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Heterogeneous Occupational Assessment and Multi-Objective Curriculum Optimization under the Impact of AIGC: A WSEM-AHP and TF-IDF Approach

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Abstract: *As Generative Artificial Intelligence (Gen-AI) reshapes the labor market, the existing higher education curriculum system exhibits a significant lag, making it difficult to cope with multi-dimensional technological shocks. To quantitatively evaluate the heterogeneous impact of AI on different occupations and optimize curriculum configuration under limited credits, this study proposes a data-model dual-driven multi-dimensional decision analysis framework. First, a quantitative framework based on the Weighted Seniority-Efficiency Model and Analytic Hierarchy Process (WSEM-AHP) is constructed. Combined with the TF-IDF algorithm to mine real recruitment demands, it achieves precise measurement from the micro-level seniority structure to macro-level dimensions. Second, by introducing carbon neutrality responsibility and ethical baseline constraints, a multi-objective curriculum configuration optimization model is established, and Sequential Quadratic Programming (SQP) is employed to solve for the optimal credit allocation. Finally, simulation experiments on three typical occupations demonstrate that the model effectively identifies occupational heterogeneous characteristics: software engineers exhibit "responsible technological expansion," graphic designers tend towards an "ethical defense-dominated" approach, and electricians display "physical skill adherence." This study provides educational planners with a systematic quantitative decision-making tool that balances comprehensive utility maximization with sustainable development.*

Keywords: *Gen-AI; multi-dimensional technological shocks; WSEM-AHP; TF-IDF algorithm; Sequential Quadratic Programming*

1. Introduction

As the global popularization of Generative Artificial Intelligence (Gen-AI) accelerates, the labor market is facing an unprecedented heterogeneous structural reshaping. However, the existing higher education curriculum system exhibits a significant lag, making it difficult to perfectly cope with multi-dimensional technological shocks. Therefore, quantitatively characterizing the impact and influence degree of AI on different occupations, and optimizing curriculum configuration under limited credit constraints, is of great significance for building a novel educational system equipped with technological foresight and social responsibility.

Regarding the impact of artificial intelligence on education and employment, academia has conducted extensive discussions. Sina Rismanchian et al. [1] studied the use of Generative AI chatbots among students, and their results showed that an improvement in knowledge level enables more precise and responsible use of AI tools. Nader Salari et al. [2] discussed the impact of Generative AI on future employment, focusing on unemployment issues while emphasizing the improvement of AI governance frameworks and policies. They clarified that when Generative AI complies with safety and ethical standards, it has the potential to enhance efficiency while reducing costs and time, thus making the introduction of green and ethics-related courses highly necessary. Meanwhile, research by Eungjoon Kim et al. [3] verified that AI provides a substantially greater enhancement for repetitive tasks. Furthermore, Azamat Zhanseitov's [4] research results indicate that a large proportion of people are concerned about potential job losses; in addition, the majority believe that skills should be upgraded to meet the demands of AI-driven employment, making the reasonable allocation and integration of AI into the curriculum

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particularly important.

Based on the flexible application of the Fuzzy Analytic Hierarchy Process (FAHP), and referring to the utilization of AHP by Haoze Ma et al. [5] and Anchal Arora et al. [6], we adopted a fusion scheme of the Weighted Seniority-Efficiency Model (WSEM) and AHP [7] to calculate the impact index of AI across different industries.

According to the research of Liang-Ching Chen [8], an extended TF-IDF method was employed to enhance keyword extraction capabilities in traditional corpus research. Concurrently, referring to Mohammed-Hassan Ajjam [9], who utilized real-time online recruitment data and integrated semantic similarity with artificial intelligence to process core skill vectors, this methodology effectively bridges the gap between industry demand and skill supply.

Addressing the issues of educational resource allocation and curriculum planning, the existing multi-objective optimization literature provides abundant mathematical programming tools. Some scholars dealt with order allocation problems and formed a unique multi-objective programming model based on the results of the first and second stages[10]. Applying this logic to our paper, we utilize a multi-objective programming model combined with meta-heuristic algorithms to seek the optimal solution for credit allocation. Furthermore, based on literature [11], Sequential Quadratic Programming (SQP) is employed to solve for optimal resource allocation, thereby accomplishing the optimal credit distribution for the curriculum proposed in this paper.

The remainder of this paper is organized as follows: Section 2 details the skill structure weight determination model based on WSEM-AHP, along with the data-model dual-driven multi-objective curriculum configuration optimization model integrating TF-IDF. Section 3 conducts experimental simulations of the proposed models using the O*NET database and real-world recruitment data, providing an in-depth analysis of the curriculum optimization results for three typical occupations. Finally, Section 4 summarizes the entire paper and puts forward corresponding policy implications.

2. Methodology

2.1 Skill Structure Weight Determination Model Based on WSEM-AHP

2.1.1 Model Objective

To quantitatively characterize the heterogeneous impact of Generative AI (Gen-AI) across different scenarios, this study constructs a dual-layer evaluation model based on structural features. Addressing the limitation of existing research that often simplifies AI impact into a single substitution rate, this framework integrates macro statistical data with micro node features. It establishes a multi-dimensional quantification system covering technological, economic, and socio-ethical dimensions to identify impact variance across fields. Furthermore, the algorithm abandons the traditional homogenization assumption by introducing hierarchical distribution variables, allowing for the precise measurement of differentiated empowerment effects across foundational, intermediate, and advanced nodes. The resulting comprehensive impact weights and adjusted efficiency coefficients are seamlessly integrated into the subsequent optimization model as key parameters, ensuring consistency in algorithmic logic throughout the study.

2.1.2 Micro-Level: Weighted Seniority-Efficiency Model (WSEM)

To achieve precise mapping from the micro-level seniority structure to macro-level curriculum weights, the model constructed in this section first utilizes the WSEM to calculate the "technological exposure intensity" of various occupations, an indicator that internalizes the seniority distribution characteristics of the occupation.

For any occupation$j$, define the seniority structure set$R = \{1,2,\dots,m\}$(corresponding to junior, mid-level, and senior). Define the seniority distribution vector $\mathrm{p}_j \in \mathbb{R}^m$and AI marginal empowerment vector $\delta_j \in \mathbb{R}^m$.

Then, the industry comprehensive efficiency coefficient of this occupation is defined as the expected value of the empowerment vector over the seniority distribution, adjusted by the industry relevance factor.:

$$\eta_j = \gamma_j \cdot \langle \boldsymbol{p}_j, \boldsymbol{\delta}_j \rangle = \gamma_j \sum_{k=1}^{m} p_{j,k} \cdot \delta_{j,k} \tag{1}$$

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Where γ_j is the industry-specific parameter, reflecting the true industry correction coefficient. A higher index of η_j indicates a more pronounced productivity enhancement effect of AI at the micro level.

2.1.3 Macro-Level: WSEM-Modified Analytic Hierarchy Process (AHP)

We directly utilize the η_j calculated by the WSEM as the input value for the "Technological Substitutability" dimension in the AHP model, replacing traditional statistical proxy indicators.

First, for any given occupation j, its multi-dimensional evaluation vector is defined as $\mathbf{S}_j \in [0,1]^4$. Each component within the vector is transformed into a standard dimensionless value via a unified normalization mapping function. The specific definition is as follows:

$$\boldsymbol{S}_j = \begin{bmatrix} S_{tech}^{(j)} \\ S_{econ}^{(j)} \\ S_{short}^{(j)} \\ S_{ethic}^{(j)} \end{bmatrix} = \begin{bmatrix} \mathcal{N}(\eta_j) \\ \mathcal{N}(G_j) \\ \mathcal{N}(D_j) \\ 1-\mathcal{N}(B_j) \end{bmatrix} \tag{2}$$

The physical meaning and calculation logic of each component are as follows:

Technological Substitutability ($S_{tech}^{(j)}$): Directly derived from the industry comprehensive efficiency coefficient (η_j) output by the micro WSEM model, mapped through the normalization function $\Phi(\cdot)$:

$$S_{tech}^{(j)} = \Phi(\eta_j) \tag{3}$$

Here, a higher η_j , indicates stronger technological penetration and substitution effects of AI on the occupation.

Economic Sensitivity ($S_{econ}^{(j)}$): Based on the output contribution degree G_j. of the industry to which the occupation belongs. Industries with higher output values (e.g., trillion-level pillar industries) exert a more significant impact on the macroeconomy when fluctuating, hence necessitating a higher weight.

Talent Shortage ($S_{short}^{(j)}$): Based on the supply-demand gap index in the labor market.

The scarcer the talent (i.e., the largerD_j), the higher the value of the "filling effect" brought about by technological shocks.

Socio-Ethical Barriers ($S_{ethic}^{(j)}$): Based on the reverse indicator of the ethical restriction score B_j Higher ethical barriers (such as in healthcare and law) make AI implementation more difficult, resulting in a smaller impact. Therefore, $1-\mathcal{N}(B_j)$is taken as the impact score.

Then, a judgment matrix $\mathbf{A} = (a_{uv})_{4\times4}$is established to quantify the relative importance among the dimensions. Based on the assumption of a "technology and economy dual-drive," the standard matrix is constructed as follows:

$$a_{ij} = \begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \cdots & \cdots & \cdots \\ a_{n1} & \cdots & a_{nm} \end{bmatrix} \tag{4}$$

By solving the characteristic equation $\mathbf{Aw} = \lambda_{max}\mathbf{w}$, the normalized eigenvector $\mathbf{w}_{AHP}$, is obtained as the baseline weight for each dimension.

Finally, the comprehensive impact index $I_{total}^{(j)}$is defined as the inner product of the evaluation vector and the weight vector:

$$I_{total}^{(j)} = C \cdot (\boldsymbol{w}_{AHP}^T \cdot \boldsymbol{S}_j) \tag{5}$$

Where C is the amplification coefficient (typically set to 100).

2.1.4 Mapping Mechanism from Impact to Curriculum

To integrate the aforementioned impact assessment index into the planning of specific educational resource allocation schemes, this section defines a feature mapping function.

This function is built upon the logical assumption that "the nature of the impact determines educational demand". We map the four dimensions of AHP into demand weights for four types of curriculum modules $\mathbf{W}_{course}^{(j)}$:

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$$\boldsymbol{W}_{course}^{(j)} = [w_{eff}, w_{green}, w_{ethic}, w_{trad}]^T = \mathcal{M}(\boldsymbol{S}_j, \eta_j) \tag{6}$$

The efficiency gain module (w_{eff})is directly controlled by the efficiency coefficient(η_j)of the WSEM model; a higher value of η_j indicates a more urgent systemic need for human-machine collaborative optimization, and the algorithmic weight of the corresponding module thus exhibits a positively correlated growth trend. Secondly, the scalar magnitude of the socio-ethical constraint module(w_{ethic})is strictly determined by the socio-ethical dimension score extracted by the AHP algorithm, serving to establish the compliance boundary of the model. Thirdly, the green computing module(w_{green})is set as a non-linear coupling variable, whose feature weight depends on the cross-evolutionary relationship between the target node's AI dependency(i.e.,η_j)and external energy consumption characteristics. Finally, the foundational consolidation module(w_{trad})exists as a residual term in the mathematical derivation, accurately reflecting the core professional characteristics and foundational abilities that still need to be preserved at the system's bottom layer under strong AI shock disturbances.

2.1.5 Externality Internalization Constraint

In the process of determining the final weights, the environmental externalities brought by AI must be considered. This model introduces the carbon responsibility constraint inequality as the boundary condition for the subsequent optimization model.

For any given occupation j, define its AI intensity coefficient α_j(derived from $S_{tech}^{(j)}$) .The model stipulates that the credit allocation for green courses, x_{green}must satisfy the following dynamic lower bound:

$$x_{green} \geq \lambda_{coupling} \cdot \alpha_j \cdot x_{efficiency} \tag{7}$$

Where $\lambda_{coupling}$ is the responsibility coupling coefficient. The geometric significance of this inequality is that as the AI intensity of an occupation increases, the minimum necessary input for its sustainable development education must grow linearly, thereby preventing educational configuration from falling into the local optimal trap of "efficiency-only" approaches.

2.2 Multi-Objective Optimization Model for Curriculum Configuration Based on a TF-IDF Fusion Weighting Algorithm

1) Skill Feature Extraction Based on TF-IDF

To quantify the explicit demands of the current labor market for different curriculum modules, this section constructs a skill feature extraction model based on Natural Language Processing (NLP). By mining massive volumes of occupational description texts, this paper extracts a "data-driven" initial weight vector.

Step 1: Corpus Construction

The U.S. Department of Labor's O*NET database is selected as the core data source. We extracted detailed task descriptions and skill inventories for the target occupations (software engineers, graphic designers, and electricians) to construct an occupational document collection.

Step 2: TF-IDF Algorithm Implementation

To identify the core skill keywords for each occupation, the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm is employed. This algorithm is capable of filtering out generic vocabulary (e.g., "work", "use") and highlighting key skills with high occupational distinctiveness (e.g., "Python", "Circuitry", "Copyright").

For a skill keyword in a specific occupational document, its weight is calculated as follows:

$$w_{t,j} = TF_{t,j} \times IDF_t = \frac{n_{t,j}}{\sum_k n_{k,j}} \times log(\frac{|\mathcal{D}|}{|\{d \in \mathcal{D}: t \in d\}|+1}) \tag{8}$$

Where:

$\mathrm{TF}_{t,j}$: Term Frequency, measuring the relative importance (core degree) of a skill within a specific occupation. IDF_t: Inverse Document Frequency, measuring the uniqueness of a skill (scarcity across different occupations). $|\mathcal{D}|$ is the total number of documents in the corpus.

Step 3: Semantic Mapping and Module Clustering

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To transform unstructured keywords into weights for the four curriculum modules, we define a semantic mapping dictionary. $\mathcal{K} = \{K_{eff}, K_{green}, K_{ethic}, K_{trad}\}$.The corresponding keywords are shown in Table 1:

Table 1: Semantic Mapping Dictionary between Keywords and Curriculum Modules

Module Category	symbol	Representative Keywords
Efficiency-Enhancement	K_{eff}	Algorithm, Optimization, Automation, AI Tools, Speed...
Green & Sustainability	K_{green}	Energy, Sustainable, Low-power, Carbon, Environmental...
Socio-Ethical & Regulatory	K_{ethic}	Privacy, Security, Copyright, Compliance, Bias, Safety…
Foundational & Traditional	K_{trad}	Sketching, Wiring, Manual testing, Soldering, Layout…

For curriculum module $m \in \{eff, green, ethic, trad\}$, its raw score $S_{m,j}$ is defined as the sum of the TF-IDF values of all keywords categorized under that specific module:

$$S_{m,j} = \sum_{t \in K_m} w_{t,j} \tag{9}$$

Step 4: Weight Normalization

Finally, the scores of each module are normalized to obtain the data-driven weight vector $\mathbf{W}_{data}^{(j)}$for the specific occupation:

$$\boldsymbol{W}_{data}^{(j)} = [\frac{S_{eff,j}}{Z}, \frac{S_{green,j}}{Z}, \frac{S_{ethic,j}}{Z}, \frac{S_{trad,j}}{Z}]^T \tag{10}$$

Where $Z = \sum_m S_{m,j}$is the normalization factor.

2) Model-Driven Revised Weights ($\mathbf{W}_{model}$)

This refers to the curriculum demand weights based on the AI impact assessment output. These weights internalize the WSEM model's analysis of the micro-occupational rank structure and the AHP's considerations of ethical and environmental dimensions, representing a "future strategic orientation." For instance, the model may significantly elevate the weight of "AI Ethics," a field that is currently undervalued by the market yet remains vital for the future.

3) Final Integrated Weights ($\mathbf{W}_{final}$)

By introducing a forward-looking coefficient to fuse the two, the final weight vector to be input into the optimization objective function is obtained as follows:

$$\boldsymbol{W}_{final} = (1 - \mu) \cdot \boldsymbol{W}_{data} + \mu \cdot \boldsymbol{W}_{model} \tag{11}$$

Where, $\mathbf{W}_{data}$ originates from the TF-IDF text mining results, $\mathbf{W}_{model}$ is derived from the WSEM-AHP evaluation results. $\mu \in [0,1]$serves as the adjustment parameter.In this study, we set $\mu = 0.6$, which implies that while respecting current market demands, we prioritize (with a 60% weight) curriculum reforms guided by the AI impact trends predicted by our model. This reflects the "proactive leading" nature of education rather than mere "passive adaptivity."

2.3 Construction of the Multi-Objective Programming Model

Based on the utility functions and weight parameters defined in the previous sections, this section formally constructs the "Multi-Objective Curriculum Optimization Model" (MOCOM) under specific constraints. The model aims to identify an optimal credit allocation vector $\mathbf{x}^*$, such that the comprehensive marginal utility of the educational system is maximized.

2.3.1 Objective Function

This is a typical Nonlinear Programming (NLP) problem. We transform the multi-dimensional educational objectives into a single scalar objective function through the Linear Scalarization method.

The expanded form is:

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$$max \underbrace{w_1 ln(1+x_1)}_{eff} + \underbrace{w_2 x_2}_{green} + \underbrace{w_3 \frac{1}{1+e^{-\beta(x_3-x_0)}}}_{enthical} + \underbrace{w_4 ln(1+x_4)}_{tradition} \tag{12}$$

Where, $x = [x_{eff}, x_{green}, x_{enthic}, x_{trad}]^T$ be the decision variables , representing the credit allocations for Efficiency-Enhancement, Green-Sustainability, Socio-Ethical, and Foundational-Traditional modules respectively. $\mathcal{W}_k$ represents the data-model dual-driven weights, reflecting the heterogeneous demand urgency of different occupations for various curriculum modules.

2.3.2 Constraint System

In order to ensure that the optimization results possess practical feasibility and social responsibility, the model must satisfy a triple constraint involving physical resources, environmental externalities, and ethical bottom lines. The feasible region Ω is defined as follows:

$$\begin{cases} \sum_{k=1}^{4} x_k = C_{total}, \textit{Resource Constraint} \\ x_2 \geq \lambda \cdot \alpha_j \cdot x_1, \textit{Carbon Neutrality Responsibility Coupling Constraint} \\ x_{enthic} \geq \epsilon, \textit{Ethical Floor} \\ x_k \geq 0, \forall k, \textit{Non-negativity Constraint} \end{cases} \tag{13}$$

Interpretation of Constraint Physical Meanings:

The model establishes an upper limit for the total credits of undergraduate core courses. $C_{total} = 20$. This reflects the scarcity of educational time—increasing the investment in any single category of courses inevitably occurs at the expense of displacing others, characterizing a zero-sum game in resource allocation.

Carbon Neutrality Responsibility Coupling Constraint serves as the pivotal innovative constraint of the proposed model.

$$x_{green} \geq \underbrace{\lambda}_{\textit{Coupling coefficient}} \cdot \underbrace{\alpha_j}_{\textit{Impact Rate}} \cdot x_{efficiency} \tag{14}$$

By imposing $\epsilon = 1.0$, the model ensures that regardless of fluctuations in the weight vector, all students are mandated to receive a baseline level of ethical and legal education. This serves as a critical safeguard against the unchecked proliferation of technocentrism.

2.3.3 Model Solution and Algorithm

Since the objective function incorporates nonlinear logarithmic and Sigmoid terms, and the constraints consist of linear inequalities, this optimization problem is categorized as a Constrained Nonlinear Programming (Constrained NLP) problem.

We employ the Sequential Quadratic Programming (SQP) algorithm for the solution. Compared to traditional gradient descent methods, SQP demonstrates superior robustness and efficiency when handling boundary constraints, particularly in complex non-convex feasible regions.

3. Experiments and Results

3.1 Data Sources

To ensure that the optimization results align with international occupational classification standards while remaining sensitive to instantaneous shifts in the current labor market, this model adopts a "Static-Dynamic Coupling" data input strategy:

Fundamental skill features are extracted from the O*NET Database (Version 27.1). This authoritative database provides standardized task descriptions for various occupations, ensuring that the keywords extracted via the TF-IDF algorithm possess a high degree of professional representativeness. The empowerment coefficients (δ)and industry correlation factors (γ), in the WSEM model are calibrated using real-time job posting data from mainstream recruitment platforms. By crawling Job Descriptions (JDs) from January 2026, we have corrected the weights of AI skills in actual recruitment scenarios, thereby overcoming the inherent update lag typical of standard databases.

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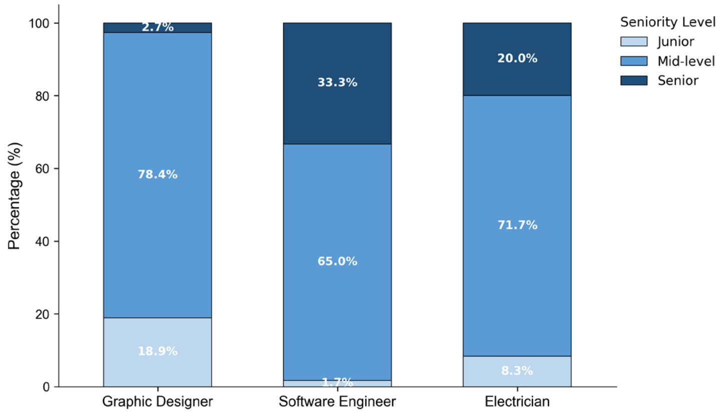

Figure 1: Data Analysis of Occupational Rank Distributions

As shown in Figure 1, to quantify the rank structure vector in the WSEM model, we analyzed the labor distribution across three representative occupations, revealing that internal skill structural heterogeneity directly determines the depth of AI impact. Graphic design exhibits a "bottom-heavy" structure where junior and mid-level practitioners comprise 97.3% of the workforce, resulting in significant efficiency gains and substitution risks due to AI's proficiency in entry-level tasks. Conversely, software engineering displays a "knowledge-intensive" structure with a high proportion of senior engineers (33.3%), suggesting AI serves primarily as "tool empowerment" for complex architectural tasks rather than direct substitution. Finally, the electrician trade, characterized by a mid-level technical backbone (71.7%) and reliance on physical operational experience, shows negligible AI impact due to the irreplaceability of physical labor.

3.2 Calculation Results of the Weighted Seniority-Efficiency Model (WSEM)

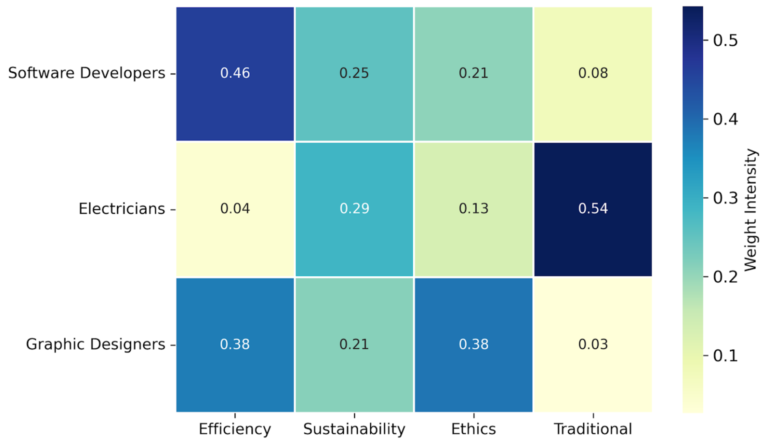

Figure 2: Weights for each occupation

As illustrated in Figure 2, the initial weight vectors extracted from the O*NET corpus reveal distinct occupational differentiation patterns. Software Engineers demonstrate an "efficiency-driven" profile, with core weights concentrated in Efficiency-Enhancement (0.46) and Green-Sustainability (0.25), reflecting the intense demand for AI-assisted programming and sustainable computing. In contrast, Graphic Designers exhibit a "bimodal" distribution where Efficiency-Enhancement and Socio-Ethical scores are tied (0.38), highlighting the creative industry's dual focus on high-efficiency output and copyright compliance. Finally, Electricians display "physical rigidity," where Foundational-Traditional skills (0.54) dominate over efficiency gains (0.04), empirically confirming the irreplaceability of physical-world operations.

3.3 Comprehensive Multi-dimensional AHP Assessment of AI Impact

The integration of multi-dimensional indicators through the AHP model reveals pronounced occupational polarization under AI impact. Software Engineers exhibit a "Techno-Economic" dual drive, with radar charts extending deeply into Economic Sensitivity and Technological Substitutability, indicating high exposure to technical shifts and significant macro-economic resonance. In contrast, Electricians present a "mono-polarized" profile characterized by low technological substitutability yet near-maximum Talent Scarcity, suggesting the primary challenge is labor supply exhaustion rather than AI substitution. Meanwhile, Graphic Designers show prominent expansion in Technological Substitutability with lower Economic Sensitivity, implying that AIGC's impact is manifested primarily as micro-level job displacement rather than macro-economic disruption .

3.4 TF-IDF Fusion Weighting Algorithm

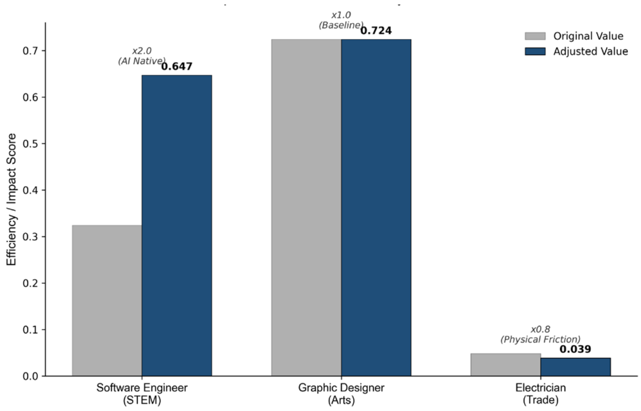

Figure 3: Integrated Weights and Industry Calibration

As illustrated in Figure 3, the introduction of the Industry Correlation Factor refines base efficiency scores to reflect variations in "Physical Friction" during AI implementation. Specifically, Software Engineers exhibit "digital native acceleration," where the absence of physical constraints allows the calibrated efficiency gain to double to 0.647, reflecting a potent technical leverage effect. Graphic Designers retain a high base gain of 0.724, indicating that efficiency improvements in image generation convert directly to productivity with minimal loss. In contrast, Electricians face significant efficiency dissipation due to physical operational rigidity, resulting in a calibrated score of 0.039 that corroborates the high impact-resistance of blue-collar trades

3.5 Final Optimized Curriculum Weights from Multi-Objective Programming

The final curriculum weights derived from the Multi-Objective Curriculum Optimization Model (MOCOM) are presented in Table 2. These results represent the optimal equilibrium point on the Pareto Frontier, balancing immediate market technical demands with long-term socio-environmental strategic foresight.

Table 2: Optimized Results of Curriculum Weights and Allocations

Occupation Category	Efficiency-Enhancement	Green-Sustainability	Socio-Ethical	Foundational-Traditional
Software Engineer	6.56	5.27	8.17	0．00
Graphic Designer	5.95	4.83	9.21	0.00
Electrician	0.00	0.50	6.38	13.12

4. Conclusion

The primary objective of this study is to resolve the structural misconfiguration between labor skill demands and the supply of higher education resources in the AIGC era. To better adapt to rapid technological shifts while incorporating occupational heterogeneity, we argue that traditional assessment methods not only overlook the micro-level variances in seniority distributions within professions but also neglect the macro-externalities—such as environmental costs and socio-ethical risks—triggered by high-intensity computing. To address this lacuna, this paper develops a scientific and transparent multi-objective decision-analysis framework, providing educational policymakers with a systemic quantitative toolkit ranging from "precise impact diagnostics" to "algorithmic curriculum allocation."

In practical implementation, this research innovatively constructs a dual-layer impact quantification

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framework based on the WSEM-AHP algorithm. By integrating real-world market recruitment data via TF-IDF extraction, we propose a multi-objective curriculum optimization model governed by carbon neutrality responsibility and ethical bottom-line constraints. Empirical simulations demonstrate that the model effectively identifies distinct occupational profiles: it successfully internalizes the green computing responsibilities for software engineers pursuing efficiency, while fortifying an ethical defense for the creative industries. Ultimately, it achieves an optimal balance between maximized educational utility and sustainable development under limited credit constraints.

While this study offers a logically self-consistent and highly structured algorithmic framework, avenues for further expansion remain. Future research may consider incorporating dynamic time-series models, such as Long Short-Term Memory (LSTM) networks or system dynamics, to track and predict the non-linear evolutionary trajectories of skill demands. Furthermore, integrating regional educational institutional variations and industrial subsidy policies as adjustment parameters, while calibrating multi-objective utility functions through long-term graduate longitudinal tracking data, will be pivotal directions for deepening this field of inquiry.

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