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A System Dynamics and NSGA-II Based Framework for Occupational Structure Evolution in the Game Industry under Generative AI

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ABSTRACT

To characterize the impact of generative AI technology development on changes in job task structures and requirements, this paper constructs a multi-level algorithmic analysis framework. First, a three-dimensional feature vector space is constructed based on O*NET data, and representative job types are selected using the feature distance maximization method. Subsequently, a multidimensional evaluation model for task decomposition is proposed, incorporating indicators such as routine nature, cognitive complexity, physical dependency, and creativity into an evaluation vector. Weights are determined using the Analytic Hierarchy Process (AHP), and a nonlinear substitution rate model incorporating a Sigmoid threshold function is constructed to calculate the job impact index. Building upon this foundation, a Logistic growth function characterizes technological maturity. Combined with system dynamics, this establishes an evolutionary model for job demand, numerically solved via the fourth-order Runge–Kutta method to simulate medium-to-long-term demand changes. Concurrently, grey relational analysis identifies key drivers, and a multi-objective optimization model under Stackelberg games is constructed. The NSGA-II algorithm is employed to obtain Pareto optimal solutions. The results demonstrate that this methodology can characterize the synergistic effects of technological substitution and efficiency gains within a unified computational framework, providing a general modeling approach for analyzing job structure evolution in complex technological environments.

KEYWORDS

Generative Artificial Intelligence; NSGA-II; System Dynamics Model

1. INTRODUCTION

In recent years, generative artificial intelligence technologies have rapidly advanced in content production, software development, and digital media, significantly impacting occupational task structures and job requirement patterns. Particularly within the digital entertainment and gaming industries, algorithm-driven content generation, automated programming, and intelligent design tools have progressively integrated into production workflows, altering the task composition and competency demands of traditional roles. Against this backdrop, how to characterize the impact of technological evolution on the task structures and changing demands of different job positions through quantitative modeling methods has become a key issue in current research.

Existing studies predominantly explore technological impacts through statistical analysis or single-indicator assessments. However, such approaches often struggle to simultaneously capture the dynamic relationships among multidimensional factors—such as task attribute differences, technological substitution thresholds, and industrial scale variations—limiting both model interpretability and predictive stability. Consequently, there is a need to develop a comprehensive algorithmic framework that integrates task feature modeling, technological evolution description, and demand dynamics simulation to systematically analyze the mechanisms of job structure evolution within changing technological environments.

To address these challenges, this paper proposes a multi-level modeling approach. First, an occupational representation vector is constructed in the feature space, with representative occupations selected through feature distance optimization. Subsequently, a multidimensional evaluation model based on task decomposition is established, combining the Analytic Hierarchy Process (AHP) with a nonlinear substitution function to calculate occupational impact indices. Building upon this foundation, a dynamic evolution model of occupational demand is developed using a logistic function to characterize technological maturity and incorporating system dynamics. Simultaneously, grey relational analysis identifies key drivers, while a multi-objective optimization model—combining Stackelberg games and the NSGA-II algorithm—enables optimized decisions for educational supply structures [1]. Modeling analysis using gaming industry-related positions validates the proposed algorithmic framework's modeling capabilities and applicability within complex technological environments.

2. OCCUPATIONAL EVOLUTION MODELING FRAMEWORK UNDER GENERATIVE AI

2.1. Strategic Career Selection

To systematically evaluate the impact of Generative AI on employment dynamics within the digital entertainment industry, a feature-maximizing stratified sampling framework is constructed for representative career selection. This framework controls for industry-specific structural heterogeneity and ensures maximal differentiation in AI exposure mechanisms across occupational categories.

(1) Mathematical Modeling of Career Selection

The future evolution of a career is modeled as the result of interactions among multiple structural attributes rather than a single dominant factor. Accordingly, each occupation is embedded into a three-dimensional skill space defined by orthogonal feature vectors.

Based on the O*NET database, the AI impact feature vector for career j is defined as $V_j = [\alpha_j, \beta_j, \gamma_j]$, where: α_j represents the substitution index, measuring the sensitivity of core occupational outputs (e.g., textual, visual, or symbolic production) to AI-driven generation. β_j denotes the physical friction index, capturing the degree of dependence on physical interaction, hardware manipulation, or location-specific constraints that limit digital automation. γ_j denotes the complexity leverage index, reflecting systemic complexity and logical architecture intensity, in which AI primarily functions as a capability amplifier rather than a direct substitute.

These indices are quantified through weighted aggregation of normalized O*NET indicators:

$$\begin{aligned}
\alpha_j &= w_1 \cdot I_{\text{Creative}} + w_2 \cdot I_{\text{Computer}}, \\
\beta_j &= w_3 \cdot I_{\text{Handling}} + w_4 \cdot I_{\text{Context}}, \\
\gamma_j &= w_5 \cdot I_{\text{Solving}} + w_6 \cdot I_{\text{Systems}} + w_7 \cdot I_{\text{Programming}}
\end{aligned} \tag{1}$$

Where I_k denotes the normalized O*NET metric score satisfying $0 \le I_k \le 1$ This formulation ensures structural independence across substitution exposure, physical resistance, and complexity amplification dimensions.

(2) Career Selection Based on Feature-Space Optimization

Occupational data related to the game industry were extracted from the O*NET database and standardized using Min–Max normalization to ensure cross-indicator comparability.

Representative careers were selected according to a maximum feature-vector distance principle within the constructed three-dimensional AI impact space. This optimization strategy guarantees that selected occupations occupy distinct extremal regions of the feature cube, thereby maximizing analytical contrast in AI exposure mechanisms.

Based on this criterion, the following three careers were identified: Game Development Engineer; Motion Capture Technician; Game Art Designer. These occupations correspond respectively to high complexity leverage, high physical friction, and high substitution exposure, forming an orthogonal analytical foundation for subsequent dynamic modeling.

2.2. Task-Based Evaluation Model

To quantitatively measure the heterogeneous impact of Generative AI across occupations, a Task-Based Evaluation Model is constructed. This framework builds upon the task-replacement theory proposed by Autor et al. (2003), which asserts that technological influence on employment is mediated through task composition rather than occupational titles.

Following the standard game development lifecycle, each selected career is decomposed into five core functional tasks, as summarized in Table 1.

Table 1. Task Decomposition of Three Careers

Game Development Engineer		Motion Capture Technician		Game Art Designer	
T_1^{GD}	Game Logic Programming	T_1^{MC}	Equipment Calibration	T_1^{GA}	Concept Design Sketch
T_2^{GD}	Engine Function Development	T_2^{MC}	Capture Data Collection	T_2^{GA}	3D Asset Modeling
T_3^{GD}	AI Algorithm Implementation	T_3^{MC}	Data Cleaning and Processing	T_3^{GA}	Material Texture Drawing
T_4^{GD}	Performance Optimization	T_4^{MC}	Animation Redirection	T_4^{GA}	Scene Level Layout
T_5^{GD}	Cross-platform Adaptation	T_5^{MC}	Real-time Preview Adjustment	T_5^{GA}	Visual Effects Production

(1) Construction of Multidimensional Evaluation Indicators

A four-dimensional evaluation vector is defined for each task: $D_i = (R_i, C_i, P_i, A_i)^T$, where each component is rated on a 10-point scale: $R_i \in [0,10]$: Routine workload, measuring procedural standardization. Higher values indicate stronger automation suitability. $C_i \in [0,10]$: Cognitive complexity, reflecting decision-chain length and knowledge depth. Higher values imply greater resistance to AI substitution. $P_i \in [0,10]$: Physical dependence, indicating reliance on physical operation and on-site interaction. $A_i \in [0,10]$: Creativity level, capturing originality and aesthetic judgment requirements.

This multidimensional representation enables structured quantification of AI exposure across heterogeneous task attributes.

(2) Weight Determination via Analytic Hierarchy Process (AHP) [2]

A pairwise judgment matrix is constructed:

$$B=\begin{bmatrix} 1 & b_{12} & b_{13} & b_{14} \\ \frac{1}{b_{12}} & 1 & b_{23} & b_{24} \\ \frac{1}{b_{13}} & \frac{1}{b_{23}} & 1 & b_{34} \\ \frac{1}{b_{14}} & \frac{1}{b_{24}} & \frac{1}{b_{34}} & 1 \end{bmatrix} \tag{2}$$

The eigenvector corresponding to the maximum eigenvalue λ_{max} is computed $\mathbf{v}=(v_R,v_C,v_P,v_A)^T$. The normalized weight vector is obtained as:

$$v_{norm}=\frac{v}{\sum_k v_k} \tag{3}$$

Consistency is verified using:

$$CR=\frac{CI}{RI}=\frac{(\lambda_{max}-4)/3}{RI}<0.1 \tag{4}$$

Where $RI=0.90$ for a fourth-order matrix. This procedure ensures structural reliability of dimension weights.

(3) Nonlinear AI Substitution Rate Model

Considering the asymmetric substitution capability of Generative AI, a nonlinear substitution function is defined:

$$S_i=\frac{v_R R_i+v_A(10-A_i)}{v_C C_i+v_P P_i+\epsilon}\times\sigma\left(\frac{R_i-\theta_R}{\tau}\right) \tag{5}$$

Where the sigmoid threshold function is:

$$\sigma(x)=\frac{1}{1+e^{-x}} \tag{6}$$

Parameter settings: $\theta_R=5.0$ is routine threshold; $\tau=2.0$ is smoothing parameter; $\epsilon=0.1$ is numerical stability factor.

The substitution rate is normalized into [0,1]:

$$S_i^{norm}=\frac{S_i-S_{min}}{S_{max}-S_{min}} \tag{7}$$

This formulation captures both structural task attributes and threshold-driven nonlinearity.

(4) Occupational AI Impact Index

Let w_i^j denote the task weight of task i in occupation j, satisfying $\sum_i w_i^j = 1$. The AI impact index for occupation j is defined as:

$$I^j = \sum_{i=1}^{n_j} w_i^j \cdot S_i^j \tag{8}$$

To incorporate collaborative productivity gains in creative roles, a synergy adjustment term is introduced:

$$I_{adjusted}^j = I^j \times (1 - \beta^j \cdot \mathrm{I}_{creative}^j) \tag{9}$$

Where $\mathrm{I}_{creative}^j$ is a binary indicator for creative leadership (1 for game development engineers and game art designers; 0 for motion capture technicians).

(5) Substitution Assessment Results

Figure 1 presents the estimated substitution rates across tasks.

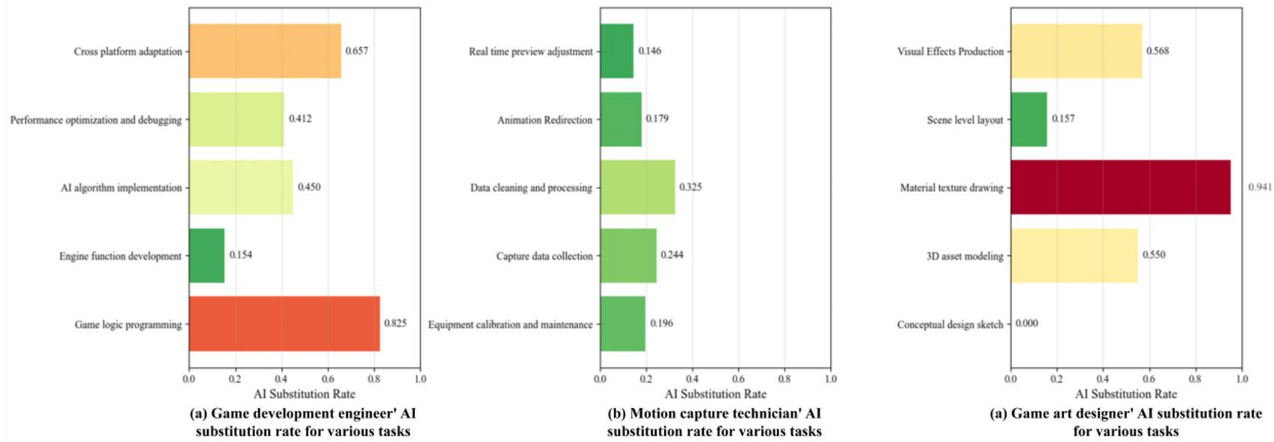

Figure 1. AI substitution rates of various tasks for each career

Game logic programming exhibits the highest substitution rate among development tasks, consistent with the increasing adoption of AI-assisted code generation.

For motion capture technicians, substitution probabilities remain relatively low, with data cleaning and processing being the most exposed task due to AI's strengths in structured data handling.

For game art designers, material texture drawing shows the highest substitution exposure, reflecting advances in AI-based image generation.

The resulting AI impact indices are: Game Development Engineer: 0.5223; Game Art Designer: 0.4463; Motion Capture Technician: 0.2319.

These results indicate that development and art roles exhibit significantly higher structural AI exposure, while motion capture retains relative resistance due to physical interaction constraints.

2.3. Labor Demand Forecasting Model Based on System Dynamics

(1) Logistic Growth Model of AI Technology Maturity

The evolution of Generative AI technological capability is modeled using a logistic growth function, reflecting an S-shaped development trajectory characterized by early-stage acceleration and late-stage saturation [3]:

$$\alpha(t) = \frac{K}{1 + e^{-r(t-t_0)}} \tag{10}$$

Where K denotes the upper bound of technological maturity, r represents the intrinsic growth rate, t_0 is the inflection point of technological acceleration.

Parameter calibration is based on empirical observations of large language model iteration cycles. The upper maturity bound is set as $K = 0.95$, the annual growth rate as $r = 0.35$, and the technological turning point as $t_0 = 2029$. This configuration captures the rapid scaling phase of Generative AI while accounting for eventual performance convergence.

(2) Coupled Dynamic System of Labor Demand

Labor demand is modeled as a nonlinear time-varying differential system incorporating three interacting effects:

$$\frac{dL_j(t)}{dt} - \lambda_j I^j \alpha(t) L_j(t) + \mu_j \alpha(t) M(t) + v \frac{dM(t)}{dt} \tag{11}$$

Where: $L_j(t)$ denotes labor demand for occupation j, I^j represents the AI impact index, λ_j is the substitution sensitivity coefficient, μ_j captures productivity amplification effects, v represents market-driven demand elasticity, $M(t)$ denotes total market size of the gaming industry.

The three components correspond respectively to:

1. Substitution Effect: AI directly reduces labor demand through task automation.
2. Productivity Effect: AI enhances output efficiency, generating complementary labor demand.
3. Market Size Effect: Industry expansion indirectly increases employment demand.

The market size evolution is modeled as:

$$M(t) = M_0 \cdot e^{gt} \cdot (1 + \delta\alpha(t)) \tag{12}$$

Where M_0 is the initial market size, g is the baseline market growth rate, δ captures AI-driven market expansion intensity.

This formulation establishes a feedback loop between technological maturity and industry growth.

(3) Ten-Year Labor Demand Forecast

The coupled differential system is solved numerically using the fourth-order Runge–Kutta method to ensure stability and accuracy. Simulation results over a ten-year horizon are presented in Figure 2.

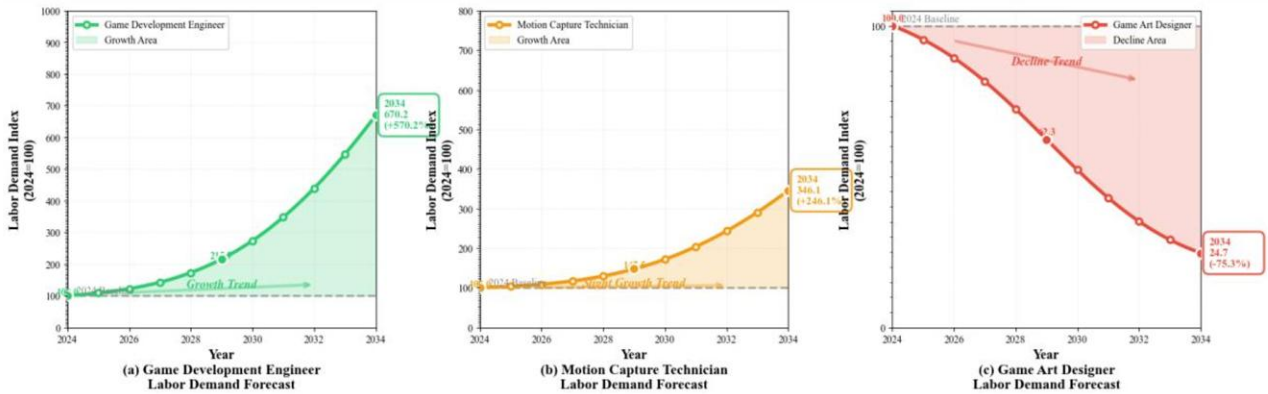

Figure 2. The forecast for labor demand in the next 10 years

According to Figure 2 (a), labor demand exhibits strong exponential growth, reaching a 570.2% increase in 2034 relative to 2024. This surge is primarily driven by the productivity effect, as AI-assisted code generation and engine integration substantially increase development throughput. Additionally, AI-enabled procedural content generation introduces hybrid technical roles that combine engineering and AI orchestration capabilities.

According to Figure 2 (a), demand increases by 246.1% over the same period. Although AI tools can synthesize basic animation sequences, high-fidelity motion capture remains essential for AAA-level production. The strong physical interaction component embedded in this occupation provides structural resistance to substitution.

According to Figure 2 (a), in contrast, labor demand declines by 75.3% by 2034. While high-level aesthetic direction and intellectual property design remain human-dominated, AI systems demonstrate high efficiency in texture synthesis, concept iteration, and asset variant generation. This dynamic is projected to reshape the occupational structure toward a hierarchical model with fewer production-level roles and greater concentration in creative supervision functions.

Overall, the simulation reveals asymmetric AI exposure across occupational categories, confirming that technological substitution and productivity amplification coexist within a unified dynamic framework.

2.4. Driving Factor Identification Model

(1) Grey Relational Analysis Framework

To identify the dominant drivers influencing labor demand dynamics, Grey Relational Analysis (GRA) is employed. Based on structural characteristics of the gaming industry, eight key driving factors are selected $X = X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8$ [4].

The selected factors are: X_1: AI text generation capability; X_2: AI image generation quality; X_3: AI animation generation quality; X_4: Engine–AI integration level; X_5: Computational cost; X_6: Cross-platform demand; X_7: Player acceptance; X_8: Regulatory policy.

The reference sequence is defined as the relative change rate of labor demand for occupation j:

$$Y_j = y_j(t_1), y_j(t_2), \ldots, y_j(t_n), y_j(t_k) = \frac{L_j(t_k) - L_j(t_1)}{L_j(t_1)} \tag{13}$$

Each driving factor forms a comparative time series $X_i = x_i(t_1), x_i(t_2), \ldots, x_i(t_n)$.

Initial value normalization is applied to remove dimensional heterogeneity:

$$x_{i'}(t_k)=\frac{x_i(t_k)}{x_i(t_1)},\quad y_{j'}(t_k)=\frac{y_j(t_k)}{y_j(t_1)} \tag{14}$$

The relational coefficient between factor X_i and occupation j at time t_k is defined as:

$$\xi_{ij}(t_k)\frac{\min_i \min_k |y_{j'}(t_k)-x_{i'}(t_k)|+\rho \max_i \max_k |y_{j'}(t_k)-x_{i'}(t_k)|}{|y_{j'}(t_k)-x_{i'}(t_k)|+\rho \max_i \max_k |y_{j'}(t_k)-x_{i'}(t_k)|} \tag{15}$$

Where $\rho=0.5$ is the resolution coefficient.

The overall grey relational degree is computed as:

$$\gamma_{ij}=\frac{1}{n}\sum_{k=1}^{n}\xi_{ij}(t_k), \text{with } \gamma_{ij}\in[0,1] \tag{16}$$

A larger value indicates stronger structural influence of driving factor X_i on occupation j.

(2) Results and Interpretation

The computed grey relational degrees are visualized in Figure 3.

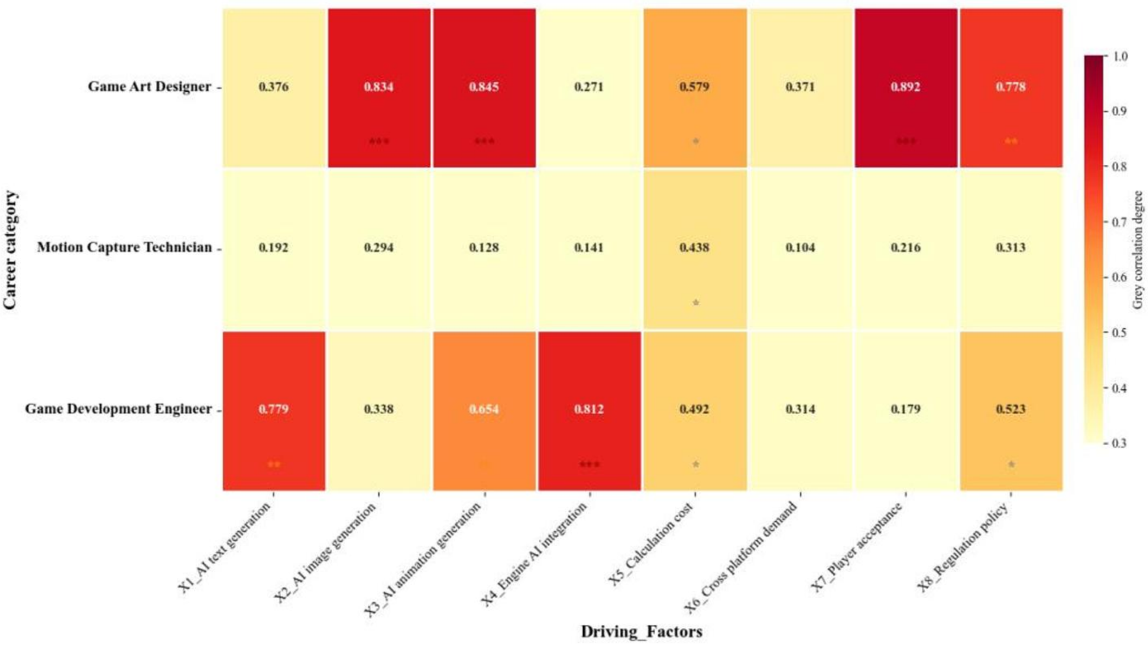

Figure 3. Grey correlation analysis heatmap of driving factors

The following conclusions can be drawn from Figure 3:

Game Art Designer: Player acceptance (X_7) exhibits the highest relational degree, indicating that market perception critically determines labor demand fluctuations in artistic roles. AI image and animation generation quality (X_2, X_3) follow as secondary drivers, reflecting rapid progress in generative visual models.

Motion Capture Technician: Overall sensitivity to AI-related factors is comparatively low. Computational cost (X_5) emerges as the most influential variable. The physical interaction barrier embedded in motion capture workflows limits direct technological substitution.

Game Development Engineer: Engine–AI integration level (X_4) is identified as the dominant driver, suggesting that deep embedding of AI tools into development engines significantly reshapes labor demand. AI text generation (X_1) and animation generation (X_3) also show notable correlation, likely due to their efficiency gains in development pipelines.

Overall, the GRA results validate that AI impact is mediated through distinct structural pathways across occupational categories, reinforcing the asymmetric exposure identified in the dynamic simulation model.

3. OPTIMIZATION MODEL BASED ON STACKELBERG GAME THEORY

Under rapid technological advancement of Generative AI, enrollment planning and curriculum reform require quantitative decision support. The interaction between industry demand and educational institutions is modeled as a Stackelberg game, where the industry acts as the leader determining labor demand, and educational institutions act as followers adjusting training supply.

The problem is formulated as a dynamic multi-objective optimization framework. Two objectives are simultaneously considered: maximizing employment competitiveness and minimizing reform cost, while accounting for technological evolution and market uncertainty [5].

3.1. Model Formulation

For career i ($i = 1, 2, 3$), decision variables are defined as: S_i is annual enrollment scale; $\beta_i \in [0,1]$ is degree of AI integration in curriculum; $\theta_i = (\theta_{i1}, \theta_{i2}, \theta_{i3}, \theta_{i4}, \theta_{i5})$ is curriculum structure parameters.

The parameters represent: θ_{i1} is proportion of traditional courses with AI integration ; θ_{i2} is number of newly added AI courses; θ_{i3} is AI practice hours ; θ_{i4} is AI ethics weight ; θ_{i5} is AI evaluation weight.

Objective 1: Employment Competitiveness Maximization

$$\max F_1 = \sum_{i=1}^{3} \omega_i \cdot C_i(S_i, \beta_i, \theta_i) \tag{17}$$

The employment competitiveness index is defined as:

$$C_i = w_1 \cdot \exp\left(-\frac{(S_i - D_i)^2}{2\sigma_i^2}\right)\left(1 - |\beta_i - \alpha_i|^\gamma\right) + w_2 \cdot \sum_{k=1}^{5} \lambda_k \left(1 - e^{-b_k \theta_{ik} \beta_i}\right) \tag{18}$$

The first term penalizes deviation between enrollment supply S_i and industry demand D_i, while the second term captures skill enhancement induced by AI curriculum integration.

Objective 2: Reform Cost Minimization

$$\min F_2 = \sum_{i=1}^{3} \left[c_1 |\Delta S_i| + c_2 (\Delta S_i)^2 + c_4 \beta_i S_i + c_5 \theta_{i2} + c_7 S_i (1 + c_8 \beta_i) \right] \tag{19}$$

This objective reflects adjustment cost, curriculum integration expenditure, and scale-dependent operational costs.

Constraints:

$$\begin{cases} S_i^{\min} \le S_i \le S_i^{\max} \\ \left|\Delta S_i / S_i^0\right| \le 0.3 \\ \sum_{i=1}^{3} S_i\left(1+c_{10}\beta_i\right) \le B_{\text{total}} \\ 0 \le \beta_i \le 1 \\ \theta_{i1}+\theta_{i4} \le 0.4 \\ 0 \le \theta_{i2} \le 8 \\ \text{ACI}_i \ge Q_{\min} \end{cases} \tag{20}$$

The constraint system ensures budget feasibility, bounded enrollment variation, curriculum structural rationality, and academic quality requirements.

3.2. Solution via NSGA-II

The dual-objective optimization problem is solved using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), which provides stable convergence toward the Pareto frontier [6, 7].

Algorithm parameters: set population size as 100 and set iterations as 200.

After generating the Pareto solution set, a compromise solution is selected using the ideal-point distance metric:

$$d_j = \sqrt{0.5\left(\frac{F_1^* - F_1^j}{F_1^* - F_1^{nadir}}\right)^2 + 0.5\left(\frac{F_2^j - F_2^*}{F_2^{nadir} - F_2^*}\right)^2} \tag{21}$$

Where F_1^* and F_2^* denote ideal values, and F_1^{nadir} and F_2^{nadir} denote worst-case values within the Pareto set.

The solution corresponding to $\min d_j$ is selected as the final decision.

3.3. Optimization Results

The resulting Pareto frontier is shown in Figure 4.

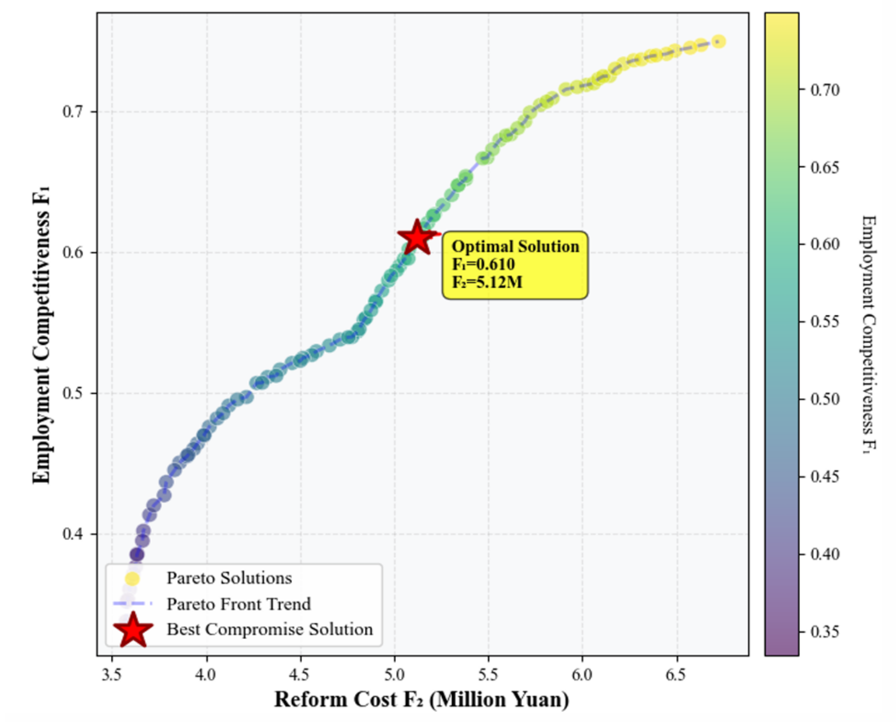

Figure 4. Pareto front and optimal solution selection

NSGA-II successfully identifies a well-distributed Pareto front. The selected compromise solution yields: Employment competitiveness index is 0.61; Reform cost is 5.12 million. The results demonstrate effective trade-off balancing between labor market alignment and institutional resource constraints.

4. CONCLUSIONS

This paper constructs an analytical framework integrating multiple algorithmic models to address changes in job task structures and requirements within the context of generative AI technology. Representative occupations are selected through feature vector space modeling and feature distance optimization methods. A multidimensional evaluation index system is established based on task decomposition, combining the Analytic Hierarchy Process (AHP) with nonlinear substitution functions to calculate job impact indices. Building upon this foundation, the Logistic Technology Readiness Model and system dynamics equations are introduced to establish a job demand evolution model, with numerical methods employed for simulation and prediction. Results indicate significant variations in job sensitivity to generative AI: Game Development Engineers and Game Art Designers exhibit impact indices of 0.5223 and 0.4463 respectively, while Motion Capture Technicians register 0.2319. Grey relational analysis further indicates that player acceptance and the level of engine-AI integration are key factors influencing job demand changes. Overall, this model framework effectively captures the combined impact of technological substitution and efficiency gains, providing quantitative references for talent development and structural adjustments in related fields. Future research may integrate additional industry data to dynamically optimize model parameters and conduct expanded analyses.

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