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Application of Human-Machine Collaborative Decision-Making Mechanism in Vocational Education Intelligent Evaluation System and Research on Employment Market Response

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Abstract. In order to solve the contradiction between "technological empowerment" and "loss of humanistic value" in the intelligent evaluation of vocational education, as well as the problems of technology supremacy, weak human-machine collaboration theory, and ambiguous correlation between evaluation and the job market in existing research, this study constructs a vocational education human-machine collaborative intelligent evaluation system with the "evaluation application feedback optimization" closed-loop as the core. Three mechanisms are designed: human-machine dynamic adaptation, consensus formation, and system evolution. Through evolutionary game verification, when the collaborative dividend is sufficient and the cost is controllable, the system can stably converge to the equilibrium of "college adoption student compliance enterprise adoption", providing a solution for the transformation of evaluation paradigm and the docking with the job market.

Keywords: human-machine collaboration, Vocational education, Intelligent evaluation system, Evolutionary game theory, Job market response

1. Introduction

Vocational education evaluation is currently in a critical period of paradigm shift [1]. When intelligent technology deeply penetrates the evaluation scene, technological empowerment should have become the key to solving the evaluation dilemma, but it gradually falls into a trap under the guidance of instrumental rationality [2]. Although intelligent evaluation tools have improved evaluation efficiency through efficient data processing and unified evaluation standards, they have alienated complex educational evaluations into mechanical calculations of data. The implicit dimensions of professional ethics, the dynamic process of skill growth, and other humanistic value elements are constantly being dissolved, forming a paradoxical contradiction between technological empowerment and the loss of humanistic values [3].

The solution to this paradox urgently needs to go beyond the simple logic of automated evaluation and move towards a new paradigm of collaborative decision-making with human-machine symbiosis and intelligent enhancement. Upon reviewing existing research, the gap between

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theory and practice has become apparent. As shown in Figure 1, research on intelligent evaluation focuses more on improving the accuracy of technology applications, falling into the cognitive bias of "technology first", simplifying evaluation into algorithm output results, and paying insufficient attention to the humanistic attributes and contextual complexity of educational evaluation, with limitations becoming increasingly prominent [4]; The exploration of human-machine collaboration research in the field of education still remains at the operational level of functional superposition, without delving into the decision-making core of educational evaluation, lacking theoretical construction of collaborative logic, and significantly lacking theoretical depth [5]; More importantly, the research on the correlation between vocational education evaluation and the job market is mostly scattered in practical experience summary, and the theoretical bridge between the two has not been systematically established. The response mechanism of evaluation results to market demand is still in a "black box" state. These theoretical gaps not only highlight the urgency of paradigm shift, but also provide a logical starting point for the development of this study.

Based on this, in order to solve the contradiction between "technological empowerment" and "loss of humanistic value" in intelligent evaluation of vocational education and the existing research deficiencies, this paper constructs a vocational education human-machine collaborative intelligent evaluation system with the "evaluation application feedback optimization" closed-loop as the core and three mechanisms including human-machine dynamic adaptation. Through evolutionary game theory, it verifies that it can stably converge to the efficient and balanced effect of "college adoption student compliance enterprise adoption", providing practical solutions for the evaluation paradigm to shift from "technology first" to human-machine collaboration.

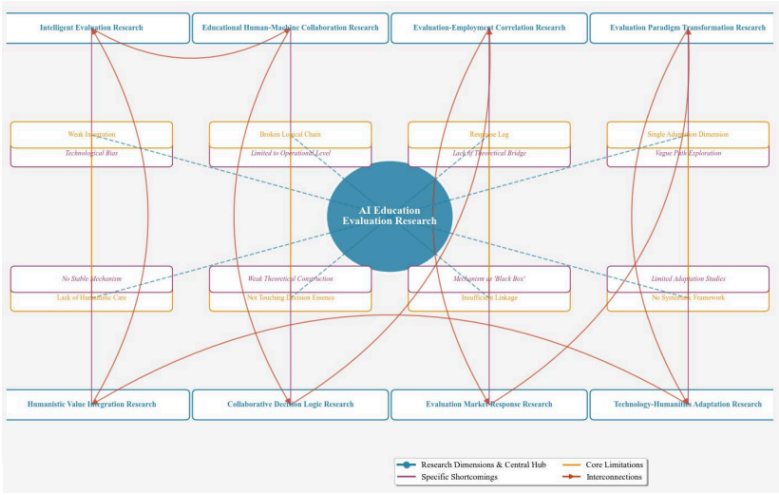

Figure 1. Schematic diagram of insufficient existing research

2. Framework design of human computer collaborative intelligent evaluation system for vocational education

2.1. Overall system design

The overall system presents an evolutionary paradigm driven by feedback, with multi-directional feedback of evaluation process, result application, and market demand as the core logic, forming a closed-loop iterative chain of "evaluation application feedback optimization". Its construction is anchored in three core principles: human in the loop, human centered, and continuous learning.

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2.2. Key mechanisms

At the level of key mechanism design, three core mechanisms need to be constructed. The human-machine function dynamic adaptation mechanism allocates decision-making power based on task uncertainty, conflict, and value sensitivity, achieving flexible adjustment of human-machine rights and responsibilities; The mechanism of human-machine consensus formation relies on the iterative optimization process of debate and counterfactual reasoning to promote human-machine cognitive convergence and resolve evaluation bias; The system evolution mechanism utilizes human feedback reinforcement learning paths to transform human feedback into model optimization signals, ensuring that the system continues to meet the needs of vocational education.

Firstly, construct a dynamic decision weight allocation function (Ψ), whose output is the machine decision weight λ^{m}_{t}:

$$\lambda_t^m = \Psi\left(U_t, C_t, V_t\right) = \sigma\left(-\omega_1 \cdot U_t - \omega_2 \cdot C_t - \omega_3 \cdot V_t\right) \tag{1}$$

Among them, U_t refers to the degree of uncertainty of all possible outcomes and their probability distributions in task t; C_t refers to the degree to which there are multiple competing or difficult to balance objectives in the evaluation criteria of task t; V_t refers to the significant degree of ethical, social, or emotional impact that the decision outcome of task t may have; σ (·) is the Sigmoid activation function, and ω_1, ω_2, and ω_3 are weight parameters calibrated by domain experts.

The mechanism of human-machine consensus formation, through multiple iterations, enables the system and experts to jointly approach an optimal decision that can be explained, defended, and robust by both parties.

After k rounds of iteration, the final consensus decision D∗ is expressed as follows:

$$D^* = \frac{\rho_m \cdot R(C_m) \cdot \text{claim}_m + \rho_n \cdot R(C_n) \cdot \text{claim}_n}{\rho_m \cdot R(C_m) + \rho_n \cdot R(C_n)} \tag{2}$$

Among them, R (·) is the robustness rating function, calculated based on the performance of claims in counterfactual tests. The more stable the performance, the higher the score. ρ_m and ρ_h are preset authoritative weight coefficients used to balance the innate authority of machines and humans in a specific field.

The system evolution mechanism relies on the reward model R_ϕ, whose task is to mimic the preference judgment of human experts and predict a scalar reward value r for any decision trajectory τ, expressed as follows:

$$\mathcal{L}\left(\phi\right) = -\mathrm{E}_{(\tau_i,\tau_j)\sim p}\left[y^{(0)} \log \sigma\left(R_\phi\left(\tau_i\right) - R_\phi\left(\tau_j\right)\right) + y^{(1)} \log \sigma\left(R_\phi\left(\tau_j\right) - R_\phi\left(\tau_i\right)\right)\right] \tag{3}$$

Among them, σ is the Sigmoid function, and D is the collected human preference dataset.

3. The impact mechanism on the job market

3.1. Payment matrix

This article uses evolutionary game theory to verify the application and employment market response of the proposed solution in the vocational education intelligent evaluation system [6]. The participants are vocational education institutions, student benefits, and enterprises.

The payment matrix is shown in Table 1.

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Table 1. Payment matrix

Strategy Combination of Players		School (S) Payoff	Student (St) Payoff	Enterprise (E) Payoff
School Strategy	Student Strategy	Enterprise Strategy		
Adopt	Comply	Trust	-Ca + Ba + αR	-Cc + Bskill + βR
		Not-Trust	-Ca + Ba - Ls	-Cc + Bskill
	Not-Comply	Trust	-Ca - Ls	-Cnc
		Not-Trust	-Ca	-Cnc
Not-Adopt	Comply	Trust	-Cn - Ls	-Cc
		Not-Trust	-Cn	-Cc
	Not-Comply	Trust	-Cn - Ls	-Cnc
		Not-Trust	-Cn	-Cnc

The parameter settings are shown in Table 2.

Table 2. Parameter settings

Parameter	Explanation
Ca	Incremental cost for the school to Adopt the human-AI collaborative system (e.g., software/hardware procurement, teacher training costs).
Cn	Operational cost for the school to Not-Adopt the new system and maintain the traditional evaluation model.
Ba	Long-term benefits for the school from successfully cultivating students by adopting the system (e.g., enhanced reputation, improved student quality, increased funding).
Cc	Personal effort cost for the student to Comply with the system's evaluation and guidance.
Cnc	Cost incurred by the student choosing Not-Comply and learning according to their own will.
Bskill	Personal benefits for the student from skill enhancement (e.g., stronger employment competitiveness, higher expected salary).
Ct	Cost savings for the enterprise to Trust and use the system's evaluation report for recruitment (e.g., reduced screening and assessment costs).
Cnt	Cost for the enterprise to Not-Trust the system and use traditional recruitment methods (e.g., large-scale written tests, interviews).
Bmatch	Benefits for the enterprise from recruiting more suitable talent (e.g., reduced onboarding training costs, increased employee productivity).
R	Collaborative Dividend, the additional incremental total benefit brought by the system to all three parties when the strategy combination is (Adopt, Comply, Trust).
α, β, γ	Distribution coefficients of the collaborative dividend Ramong the three parties, satisfying α + β + γ = 1.
Ls	Loss to the School due to strategy mismatch (e.g., reputational damage when an enterprise trusts an evaluation from a school that did not adopt the system).
Le	Loss to the Enterprise due to strategy mismatch (e.g., costs from failed recruitment due to trusting an incorrect evaluation).

3.2. Stable strategy

According to the payment matrix, the Jacobian matrix expression is obtained as follows:

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$$J = \begin{pmatrix} \frac{\partial F(x)}{\partial x} & \frac{\partial F(x)}{\partial y} & \frac{\partial F(x)}{\partial z} \\ \frac{\partial F(y)}{\partial x} & \frac{\partial F(y)}{\partial y} & \frac{\partial F(y)}{\partial z} \\ \frac{\partial F(z)}{\partial x} & \frac{\partial F(z)}{\partial y} & \frac{\partial F(z)}{\partial z} \end{pmatrix}$$

$$= \begin{pmatrix} (1-2x)[U_{s1}-U_{s2}] & x\left(1-x\right)\frac{\partial(U_{s1}-U_{s2})}{\partial y} & x\left(1-x\right)\frac{\partial(U_{s1}-U_{s2})}{\partial z} \\ y\left(1-y\right)\frac{\partial(U_{st1}-U_{st2})}{\partial x} & (1-2y)[U_{st1}-U_{st2}] & y\left(1-y\right)\frac{\partial(U_{st1}-U_{st2})}{\partial z} \\ z\left(1-z\right)\frac{\partial(U_{e1}-U_{e2})}{\partial x} & z\left(1-z\right)\frac{\partial(U_{e1}-U_{e2})}{\partial y} & (1-2z)[U_{e1}-U_{e2}] \end{pmatrix} \quad (4)$$

When R is large enough, that is, the human-machine collaborative system can effectively create incremental value, and the costs of Ca, Cc, etc. are controlled within a reasonable range, the system will stably converge to the efficient equilibrium point of (1,1,1), namely (adoption, compliance, acceptance).

3.3. Simulation and emulation

The parameter settings are as follows: Cn = 1, Ba = 3, Cc = 1, Cnc = 0.5, Bskill = 2.5, Ct = 1, Cnt = 1.5, Bmatch = 3, Ls = 0.5, Le = 1, α=0.4, β=0.3, γ=0.3.

Initial strategy ratio: (x0, y0, z0)=(0.3, 0.3, 0.3).

The simulation results are shown in Figure 2.

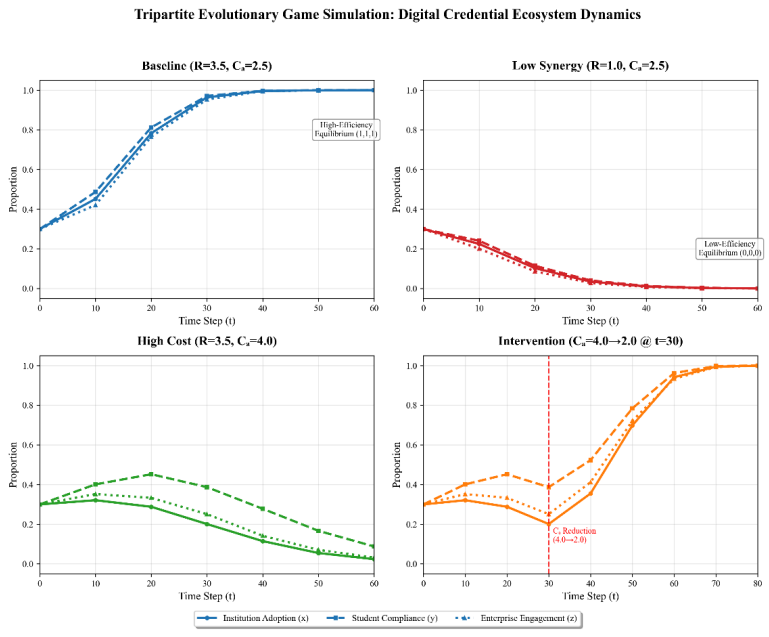

Figure 2. Simulation simulation

The image results show that under the intervention of the proposed scheme in this article, the system's decline trend has been successfully reversed and guided back to an efficient equilibrium path. Proved the effectiveness of the proposed scheme in this article.

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4. Conclusion

This study constructed a vocational education human-machine collaborative intelligent evaluation system with a "evaluation application feedback optimization" closed-loop as the core, including three key mechanisms: dynamic adaptation of human-machine functions, formation of human-machine consensus, and system evolution. It achieved flexible allocation of human-machine rights and responsibilities, resolution of evaluation deviations, and continuous optimization of the system, providing a practical technical framework. Through evolutionary game analysis and simulation verification, when the system synergy dividend is large enough and the costs of college adoption and student compliance are controlled within a reasonable range, the system can stably converge to an efficient equilibrium of "college adoption student compliance enterprise adoption", and intervention measures such as reducing college adoption costs can reverse the system's decline trend and help achieve a win-win situation for all three parties. This study provides practical solutions for the transformation of vocational education evaluation paradigms, promoting precise alignment between vocational education evaluation and job market demand, and alleviating the structural contradiction between talent cultivation and market demand.

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