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The Assessment of Generative AI's Impact on Occupations and the Optimization of Educational Resources Based on Game Theory Weighting and Lotka-Volterra Dynamics

Liye Wang[1], Yinuo Chen[2], Zheng Hou[3]*

[1]China School of Banking and Finance, University of International Business and Economics, Beijing 100029, China

[2]School of International Development and Cooperation, University of International Business and Economics, Beijing 100029, China

[3]School of Foreign Studies, University of International Business and Economics, Beijing 100029, China

*Rochelimit2025@outlook.com

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ABSTRACT

The rapid development of generative artificial intelligence is profoundly reshaping the global labor market, compelling higher education institutions to undertake structural reforms. This study constructs a data-driven comprehensive evaluation and optimization framework aimed at precisely quantifying the impact of AI on different occupations and providing scientifically grounded educational strategies. The study first integrates the Nash equilibrium theory with the Analytic Hierarchy Process (AHP) and the Entropy Weighting Method to construct an occupational resilience evaluation model comprising five criterion levels and 13 indicators. The evaluation results show that musicians exhibit the highest resilience due to high barriers to imitation, while software engineers are the most vulnerable because their core skills are highly exposed to large language models. Subsequently, the study utilizes the Bass diffusion model to predict the macro-level penetration rate of Gen-AI and couples it with an improved Lotka-Volterra predator-prey framework to simulate the evolutionary trajectory of the human-machine labor market. Projections indicate that by 2040, employment for software engineers and welders will experience positive growth, whereas musicians will face the severe challenge of niche contraction. Finally, this study developed an educational resource allocation optimization model. Solving it via a sequential quadratic programming algorithm revealed that a collaboration-driven curriculum strategy is the global optimal solution for enhancing graduates' market competitiveness. Sensitivity analysis confirms that this strategy maintains extremely high robustness under fluctuations in multiple parameters.

KEYWORDS

generative artificial intelligence, occupational resilience, lotka-volterra model

INTRODUCTION

The proliferation of generative artificial intelligence (Gen-AI) marks a structural rupture in labor economics. Unlike traditional automation targeting repetitive physical labor, Gen-AI demonstrates the ability to produce complex cognitive outputs such as code generation and artistic creation, meaning that automation risks are no longer defined solely by educational attainment but depend on the specific nature of the task being performed. Against this backdrop, higher education institutions face an urgent mandate for reform, requiring a shift in teaching focus from “knowledge retention” to “AI-complementary skills”. While previous studies have largely employed task-based frameworks or Skill-Biased Technological Change (SBTC) theory to deconstruct technological shocks, quantitative research addressing the dynamic process of AI penetration and the co-evolution of human-machine symbiosis remains limited [1,2]. The innovation of this section lies in the first-ever incorporation of the Nash equilibrium from game theory into the weighting of evaluation indicators to balance subjective and objective biases, and the creative application of predator-prey models from ecology to the dynamic game between AI and the labor market, thereby achieving a closed-loop research framework that progresses from static assessment to dynamic simulation and ultimately to strategy optimization. The overall research framework is as follows: First, authoritative data from multiple sources, such as O*NET and the BLS, are collected to establish occupational resilience benchmarks using a combination of game-theoretic weighting and the TOPSIS method; second, the Bass model is employed to characterize technology diffusion curves, and the Lotka-Volterra equations are utilized to forecast long-term employment trends; Finally, a multi-objective optimization model targeting employment, innovation, and social responsibility is established to determine the optimal curriculum allocation ratio, and exhaustive sensitivity tests are conducted to verify the generalizability of the conclusions [3].

ASSESSING GEN-AI’S OCCUPATIONAL IMPACT VIA GAME THEORY COMBINATION WEIGHTING

Data Description and Preprocessing

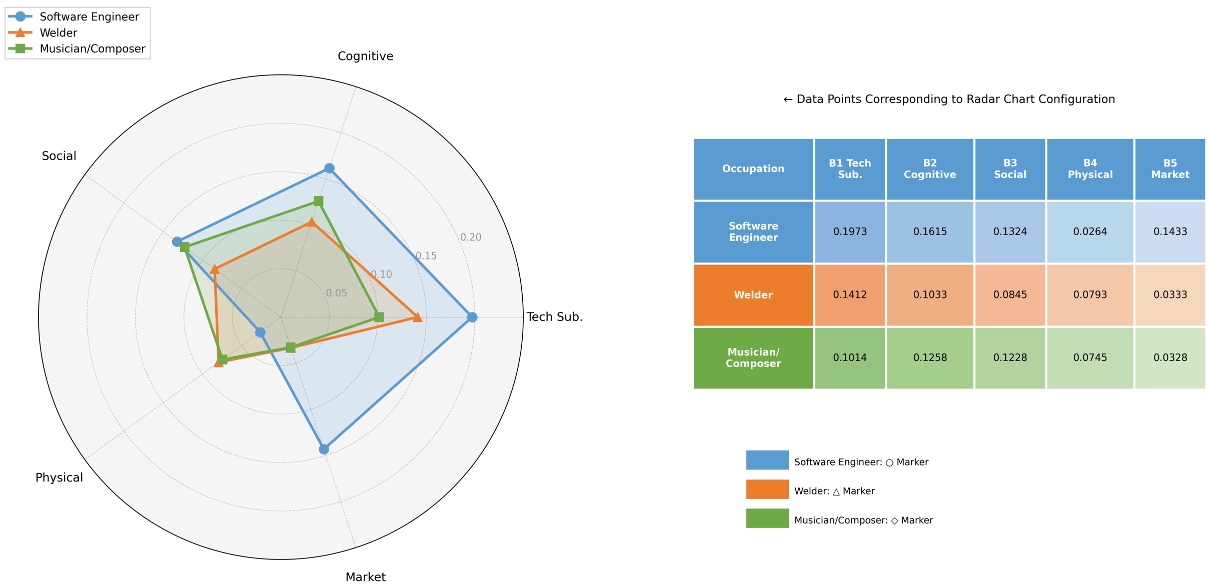
The complete indicator system for this study is presented in Table 1. Table 1 employs the Min-Max transformation method to eliminate dimensional differences. Based on the direction of contribution to occupational resilience, benefit-oriented and cost-oriented indicators undergo positive and inverse standardization, respectively. Data is uniformly mapped to the [0, 1] range, ensuring higher values indicate stronger occupational resilience to meet subsequent modeling requirements [4,5].

Table 1. Gen-AI occupational impact evaluation indicator system

Criterion Level	ID	Indicator Name	Data Source	Type
B1 Technology Substitution	C1	Probability of Traditional Automation	Frey & Osborne	Negative
	C2	LLM Task Exposure	Eloundou et al.	Negative
	C3	Job Repetitiveness	O*NET	Negative
B2 Cognitive Barriers	C4	Originality	O*NET	Positive
	C5	Critical Thinking	O*NET	Positive
	C6	Complex Problem Solving	O*NET	Positive
B3 Social Barriers	C7	Social Perceptiveness	O*NET	Positive
	C8	Persuasiveness	O*NET	Positive
	C9	Caring for Others	O*NET	Positive
B4 Physical Barriers	C10	Manual Dexterity	O*NET	Positive
	C11	Finger Dexterity	O*NET	Positive
B5 Market Performance	C12	Employment Growth Rate	BLS	Positive
	C13	Median Annual Salary	BLS	Positive

Multidimensional Data Visualization Analysis

Figure 1 displays the distribution and scores of the five standardized indicators for software engineers, welders, and musicians [6,7].



Occupation	B1 Tech Sub.	B2 Cognitive	B3 Social	B4 Physical	B5 Market
Software Engineer	0.1973	0.1615	0.1324	0.0264	0.1433
Welder	0.1412	0.1033	0.0845	0.0793	0.0333
Musician/ Composer	0.1014	0.1258	0.1228	0.0745	0.0328

Figure 1. Five-dimensional capability radar chart and standardized score table

As seen in Figure 1, software engineers exhibit cognitive dominance yet face typical “high-skill fragility” due to the digital-centric nature of their professional outputs, which currently lack the physical interaction constraints (Moravec Paradox) that provide natural resilience for manual-intensive roles. Welders validate the Moravec Paradox through physical dexterity, establishing a robust defense against digital automation. Musicians leverage high originality and social obstacles to secure survival advantages difficult for algorithms to replicate [8].

Establishing a Game-Theoretic Weighting Model

To ensure scientific evaluation, this study introduces a game-theoretic combination weighting model. Treating AHP and entropy weighting as two players in a game, it minimizes combination bias by identifying Nash equilibrium points, effectively achieving a Pareto-optimal fusion of subjective expertise and objective data.

Player I: Subjective Weighting Based on AHP

First, the subjective weight vector is constructed using the Analytic Hierarchy Process (AHP). Based on the findings of Eloundou et al [4], the criterion-level judgment matrix A is established as follows:

$$A = \begin{bmatrix} 1 & 2 & 2 & 3 & 3 \\ 1/2 & 1 & 1 & 2 & 2 \\ 1/2 & 1 & 1 & 2 & 2 \\ 1/3 & 1/2 & 1/2 & 1 & 1 \\ 1/3 & 1/2 & 1/2 & 1 & 1 \end{bmatrix} \tag{1}$$

The weight vector W_1 is solved using the eigenvalue method. Calculations yield the maximum eigenvalue $\lambda_{\max} = 5.0058$. The consistency index CI and consistency ratio CR (with $RI = 1.12$) are calculated as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} = \frac{5.0068 - 5}{4} = 0.0017 \tag{2}$$

$$CR = \frac{CI}{RI} = \frac{0.0017}{1.12} = 0.0015 < 0.10 \tag{3}$$

Since $CR < 0.1$, the judgment matrix passes the consistency test, and the obtained weight vector W_1 is valid [9].

Player II: Objective Weighting Based on Entropy Weighting

Next, the entropy weight method is employed to extract objective information from the data. For the j-th indicator, its information entropy e_j is defined as:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} p_{ij}\ln p_{ij} \tag{4}$$

where $p_{ij} = z_{ij}/\sum_{i=1}^{m} z_{ij}$ represents the proportion of the j-th sample in the i-th indicator. The greater the coefficient of variation $d_j = 1 - e_j$ for an indicator, the more it distinguishes between evaluation subjects, thereby providing more information and justifying a higher weight:

$$w_j = \frac{d_j}{\sum_{k=1}^{n} d_k} \tag{5}$$

Core Game: Derivation and Solution of Nash Equilibrium Weights

To integrate W_1 and W_2 , we construct a game-theoretic portfolio weighting model.

Step 1: Define the composite weight vector as a linear combination:

$$W = \alpha W_1^T + \beta W_2^T \tag{6}$$

where α and β represent the combination coefficients for subjective and objective weights, respectively, and $\alpha, \beta > 0$

Step 2: Establish a game objective function to minimize the Euclidean distance deviation between the combined weight and the subjective/objective weights:

$$\min\left(\| \alpha W_1^T + \beta W_2^T - W_1^T \|_2^2 + \| \alpha W_1^T + \beta W_2^T - W_2^T \|_2^2\right) \tag{7}$$

Step 3: Model Solution and Results. Based on the first-order differentiation principle, differentiate α and β and set them equal to zero to construct a system of linear equations for solution. After normalization processing, the optimal combination coefficients are obtained:

$$\alpha = 0.6353, \beta = 0.3647 \tag{8}$$

Geometric Visualization of Game Equilibrium

To intuitively grasp the mathematical principles of combinatorial weighting in game theory, we introduce a geometric visualization framework to explain the process of solving Nash equilibria in Figure 2.

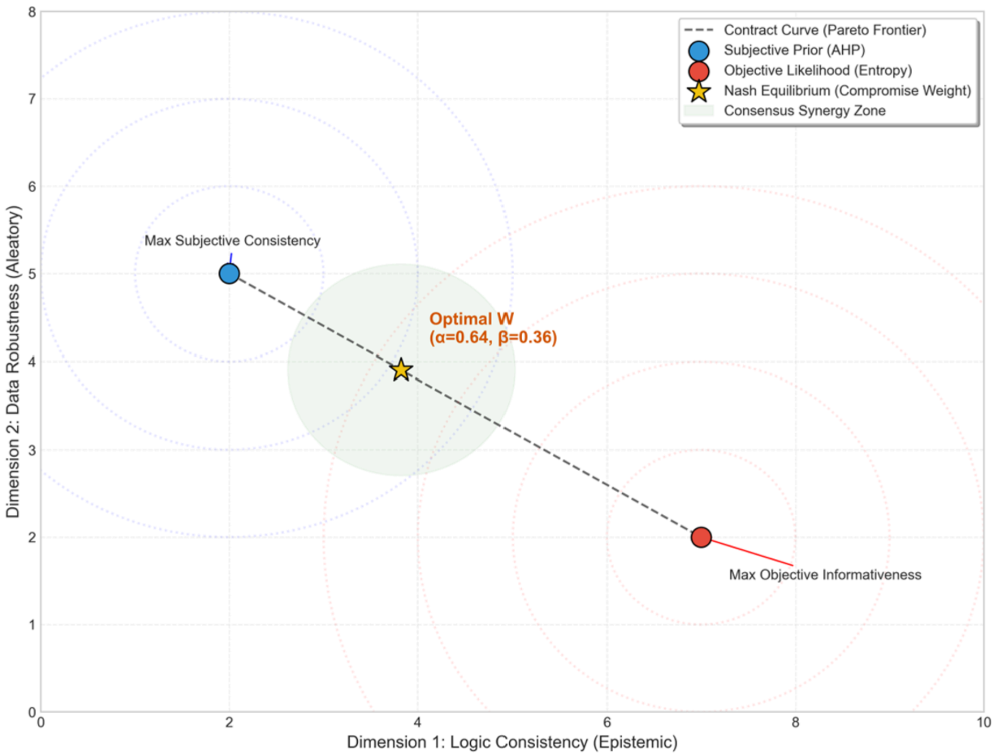


Figure 2. Geometric visualization of game-theoretic combination weighting

The golden star position in the figure represents the computed optimal weight W^* , i.e., the Nash equilibrium point. At this state, any unilateral adjustment of weight ratios by any player would disrupt the equilibrium [10-12].

Final Combined Weight Distribution

After combination weighting, the final weight distribution for the 13 indicators is shown in Figure 3.

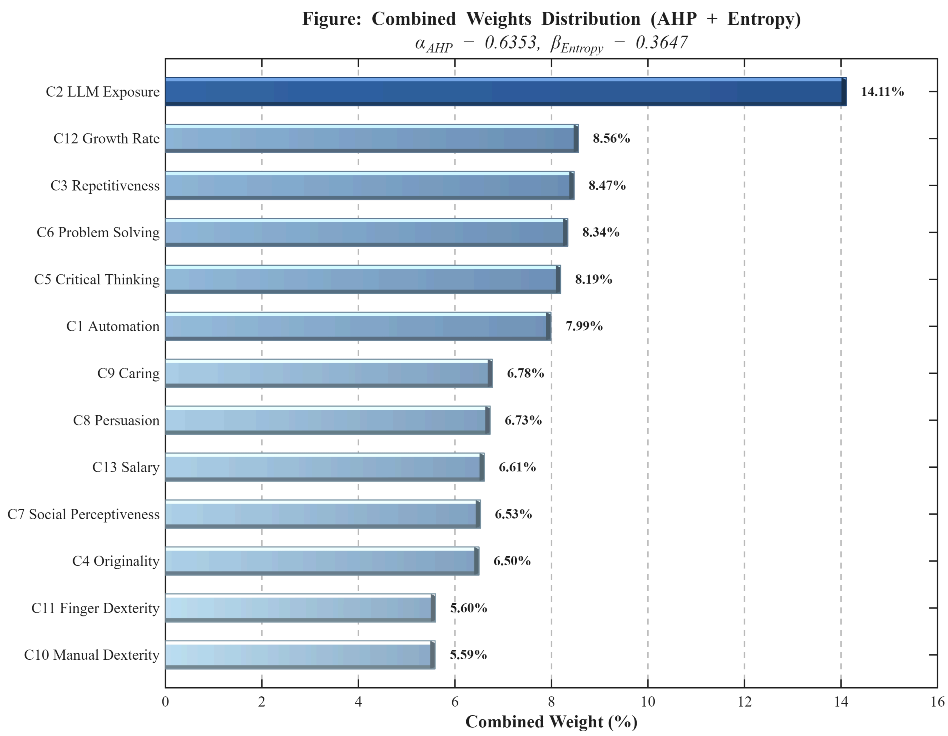


Figure 3. Combined weight distribution of 13 indicators ($\alpha_{AHP} = 0.6353$, $\beta_{Entropy} = 0.3647$)

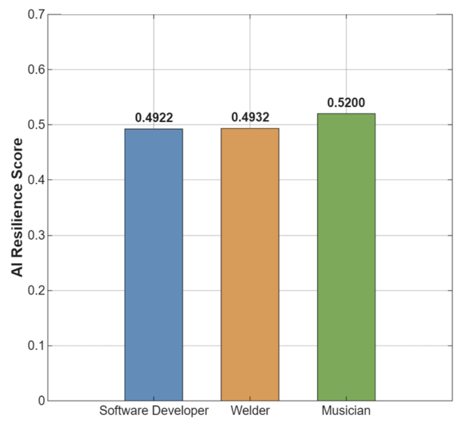
C2 (LLM Task Exposure) dominates with a weight of 14.11%-roughly 1.6 times that of the second-ranked metric. However, this weight reflects the state of widespread Gen-AI adoption by 2024. Noting that while AI technology has evolved for decades, the launch of ChatGPT in late 2022 marked the definitive inflection point for widespread public awareness and rapid industrial-scale labor market penetration [13-15].

Model Solving and Occupational Resilience Analysis

The TOPSIS method calculates the relative proximity (C_i) by measuring the Euclidean distance between the evaluation object and both the 'positive ideal solution' (D^+ , where all indicators are optimal) and the 'negative ideal solution' (D^- , where all indicators are suboptimal):

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{9}$$

A higher value indicates greater resilience for the profession in the Gen-AI era. The calculation results are shown in Figure 4.



Rank	Occupation	D+	D-	AI Resilience Score	Rating
1	Musician (Arts)	0.1002	0.1085	0.5200	High
2	Welder (Trade)	0.1211	0.1179	0.4932	Medium
3	Software Engineer (STEM)	0.1218	0.1180	0.4922	Low

Musician (Arts): High   Welder (Trade): Medium   Software Engineer (STEM): Low

Figure 4. AI resilience composite score bar chart

This ranking reveals a distinct logic of occupational differentiation: Musicians top the list $S = 0.5200$, facing minimal disruption due to their high originality and social barriers; While software engineers face the greatest risk of technological displacement $S = 0.4922$, owing to the extreme exposure of core coding skills to large language models.

Notably, these scores represent a static snapshot from 2024. Chapter 3 will reveal a crucial dynamic pattern: as Gen-AI proliferates, software engineers' resilience scores will decline from 0.607 in 2015 to 0.512 in 2040, while welders' scores will rise from 0.295 to 0.430. This structural redistribution of labor among occupations profoundly validates Gen-AI's differentiated impact mechanism across occupations [16].

EMPLOYMENT EVOLUTION: RESILIENCE ASSESSMENT AND FORECASTING UNDER AI SHOCK

Data Description and Macro Diffusion Model

Parameter Fitting for Occupational Natural Growth Rates

In order to accurately isolate the impact of Gen-AI, an interference-free baseline trend must be established. Based on BLS historical data from 2015 to 2024, macroeconomic factors were excluded, and the differential method was employed to calculate the natural growth rate (r) for each occupation, serving as the prediction benchmark [17,18].

Software Engineer: $r_{SoftwareEngineer} = -0.53\%$. The baseline growth rate calculated here reflects the mature and saturated state of the traditional software engineering labor market before the intervention of generative AI. This low-growth baseline can effectively isolate the impact of non-AI factors and provide an accurate comparative background for evaluating the 'Jevons Paradox' (i.e., efficiency improvement driving demand growth) brought by AI empowerment. This figure indicates the industry has entered a mature phase, exhibiting a slight negative growth trend due to market saturation.

Welder: $r_{Welder} = +0.79\%$. This growth rate benefits from the rigid demand driven by physical infrastructure development and energy transition, enabling the profession to maintain stable natural growth.

Musician: $r_{Musician} = -14.14\%$. This staggering decline rate reveals that the future decline of this profession may stem primarily from the deterioration of the industry's ecosystem itself, rather than solely from AI substitution.

Macro Adoption Rate Prediction for Gen-AI Based on the Bass Model

To quantify the temporal dimension of "technological shock," we introduce the Bass Diffusion Model. This classic tool for predicting market diffusion of innovative technologies assumes adoption is driven by two groups: "innovators" and "imitators."

Step 1: Construct the differential equation for the change rate of Gen-AI adoption rate $f(t)$ at time t

$$f(t) = \frac{dF(t)}{dt} = (p + qF(t))(1 - F(t)) \tag{10}$$

Where:

$F(t)$: Cumulative market adoption rate ($0 \leq F(t) \leq 1$) up to time t

p: Coefficient of Innovation

q: Coefficient of Imitation

Step 2: Select empirical data.

McKinsey global survey Gen-AI adoption rates is shown in Table 2.

Table 2. Gen-AI enterprise adoption rates based on McKinsey Global Surveys (2024-2025)

Year	2022	2023	2024	2025
Gen-AI Adoption Rate	33%	55%	71%	79%

The 79% ratio here refers to enterprises integrating AI tools in some business processes to improve productivity, rather than the full automation of positions in the industry.

Nonlinear least squares were employed to optimize the parameters of the Bass model, yielding the following optimal parameter estimates:

$$p = 0.30, q = 0.92 \tag{11}$$

Combining the values of p and q, the diffusion curve of Gen-AI exhibits a “front-loaded burst” characteristic. It skipped the lengthy market introduction phase and entered the exponential growth stage almost immediately, which means AI’s impact on employment will be swift and severe [19,20].

Dynamic Weight-Based Modified TOPSIS Evaluation

Construction of the LLM Exposure Weight Growth Equation

To quantify the dynamic evolution of LLM exposure weights (denoted as C2) over time, we developed a weight growth equation mapping adoption rate $F(t)$ to weight space $w_{C2}(t)$:

$$w_{C2}(t) = w_{C2,min} + \left(w_{C2,max} - w_{C2,min}\right) \cdot F(t) \tag{12}$$

Where:

$w_{C2,min} = 0.02$: Initial weight prior to Gen-AI surge

$w_{C2,max} = 0.1411$: Saturated weight derived from entropy weighting.

Figure 5 reveals the dynamic transmission chain of “macro diffusion-micro evaluation”: During the initiation phase (2022-2024), driven by a high innovation coefficient p, AI risks begin to emerge; in the acceleration phase (2025-2030), propelled by a high imitation coefficient q, sharply rising weights trigger a “paradigm shift” in occupational evaluations; Finally, during the Saturation Phase (2035–2040), the chain stabilizes at 0.1411, signifying the transformation of AI risk from a dynamic variable into a constant constraint, completing the long-term internalization of technological disruption.

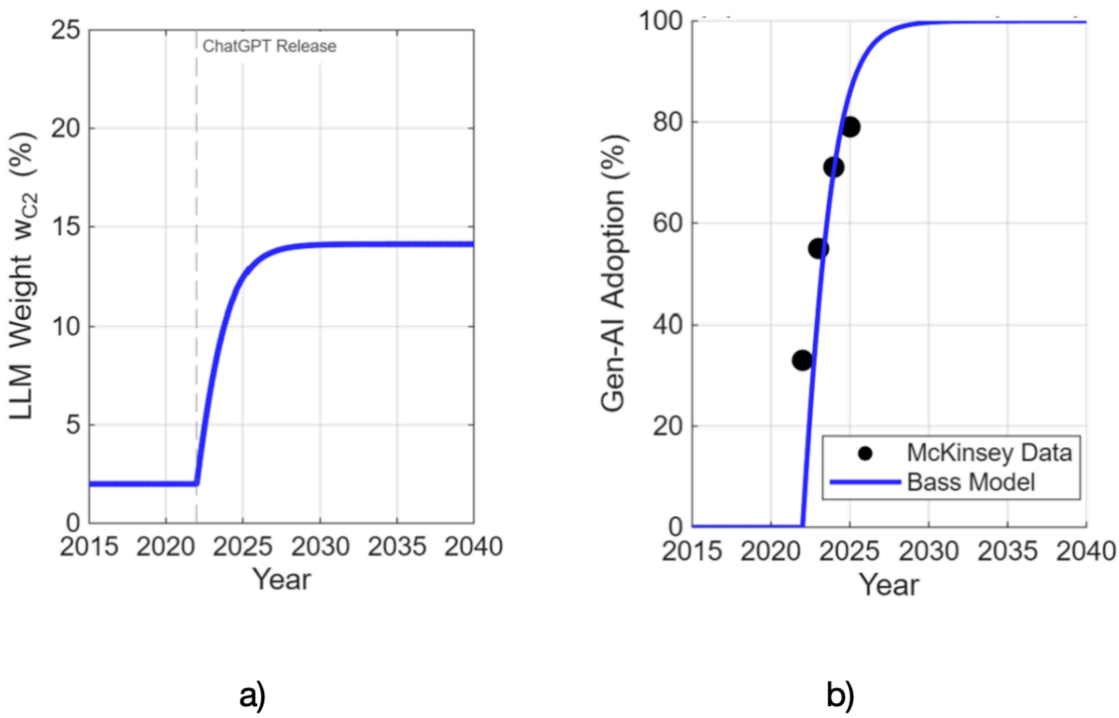


Figure 5. The coupling mechanism of Gen-AI diffusion and dynamic weight evolution: (a) Gen-AI diffusion curve based on Bass model; (b) Dynamic evolution of C2 indicator weights

As shown in Figure 5(a), in the startup phase (2022–2024), driven by the high innovation coefficient p, AI risks begin to emerge; as shown in Figure 5(b), in the acceleration phase (2025–2030), driven by the high imitation coefficient q, the rapid rise of weights triggers a “paradigm shift” in occupational assessment.

Dynamic TOPSIS Score Calculation

Based on the time-varying weight vector $W(t)$, we dynamically extend the standard TOPSIS process to compute the annual resilience score for each profession. The dynamic resilience score $S_i(t)$ for occupation i at time t is defined as the relative proximity to the negative ideal solution:

$$S_i(t) = \frac{D_i^-(t)}{D_i^+(t) + D_i^-(t)} \tag{13}$$

Based on the above model, we obtained the resilience score evolution data for the three target occupations from 2015 to 2040 (see Table 3).

Table 3. Dynamic TOPSIS scores for occupations, 2015-2040

Year	Software Engineer (SE)	Welder	Musician
2015	0.607	0.295	0.637
2022	0.607	0.295	0.637
2024	0.550	0.380	0.626
2030	0.512	0.430	0.618
2040	0.512	0.430	0.618

Table 3 highlights a significant disparity in occupational resilience. Software engineers face the risk of "de-skilling" due to high LMM exposure. Conversely, welders are less affected by these trends because their physical skills are irreplaceable, which aligns with the "Moravec Paradox." Conversely, musicians demonstrate relatively high resilience by leveraging the "humanity" barrier that is inherent in the process of artistic creation.

Employment Evolution Prediction Based on the Lotka-Volterra Model

Parameter Transformation and Coupling with Occupation-Specific Penetration Rate

We first define the dynamic Vulnerability Coefficient $V_i(t)$ to translate abstract resilience scores into concrete employment impacts:

$$V_i(t) = 1 - S_i(t) \tag{14}$$

This coefficient directly measures the exposure of occupation i to technological displacement at time t. The macro Gen-AI adoption rate $F(t)$ represents the overall technological water level across society, but different occupations face varying degrees of actual "flooding." By multiplying the macro adoption rate with micro vulnerability, we obtain the occupation-specific penetration rate:

$$F_{career,i}(t) = F(t) \cdot V_i(t) \tag{15}$$

Figure 6 clearly reveals a divergent trend: the vulnerability of software engineers increases over time, while that of welders decreases. This results in AI penetration rates approaching 50% for software engineers by 2030, compared to only around 38% for musicians.

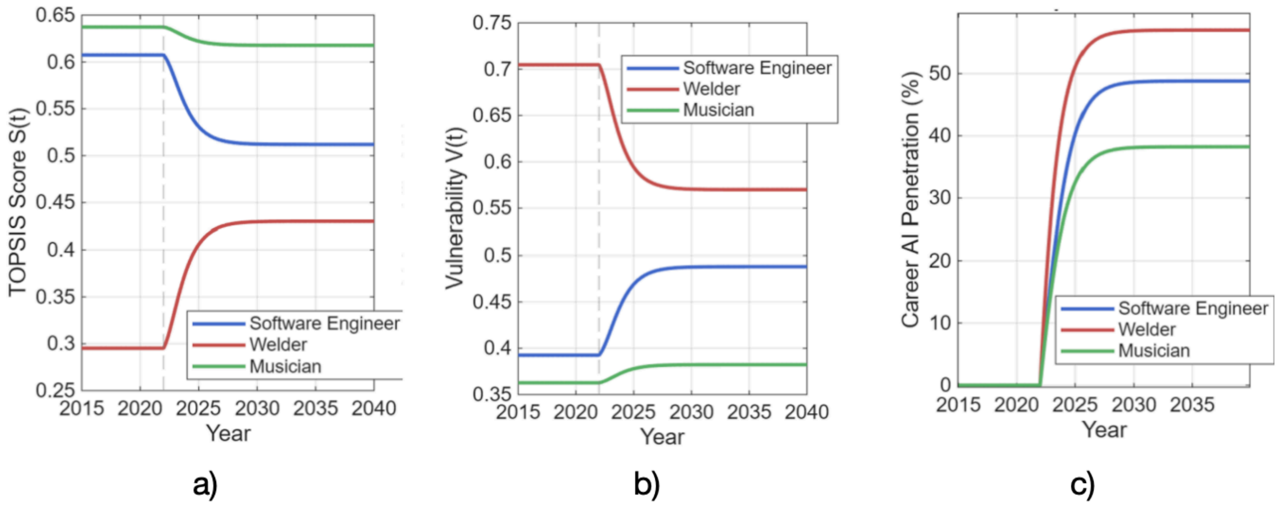


Figure 6. The transmission chain of AI impacto: (a) Evolution of dynamic vulnerability coefficients; (b) Occupation-specific AI penetration rates; (c) Integrated impact transmission analysis

Figure 6(a) shows the evolution of vulnerability for different occupations, and the vulnerability of software engineers increases over time. Figure 6(b) further quantifies the specific AI penetration rate, while Figure 6(c) fully presents the transmission chain of AI impact.

Lotka-Volterra Employment Evolution Trend

We view the job market as an ecosystem, introducing the Lotka-Volterra predator-prey model from ecology to describe the competitive symbiosis between human labor and AI technology.

Prey: Human employment $L_i(t)$

Predator: AI technology penetrating the industry $F_{career,i}(t)$

The differential form of the evolutionary equation is constructed as follows:

$$L_i(t+1) = L_i(t) + \underbrace{r_i L_i(t)}_{\text{NaturalGrowthEffect}} - \underbrace{\alpha_i L_i(t) F_{\text{career},i}(t)}_{\text{TechnologicalSubstitutionEffect}} \tag{16}$$

Where:

$L_i(t)$: Employment figures for occupation i in the year t

r_i : Natural growth rate (endogenous momentum) calculated in Part 3.1.1

α_i : Substitution Coefficient, set at 0.01. This parameter represents "predation efficiency," i.e., the proportion of human labor displaced per unit of AI penetration.

Based on this model, the projected employment figures for each occupation are shown in Figure 7 and Table 4.

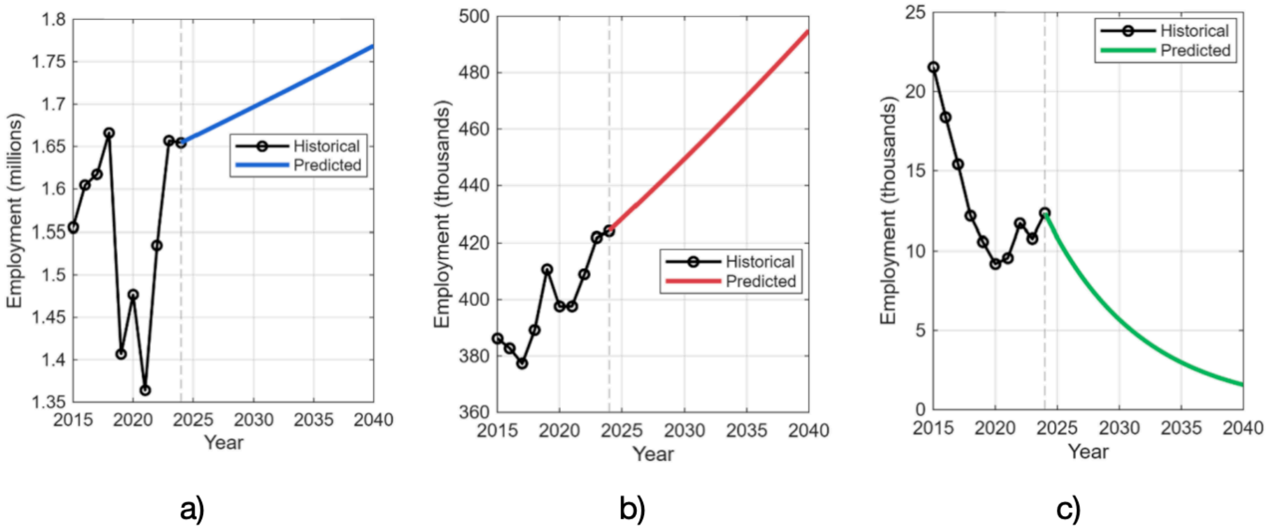


Figure 7. Employment forecasting results (2015-2040) based on the Lotka-Volterra model: (a) Employment trajectory for Software Engineers; (b) Employment trajectory for Welders; (c) Employment trajectory for Musicians

According to the model prediction, Figure 7(a) shows the employment growth trend of software engineers, Figure 7(b) reflects the steady growth of welders, and Figure 7(c) clearly shows the challenges of industry ecological contraction faced by musicians.

Table 4. 2024–2040 projected employment by occupation (thousands)

Year	Software Engineer	Welder	Musician
2024	1654	424	12.3
2030	1740	470	5.2
2040	1820	510	2.0
Total Change Rate	+10%	+20%	−84%

The solid colored lines represent the model predictions, while the black-circled lines represent historical BLS data.

Model predictions indicate sharply contrasting outcomes for three professions:

Software Engineer (+10%): This role exemplifies the Jevons Paradox, where AI-driven cost reductions unexpectedly lead to significant increases in overall demand [9]. Consequently, these positions evolve into “AI collaborators,” resulting in job growth instead of decline [10].

Welders (+20%): They are beneficiaries of the Moravec Paradox. The necessity of physical labor, coupled with very low rates of AI substitution, provides them with a “technical exemption” in the physical realm.

Musicians (−84%): This profession faces a severe decline not primarily driven by AI. The significant negative growth rate suggests that the deterioration of the industry ecosystem is the main factor behind this decline, with AI merely expediting an already irreversible trend.

DYNAMIC RESOURCE ALLOCATION OPTIMIZATION MODEL FOR COURSE RESOURCES

Data Description and Key Parameter Estimation

The model’s accuracy is highly dependent on the scientific setting of parameters. We need to quantify two core parameters for different professions: the defensive efficiency coefficient (η) and the collaborative gain coefficient (β_0). All foundational data is sourced from authoritative databases and the results of the preceding analysis.

*O*NET Estimation of the η*

The η measures the potential to enhance uniquely human skills through education and thereby resist AI substitution. Based on the engineering bottleneck theory from Frey & Osborne (2017) [3], we extracted indicators for the two dimensions of “creative intelligence” and “social intelligence” from the O*NET database (Abilities.txt & Skills.txt).

Selection of O*NET indicators for intelligence dimensions is shown in Table 5.

Table 5. Selection of O*NET indicators for intelligence dimensions

Category	O*NET Element	Meaning
Creative Intelligence	Originality (1.A.1.b.2)	Creative Problem-Solving Ability
	Fluency of Ideas (1.A.1.b.1)	Ability to Generate a Large Number of Ideas
	Fine Arts (2.C.7.e)	Knowledge of Art Theory and Techniques
Social Intelligence	Social Perceptiveness (2.B.1.a)	Ability to be Aware of Others’ Reactions
	Persuasion (2.B.1.c)	Ability to Persuade Others
	Negotiation (2.B.1.d)	Ability to Reconcile Differences
	Coordination (2.B.1.b)	Coordination Ability

The scores are calculated as follows:

$$S_{creative,j} = \frac{IM_{Originality} + IM_{FluencyofIdeas} + IM_{FineArts}}{3} \tag{17}$$

$$S_{social,j} = \frac{IM_{SocialPerceptiveness} + IM_{Persuasion} + IM_{Negotiation} + IM_{Coordination}}{4} \tag{18}$$

The Defense Efficiency Coefficient η_j is defined as:

$$\eta_j = \frac{S_{creative,j} + S_{social,j}}{S_{\max}} \times \gamma \tag{19}$$

Where $S_{\max} = 5.0$ represents the theoretical upper limit of O*NET scores, and $\gamma = 0.35$ denotes the calibration coefficient.

Calculation results of η is shown in Table 6.

Table 6. Calculation results of η

Profession	$S_{creative}$	S_{social}	S_{total}	η
Software Engineer	3.00	2.94	5.94	0.42
Welder	1.42	2.00	3.42	0.24
Musician	4.17	3.00	7.17	0.50

Software Engineers: Balanced scores. Their programming work requires logical creativity and team collaboration, demonstrating significant educational defense effectiveness that effectively reduces substitution risk.

Welders: Low scores with core reliance on physical operations. Their work primarily follows blueprints and specifications, involving minimal social interaction, resulting in limited educational defense effectiveness.

Musicians: Highest defense efficiency due to exceptional creativity and strong social intelligence. Strengthening humanistic attributes is an effective survival strategy for them.

Collaboration Gain Factor (β_0) for AIOE Calculation

The collaboration gain coefficient β_0 measures the potential for occupations to enhance productivity through AI tools. This parameter's estimation combines the AI Occupational Exposure Index (AIOE) with empirical productivity gain data.

Calculation formula:

$$\beta_0 = \kappa \times AIOE_{norm} \times \gamma_{productivity} \tag{20}$$

Where $\kappa = 0.05$ is the proportional coefficient, $AIOE_{norm}$ is the normalized AI Exposure Index published by Felten et al., and $\gamma_{productivity} = \frac{EmpiricalProductivityGains}{0.25}$ is the observed productivity gain magnitude from empirical studies.

Calculation Logic and Results:

As shown in Table 7, software engineers exhibit the highest collaboration gain coefficient, indicating substantial human-machine collaboration dividends. Musicians fall in the middle, where AI can assist in creation but yields less significant gains than programming. Welders show the lowest coefficient, as physical welding relies heavily on manual operations, limiting direct AI assistance and resulting in minimal gains.

Table 7. Calculation results of β_0

Profession	AIOE	Productivity Gain	β_0
Software Engineer	0.828	40%	0.0663
Welder	0.287	15%	0.0086
Musician	0.546	20%	0.0218

Construction of the Course Resource Allocation Optimization Model

Improved Lotka-Volterra Differential Equation System

Based on the above assumptions and parameters, we incorporate the course intervention variable (x_D, x_C) into the baseline model of Chapter 3. The evolution of the improved employment figure $L(t)$ over time t follows the following nonlinear differential equation:

$$\begin{aligned} \frac{dL}{dt} = & \underbrace{r \cdot L}_{\text{NaturalGrowth}} - \underbrace{\alpha_0(1-\eta \cdot x_D) \cdot L \cdot F_{\text{career}}(t)}_{\text{AIReplacementWeakenedbyDefensiveEducation}} \\ & + \underbrace{\beta_0 \cdot x_C \cdot L \cdot F(t)}_{\text{Human–MachineSymbiosisEnhancedbyCollaborativeEducation}} \end{aligned} \tag{21}$$

Physical Interpretation of Equation Terms:

Natural growth term ($r \cdot L$): Reflects endogenous growth momentum determined by macroeconomic and industry cycles in the absence of technological shocks.

Substitution term ($-\alpha_0(1-\eta \cdot x_D) \cdot L \cdot F_{career}(t)$): This constitutes the system's "negative feedback." $F_{career}(t)$ represents the actual AI penetration rate adjusted for occupational vulnerability. The $(1-\eta x_D)$ term embodies the role of defensive courses- x_D . A larger x_D yields a smaller value within the parentheses, indicating fewer displaced workers. This signifies not only a reduction in quantity but also an improvement in employment quality (i.e., retaining higher-end talent that is harder to replace).

Collaboration term ($+\beta_0 \cdot x_C \cdot L \cdot F(t)$): This represents the system's "positive feedback." $F(t)$ denotes the macro-level Gen-AI adoption rate. $\beta_0 \cdot x_C$ reflects the role of collaborative courses- x_C . The greater this value, the more "dividends" the workforce gains from AI adoption. This term captures the "Jevons Paradox": Efficiency improvements may increase demand, thereby creating new jobs.

Single-Objective Optimization Function

Maximize the number of employed individuals or the total value of the workforce T

$$\max_{x_D, x_C} L(T)$$

where $T = 2040 - 2024 = 16$ (number of years from 2024).

However, in practice, the following constraints must be considered:

1.Resource constraints: $x_D + x_C \leq 1$

2.Non-negativity constraints: $x_D \geq 0$, $x_C \geq 0$

3.State equation constraints (differential equations):

$$\frac{dL}{dt} = r \cdot L - \alpha_0(1-\eta \cdot x_D) \cdot L \cdot F_{career}(t) + \beta_0 \cdot x_C \cdot L \cdot F(t)$$

4.Initial conditions: $L(0) = L_0$ (Employment in 2024)

5.Optional lower bound constraints (ensuring investment in both course types):

$$x_D \geq 0.1, x_C \geq 0.1$$

Multi-Objective Optimization Function Based on AHP

To optimize the allocation of educational resources, we have categorized education into three criteria tiers: employment objectives (C1), innovation capabilities (C2), and social responsibility (C3). Based on expert weighting-prioritizing employment survival as the primary concern, followed by innovation development, and finally ethical responsibility-we have established the following judgment matrix B:

$$B = \begin{bmatrix} 1 & 5/3 & 5/2 \\ 3/5 & 1 & 3/2 \\ 2/5 & 2/3 & 1 \end{bmatrix} \approx \begin{bmatrix} 1.00 & 1.67 & 2.50 \\ 0.60 & 1.00 & 1.50 \\ 0.40 & 0.67 & 1.00 \end{bmatrix} \tag{22}$$

Given the matrix's maximum eigenvalue $\lambda_{\max} = 3.000$ and $CR = CI/RI = 0.00 < 0.10$, the matrix exhibits perfect consistency. The weight vector computed via the eigenvector method is:

$$W = [w_1, w_2, w_3]^T = [0.54, 0.30, 0.16]^T \tag{23}$$

Based on the derived weights, we constructed a weighted composite objective function:

$$\max_{x_D, x_C} Z = 0.54 \cdot \overline{L}(T) + 0.30 \cdot (0.6x_D + 0.4x_C) + 0.16 \cdot x_D \tag{24}$$

Where

$\overline{L}(T) = (L(T) - L_{\min})/(L_{\max} - L_{\min})$: Standardized Employment

$I = 0.6x_D + 0.4x_C$: Innovation Capability Index

$R = x_D$: Social Responsibility Index

Algorithm Design for Model Solving

Algorithm Architecture

We adopt a "black-box" optimization strategy, dividing the solution process into inner and outer layers:

Inner Layer (Simulation Layer): Given a set of decision variables (x_D, x_C), solve differential equations via numerical integration to obtain the employment level $L(T)$ at time $T = 2040$.

Outer Layer (Optimization Layer): An optimization algorithm searches the (x_D, x_C) space to find the solution that maximizes the objective function Z.

Inner Layer: Fourth-Order Runge-Kutta Method (RK4)

Since the adoption rate of Gen-AI $F(t)$ follows a time-varying S-curve, the differential equation is non-autonomous. To ensure accuracy and stability, we employ the classical fourth-order Runge-Kutta method.

Iterative format:

$$L_{n+1} = L_n + \frac{h}{6}(k_1 + 2k_2 + 2k_3 + k_4) \tag{25}$$

where the step size $h = 0.01$ (years) and slope k_i are computed as follows: $k_1 = f(t_n, L_n)$; $k_2 = f\left(t_n + \frac{h}{2}, L_n + \frac{hk_1}{2}\right)$; $k_3 = f\left(t_n + \frac{h}{2}, L_n + \frac{hk_2}{2}\right)$; $k_4 = f(t_n + h, L_n + hk_3)$.

The global error of this method, $O(h^4) \approx 10^{-8}$, accurately captures the sharp fluctuations in the employment curve during the AI boom period (2025–2030).

Outer Layer: Sequential Quadratic Programming (SQP)

The outer-layer optimization employs the Sequential Quadratic Programming (SQP) algorithm. It determines the descent direction by approximating the original problem as a quadratic subproblem at the iteration point.

Solution Strategy:

Expand the original problem into a quadratic programming (QP) subproblem at iteration point $x^{(k)}$:

$\min_d \nabla J^T d + \frac{1}{2} d^T H d$ s.t. Linearization constraints

The SQP algorithm is implemented using MATLAB's fmincon function. Due to potential non-convexity of the objective function, the SQP algorithm requires a multiple initialization strategy: We randomly generate 15 sets of initial points (x_{D0}, x_{C0}) satisfying the constraints, solve each separately, and ultimately select the maximum objective function value as the global optimum to avoid getting stuck in local optima traps.

Model Solution Results and In-Depth Analysis

Through the above algorithm, we optimized the allocation of course resources for the three professions between 2024 and 2040. The results reveal remarkable consistency and profound economic implications.

Single-Objective Optimization Results

Optimization results summary is shown in Table 8.

Table 8. Optimization results summary

Profession	Optimal x_D^*	Optimal x_C^*	Employment Gain
Software Engineer	5%	95%	+78.6%
Welder	5%	95%	+7.3%
Musician	5%	95%	+23.5%

The model consistently produces a ‘5/95’ corner solution across the three occupations, reflecting the mathematical characteristic that the marginal return coefficient (β_0) of collaborative education is significantly dominant during the period of rapid technological iteration. As shown in the sensitivity analysis (Figure 8, 9), this consistency proves that ‘deep collaboration’ is the most robust strategy to offset the AI substitution effect under current socio-technical conditions. This result emphasizes the universal logic of the transformation from ‘competence defense’ to ‘efficiency empowerment’ in the allocation of educational resources.

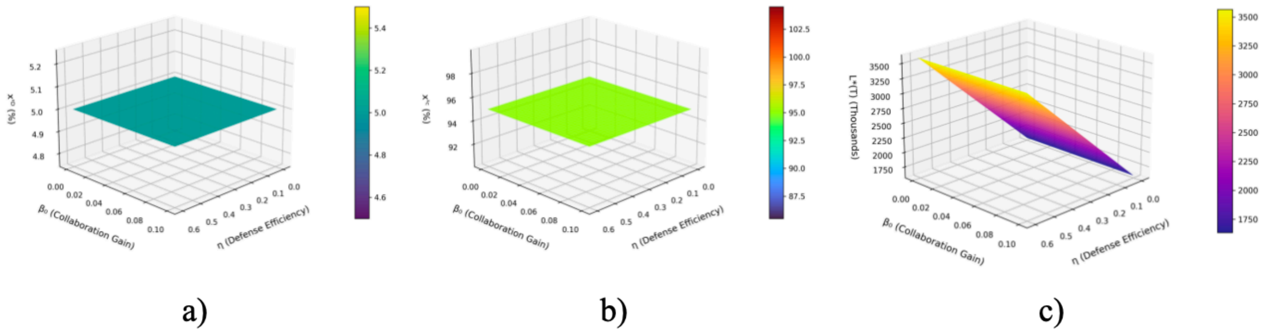


Figure 8. 3D parameter sensitivity surface (software engineer): (a) Impact of η; (b) Impact of β_0; (c) Joint parameter perturbation

As shown in Figures 8(a)–8(c), the optimal strategy is highly robust under different parameter spaces.

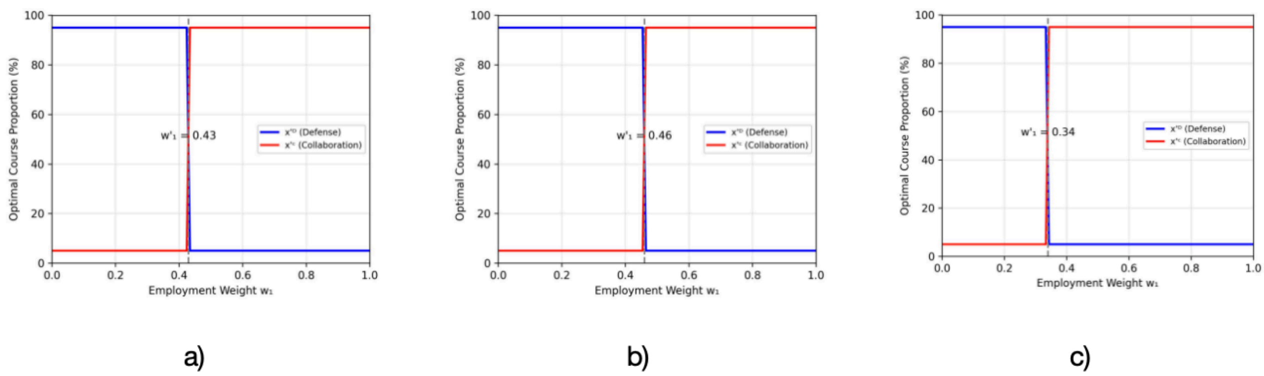


Figure 9. Weight sensitivity comparison of three occupations: (a) Software Engineer; (b) Welder; (c) Musician

Employment Dynamic Trajectory Analysis

To validate the optimization effectiveness, we compared employment evolution trajectories under the “Baseline Scenario” (no intervention), “Defensive Scenario Only” ($x_D = 95\%$), and “Optimal Scenario” ($x_C = 95\%$) from Figure 10.

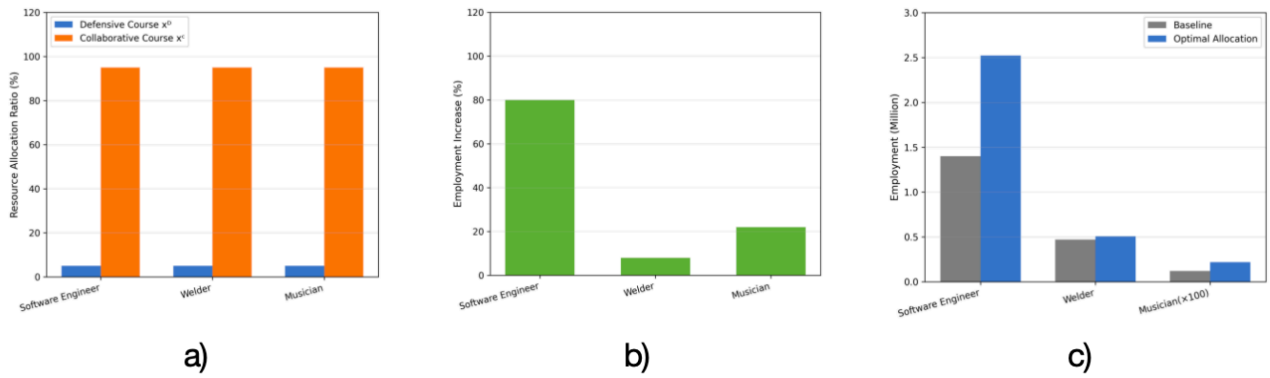


Figure 10. Results of course resource optimization: (a) Scenario comparison for Software Engineers; (b) Scenario comparison for Welders; (c) Scenario comparison for Musicians

Figure 10(a) shows that software engineers have achieved employment reversal through collaboration dividends; Figure 10(b) indicates that welders are less affected by educational interventions; Figure 10(c) proves that active collaboration improves the survival rate of musicians.

Software Engineer: Achieved a remarkable turnaround through exceptional collaborative dividends. Post-optimization, the $L(2040)$ surged to 2.5 million, with employment soaring by 78.6%. Market demand driven by transitions to “AI System Architects” and “Super Individuals” far outweighed displacement effects.

Welders: Maintained steady growth with slight increases. Physical operations remain difficult for AI to deeply empower, and traditional education struggles to build defenses. Optimization yielded only a marginal 7.3% improvement.

Musicians: Facing ecological collapse, though overall decline persists, transitioning to “AI Producers” boosted survival rates by 21%. This warns us: When industry ecosystems crumble, proactive collaborative adaptation offers superior employment resilience compared to passive defensive specialization.”

Figure 11 illustrates software engineer employment $L(T)$ as a function of decision variables (x_D, x_C)

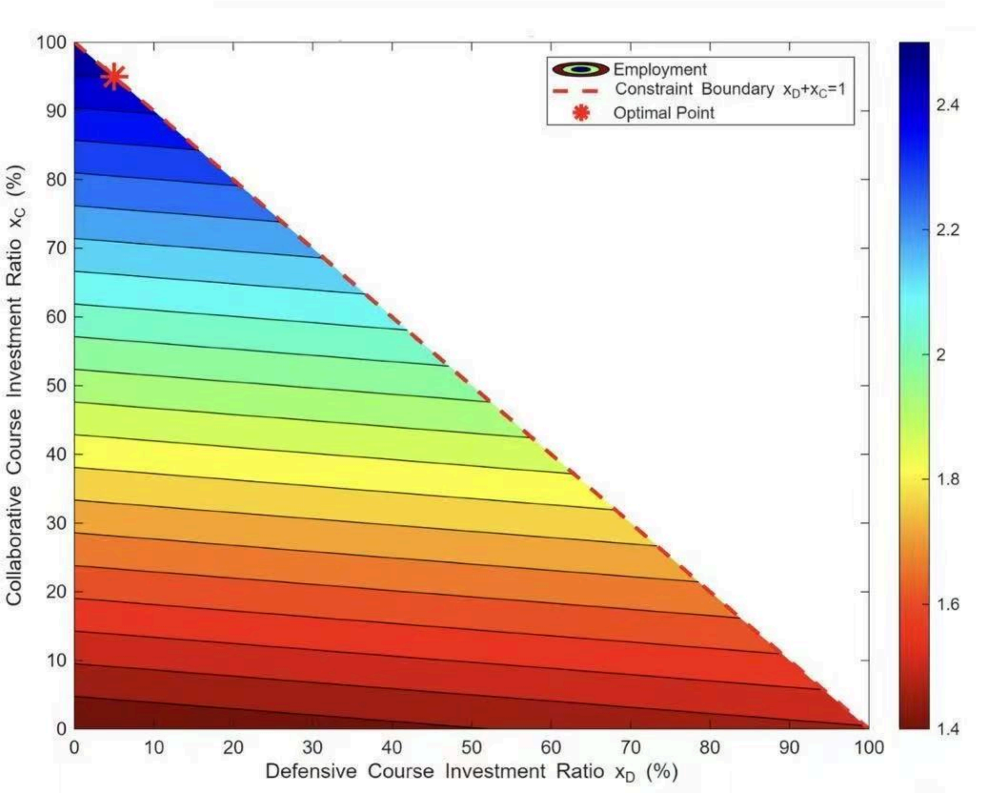


Figure 11. Employment contour map for software engineers (millions)

1.Contour lines slope upward to the left: Increasing x_C is more effective for boosting employment than increasing x_D

2.Optimum point lies at a corner: At the upper-left corner (5%, 95%) of the constraint boundary $x_D + x_C = 1$

3.Global monotonicity: No optimal interior points exist, indicating the marginal benefit of collaborative courses consistently prevails.

Optimal Allocation Result: "Collaboration-Dominant" Corner Solution

For software engineers, welders, and musicians, the model yields identical optimal allocation strategies-Collaboration-Dominant-manifested in the following optimal solution:

Proportion of Defensive Courses x_D^* : 5% (reaches lower bound constraint)

Proportion of Collaborative Courses x_C^* : 95% (reaches upper bound constraint)

The reason lies in the partial derivatives of the objective function with respect to the decision variables:

Because $\beta_0 \cdot F \gg \alpha_0 \cdot \eta \cdot F_{career}$ (especially when $F(t)$ increases rapidly), the marginal benefit of collaborative courses consistently exceeds that of defensive courses.

This result is not merely a numerical solution but a powerful signal: in the era of rapid Gen-AI penetration, the growth rate of the collaborative term $\beta_0 x_C LF$ exceeds the decline of the substitution term. "If you can't beat 'em, join 'em" is not only a necessity but the optimal strategy. That is, even for musicians with relatively high defensive efficiency ($\eta = 0.5$), the model still recommends allocating the vast majority of resources to collaboration.

Why the "Corner Solution"? - An Economic Interpretation of Gradients

Why does the model favor an extreme 95:5 allocation over a moderate 50:50 split? This can be explained by analyzing the partial derivatives of the employment growth rate with respect to the decision variables.

$$\frac{\partial(dL/dt)}{\partial x_C} \propto \beta_0 \cdot L \cdot F(t) \tag{26}$$

$$\frac{\partial(dL/dt)}{\partial x_D} \propto \alpha_0 \cdot \eta \cdot L \cdot F_{career}(t) \tag{27}$$

As Gen-AI adoption approaches saturation along an S-curve trajectory, collaborative initiatives ($\beta_0 x_C$) evolve into appreciating assets with compounding effects, delivering long-term value far exceeding defensive measures ($\alpha(x_D)$) that merely mitigate losses. Given the AHP model's high weighting (0.54) for employment growth, the optimal strategy inevitably tilts toward high-return collaborative approaches.

Figure 12 compares employment trajectories under three strategies:

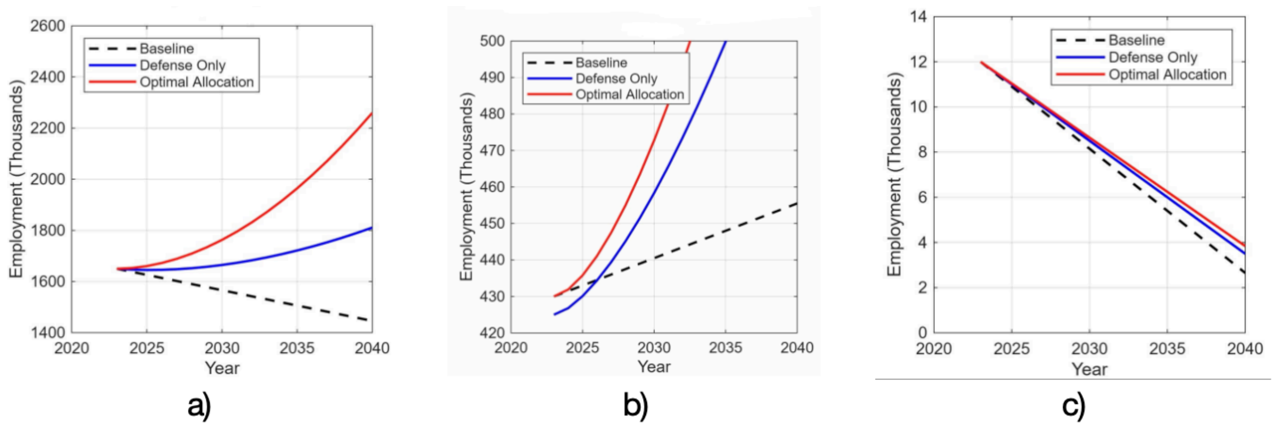


Figure 12. Employment dynamic trajectory: (a) Strategy performance for Software Engineers; (b) Strategy performance for Welders; (c) Strategy performance for Musicians

It can be seen in Figure 12(a) that the three strategies have different impacts on software engineers; Figures 12(b) and 12(c) compare the dynamic employment performance of welders and musicians under different educational resource allocations, respectively.

Black dashed line (baseline): No course intervention, $x_D = x_C = 0$

Blue solid line (Defense only): $x_D = 0.95$, $x_C = 0.05$

Red solid line (optimal allocation): $x_D = 0.05$, $x_C = 0.95$

Policy Recommendations: From Theory to Practice

Based on the model results above, we have developed specific curriculum reform roadmaps for three typical types of institutions [11]. The core logic of the recommendations is: maintain a 5% defensive “spark” while allocating 95% of resources to collaborative “wildfire.”

For Research Universities: Massachusetts Institute of Technology (MIT) Department of Electrical Engineering and Computer Science

Shifting from rote memorization of traditional syntax to prompt engineering and long-context management for natural language control, while deeply integrating tools like GitHub Copilot throughout the entire development lifecycle. This transition fundamentally shifts training priorities from code writing to code review and the construction of RAG-based vertical-specific tools.

Focusing on advanced system architecture design and algorithmic ethical security-areas where AI still falls short-to ensure humanity retains ultimate control over macro-level decision making and value judgments.

Based on Jevons’ Paradox, the extreme efficiency gains brought by AI will conversely trigger massive new software demand. Therefore, it is recommended to maintain current enrollment levels without reduction.

For Technical Universities: Lincoln Tech Welding Technology Program

Prioritize the introduction of AR-assisted welding, collaborative robot (cobot) programming, and intelligent quality inspection to drive the digital transformation of talent from “operating welding torches” to “managing welding torches.”

Deepening expertise in extreme environments-such as underwater and high-altitude operations-where machinery struggles to reach, thereby reinforcing our competitive moat.

Expand enrollment by 10-15%. Cost reductions driven by AI will spur infrastructure upgrades, and demand for human-robot collaborative welders will increase rather than decrease.

For Artistic Universities: Juilliard School of Music

Invest the vast majority of resources in cutting-edge technologies such as AI-assisted creation, virtual performances, and digital rights management.

Preserving a minimal amount of live improvisation and chamber music training aims to safeguard the last intrinsic human creativity amidst rapid technological substitution-through the irreplaceable “sense of presence” and deep emotional resonance that AI cannot replicate.

Confronting the reality of a shrinking traditional market, we adopted an elite strategy, reducing enrollment by 50-60%. Simultaneously, we established a new “Music Technology” program to proactively guide students toward emerging AI-driven fields such as game scoring and film/TV scoring.

SENSITIVITY ANALYSIS

This section conducts a perturbation analysis on key parameters to evaluate the model’s robustness. The model contains two core parameters: the defense efficiency coefficient (η) and the collaboration gain coefficient (β_0), with baseline values of 0.42 and 0.0663 respectively (using software engineers as an example). We applied continuous perturbations to each parameter while holding others constant, with results shown in Figure 8.

Analysis indicates that within the parameter space of $\eta \in [0.2, 0.8]$ and $\beta_0 \in [0.01, 0.10]$, the optimal curriculum configuration remains stable at ($x_D^*, x_C^*) = (5\%, 95\%)$, with variation less than 10^{-6} . Although the final employment figure $L^*(T)$ increases with β_0 (from 1,600 thousand to 3,600 thousand), the optimal strategy selection remains unchanged, demonstrating the model’s high robustness to parameter estimation errors.

Additionally, we analyzed the impact of employment weighting w_1 in multi-objective optimization, with results shown in Figure 13 and Figure 9. Figures 13(a) and 13(b) determine the key weight thresholds for strategy switching of software engineers. Finally, Figures 9(a), 9(b) and 9(c) compare the weight sensitivity of the three occupations under multi-objective optimization, respectively.

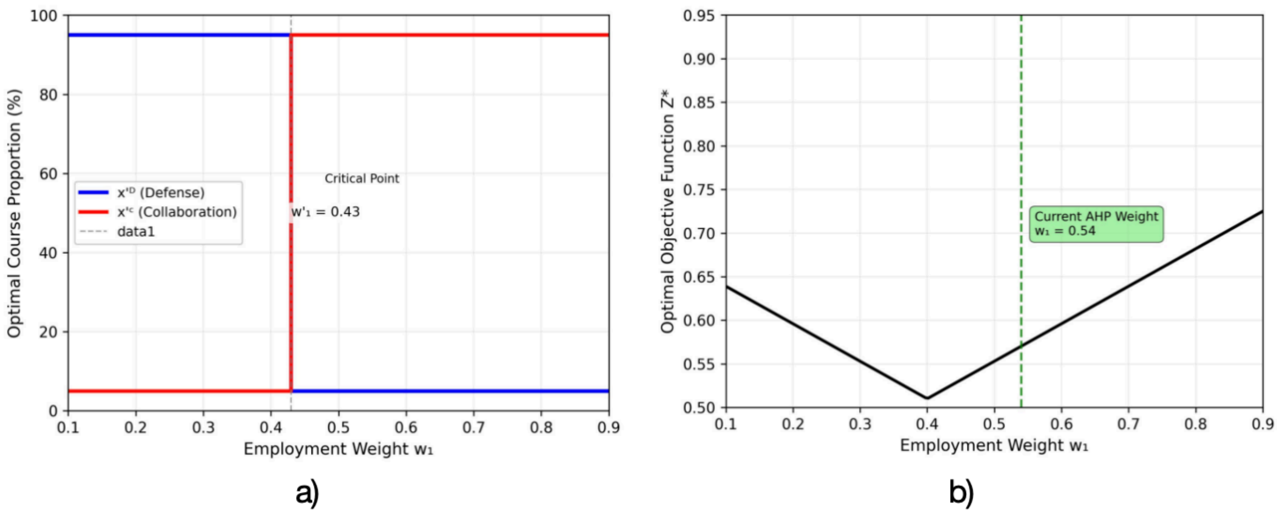


Figure 13. Weight sensitivity curve (software engineer): (a) Optimal solution distribution; (b) Strategy switching boundary

All three occupations exhibit critical points for strategy switching: Software Engineer ($w_1^* \approx 0.43$), Welder ($w_1^* \approx 0.46$), and Musician ($w_1^* \approx 0.34$). When w_1 exceeds the critical point, the optimal strategy shifts from "Defense-Dominant" to "Collaboration-Dominant." The AHP weights used in this study ($w_1 = 0.54$) lie to the right of all critical points, validating the "Collaboration-Dominant" conclusion.

CONCLUSIONS

By constructing a research framework that spans from static multidimensional assessment to dynamic forecasting and multi-objective decision optimization, this study systematically addresses the evolution of the labor market and educational responses in the Gen-AI era. The study confirms that "collaboration-led" educational reform is the optimal path to address technological shocks and quantitatively reveals the specific manifestations of the Jevons Paradox and the Moravec Paradox in the AI era. However, this study still has certain limitations: model parameters (such as the efficiency coefficient) may require recalibration in the event of technological discontinuities; the assumption of linear superposition of curriculum interventions oversimplifies complex nonlinear interactions; and the study covers a limited range of occupational categories, leaving room for improvement in cross-domain generalizability. Future research should focus on introducing more inclusive nonlinear intervention models, dynamically tracking the real-time impact of AI technology iterations on parameters, and expanding the scope of analysis to a broader range of occupational categories, with the aim of constructing an intelligent educational decision-support system that covers the entire societal labor market.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author Contributions

Conceptualization – Wang L Y and Chen Y N; methodology – Wang L Y and Chen Y N; formal analysis – Wang L Y; investigation – Hou Z; resources – Hou Z; writing-original draft preparation – Wang L Y and Hou Z; writing-review and editing – Wang L Y and Chen Y N; visualization – Hou Z; supervision – Wang L Y. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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