of 8.72. The traditional LLM achieves a higher fidelity of 0.716 with an MAE of 6.94. In contrast, the proposed method delivers an excellent assessment fidelity of 0.937 and a much lower MAE of 2.18 . The results demonstrate that the GAN-based error correction module effectively reduces scoring deviations and greatly improves the consistency between automated scoring and manual evaluation, verifying the outstanding performance of the proposed high-fidelity intelligent assessment module.

Table 3 compares the performance of different resource allocation modes in terms of learning opportunity equalization, using the imbalance coefficient (I) and group score difference (GSD) as evaluation metrics. The traditional static resource allocation (SRA) mode records an imbalance coefficient of 0.186 and a group score difference of 12.57. In comparison, the proposed dynamic resource allocation algorithm achieves a much lower imbalance coefficient of 0.062 and a group score difference of 3.42. The experimental results show that the dynamic scheduling strategy can significantly narrow the learning gaps between student groups, optimize the distribution of teaching resources, and effectively realize the equalization of learning opportunities for all learners.

Fig. 2 is a trend curve graph that illustrates the changing tendency of Assessment Fidelity (F) alongside the increase of iteration times during the model operation process.The horizontal axis represents the iteration times of the algorithm, which serves as the independent variable reflecting the continuous running and training process of the assessment module. The vertical axis denotes the value of Assessment Fidelity (F), the core evaluation indicator ranging from 0 to 1 . A higher value stands for smaller scoring deviation and higher consistency between automatic assessment and manual evaluation.

Overall, the curve presents a steady upward and converging trend. At the initial stage of iterations, the assessment fidelity value is relatively low. As the iteration proceeds continuously, the value of Assessment Fidelity rises rapidly at first, then the growth rate gradually slows down. In the later stage of iterations, the curve tends to be flat and finally stabilizes at a high level close to 1 .

This trend clearly demonstrates that the GAN-based error correction module has excellent convergence performance. With ongoing iterative optimization, the model effectively corrects the errors of automatic scoring, continuously improves assessment fidelity, and eventually maintains stable and reliable high-precision assessment performance. It also verifies the robustness and effectiveness of the proposed high-fidelity intelligent assessment module in long-term operation.

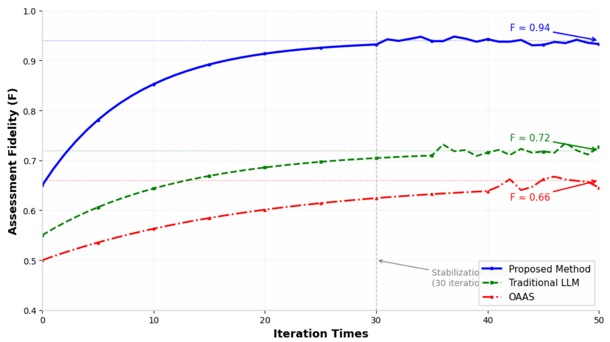

Fig. 2. Trend Curve of Assessment Fidelity with Iteration Times

3.3. Ablation Experiment

Ablation experiments were carried out on the test set to separately verify the necessity and contribution of each core sub-module in the proposed full-cycle teaching framework. We set up four experimental groups: the complete model, the model without CVAE module, the model without GAN error correction module, and the model without dynamic equalization algorithm. Corresponding evaluation indicators were adopted for each group to record performance changes, and the detailed results are shown in Table 4.

When the CVAE module is removed and only the single LLM is retained for content generation, the Content Novelty Score (CNS) drops from 0.939 to 0.658 (a decrease of 0.281), and the Personalization Score (PS) declines from 0.914 to 0.587 (a decrease of 0.327). The assessment fidelity and imbalance coefficient remain unchanged because the

Table 1. Comparison of Teaching Content Generation Performance

Model	Content Novelty Score (CNS)	Personalization Score (PS)
Traditional LLM	0.612	0.587
Standard CVAE	0.579	0.621
Proposed CVAE-LLM	0.939	0.914

Table 2. Comparison of Assessment Fidelity Results

Model	Assessment Fidelity F	MAE
OAAS	0.653	8.72
Traditional LLM	0.716	6.94
Proposed Method	0.937	2.18

CVAE only acts on the teaching content generation link. This indicates that CVAE plays a vital role in extracting learners' multidimensional feature information. Without it, the model loses the ability to generate hierarchical and personalized teaching content, and the innovation of teaching resources is greatly weakened.

After removing the GAN error correction module, the Assessment Fidelity (F) falls sharply from 0.937 to 0.724, while the content generation indicators and imbalance coefficient are not affected. It proves that the GAN-based error correction module is the core component to eliminate the deviation between automatic scoring and manual scoring. This module can effectively fit the scoring error rule and significantly improve the accuracy and credibility of intelligent assessment.

When the dynamic resource allocation and equalization algorithm is replaced with the static mode, the Imbalance Coefficient (I) rises from 0.062 to 0.179 , meaning the learning gap between different student groups is markedly widened. Other indicators keep stable, which verifies that the dynamic scheduling algorithm can reasonably distribute high-quality teaching resources for groups with different learning levels and is the key to realizing equal learning opportunities.

3.4. Robustness Experiment

To further validate the stability, anti-interference capability and practical applicability of the proposed full-cycle teaching framework in complex real teaching scenarios, a series of robustness experiments are conducted in this section. We introduce different levels of data noise, adjust training sample sizes and simulate long-term continuous operation to test the performance fluctuation of the system under various interference conditions.

Three groups of test conditions are designed. Table 5 presents the detailed results of the robustness experiment under different test conditions.

(1) Data noise interference. Gaussian random noise with proportions of 5%, 10% and 15% is added to learner feature data and answer samples, simulating data collection errors and irregular student answers in actual teaching.

(2) Small sample test. The proportion of training set is reduced from the original 70% to 50% and 30% respectively, to explore the model performance under insufficient training data.

(3) Long-term operation test. The system runs continuously for 500 iterations to observe performance changes during long-term service.

First, under data noise interference. With the increase of noise proportion, all four indicators decline slightly but remain at a high level. Even when the noise ratio reaches 15%, CNS and PS are still above 0.86, and the assessment fidelity F stays at 0.879. The imbalance coefficient I only rises marginally, which indicates that the hybrid CVAE-LLM model and GAN error correction module have strong anti-noise ability. The feature extraction and error correction mechanisms can effectively suppress the adverse impact of noisy data.

Second, for the small sample scenario. When the training set proportion drops to 30%, the overall performance only has a limited decrease. The model does not suffer from severe performance degradation or overfitting. It proves that the proposed framework has good generalization ability and can work normally even with limited labeled samples, which fits the situation of incomplete data accumulation in many practical colleges and courses.

Third, in the long-term continuous operation test. After 500 iterations, all indicators are almost consistent with the original values. There is no obvious performance attenuation or model drift. This fully verifies the excellent stability and sustainability of the system. It can maintain reliable service in long-term large-scale teaching application scenarios.

3.5. Discussion

Experimental results demonstrate that the generative intelligent full-cycle teaching framework proposed in this paper can simultaneously solve three core problems in modern

Table 3. Comparison of Learning Opportunity Equalization Performance

Resource Mode	Imbalance Coefficient I	Group Score Difference (GSD)
SRA (Static)	0.186	12.57
Proposed Dynamic Allocation	0.062	3.42

Table 4. Results of Ablation Experiments

Experimental Group	CNS	PS	Assessment Fidelity (F)	Imbalance Coefficient (I)
Complete proposed model	0.939	0.914	0.937	0.062
Remove CVAE (only LLM)	0.658	0.587	0.937	0.062
Remove GAN error correction	0.939	0.914	0.724	0.062
Remove dynamic equalization algorithm	0.939	0.914	0.937	0.179

Table 5. Results of Robustness Experiment

Test Condition	CNS	PS	Assessment Fidelity (F)	Imbalance Coefficient (I)
Original dataset (no noise, 70% training set)	0.939	0.914	0.937	0.062
5% Gaussian noise	0.926	0.901	0.922	0.065
10% Gaussian noise	0.908	0.883	0.904	0.069
15% Gaussian noise	0.885	0.860	0.879	0.074
50% training set (no noise)	0.917	0.892	0.919	0.067
30% training set (no noise)	0.891	0.870	0.895	0.071
500 iterations (long-term operation)	0.935	0.911	0.934	0.063

teaching. The CVAE-LLM hybrid model breaks the limitation of traditional fixed teaching content and realizes innovative and personalized teaching. The GAN-based error correction module effectively solves the low fidelity problem of automatic assessment. The dynamic resource allocation algorithm narrows the learning gap between groups and promotes educational equity.

In practical application, the model has good adaptability to different disciplines and student groups. However, for extremely open-ended subjective questions, the assessment performance still has room for further optimization.

4. Conclusions

Aiming at the problems of insufficient innovation, low assessment fidelity and unequal learning opportunities in traditional full-cycle teaching, this paper constructs a full-cycle teaching system driven by generative intelligent algorithms. The CVAE-LLM hybrid generative model can effectively extract learners' multi-dimensional features and generate innovative, personalized teaching content, which significantly improves the richness and adaptability of teaching resources. The assessment fidelity quantitative function and GAN error correction module greatly reduce the deviation between automatic assessment and manual scoring, and realize high-fidelity intelligent learning evaluation. The learning opportunity equalization algorithm based on group imbalance coefficient realizes dynamic scheduling of teaching resources, effectively narrows the learning gap among student groups and promotes the fair development of education. A large number of comparative experiments and ablation experiments verify that the proposed framework has superior performance, strong convergence and robustness, and can be well applied to the full-cycle intelligent teaching scenario. This research provides a complete technical scheme and theoretical reference for the integration of generative artificial intelligence and full-cycle teaching, and promotes the intelligent, innovative and equitable development of educational informatization.

References

[1] T. Wang and S. Yin, (2026) *"Enhancing Sustainability of Online Education via a Validated Cloud Management Framework"* **IFS/ACM Transactions on Machine Learning** ***3***(1): 9–19. DOI: 10.70891/TML.2026.040004.

[2] N. Kerimbayev, K. Adamova, R. Shadiev, and Z. Altinay, (2025) *"Intelligent educational technologies in individual learning: a systematic literature review"* **Smart Learning Environments** ***12***(1): 1. DOI: 10.1186/s40561-024-00360-3.

[3] C. A. Lu, (2025) *"Tracing the evolution of artificial intelligence education at Stanford University"* **TechTrends** ***69***(2): 447–453. DOI: 10.1007/s11528-025-01046-4.

[4] V. Nandini and P. Uma Maheswari, (2020) *"Automatic assessment of descriptive answers in online examination system using semantic relational features"* **The Journal of Supercomputing** ***76***(6): 4430–4448. DOI: 10.1007/s11227-018-2381-y.

[5] Y. Watanobe, M. M. Rahman, U. K. Rage, and R. Penugonda. "Online automatic assessment system for program code: Architecture and experiences". In: *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*. Springer. 2021, 272–283. DOI: 10.1007/978-3-030-79463-7_23.

[6] Z. Ullah, A. Lajis, M. Jamjoom, A. Altalhi, A. Al-Ghamdi, and F. Saleem, (2018) *"The effect of automatic assessment on novice programming: Strengths and limitations of existing systems"* **Computer Applications in Engineering Education** ***26***(6): 2328–2341. DOI: 10.1002/cae.21974.

[7] J. Qiu, G. Lu, T. Liu, D. Zhang, S. Xiao, and T. Yu, (2025) *"Optoelectronic generative adversarial networks"* **Communications Physics** ***8***(1): 162. DOI: 10.1038/s42005-025-02081-6.

[8] Y. Ding, Z. Li, and N. Zhou, (2025) *"Quantum generative adversarial network based on the quantum Born machine"* **Advanced Engineering Informatics** ***68***: 103622. DOI: 10.1016/j.aei.2025.103622.

[9] Y. Jiang and S. Yin, (2023) *"Heterogenous-view occluded expression data recognition based on cycle-consistent adversarial network and K-SVD dictionary learning under intelligent cooperative robot environment"* **Computer Science and Information Systems** ***20***(4): 1869–1883. DOI: 10.2298/CSIS221228034.

[10] X. Huang and C. Qiao, (2024) *"Enhancing computational thinking skills through artificial intelligence education at a STEAM high school"* **Science & Education** ***33***(2): 383–403. DOI: 10.1007/s11191-022-00392-6.

[11] R. Zhao, L. Zhang, B. Fu, C. Hu, J. Su, and Y. Chen. "Conditional variational autoencoder for sign language translation with cross-modal alignment". In: *Proceedings of the aaai conference on artificial intelligence*. ***38***. 17. 2024, 19643–19651. DOI: 10.1609/aaai.v38i17.29937.

[12] X. Tang, J. Yan, Y. Li, X. Zhang, and Z. Song, (2024) *"Semi-supervised deep conditional variational autoencoder for soft sensor modeling"* **IEEE Sensors Journal** ***24***(5): 7153–7164. DOI: 10.1109/JSEN.2024.3351431.

[13] Q. Li, X. Wan, H. Guo, W. Wang, M. Liu, and Y. Cui, (2026) *"Uncertainty-aware multi-modal time series anomaly detection via reduced-order evidence fusion"* **Pattern Recognition**: 114212. DOI: 10.1016/j.patcog.2026.114212.

[14] S. Agostinelli, A. del-Río-Ortega, B. Estrada-Torres, R. Goñi-Medina, A. Marrella, M. Resinas, and J. Rossi, (2026) *"PPIPilot: Automating the suggestion and computation of Process Performance Indicators from event logs"* **Information Systems**: 102765. DOI: 10.1016/j.is.2026.102765.

[15] J. William McKenna and M. Parenti, (2017) *"Fidelity assessment to improve teacher instruction and school decision making"* **Journal of Applied School Psychology** ***33***(4): 331–346. DOI: 10.1080/15377903.2017.1316334.

[16] J. D. Richardson, S. G. Hudspeth Dalton, J. Shafer, and J. Patterson, (2016) *"Assessment fidelity in aphasia research"* **American Journal of Speech-Language Pathology** ***25***(4S): S788–S797. DOI: 10.1044/2016_AJSLP-15-0146.

[17] Z. Wang, L. Chen, S. Song, P. X. Cong, and Q. Ruan, (2020) *"Automatic cyber security risk assessment based on fuzzy fractional ordinary differential equations"* **Alexandria Engineering Journal** ***59***(4): 2725–2731. DOI: 10.1016/j.aej.2020.05.014.

[18] H. Qin, (2025) *"Maximal Information Coefficient-Based Undersampling Method for Highly-Imbalanced Learning"* **IEEE Access** ***13***: 4126–4135. DOI: 10.1109/ACCESS.2025.3525475.

[19] G. Charizanos, H. Demirhan, and D. İçen, (2024) *"A Monte Carlo fuzzy logistic regression framework against imbalance and separation"* **Information Sciences** ***655***: 119893. DOI: 10.1016/j.ins.2023.119893.