Gen-AI is Coming: The Future of Three Career Paths and University Education

Kezhen Pan*

School of Space Science and Technology, Xidian University, Xi'an, Shaanxi 710071, P. R. China

*Corresponding Author: 3669881448@qq.com

Abstract. Generative Artificial Intelligence (Gen-AI) reshapes occupational prospects and higher education. This study selects software engineers, chefs and painters as typical occupations, constructing a nonlinear regression model with Ridge Regression and Logit Transformation to predict their 2027–2030 trends via 2014–2025 U.S. BLS and Levels.fyi data. A value-creation model with Greedy Algorithm identifies Gen-AI era core skills, providing targeted curriculum reform for three universities. Human well-being factors are added to form a scalable AI-adaptive training framework, offering data-driven references for occupational planning and higher education optimization.

Keywords: enerative AI; Career Development; Higher Education Curriculum; Mathematical Modeling; Greedy Al- gorithmenerative AI; Career Development; Higher Education Curriculum; Mathematical Modeling; Greedy Algorithm G

1 Introduction

1.1 Problem Background

Generative AI (Gen-AI) permeates industries and reshapes workplace demand[1]. Unlike traditional AI, it generates original content, leading to heterogeneous occupational impacts: displacing repetitive labor, boosting creative field efficiency, and minimally affecting human-centric roles[2]. This transformation requires students to consider Gen-AI's career implications and educational institutions to adapt talent cultivation strategies, with accurate impact prediction critical for aligning education with labor market needs.

1.2 Restatement of the Research Problem

The core research problems are:

1) Predict demand shifts and skill requirements of STEM / trade / art occupations under Gen-AI with mathematical models.

J. Rak et al. (eds.), *Proceedings of the 2026 11th International Conference on Social Sciences and Economic Development (ICSSED 2026)*, Advances in Economics, Business and Management Research 391,
https://doi.org/10.2991/978-94-6239-701-9_96

2) Propose data-driven curriculum and enrollment strategies for corresponding educational institutions.
3) Integrate human well-being factors to improve model scalability.
4) Assess the generalizability of recommendations to other institutions.

1.3 My Work

A "data-model-prediction-strategy" framework is adopted,as shown in Fig.1:

• Task 1: Construct a nonlinear regression model for occupational prospects with five core indicators and three Gen-AI metrics.

• Task 2: Build a value-creation model to identify core skills and propose curriculum reform for three typical institutions.

• Extended Research: Incorporate human well-being factors to form a scalable AI-Adaptive Resilience framework.

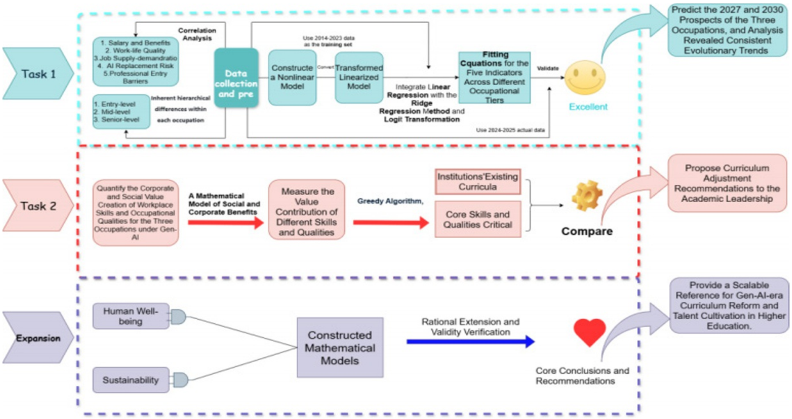

Fig. 1. Research Framework and Technical Route.

2 Assumptions and Justifications

Three key assumptions ensure model validity:

1) Consistent Statistical Standards: Gen-AI indicators use unified data cleaning for cross-temporal comparability, including outlier removal and normalization.

2) Industry-Aligned AHP Weights: Occupational tier weights are determined via Delphi method ($CR < 0.1$), aligning with real- world industry structures.

3) Exclude Extreme Shocks: Wars and pandemics are excluded to focus on Gen-AI's direct impact, a common technological impact research practice.

3 Notations and Definitions

Key symbols are summarized in Table 1, covering variables, parameters and influencing factors.

Table 1. Key Symbols and Definitions.

Symbol	Category	Range	Definition
Yi,j	Dependent	[0 , +∞)	Prospect index of i-th occupation at j-th tier
W	Dependent	[0 , +∞)	Annual value creation (10k USD)
Ct /It /Pt	Independent	[0 , +∞)	Gen-AI talent/investment/policy index
σj	Parameter	[0 , +∞)	Occupational tier adjustment coefficient
α/β/γ	Parameter	R	Elasticity coefficients of Gen-AI metrics
Ej	Factor	[0 , 1]	AI skill exposure rate
Φ(H, S)	Extended	[0 , 1]	Sustainable Productivity Coefficient

4 Task 1: Occupational Prospect Modeling

4.1 Indicator Quantification

1) Dependent Variables (Occupational Prospects): Four core indicators for occupational prospects:

1) Salary and Welfare (Y1): $Y_1 = \frac{Annual\ Income}{Cost\ of\ Living\ Index}$ adjust for regional cost differences(Levels fyi,2014-2024)[3].

2) Quality of Life (Y2): Proxy by paid vacation days and weekly working hours (U.S.Bureau of Labor Statistics[BLS],2025)[4].

3) Unreplaced Risk (Y4): $Y_4 = 1 - AI\ exposure\ rate\ (AHP\ weighted)$, reflecting non-automatable task proportion.

4) Entry Barrier (Y5): $Y_5 = Education \times 0.6 + Training\ Cost \times 0.4$, combining educational and financial barriers.

2) Independent Variables (Gen-AI Metrics): Three Gen-AI development indicators:

1) Talent Supply (Ct): New AI professionals (ACM/BLS data), reflecting AI expertise labor supply(Center for Security and Emerging Technology[CSET],2014-2024)[5].

2) Investment (It): Annual VC + R&D + government funding (Crunch base), measuring industry investment intensity.

3) Policy Index (Pt): Pt = Supervision×0.4+Legal Restrictions× 0.6, quantifying regulatory environment.

4.2 Mathematical Model

1) Core Nonlinear Model: Considering nonlinear correlations, the core model is:

$$Y_{i,j} = \sigma_j \cdot \frac{C_t^{\alpha} \cdot I_t^{\beta}}{P_t^{\gamma}} \cdot M^{(t-T_0)} \quad (1)$$

where T0 = 2014, M > 1 (technology maturity factor), and α/β/γ are metric sensitivity elasticity coefficients.

2) Model Optimization: Three optimization techniques for estimation challenges: - Linearization via natural logarithm:

$$\ln Y_{i,j} = \ln \sigma_j + \alpha \ln C_t + \beta \ln I_t - \gamma \ln P_t + (t - T_0) \ln M \tag{2}$$

- Logit transformation for Y4 (boundary-constrained):

$$logit(p) = \ln\left(\frac{p}{1-p}\right) \tag{3}$$

- Ridge Regression for Ct and It multicollinearity (L2 regularization: $Loss = \sum(\ln Y - \widehat{\ln Y})^2 + \lambda \sum \beta_m^2$).

4.3 Prediction Results

Normalized 2027–2030 prediction results show core conclusions:

• Software Engineers: High-end expand (risk < 0.1), mid-end stable, low-end shrink (risk > 0.8) via routine task automation,as shown in Fig.2.

• Chefs: High-end scarce (risk < 0.1), mid-end stable, low-end eliminated (risk > 0.9) via AI-assisted kitchen automation,as illustrated in Fig.3.

• Painters: High-end leading (risk < 0.05), mid/low-end stable (risk ≈ 0.4), with Gen-AI as a productivity tool,as depicted in Fig.4.

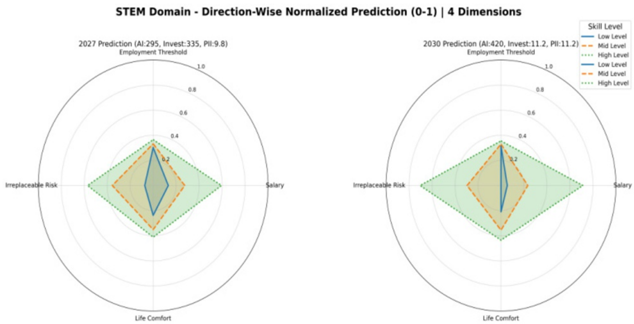

Fig. 2. Normalized Prediction of Software Engineers (2027–2030).

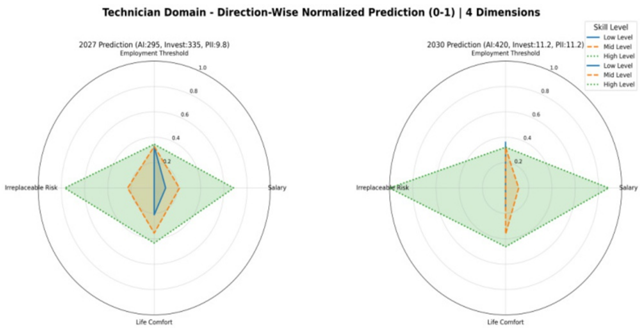

Fig. 3. Normalized Prediction of Chefs (2027–2030).

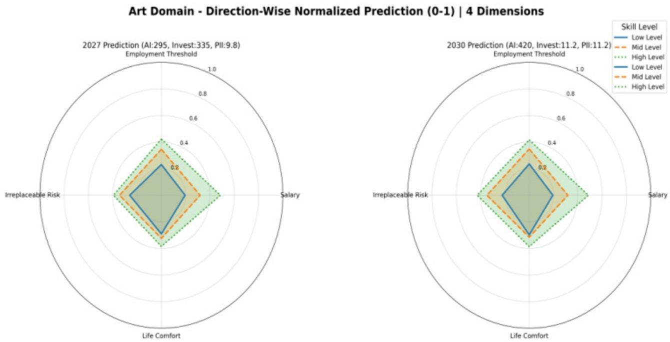

Fig. 4. Normalized Prediction of Painters (2027–2030).

5 Task 2: Curriculum Analysis and Recommendations

5.1 Value-Creation Model

This model quantifies graduates' societal and enterprise value by distinguishing AI-augmentable and human-unique skills, pro- viding a measurable basis for curriculum design with efficiency and sustainability considered.

$$W = \left(\sum_{i=1}^{n} F_i\right) \cdot \left(\sum_{j=1}^{m} B_j \left[(1 - E_j) + \mu_{job} A \cdot E_j\right]\right) - Cost \tag{4}$$

where F_i = capability contribution coefficient, B_j = work quality indicator, A = AI efficiency improvement, E_j = AI exposure rate, and Cost = AI tool and training cost. Greedy Algorithm selects the top 5 core capabilities (Table 2), reflecting key Gen-AI era qualities valued by enterprises and society.

Table 2. Top 5 Core Capabilities by Occupation.

Software Engineer			Chef			Painter		
Rank	Capability	Value	Rank	Capability	Value	Rank	Capability	Value
1	Dependability	80.59	1	Dependability	30.61	1	Dependability	37.44
2	Attention to Detail	72.13	2	Attention to Detail	20.71	2	Innovation	29.30
3	Intellectual Curiosity	49.84	3	Stress Tolerance	12.80	3	Cooperation	21.71
4	Integrity	43.54	4	Self-Control	9.76	4	Attention to Detail	20.85
5	Achievement Orientation	35.77	5	Cooperation	9.58	5	Adaptability	20.30

5.2 Curriculum Recommendations

Based on the core capabilities identified by the value-creation model, targeted curriculum adjustment plans are proposed for three representative educational institutions. The core goal is to strengthen cultivation of irreplaceable human skills while integrating AI tools into teaching, so that graduates can better adapt to workplace changes in the Gen-AI era.

1) Rutgers University (Software Engineering): - Strengths: The core course Computer Architecture effectively helps students establish systematic thinking and professional debugging capabilities.

- Gaps: Lack of systematic training in Gen-AI model fine-tuning, practical application deployment and AI ethical norms.

- Recommendations:

1. Offer practical courses on Gen-AI Fine-tuning & Deployment based on Hugging Face and TensorFlow platforms.

2. Add the module of AI-Driven Requirements Engineering to improve students' practical application capabilities.

3. Regularly organize AI Ethics and Academic Integrity themed workshops to strengthen professional ethics education.

2) Du Page College (Culinary Arts): - Strengths: Culinary Measurement lays a solid foundation for students' flavor control and cooking standardization capabilities.

- Gaps: Insufficient training in innovative fusion cuisine development and professional pressure resistance capabilities.

- Recommendations:

1. Set up AI-Assisted Fusion Cuisine Workshop to combine AI flavor matching tools with human culinary creativity.

2. Add Stress Management for Chefs courses to enhance students' professional psychological resilience.

3. Replace part of mechanical and repetitive cooking training with AI-assisted intelligent cooking equipment to improve training efficiency.

3) CSULB (Fine Arts): - Strengths: Fiber Sculpture ef- fectively cultivates students' visual expression capabilities and innovative thinking.

- Gaps: Lack of systematic training in the integration of AI creative tools and physical art creation.

- Recommendations:

1. Develop AI-Driven Brand Visual Design courses to combine AI visual generation tools with human creative design thinking.

2. Offer interdisciplinary courses on Physical Art & AI Installa- tions to expand students' creative expression forms.

3. Strengthen the training of AI prompt engineering and creative control capabilities to enable students to effectively use AI tools to serve artistic creation.

6 Extended Research: Human Well-Being Integration

To address ”human value depreciation” from excessive application of technological means in the workplace, the Sustainable Productivity Coefficient (Φ) is introduced to incorporate human well-being factors into the value-creation model:

$$W_{total} = \Phi(H, S) \cdot [W - (Cost_{AI} + Cost_{burnout})] \tag{5}$$

where $\Phi(H, S) \in [0, 1]$ is a comprehensive coefficient related to mental health H and social support S of practitioners, CostAI refers to direct AI application cost, and Cost burnout represents hidden occupational burnout cost from excessive work pressure.

Generalized Training Framework:

1) AI+X Technical Synergy (70%): Integrate AI tools as practical auxiliary means (such as AI-assisted coding and creative design) to enhance students' core professional skills.

2) Meta-Competency Development (20%): Focus on the cultiva- tion of non-automatable core competencies such as critical thinking evaluation and complex problem decomposition.

3) Resilience & Ethics Buffer (10%): Set up career adaptability training workshops and AI professional ethics courses to balance the development of technical capabilities and human well-being.

7 Conclusion and Limitations

7.1 Key Conclusions

1. The impact of Gen-AI on different occupations shows obvi- ous heterogeneity: it has a high substitution effect on repetitive and standardized work, while it has a low substitution effect on creative and human-centric roles, which fully reflects the irreplaceable value of human unique capabilities such as creative thinking and emotional communication.

2. The core competencies required for various occupations in the Gen-AI era integrate professional technical expertise and non-automatable human qualities (such as reliability, innovation awareness), and the balanced cultivation of these two types of capabilities is the core direction of higher education reform.

3. Higher education institutions need to transform from the traditional ”knowledge acquisition” oriented training model to the ”value enhancement” oriented model, and balance the cultivation of AI technology application capabilities and human unique skills while paying attention to the integration of human well-being factors in curriculum design.

7.2 Limitations

1. Geographical limitation: The research data is mainly based on the U.S. labor market, and follow-up research should incor- porate global multi-country datasets to improve the universality of conclusions.

2. Temporal limitation: This study only conducts short-term prediction for 2027–2030, and the long-term development trend of occupations requires more long-term tracking data for verifi- cation.

3. Model simplification: The constructed model does not consider the impact of regional policy differences on occupational development, and follow-up research should refine the model by adding these heterogeneous factors.

References

1. T. Eloundou, et al., ”GPTs are GPTs: An initial analysis of the potential impact of large language models on the labor market,” *arXiv preprint arXiv:2303.10130*, 2023.
2. Stanford HAI, ”2025 AI Index Report: A comprehen- sive analysis of artificial intelligence development,” https: //aiindex.stanford.edu/report/, 2025.
3. Levels.fyi, (2014-2024).December salary report:Occcupational salary level and welfare status statistics,”[data set] https://levels.fyi/ .
4. Bureau of Labor Statistics (BLS), ”2025 Occupational Out- look Handbook: Labor market demand and occupational development trends,” https://www.bls.gov/ooh/, 2025.
5. CSET, ”Research on the dynamic relationship between artificial intelligence and labor market,” https://cset.georgetown. edu/research/, 2014-2024.