Research on the Impact and Evolutionary Prediction of Generative Artificial Intelligence on Occupations: Taking STEM, Technical, and Artistic Professions as Examples

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Abstract: The rapid development of generative artificial intelligence is reshaping occupational structures, yet the mechanisms through which it affects different types of occupations and their evolutionary trends require further in-depth exploration. This paper takes three major industries-STEM, technical trades, and the arts-as its research subjects, selecting engineers, maintenance workers, and dancers as typical representatives of each industry. It constructs a seven-dimensional factor analysis framework encompassing AI penetration rate, economic environment impact, skill complexity, education and training investment, time series trends, industry characteristics, and technological growth factors. Based on occupational wage data from the U.S. Bureau of Labor Statistics from 2019 to 2024, data were collected using a combination of literature review and web crawling methods. A grey correlation model was first used to identify the key influencing factors for each occupation, followed by the construction of a ridge regression occupational demand prediction model to forecast the development trends of the three types of occupations. Cross-validation results indicate that the goodness of fit of the ridge regression model is significantly better than that of traditional regression models. The study reveals that the impact of generative AI on the three types of occupations shows significant heterogeneity: STEM occupations exhibit a trend of technological synergy and enhancement, technical occupations demonstrate a strong buffering capacity against substitution, while artistic occupations face a complex situation involving the reconstruction of creative boundaries.

Keywords: Generative Artificial Intelligence; Occupational Impact; Grey Correlation Analysis; Ridge Regression Analysis; Occupational Evolution Prediction

1. Introduction

The explosive growth of generative artificial intelligence (Generative Artificial Intelligence, Gen-AI) is reshaping the global economy and social structure at an unprecedented pace. It is projected that the global artificial intelligence market size will surge from $184.04 billion in 2024 to $826.73 billion by 2030, with the core market for generative AI technologies expected to grow nearly fivefold between 2025 and 2030. Large language models and multimodal generative models, represented by ChatGPT, Sora, and DeepSeek, have evolved from simple assistive tools into “human-like intelligent agents” capable of deep participation in knowledge production, content creation, and technological innovation. Their penetration is rapidly expanding from traditional manufacturing and information technology industries into various service sectors such as finance, education, healthcare, and the arts. While this technological transformation drives significant gains in production efficiency, it has also sparked widespread societal concerns about “technological unemployment” and the restructuring of employment [1,2].

The impact of technological progress on employment has long been a central topic in economics and sociology. From the Luddite movement during the Industrial Revolution to the replacement of humans by machines in the information age, every technological revolution has been accompanied by the displacement and creation of jobs [3,4]. However, unlike previous automation technologies that primarily substituted repetitive manual labor, generative artificial intelligence demonstrates the potential to replace mental labor, creative work, and even complex cognitive tasks, with a breadth and depth of impact far exceeding that of previous technological revolutions [5,6]. Scholars worldwide have conducted extensive research on the impact of artificial intelligence on total employment, employment structure, income distribution, and labor relations. It is generally agreed that AI exhibits capital-biased, skill-biased, and task-biased characteristics, exerting structural impacts on the labor market through the dynamic interplay of substitution effects and creation effects [7-9]. In terms of employment structure, studies have found that AI may exacerbate the "polarization" between high-skill and low-skill occupations, drive the shift of labor from manufacturing to services, and trigger profound changes in spatial employment structures and inter-industry wage gaps [10,11]. Although existing research has laid a solid foundation for understanding the employment effects of artificial intelligence, several key gaps remain. First, most studies focus on broad intelligent technologies such as industrial robots and automation, lacking systematic analysis of the occupational impact of generative AI as an emerging technological form. Second, existing literature primarily approaches the issue from macro or industry-level perspectives, lacking micro-level comparisons and quantitative predictions of the internal evolutionary mechanisms of different occupational types (such as STEM, technical trades, and the arts). Third, research methods are predominantly based on static panel regressions or theoretical reasoning, making it difficult to capture the dynamic evolutionary paths of occupational demand under technological shocks. Particularly against the backdrop of rapid generative AI penetration, whether different occupations face "synergistic enhancement" or "substitution and elimination," along with their evolutionary trends and key influencing factors, remains insufficiently explored.

Based on this, this study takes three major industries-STEM, technical trades, and the arts-as its research objects, selecting biological engineers, maintenance workers, and dancers as typical representatives. It constructs a seven-dimensional factor analysis framework encompassing AI penetration rate, economic environment impact, skill complexity, education and training investment, time series trends, industry characteristics, and technological growth factors. Using occupational wage and employment data from the U.S. Bureau of Labor Statistics from 2019 to 2024, the study employs a combination of grey correlation analysis and deep learning prediction methods to identify key factors influencing the development of each occupation and to quantitatively forecast occupational demand trends over the next five years. The value and significance of this research are mainly reflected in three aspects: First, theoretically, by constructing a multi-dimensional factor analysis framework, it reveals the heterogeneous mechanisms through which generative AI affects different types of occupations, addressing the lack of micro-level investigation into occupational mechanisms in existing research. Second, methodologically, it combines grey correlation analysis with deep learning models to achieve high-precision predictions of occupational evolution trends, providing new analytical tools for labor market research under technological shocks. Third, in practical terms, the findings can provide scientific evidence for governments to formulate differentiated vocational education policies, for enterprises to optimize talent structures, and for workers to engage in career planning, thereby contributing to the dynamic balance between technological progress and high-quality employment.

2. Model Establishment and Solution Analysis

2.1 Occupational Analysis

To comprehensively assess the evolutionary trends of various occupations, data were collected from the STEM industry, technical trade industry, and art industry, each comprising 20 occupations with a total of 3,000 data entries. The grey correlation model was employed to select occupations significantly affected by generative AI from the three industries. The following three core indicators were used as criteria for selection:

(1) **Average wage**: the arithmetic mean of hourly wages from 2019 to 2024.

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{1}$$

(2) **Median wage**: the median value of hourly wages from 2019 to 2024.

(3) **Wage growth rate**: using the compound annual growth rate (CAGR).

$$CAGR = \left(\frac{P_{2024}}{P_{2019}}\right)^{\frac{1}{5}} - 1 \tag{2}$$

Where, P_{2019} is the wage in 2019, and P_{2024} is the wage in 2024.

2.2 Grey Correlation Model

Step 1: Determine the reference sequence and comparison sequences.

(1) Reference sequence x_0: composed of the maximum values of each indicator, representing the ideal occupation. (2) Comparison sequences x_i: the values of the i-th occupation

Step 2: Data standardization: using the mean normalization method to eliminate dimensional effects:

$$x_i'(k) = \frac{x_i(k)}{\frac{1}{n}\sum_{i=1}^{n} x_i(k)} \tag{3}$$

Step 3: Calculate the grey correlation coefficient

$$\xi_i(k) = \frac{\min_i \min_k |x_0(k)-x_i(k)| + \rho \max_i \max_k |x_0(k)-x_i(k)|}{|x_0(k)-x_i(k)| + \rho \max_i \max_k |x_0(k)-x_i(k)|} \tag{4}$$

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

Step 4: Calculate the grey relational degree:

$$r_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \tag{5}$$

The higher the relational degree, the closer the occupation is to the ideal occupation, and the more suitable it is to be selected as a typical representative.

Based on the grey correlation model, 20 occupations were selected from each of the three industries, and their grey relational degrees were calculated. The results are shown in Figures 1 to Figure 3.

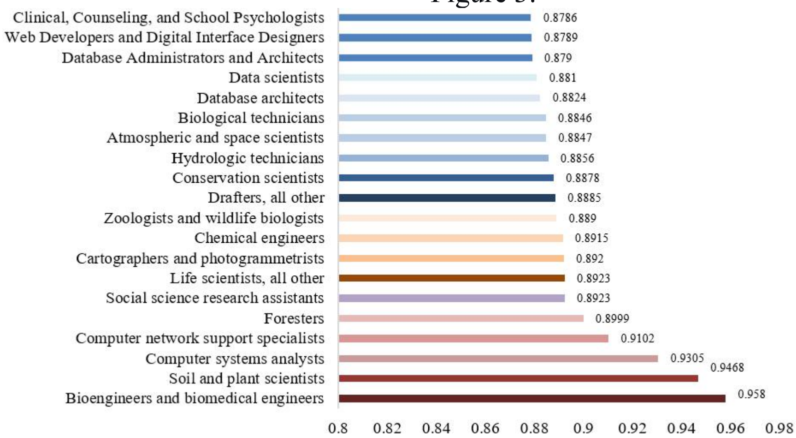

Figure 1. Impact of Generative AI on STEM Profession

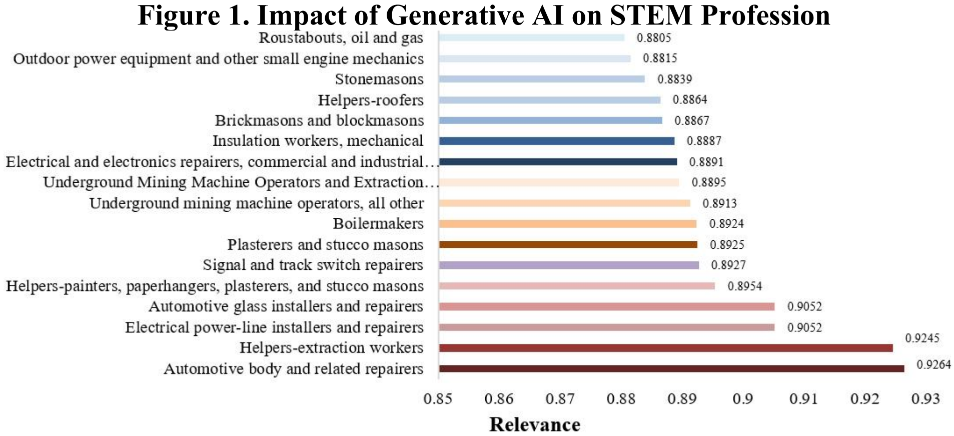

Figure 2. Impact of Generative AI on Trade Professions

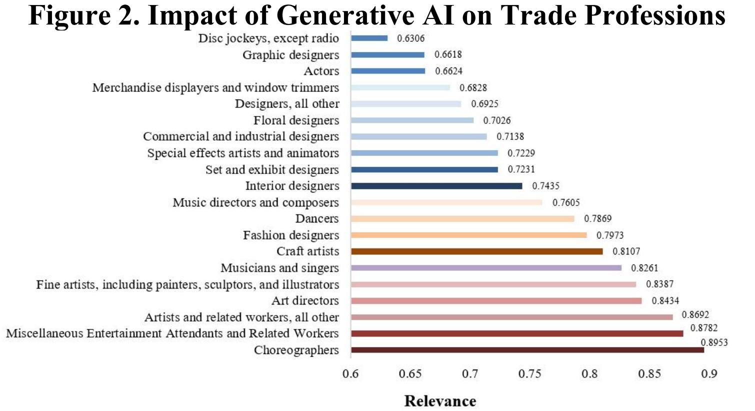

Figure 3. Impact of Generative AI on Artistic Professions

As shown in Figures 1 to Figure 3, the three types of industries exhibit significant differences in their exposure to generative artificial intelligence. Arts-related occupations have the widest score range (0.6306–0.8953), indicating the most pronounced differentiation in the degree of impact. The top-ranked occupations are mostly those involving physical performance or supportive roles, such as choreographers and entertainment service workers, while traditionally creative core occupations like graphic designers and actors rank relatively lower. This suggests that the impact of generative AI on arts-related occupations tends to focus more on replacing repetitive or auxiliary tasks, while its penetration into core creative processes remains bounded. STEM occupations generally show a high and relatively balanced level of impact, with scores mostly concentrated between 0.88 and 0.96, covering knowledge-intensive roles such as biomedical engineers, computer systems analysts, and data scientists. This reflects that generative AI has already demonstrated strong potential for both substitution and enhancement in areas such as data analysis, system design, and scientific research support. Trade occupations exhibit the highest and most concentrated level of impact. Frontline technical roles such as equipment installers, repair workers, blasters, and extraction workers have consistently high scores (0.8805–0.9611), indicating that generative AI possesses a high degree of substitutability in fields characterized by standardized operations, equipment diagnostics, and process optimization-areas with clear rules and procedures-suggesting that large-scale applications are likely to emerge first in these occupations in the future.

3. Ridge Regression Prediction Model

3.1 Model Construction

Based on the analysis in Section 2, one occupation is selected from each of the three industries: engineer, maintenance worker, and dancer, as the research objects. Considering the complexity of industry data and the limited sample size, and in order to avoid underfitting and overfitting, this paper constructs a ridge regression model to predict the demand for the three occupations. Nine independent variables are selected, including: GDP (100 million yuan), unemployment rate (%), population (10,000 persons), HumanEval score, AI penetration rate, technology growth factor, year, risk index, and comprehensive automation potential. The ridge regression model is specified as follows:

$$\min_{\beta}\left\{\sum_{i=1}^{n} (y_i - x_i^T \beta_i)^2 + \gamma \sum_{j=1}^{p} {\beta_j}^2\right\} \qquad (6)$$

Where y_i is the observed value of the dependent variable for the -th sample, x_i is the p-dimensional vector of independent variables for the -th sample and β_i represents the model parameters, i.e., the regression coefficients. β is the vector of regression coefficients; $\gamma \geq 0$ is the regularization parameter that controls the strength of the penalty.

3.2 Prediction Analysis

Based on Model (1) and combined with data from the U.S. Bureau of Labor Statistics and universities on the demand for engineers, maintenance workers, and dancers (unit: 10,000 persons) during the period 2019–2024, the model parameters are obtained as shown in Table 1. By writing Python code, the changes in demand for the three occupations are obtained as shown in Figure 4 to Figure 6, where the goodness of fit is defined as $R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2}$, with y_i being the observed values, $\hat{y}_i$ the predicted values, and $\bar{y}$ the mean of the observed y_i values.

From the prediction results graphs, it can be seen that the fitting effects for the hiring volumes of the three occupations are all very ideal. The R^2 for engineers reaches 0.9822, for maintenance workers 0.9897, and for dancers 0.9812. In the time series curves, the actual values almost completely overlap with the predicted values, and the points in the prediction accuracy plots are tightly clustered around the ideal line, indicating that the model captures the patterns of change in hiring volumes for these three occupations very accurately, and the overall predictive capability is reliable and stable.

Table 1. Ridge Regression Prediction Model Parameters

Occupation	Model parameters								
	β_1	β_2	β_3	β_4	β_5	β_6	β_7	β_8	β_9
Engineer	10736.3365	-2795.7740	16737.4339	-23787.1197	-7064.4572	7836.0566	-4098.4364	1592.9762	-675.3037
Maintenance Worker	925.7496	-199.3449	286.1171	-3574.7965	-8.0519	2570.2523	-270.7305	623.2810	163.1282
Dancer	-2259.1904	-492.0814	3429.1541	-1563.2407	2887.5569	-2252.8175	224.6729	1535.0442	506.3969

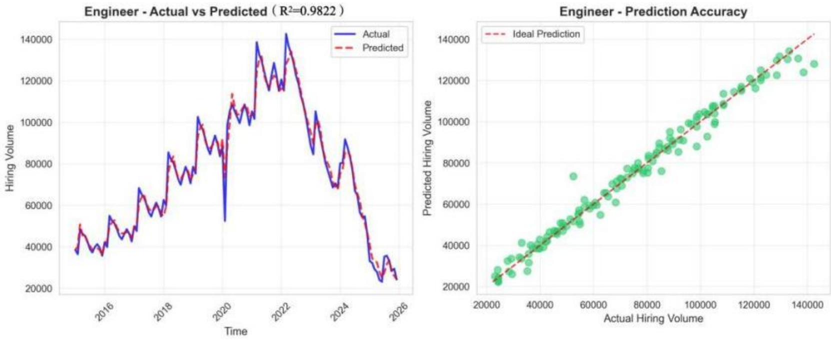

Figure 4. Comparison of Predicted and Actual Demand for Engineers under the Influence of Generative AI

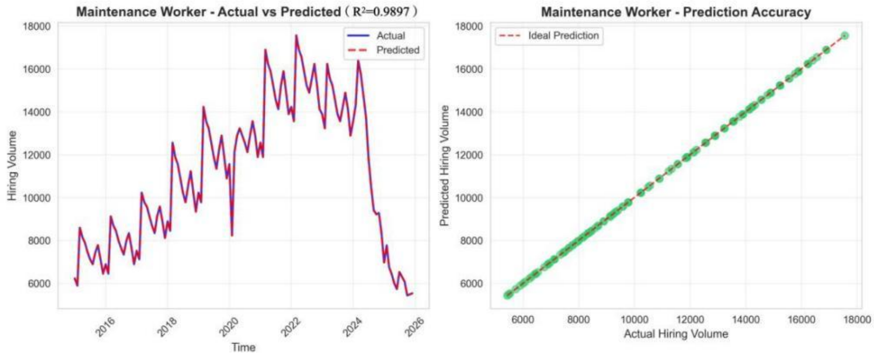

Figure 5. Comparison of Predicted and Actual Demand for Maintenance Workers under the Influence of Generative AI

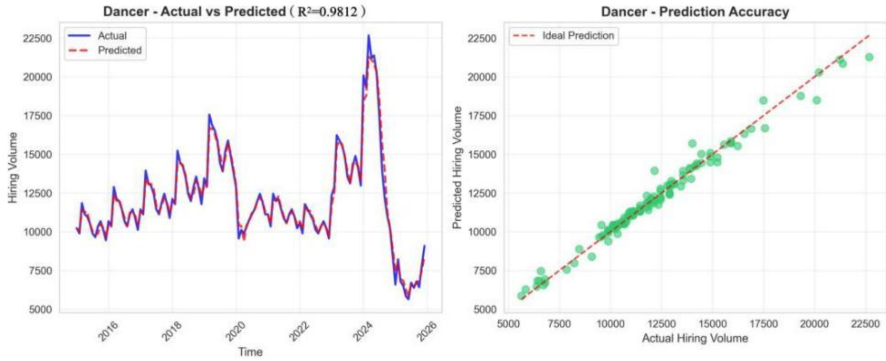

Figure 6. Comparison of Predicted and Actual Demand for Dancers under the Influence of Generative AI

4. Conclusion

This paper takes three major industries-STEM, technical, and artistic-as the research objects, selecting engineers, maintenance workers, and dancers as typical representatives. It comprehensively employs grey correlation analysis and ridge regression prediction models to explore the impact mechanisms and evolutionary trends of generative artificial intelligence on these three occupations. The study finds that the impact of generative AI on the three occupations exhibits significant heterogeneity: STEM occupations show a trend of technological synergy and enhancement, technical occupations demonstrate a strong buffering capacity against substitution, while artistic occupations face a complex situation involving the reconstruction of creative boundaries. Prediction results based on data from 2019 to 2024 show that the goodness of fit for engineers, maintenance workers, and dancers reaches 0.9822, 0.9897, and 0.9812, respectively, indicating that the model can accurately capture the evolutionary patterns of each occupation under technological shocks. The above conclusions provide empirical evidence for understanding the differentiated impact of generative AI on the labor market and can serve as a reference for the formulation of vocational education policies, the optimization of corporate talent structures, and the career planning of workers.

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