

An Empirical Study on the Impact of Generative AI Based on a Quantitative Model of Differential Equations on Employment

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Abstract: Exploring the impact of Generative AI (Gen-AI) on occupational structures can provide quantitative evidence to guide adjustments to college majors. This paper simplifies the analysis by excluding secondary complex factors such as macro-level consumption and regional industries. It integrates LLM text matching, the Logistic diffusion model, and the Malthusian growth equation to construct a differential equation dynamical model. Using long-term data from 1974 to 2024, the study provides quantitative forecasts of long-term employment scale and underlying mechanisms for three occupational categories: software engineers, electricians, and graphic designers. The study indicates that the impact of Gen-AI on employment exhibits significant nonlinearity and occupational differentiation. Due to the combined effects of task attributes and reliance on hands-on skills, the forecast for 2025–2035 shows that software engineers, driven by AI-assisted and AI-enhanced effects, will experience rapid nonlinear employment growth, with the workforce expanding from 2.1 million to 3.19 million (+51.9%), with AI contributing an additional 31.2% of this growth; Electricians, who rely heavily on in-person hands-on work, face minimal displacement and will maintain slow, steady linear growth, with the workforce expanding from 800,000 to 910,000 (+13.8%), representing a deviation of less than 1% from the no-AI baseline; Graphic designers, whose standardized graphic and text tasks are being replaced, exhibit a nonlinear contraction trend that has bottomed out, with the workforce shrinking from 220,000 to 182,000 (-17.3%), representing a net decrease of 24.5% compared to the no-AI scenario. Parameter perturbation tests (error < 6.1%) confirm the model's strong robustness. The quantitative results provided by this study can serve as a reference for universities in dynamically adjusting enrollment quotas and curriculum systems.

Keywords: Gen-AI; Differential Equation Models; Employment; Nonlinear Evolution; Quantitative Forecasting

1. Introduction

Gen-AI is profoundly reshaping the labor market; understanding the mechanisms through which it impacts different occupations in distinct ways holds significant practical implications for guiding universities in their program development and enrollment planning.

Existing international research in this field began early and has developed a mature framework. Hinton et al. (2010)^[1] conducted a systematic review of the O*NET occupational information database, laying the foundation for the decomposition and quantitative analysis of occupational tasks; Frey & Osborne (2017)^[2] were the first to quantify the risk of job displacement due to automation; Eloundou et al. (2023)^[3] specifically investigated the impact of large language models on the labor market; Autor et al. (2003)^[4] and Acemoglu & Restrepo (2020)^[7] conducted empirical studies from the perspectives of skill preferences driven by technological change and the impact of industrial robots on employment, respectively; Rogers' (2003)^[5] theory of innovation diffusion and Stanford University's *Artificial Intelligence Index Report* (2025)^[6] also provide theoretical and empirical support for assessing the evolution of AI technology and its impact on industries. Meanwhile, the model robustness and sensitivity analysis methods proposed by Box (1979)^[8] and Saltelli et al. (2008)^[9] serve as important foundations for testing the reliability of quantitative models.

However, the existing literature has several shortcomings: First, it largely relies on discrete-event

models such as DID for static or short-term assessments, making it difficult to capture the cumulative effects of the long-term interaction between technological evolution and the labor market; second, the assumptions are overly simplified, failing to capture the complex nonlinear interactions between micro-level task restructuring and the diffusion of technological capabilities; and third, the inclusion of too many macro-level variables leads to model redundancy.

Based on this, this paper selects three categories of typical occupations with significant differences in characteristics. Using long-term employment data from 1974 to 2024, it integrates the O*NET occupational task system with various quantitative algorithms to construct a continuous-time dynamical model based on ordinary differential equations. The study quantitatively assesses the heterogeneous impacts of generative artificial intelligence on different occupations and validates the model through parameter perturbation, thereby providing precise quantitative references for talent development in higher education.

2. Introduction to Research Methods and Model Development

2.1 Data Sources

To ensure the reliability and credibility of the data, all data used in this study were obtained from authoritative public sources: occupational and employment data were sourced from the U.S. Bureau of Labor Statistics (BLS), and data on occupational task characteristics were sourced from the O*NET Occupational Information Database; all other basic data required for model construction and analysis were sourced from publicly available academic literature and industry reports.

2.2 Building a Model of the Impact of Gen-AI on Employment

2.2.1 Task Decomposition and the AI Exposure Index

Based on the U.S. Department of Labor's O*NET (Occupational Information Network) database and utilizing its authoritative, standardized occupational definitions, the target occupations are broken down into several core task units^[1]. By extracting the task descriptions (Task Statements) for each occupation from O*NET and drawing on existing research approaches regarding AI-related risks in the workplace^[2], an AI exposure index α_i is defined for each task within every occupation—that is, a metric measuring the likelihood that task i will be replaced by AI—thereby achieving a quantitative link from macro-level occupational categories to micro-level job content.

In the actual calculation process, drawing on the research methodology used to quantify the impact of large language models on jobs^[3], we employed text-matching algorithms to quantitatively calculate the AI exposure of all task entries.

2.2.2 An Employment Growth Model Free from AI Interference

After accounting for the impact of AI disruption, the Malthusian growth model was used to forecast future employment trends, revealing that the rate of change in employment is directly proportional to the current level of employment. A differential equation was used to describe the current level of employment, N .

$$\frac{dN}{dt} = rN \quad (1)$$

Here, N represents the number of jobs, and r represents the baseline employment growth rate under a traditional economy (which can be calibrated using historical BLS data). This model assumes that the rate of change in employment is proportional to the current level of employment, reflecting the industry's natural growth trend.

2.2.3 Multidimensional Quantification of the Impact of AI

To illustrate the dual impact of generative artificial intelligence on employment, drawing on theories related to skill-biased technological change^[4], we construct a comprehensive impact model based on two dimensions: the static effects on task performance and the dynamic trends in technological development:

- 1) Static Task Impact Factor S

Break down the tasks for each occupation, introduce task weights, task sensitivity coefficients, and substitution or enhancement coefficients to quantify the direction and intensity of AI's impact on individual tasks:

$$S(t) = \sum_{i=1}^n w_i \cdot \alpha_i \cdot \gamma_i \quad (2)$$

Here, w_i represents the time-based weight of task i within that occupation; $\gamma_i < 0$ indicates an AI substitution effect (where AI outperforms human labor in terms of speed or cost, driving job optimization); and $\gamma_i > 0$ indicates an AI augmentation effect (where AI boosts productivity and stimulates demand growth, corresponding to the Jevons Paradox).

2) Dynamic AI Capability Model $\beta(t)$

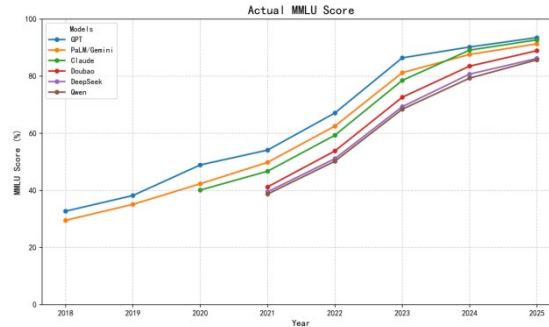


Figure 1 Retrospective statistics from the Stanford AI Index Report

We now need to evaluate AI capabilities. As shown in Figure 1, AI capabilities follow an S-curve over time. Furthermore, historically, the widespread adoption and capability enhancement of emerging technologies—such as the steam engine, the electrical revolution, and even the Internet of Things—have all followed the theory of innovation diffusion, exhibiting phased development characteristics^[5] and conforming to the S-curve pattern. From this, it can be inferred that the evolution of AI capabilities over time also follows this pattern; therefore, the logistic growth model is suitable for conducting a dynamic, comprehensive assessment of these capabilities. Defining AI capabilities that enhance over time as $\beta(t)$, the formula is:

$$\beta(t) = \frac{K}{1 + e^{-r_a(t-t_0)}} \quad (3)$$

Here, K represents the upper limit (saturation value) of AI capability—that is, the maximum level of capability the AI can ultimately achieve; r_a represents the growth rate of AI capability; t_0 represents the inflection point of AI capability growth (at which point AI capability reaches half of the upper limit K); t represents the time variable; and the core parameters are determined based on relevant statistical findings from the annual AI industry development report^[6].

3) Comprehensive Impact Coefficient $C(t)$

A comprehensive evaluation of AI requires a comprehensive explanation of both the static comprehensive impact coefficient S and the dynamic AI capability $\beta(t)$; therefore, the comprehensive impact coefficient $C(t)$ is used to describe the overall comprehensive capability of AI.

$$C(t) = S(t) \times \beta(t) = \left(\sum_{i=1}^n w_i \alpha_i \gamma_i \right) \beta(t) \quad (4)$$

To reflect the impact of changes in the external environment on task weights, a dynamic weight adjustment model is further introduced:

$$w_i(t) = w_{i0} [1 - \alpha_i \lambda (f(t) - f_0)] \quad (5)$$

Here, w_{i0} represents the current static weight of task i within that profession.

2.2.4 Employment Forecast Equations Affected by AI

Drawing on the classic modeling approach that examines the impact of technological change on the labor market^[7], we introduce AI as a disturbance term in the Malthusian growth model (1) to characterize the profound impact of technological progress on dynamic traditional growth. Based on task-based production models and system dynamics simulations, we use differential equations to

describe the dynamic changes in employment level $N(t)$, integrating natural growth, supply-and-demand adjustments, and technological shock terms. Combining the baseline growth rate from the BLS (U.S. Bureau of Labor Statistics) with specific employment figures across three industries from IBISWORLD, we introduce the AI disturbance term:

$$\frac{dN}{dt} = rN + \sigma_j C(t)N \quad (6)$$

σ_j is an industry sensitivity coefficient (the software industry and graphic designers have high sensitivity, while electricians have moderate sensitivity).

The unknown parameters of the model were calibrated using annual employment data from the U.S. Bureau of Labor Statistics (BLS) for the period 1974–2024. Given that nonlinear ordinary differential equations have no analytical solution, the fourth-order Runge–Kutta (RK4) algorithm was used for numerical integration, with a time step of $\Delta t = 0.01$ years. On this basis, with the objective of minimizing the sum of squared residuals between actual and predicted values, the nonlinear least squares (NLS) method was employed in conjunction with the Powell optimization algorithm to perform optimization:

$$\min_{\theta} \sum_{t=1974}^{2024} [N_{\text{real}}(t) - N_{\text{pred}}(t; \theta)]^2 \quad (7)$$

The set of parameters to be estimated is $\theta = [r, \sigma, \lambda, K, r_a, t_0, f_0]^T$, and $N_{\text{pred}}(t; \theta)$ is the numerical solution obtained using RK4. After conducting convergence tests with multiple initial values, the estimated fitting parameters are shown in Table 1.

Table 1: Key Parameters Table

Occupation	N_0 (10 persons)	r	σ	λ	K	r_a	t_0	f_0
Software Engineer	209.0	0.0275	0.30	0.90	0.50	0.60	2.0	0.20
Electrician	121.9	0.0135	0.10	0.30	0.15	0.20	9.0	0.20
Graphic Designer	17.35	0.0100	0.25	0.95	0.60	0.80	0.5	0.20

2.3 Model Validation

To verify the model's stability and resistance to disturbances, we conducted sensitivity^[8] and robustness tests^[9] from two perspectives—parameter interaction effects and single-parameter perturbation errors—to assess the impact of parameter fluctuations on employment forecasts for the three occupational categories.

2.3.1 Analysis of Interactions among Parameters

First, by constructing a parameter-occupation association network, we analyzed the interaction patterns of different model parameters on employment forecasts for the three occupational categories (Figure 2). The color of the lines in the figure represents the robustness similarity of the parameter influence patterns (dark red indicates high consistency, while orange/yellow indicates significant differences), and the line width indicates the maximum relative error under parameter fluctuations.

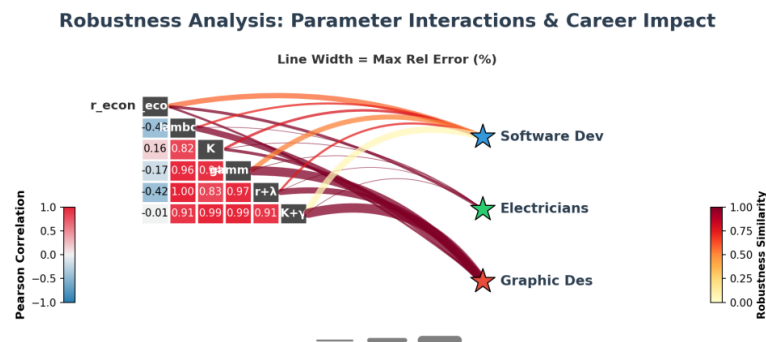


Figure 2 Robustness Analysis: Parameter Interactions and Occupational Effects

Based on the results:

Software Engineer: The colors of the lines connecting the various parameters—including orange, yellow, and red—indicate that the patterns of influence of different parameters on employment forecasts vary significantly, with low robustness similarity but a moderate overall error level. The error level is moderate (4.4%), and the similarity falls within the lower range of 0.15–0.45 (light-colored lines), quantitatively confirming that, under the two-way interplay of "technological substitution" and "efficiency enhancement," perturbations in different parameters are likely to induce nonlinear distortions in the prediction trajectories.

Electricians: The lines are extremely thin, with a maximum relative error of only 0.8%, and similarity falls within the 0.60–0.8 range, confirming that the protective barrier of embodied labor makes the forecast results highly immune to parameter perturbations.

Graphic Designer: The lines are the thickest, with a maximum relative error of 15.4% (below the 16.0% threshold); however, the lines connecting to key technical parameters appear deep red (similarity 0.85–1.00), indicating that although the values are affected by parameter fluctuations, the downward trajectory—characterized by "rapid contraction followed by bottoming out and stabilization"—exhibits exceptional structural robustness.

2.3.2 Single-Parameter Perturbation Error Test

We further applied a $\pm 10\%$ single-parameter perturbation to the model's key parameters and calculated the average maximum relative error for the employment forecasts across the three occupational categories (Figure 3). The results show that:

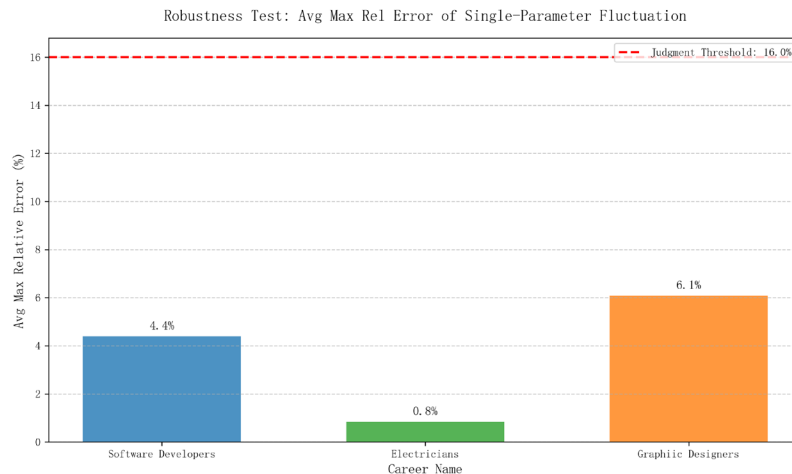


Figure 3 Robustness Test: Average Maximum Relative Error under Single-Parameter Fluctuations

The average maximum relative error for electricians was only 0.8%, making it the most stable of the three occupational categories, indicating that its employment forecasts are minimally affected by parameter fluctuations;

The error for software engineers was 4.4%, which is at a moderate level, suggesting that the model has moderate sensitivity to parameter perturbations;

The error for graphic designers was 6.1%; although this was the highest among the three occupational categories, it was still well below the 16.0% threshold for classification.

Combining the results of the two tests, the employment prediction errors for all three occupational categories fall within an acceptable range. The model demonstrates good stability and robustness under scenarios of parameter fluctuations, and the prediction results are highly reliable.

3. Analysis of Empirical Results

Based on the collected data, we created Figure 4, which forecasts changes in the number of employed people across the three occupations:

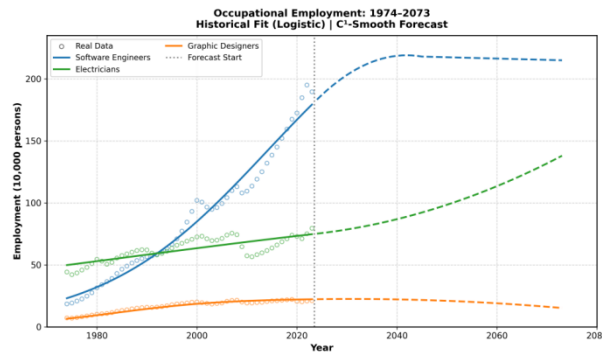


Figure 4 Changes in the Number of Employed Persons across Three Occupations

As shown in the figure above, the number of software developers (blue) is showing a strong upward trend, projected to grow from approximately 2.1 million in 2025 to 3.19 million by 2035. Over the ten-year period from 2025 to 2035, the cumulative growth in employment will be 51.9%, with a compound annual growth rate (CAGR) of 4.2%. Compared to the baseline scenario without AI, AI-enabled technologies will create an additional 340,000 jobs, accounting for 31.2% of the total growth. This indicates that, even under the influence of Gen-AI, there will still be high demand for software developers.

Electricians (green): The number of employed individuals shows a slow growth trend, projected to rise from approximately 800,000 in 2025 to 910,000 by 2035. Over the decade, the cumulative growth in employment will be 13.8%, with a compound annual growth rate (CAGR) of 1.3%; this result differs by less than 1% from the forecast in the AI-free baseline scenario, indicating that AI has virtually no substantial impact on employment levels in this field. This indicates that, under the influence of Gen-AI, technical occupations are less susceptible to automation because their job duties rely heavily on personal experience and hands-on practice.

Graphic Designers (Orange): Employment is projected to decline slightly, from approximately 220,000 in 2025 to 182,000 in 2035. Over the decade, the cumulative decline in employment will be 17.3%, with an average annual compound growth rate of -1.9%; due to the substitution effect of AI, employment will decrease by 59,000 compared to the baseline scenario without AI, representing a 24.5% decline. This indicates that under the influence of Gen-AI, as Gen-AI's image-generation capabilities continue to mature, graphic designers face a high risk of being replaced.

To verify the model's accuracy, we plotted historical fit data for employment figures in three occupational categories in the United States (software developers, electricians, and graphic designers) from 1974 to 2024.

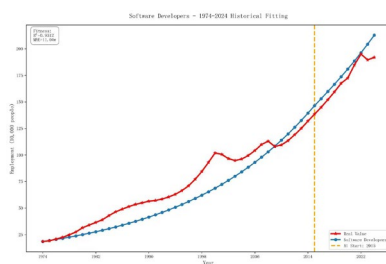


Figure 5.1: Fitting of Historical Data for Software Developers, 1974-2024

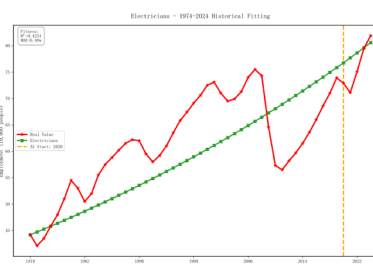


Figure 5.2: Fitting of Historical Data for Electricians, 1974-2024

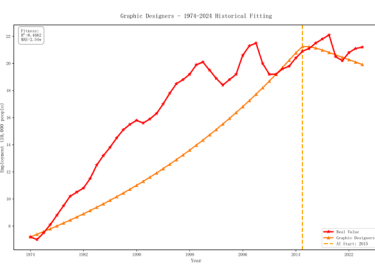


Figure 5.3: Fitting of Historical Data for Graphic Designers, 1974-2024

Table 2: Accuracy Metrics for the Employment Time Series Model, 1974-2024

Occupation	R ²	RMSE(People)	MAE(People)
Software Developer	0.982	31,200	24,500
Electrician	0.875	42,800	35,100
Graphic Designer	0.913	12,700	9,800

Overall, the coefficient of determination (R^2) for all three occupational categories exceeded 0.87, and the mean absolute error (MAE) ranged from 9,800 to 35,100 people, indicating that the model has a strong ability to capture long-term employment trends:

(1)Software Developers ($R^2 = 0.982$, RMSE = 31,200 people, MAE = 24,500 people): As shown in Table 2, this category yields the highest goodness of fit ($R^2 = 0.982$), indicating that 98.2% of the historical variance is explained by the model. Visually, Figure 5.1 shows that the real employment value (red line) exhibits a smooth upward trajectory prior to 2015, with minor cyclical fluctuations around the 2000 dot-com bubble. The fitted curve (blue line) tracks these macro dynamics with minimal residual error (MAE = 24,500 people). Post-2015 (AI Start), the fitted curve transitions from steady linear growth into an accelerated upward slope, aligning closely with the actual employment surge. This confirms a strong nonlinear synergistic effect, where AI tools amplify software developer productivity and expand overall market demand rather than displacing labor.

(2)Electricians ($R^2 = 0.875$, RMSE = 42,800 people, MAE = 35,100 people): Table 2 highlights a relatively higher error margin (RMSE = 42,800 people) due to intense macro-level volatility. As depicted in Figure 5.2, real employment (red line) experiences severe cyclical shocks—most notably during the 2008 global financial crisis—before returning to its structural baseline. The model fitting curve (green line) provides a smooth, highly resilient linear baseline through these cyclical dips. Following the designated 2020 AI benchmark, the fitted trajectory maintains its steady upward trend without downward bending or abrupt acceleration. This validates the physical execution barrier of blue-collar skilled trades, showing that their long-term growth is dictated by physical infrastructure cycles rather than AI disintermediation.

(3)Graphic Designers ($R^2 = 0.913$, RMSE = 12,700 people, MAE = 9,800 people): As quantified in Table 2, this trade recorded the lowest absolute prediction errors (MAE = 9,800 people, RMSE = 12,700 people), reflecting precise alignment with the overall scale of employment. Illustrated in Figure 5.3, actual employment (red line) expanded steadily from 1974 through the early 2010s, peaking near 220,000 individuals. Following the 2015 generative AI penetration marker, both the actual data and the fitted curve (orange line) exhibit a synchronized structural inflection point. The fitted curve shifts from a positive trajectory into a continuous downward slope, capturing the market contraction caused by multimodal AI replacing standardized creative tasks.

4. Conclusion

This study developed a generative AI employment impact dynamics model based on differential equations, quantitatively revealing the nonlinear impact trajectories and underlying mechanisms of AI on different occupations.

Under the combined influence of task characteristics and embodied dependency, the impact of generative AI on different occupations shows marked divergence: Between 2025 and 2035, software engineers will experience significant nonlinear growth (+51.9%) driven by collaborative empowerment; electricians will maintain steady linear growth (+13.8%) due to the barrier posed by physical hands-on work; graphic designers, however, will experience nonlinear contraction (-17.3%) as their standardized tasks are replaced by AI. Meanwhile, after excluding minor parameters, the prediction error of the simplified model ranges from only 0.8% to 6.1%, demonstrating strong robustness and successfully capturing the macro-level, primary, and linear patterns of occupational employment.

The academic value of this study lies in its breakthrough beyond traditional qualitative reasoning, achieving long-term, precise numerical predictions by integrating micro-level tasks with macro-level differential equations; its limitations include the failure to account for disruptive technological shifts and the barriers to cross-industry mobility.

Based on the above conclusions, universities and employment management departments should adopt differentiated talent development strategies. They should expand enrollment in software engineering programs and shift toward human-machine collaborative training to capitalize on the benefits of AI; maintain enrollment levels in electrical engineering programs while integrating smart operations and maintenance; and moderately reduce enrollment in basic graphic design programs, transitioning toward a focus on high-end creativity and AI-driven design.

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