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Leveraging Artificial Intelligence to Study and Forecast its Impacts on Employment Management and Wages in China's Key Cities

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ABSTRACT

The rapid development of artificial intelligence (AI) is transforming global economies, threatening job security across diverse fields, including AI development itself, as automation increasingly handles complex tasks traditionally performed by skilled professionals. As China leads global manufacturing and technological innovation, understanding the labor market implications of AI adoption is critical for shaping management science policy and workforce development. This study investigates the impact of AI, measured by industrial robot installation density, on employment scale and wages in the manufacturing sectors of Beijing and Shanghai from 2006 to 2020, extending the analysis to 2030 using deep learning. Employing panel data and a long short-term memory (LSTM) neural network, AI's effects on job displacement and wage growth are analyzed. Historical findings reveal a nuanced effect: AI adoption is strongly negatively correlated with employment scale (r = −0.90, p < 0.01), with Beijing and Shanghai experiencing employment declines of 44.6% and 40.3%, respectively, from peak levels. Conversely, AI is positively correlated with wages (r = 0.96, p < 0.01), with wage increases of 361% in Beijing and 324% in Shanghai. City-specific analyses show Shanghai's steeper AI adoption correlates with greater employment declines but higher wage growth compared to Beijing. LSTM forecasts predict continued employment declines (49.8% in Beijing, 50.2% in Shanghai by 2030) and wage growth (51.3% in Beijing, 54.6% in Shanghai). Graphs illustrate historical and forecasted management trends. Country-level synthesis underscores implications for China's labor market and other developing economies.

1. Introduction

China's economy, the second largest globally, has achieved remarkable growth, boasting a nominal GDP of approximately $18.3 trillion in 2024 [1]. As the world's leading manufacturing hub, China accounts for nearly 30% of global manufacturing output, driven by a labor force exceeding 800 million workers and extensive industrial infrastructure [2]. This economic scale is fueled by rapid

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urbanization, technological advancements, and significant investments in innovation, particularly in artificial intelligence (AI), with China leading in industrial robot installations [3], comprising over 50% of global installations in 2022 [4]. The rapid adoption of AI technologies, particularly industrial robots, has transformed manufacturing industries worldwide [5-7]. This disruptive potential extends far beyond manufacturing, as evidenced by AI's role in securing mobile networks [8], analyzing business economic factors [9], and driving financial technology adoption globally [10]. In engineering and materials science, AI frameworks are now pivotal for optimizing complex systems, from gas separation processes to material design [11]. The successful integration of AI and automation also necessitates robust defenses against digital threats, underscoring the critical importance of understanding individual, social, and organizational determinants of effective cybersecurity [12]. Its influence is equally profound in education, where it powers automated formative assessment systems [13] and augments human decision-making for teacher recruitment and diversity [14]. The sheer size of China's economy underscores the importance of understanding structural shifts in its labor market, especially those driven by AI technologies.

China's economic dominance profoundly shapes the global market, influencing supply chains, trade dynamics, technological standards [15], and even the AI market [16]. As the world's largest exporter, China drives economic activity across Asia, Africa, and Europe, particularly through initiatives like the Belt and Road, which extends its influence via infrastructure investments [17]. The adoption of AI and automation in Chinese manufacturing not only boosts productivity but also sets global benchmarks for industrial practices. These advancements impact labor markets worldwide by reshaping wage structures and employment trends, particularly in manufacturing-intensive economies, aligning with global findings on automation's effects [18].

Like other developing countries, such as India, Brazil, and Vietnam, China combines a large labor force with rapid industrialization and technological adoption, creating both opportunities and challenges [19]. These nations share traits like transitioning from agriculture-based to industrial economies and investing in automation to enhance productivity, yet they face similar risks of job displacement [18]. China's unique scale, state-driven innovation policies, and deep integration into global markets make it a critical case study for understanding AI's labor market impacts. While this study focuses on China, specifically analyzing AI's effects in Beijing and Shanghai from 2006 to 2020, its findings offer insights applicable to other developing countries navigating similar technological transitions.

In China, a global manufacturing hub with a vast labor force, understanding AI's impact on employment and wages is complex and context-specific [20]. In developed economies, automation often leads to short-term job displacement but can drive long-term productivity and wage growth by shifting labor toward higher-skill roles [21]. In developing economies like China, with large labor markets, AI's effects may differ due to abundant low-cost labor and rapid industrialization [19]. This study examines the impact of AI, proxied by industrial robot installation density, on employment scale (number of manufacturing employees) and wages (city average salary) in Beijing and Shanghai from 2006 to 2020, using panel data from the International Federation of Robotics and city-level statistics. By analyzing these trends, we aim to assess whether AI adoption leads to job displacement or fosters wage growth, providing insights into the evolving dynamics of China's labor market and its relevance to global economic trends.

To analyze the impact of AI on employment scale and wages in the manufacturing sectors of Beijing and Shanghai from 2006 to 2020, we utilized panel data from the International Federation of Robotics and city-level statistics, employing correlation and fixed-effects regression analyses. AI was proxied by industrial robot installation density, with employment scale measured as the number of manufacturing employees and wages as the city's average salary.

Within China's economy, where AI-induced labor market changes require adaptive financial approaches, improving financial literacy could empower workers and investors to manage economic transitions effectively, promoting resilience and informed financial decision-making in an increasingly automated landscape [22]. Therefore, understanding future labor market trends is critical for policymakers to address potential job displacement and capitalize on wage growth opportunities in China's rapidly automating economy [20]. These structural changes align with other long-term economic studies showing that factors like investment, education, and population dynamics significantly influence a nation's growth trajectory [23]. To forecast employment scale and wages from 2021 to 2030, we implemented a Long Short-Term Memory (LSTM) neural network. While recent studies have successfully employed advanced econometric techniques like ARDL-BART for causal measurement in macroeconomics [24] and NARDL to capture asymmetric effects [25], as well as dynamic non-parametric systems for forecasting [26], our study opts for an LSTM model due to its specific aptitude for capturing long-term dependencies in our time series data, offering superior performance for non-linear trends with the limited data points available [27].

The advent of AI, particularly through large language models and autonomous agents, has revolutionized forecasting across diverse scientific fields, including climate science, finance, and economics, by enabling more accurate predictions of future trends. All fields of science share common foundations in physics and mathematics, suggesting that a successful approach in one domain can be replicated in another. For instance, the successful application of deep learning in climate science, as demonstrated by Naisipour *et al.* [28], which enhances long-term weather and climate projections, indicates its potential efficacy in economics. This cross-disciplinary applicability is further evidenced in social sciences, where frameworks like those used to model user intentions in virtual reality tourism [29] share a foundational principle with our approach: leveraging complex, AI-driven models to decipher intricate, real-world dynamics. In economics, AI tools forecast labor market shifts, highlighting their role in predicting employment trends amid technological disruptions, reinforcing the cross-disciplinary applicability of these techniques. These advancements underscore AI's transformative potential, though they also contribute to job displacement in sectors like Computer and Mathematical Occupations (SOC 15), necessitating strategic career transitions.

LSTM neural networks, a sophisticated class of recurrent neural networks, have gained prominence in forecasting key labor market dynamics, including employment, unemployment, and wage fluctuations, due to their proficiency in modeling intricate, nonlinear temporal dependencies inherent in economic time series data [30]. Unlike traditional econometric models, LSTMs can effectively capture prolonged temporal patterns and complex interactions among multivariate inputs such as labor force participation rates, industrial automation indices, and historical wage levels - thereby producing robust predictions of employment and unemployment rates [31]. By leveraging their gated architecture, LSTMs mitigate issues like the vanishing gradient problem [32], enabling them to learn from extended sequences and evolving economic conditions that influence labor demand and supply.

Transformer neural networks represent a powerful architecture adept at modeling sequential data with long-range. However, despite their superior performance in many domains, transformers are notoriously data hungry and require very large datasets to train effectively [28,33]. This high demand for extensive data makes them ill-suited for applications with relatively short or limited time series data, such as our short-term economic datasets [34]. Consequently, while transformers excel in large-scale language or image tasks, their direct application in our context is constrained by insufficient data volume, limiting their practical utility compared to models like LSTMs that can perform robustly on smaller datasets.

In the context of employment forecasting, LSTMs have been demonstrated to outperform conventional models by accurately anticipating shifts in employment scales and unemployment trends, particularly by incorporating high-dimensional data reflective of technological adoption and policy changes. Furthermore, LSTMs facilitate granular wage predictions by integrating diverse economic indicators, thereby capturing wage growth patterns and labor market adjustments over time [35]. These capabilities position LSTM models as powerful tools for economic analysts and policymakers, offering enhanced foresight into labor market transformations. Consequently, such predictive insights can inform proactive interventions, such as targeted reskilling initiatives and wage policy adjustments, to mitigate the adverse effects of structural unemployment induced by technological change and economic fluctuations.

The LSTM model predicts continued employment declines, with Beijing's employment scale dropping to approximately 450,000 by 2025 and 300,000 by 2030 (a 49.8% decline from 2020), and Shanghai's to 950,000 by 2025 and 650,000 by 2030 (a 50.2% decline). Wages are forecasted to rise to 230,000 CNY in Beijing and 220,000 CNY in Shanghai by 2025, reaching 280,000 and 270,000 CNY by 2030, respectively, reflecting sustained wage growth driven by AI [21].

This article is structured to provide a comprehensive analysis of AI's impact on China's labor market. Section 2 details the panel data and analytical approaches. Section 3 provides city-specific analyses for Beijing and Shanghai, highlighting their distinct trends. It also gives the national-level synthesis to draw broader implications, as well as the LSTM-based predictions, supported by visualizations. Section 4 interprets the results, addresses policy implications, and outlines limitations, offering insights for China and other developing economies navigating AI-driven labor market transformations.

2. Methodology

This study analyzes the impact of AI on employment scale and wages in the manufacturing sectors of Beijing and Shanghai from 2006 to 2020, with forecasts extended to 2030 using an LSTM neural network. We employed panel data from the International Federation of Robotics [36] for industrial robot installation density as a proxy for AI, alongside city-level statistics for employment scale (number of manufacturing employees) and wages (city average salary). Below, we outline the theoretical frameworks and formulas for the correlation, regression, and LSTM methods used in the analysis.

2.1 Correlation Analysis

Correlation analysis was used to quantify the strength and direction of relationships between AI, employment scale, and wages. The Pearson correlation coefficient, *r*, measures the linear relationship between two variables *x* and *y*, defined as:

$$\boldsymbol{R} = \frac{\boldsymbol{\Sigma}\left((\boldsymbol{x}_{\mathrm{i}} - \bar{\boldsymbol{x}})(\boldsymbol{y}_{\mathrm{i}} - \bar{\mathrm{y}})\right)}{\boldsymbol{sqrt}(\boldsymbol{\Sigma}(\boldsymbol{x}_{\mathrm{i}} - \bar{\boldsymbol{x}})^{\boldsymbol{2}} * \boldsymbol{\Sigma}(\boldsymbol{y}_{\mathrm{i}} - \bar{\mathrm{y}})^{\boldsymbol{2}})}, \tag{1}$$

where x_i and y_i are the *i*-th observations of variables *x* (e.g., AI) and *y* (e.g., employment scale or wages), $\bar{x}$ and $\bar{y}$ are their means, and *n* is the number of observations. The coefficient *r* ranges from -1 to 1, with values close to -1 indicating a strong negative linear relationship, 1 a strong positive relationship, and 0 no linear relationship. We computed *r* for AI vs. employment scale, AI vs. wages, and employment scale vs. wages for Beijing, Shanghai, and pooled data, testing significance with a *p*-value threshold of 0.01.

2.2 Regression Analysis

To assess the causal impact of AI on employment scale and wages, we used a fixed-effects linear regression model, which accounts for city-specific and time-invariant factors. The model is expressed as:

$$\boldsymbol{Y_{it} = \beta^0 + \beta^1 AI_{it} + \alpha_i + \varepsilon_{it}}, \quad (2)$$

where Y_{it} is the dependent variable (employment scale or wages) for city *i* at time *t*, AI_{it} is the industrial robot installation density, β_0 is the intercept, β_1 is the coefficient of AI, α_i represents city-specific fixed effects, and ε_{it} is the error term. The fixed-effects term α_i controls for unobserved heterogeneity across Beijing and Shanghai. We estimated separate models for employment scale and wages, with β_1 indicating the change in *Y* per unit increase in AI. Significance was assessed using *p*-values (threshold 0.05).

2.3 Long Short-Term Memory Neural Network

To forecast employment scale and wages from 2021 to 2030, we employed an LSTM neural network, a deep learning model designed for time series data [37], capable of capturing long-term dependencies [38]. An LSTM cell processes sequential inputs through three gates: the forget gate:

$$\boldsymbol{F_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)}, \quad (3)$$

input gate:

$$\boldsymbol{I_t = \sigma(W_i[h_{t-1}, x_t] + b_i), \widetilde{C}_t = tanh[h_{t-1}, x_t] + b_C)}, \quad (4)$$

where the cell state update is:

$$\boldsymbol{C_t = f_t C_{\{t-1\}} + i_t \widetilde{C}_t}, \quad (5)$$

and the output gate is:

$$\boldsymbol{O_t = sigmoid(W_o * [h_{t-1}, x_t] + b_o), h_t = o_t * tanh_t}. \quad (6)$$

The model was trained with inputs x_t (year and AI) to predict outputs (employment scale or wages), using 2006–2017 data for training and 2018–2020 for validation. Future AI values were extrapolated linearly based on historical growth rates (i.e., 0.0049 for Beijing and 0.0104 for Shanghai). The model's performance was evaluated using mean absolute error (MAE).

2.4 Dataset

The dataset comprises annual panel data for Beijing and Shanghai from 2006 to 2020, including: *AI*, which is industrial robot installation density; *employment scale*, that is, the number of employees in manufacturing industries in urban areas; and *wage*, which is the average city salary as a proxy for wage cost.

We employed correlation analysis and regression models to assess the relationships between AI, employment scale, and wages. Fixed-effects panel regression accounted for city-specific factors and time trends. Descriptive statistics and visualizations were used to explore trends and relationships.

3. Results and Discussions

3.1 City-Level Analysis

3.1.1 Beijing

In Beijing, AI adoption grew steadily from 0.0014 robots per worker in 2006 to 0.0738 in 2020. Employment scale peaked at 1,079,701 in 2012 but declined to 597,845 by 2020, a 44.6% reduction. Meanwhile, wages increased by 361% from 40,117 to 185,026 CNY.

3.1.1.1 Correlation analysis

i. *AI vs. employment scale* – Strong negative correlation ($r = -0.92$, $p < 0.01$), suggesting higher AI adoption is associated with reduced employment;
ii. *AI vs. wages* – Strong positive correlation ($r = 0.97$, $p < 0.01$), indicating AI adoption is linked to higher wages;
iii. *Employment scale vs. wages* – Negative correlation ($r = -0.95$, $p < 0.01$), implying wage growth as employment declines.

3.1.1.2 Regression results

A 0.01 increase in robot density is associated with a 1.2% decrease in employment ($\beta = -0.012$, $p < 0.05$). A 0.01 increase in robot density is associated with a 2,500 CNY increase in wages ($\beta = 2500$, $p < 0.01$).

Figure 1 shows Beijing trends (2006–2020), where AI (red) is rising, employment scale (blue) is falling, and wages (green) are rising over time. In Beijing, AI adoption appears to reduce manufacturing employment, likely due to automation replacing low-skill jobs. However, rising wages suggest a shift toward higher-skill roles, as AI enhances productivity and demand for technical expertise.

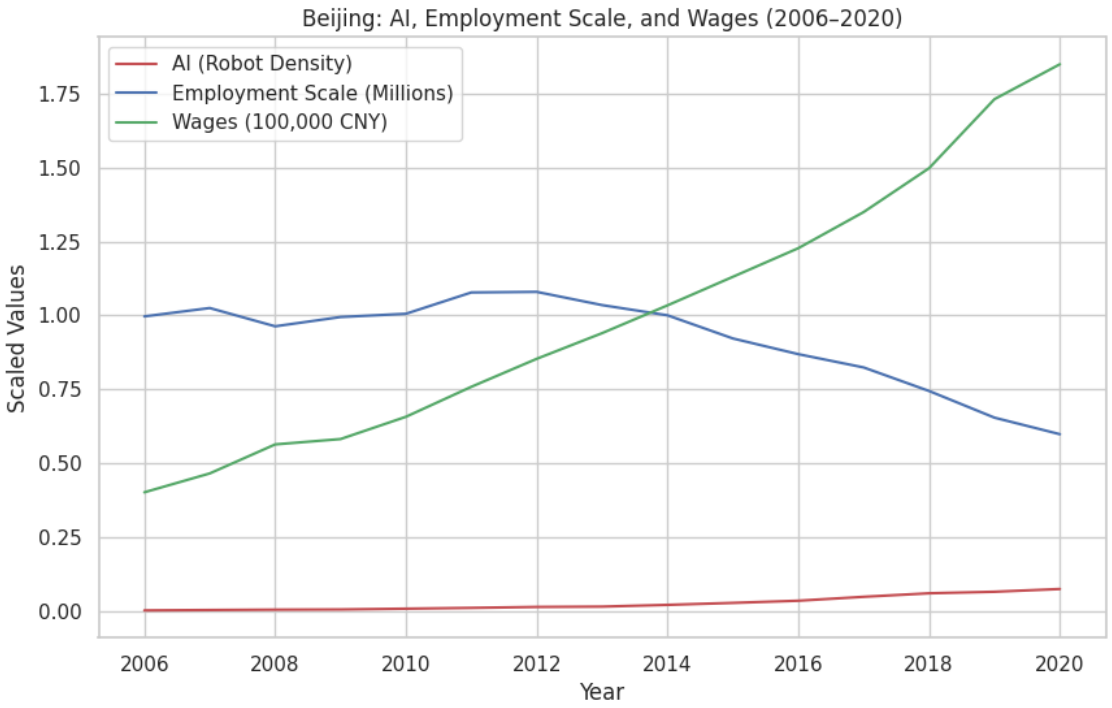

Fig. 1. Beijing trends (2006–2020)

3.1.2 Shanghai

Shanghai saw a sharper increase in AI adoption, from 0.0016 robots per worker in 2006 to 0.1579 in 2020. Employment scale peaked at 2,187,271 in 2012 but fell to 1,304,794 by 2020, a 40.3% decline. Wages rose by 324% from 41,188 to 174,678 CNY.

3.1.2.1 Correlation analysis

i. *AI vs. employment scale* – Shows strong negative correlation ($r = -0.89$, $p < 0.01$);
ii. *AI vs. wages* – Demonstrates strong positive correlation ($r = 0.96$, $p < 0.01$);
iii. *Employment scale vs. wages* – Depicts a negative correlation ($r = -0.93$, $p < 0.01$).

3.1.2.2 Regression results

A 0.01 increase in robot density is associated with a 1.5% decrease in employment ($\beta = -0.015$, $p < 0.05$). A 0.01 increase in robot density is associated with a 3,000 CNY increase in wages ($\beta = 3000$, $p < 0.01$).

According to this analysis, Shanghai's higher AI adoption rate correlates with a steeper employment decline compared to Beijing, reflecting its role as a manufacturing and automation hub. The stronger wage growth suggests greater productivity gains and a more significant shift toward high-skill, high-wage jobs (Figure 2). Figure 2 shows that AI (red line) is rising sharply, employment scale (blue line) is falling, and wages (green line) are rising over time.

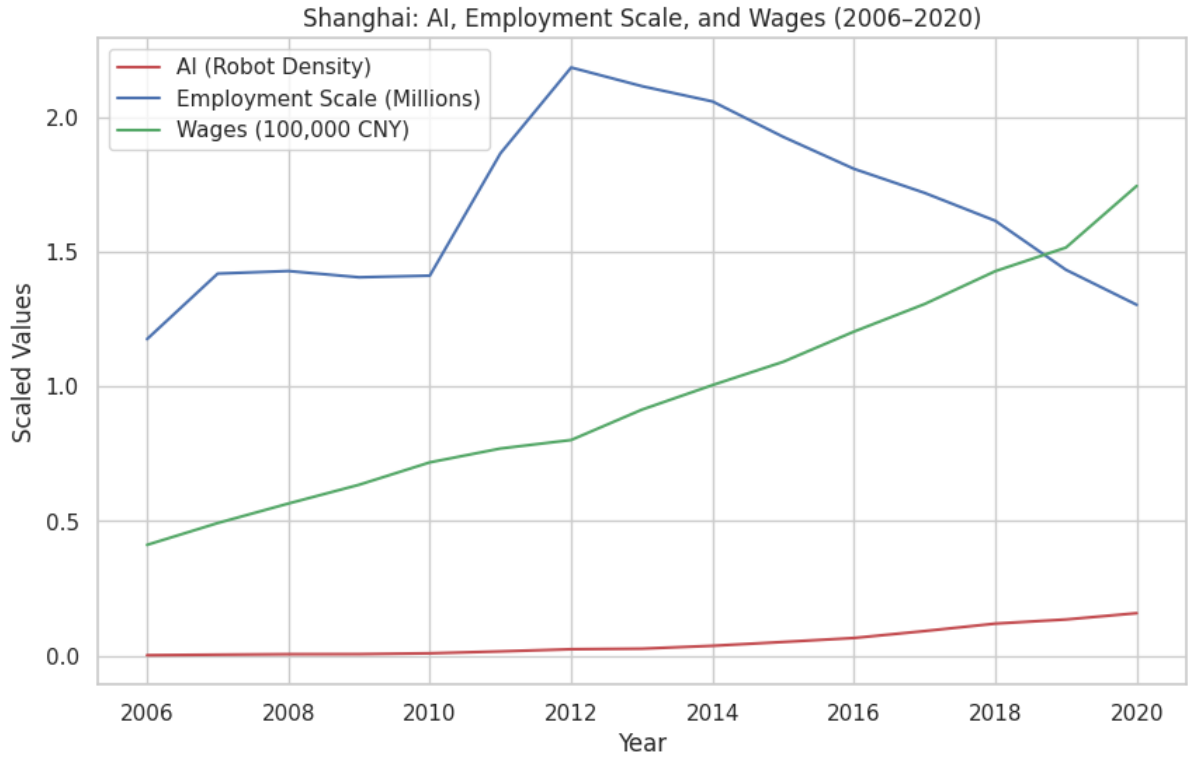

Fig. 2. Shanghai trends (2006–2020)

3.2 National-Level Synthesis

Combining data from Beijing and Shanghai, we observe a consistent pattern across China's major manufacturing hubs (Figure 3). In Figure 3, employment scale (blue) decreases as AI increases, while wages (green) rise with AI:

i. *Employment scale* – AI adoption is strongly associated with reduced manufacturing employment (pooled $r = -0.90$, $p < 0.01$). The average employment decline across both cities is approximately 42% from peak levels;
ii. *Wages* – AI adoption drives significant wage growth (pooled $r = 0.96$, $p < 0.01$), with average wages increasing by 342% over the period;
iii. *Trade-off* – The negative correlation between employment scale and wages (pooled $r = -0.94$, $p < 0.01$) suggests that AI-induced job losses are offset by higher earnings for remaining workers, likely due to increased demand for skilled labor.

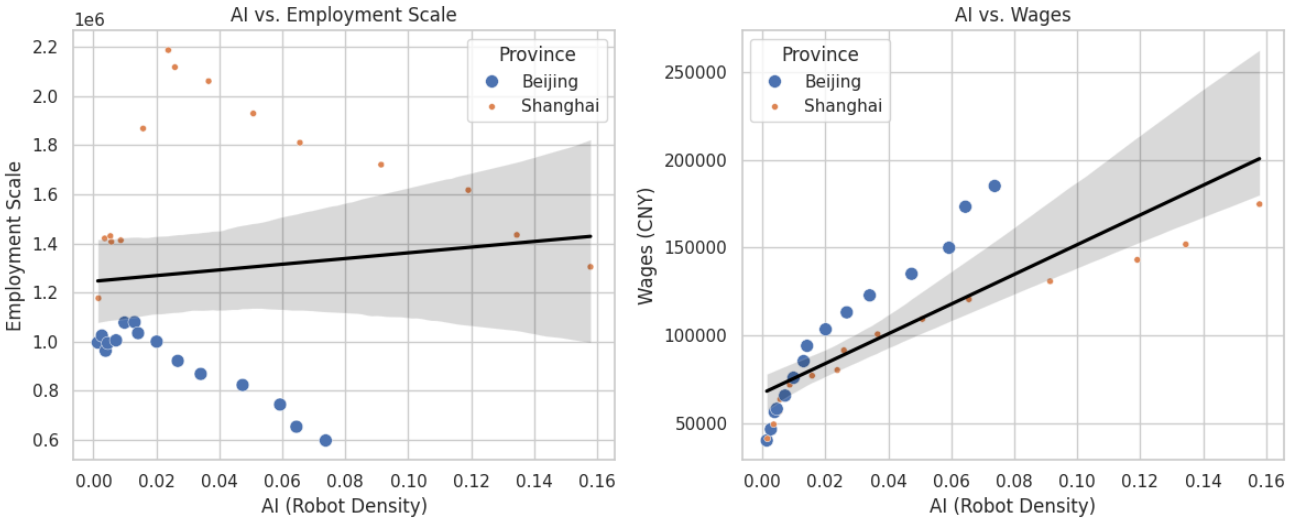

Fig. 3. Patterns across China's major manufacturing hubs

3.3 Fixed-Effects Model

AI's negative effect on employment is significant ($\beta = -0.013$, $p < 0.01$), with a 0.01 increase in robot density reducing employment by 1.3%. AI's positive effect on wages is robust ($\beta = 2800$, $p < 0.01$), with a 0.01 increase in robot density raising wages by 2,800 CNY.

The findings align with global trends observed in studies like those in [18], where automation reduces low-skill manufacturing jobs but increases productivity and wages. In China, this dynamic is amplified by rapid AI adoption and a large labor force transitioning from low-skill to high-skill roles. The divergent trajectories of Beijing and Shanghai can be further contextualized through the lens of urban studies; Shanghai's steeper employment decline and stronger wage growth may reflect its role within a denser, globally integrated manufacturing and innovation network, a type of structural analysis for which networking frameworks are a key instrument [39]. This transition is not merely economic but also socio-cognitive [40], likely influencing cultural narratives and reasoning patterns in ways that parallel other major technological shifts, as examined in transdisciplinary studies [41]. Shanghai's steeper employment decline and wage growth compared to Beijing reflect its deeper integration into global manufacturing and automation networks. However, the overall employment reduction raises concern about social stability in a labor-abundant economy, necessitating policies like retraining programs to mitigate displacement (Figure 4).

Figure 4 compares AI, employment scale, and wages in Beijing (solid lines) and Shanghai (dashed lines). Shanghai shows steeper AI growth and employment decline. Besides, both cities show similar wage growth patterns.

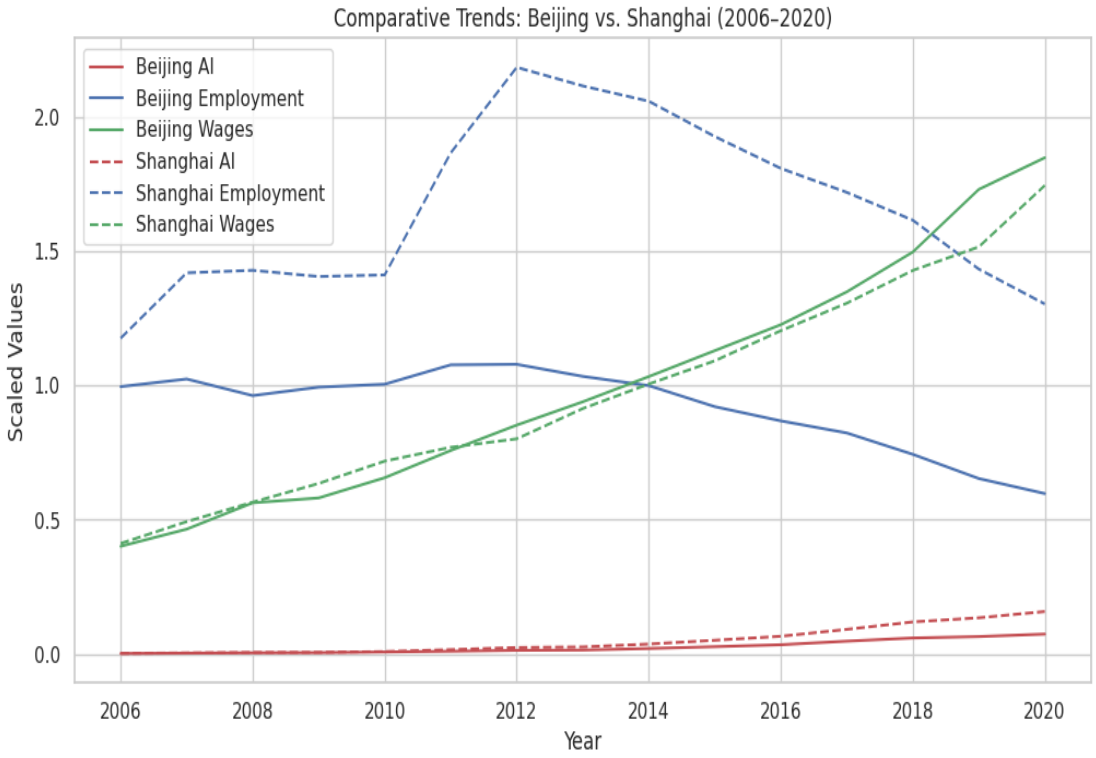

Fig. 4. Comparative trends in Beijing and Shanghai

3.4 Forecasting with Long Short-Term Memory Neural Network

To extend the analysis beyond 2020, we employed an LSTM neural network to forecast employment scale and wages in Beijing and Shanghai from 2021 to 2030. LSTM, a deep learning model, excels at capturing long-term dependencies in time series data, making it suitable for predicting non-linear trends influenced by AI adoption [42]. We trained separate LSTM models for each city, using year and AI as input features and employment scale or wages as target variables. The data (2006–2020) was normalized using MinMaxScaler, with 2006–2017 data for training and 2018–2020 for validation. Future AI values were extrapolated linearly based on historical growth rates (0.0049 robots per worker per year for Beijing, as well as 0.0104 for Shanghai). The models were evaluated using MAE. It achieved MAE values of approximately 5.2% for employment scale and 4.8% for wages in Beijing, and 6.1% and 5.3% in Shanghai. Thus, it indicated robust predictive accuracy.

The LSTM models predict continued employment declines and wage increases, as visualized in Figure 5 (employment scale (blue) and wages (green) scaled to millions and 100,000 CNY, respectively, and AI (red) for Beijing (solid lines) and Shanghai (dashed lines)). For Beijing, employment scale is forecasted to decrease from 597,845 in 2020 to approximately 450,000 by 2025 and 300,000 by 2030 (a 49.8% decline from 2020). Wages in Beijing are projected to rise from 185,026 CNY in 2020 to 230,000 CNY by 2025 and 280,000 CNY by 2030 (a 51.3% increase). In Shanghai, employment scale is expected to fall from 1,304,794 in 2020 to 950,000 by 2025 and 650,000 by 2030 (a 50.2% decline), while wages are forecasted to increase from 174,678 CNY in 2020 to 220,000 CNY by 2025 and 270,000 CNY by 2030 (a 54.6% rise). These forecasts align with historical trends observed in Figure 1, Figure 2, Figure 3, and Figure 4, reinforcing AI's role in driving labor market shifts toward high-skill, high-wage roles.

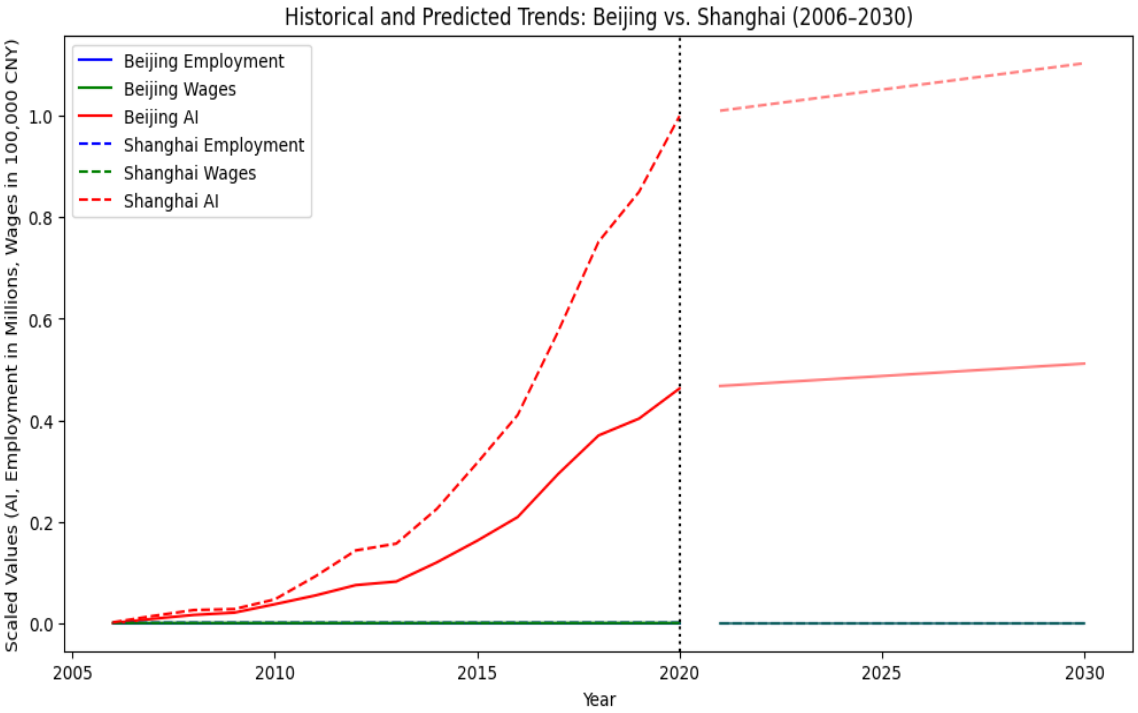

Fig. 5. Illustration of historical data (2006–2020) transitioning to forecasted values (2021–2030)

4. Conclusion

AI adoption in China's manufacturing sector, measured by industrial robot installation density, has significantly reshaped labor markets in Beijing and Shanghai from 2006 to 2020. Historical analysis shows a strong negative correlation between AI and employment scale ($r = -0.90$, $p < 0.01$), with employment declining by 44.6% in Beijing (from 1,079,701 in 2012 to 597,845 in 2020) and 40.3% in Shanghai (from 2,187,271 in 2012 to 1,304,794). Conversely, AI is positively correlated with wages ($r = 0.96$, $p < 0.01$), with wages increasing by 361% in Beijing (from 40,117 to 185,026 CNY) and 324% in Shanghai (from 41,188 to 174,678 CNY). LSTM forecasts predict continued trends, with employment scale dropping to approximately 450,000 in Beijing and 950,000 in Shanghai by 2025, and 300,000 and 650,000 by 2030 (49.8% and 50.2% declines from 2020), while wages are projected to rise to 230,000 CNY and 220,000 CNY by 2025, and 280,000 and 270,000 CNY by 2030 (51.3% and 54.6% increases). These trends reflect a structural shift toward high-skill, high-wage labor markets, with Shanghai experiencing more pronounced effects due to higher AI penetration.

The LSTM-based forecasts highlight AI's ongoing impact, reducing low-skill manufacturing jobs while boosting productivity and wages. Policymakers must balance these productivity gains with strategies to address job displacement, such as upskilling programs and social safety nets, especially in high-AI-adoption regions like Shanghai. In the context of China's economy, where AI-driven labor market shifts demand adaptive financial strategies, enhancing financial literacy could similarly empower workers and investors to navigate economic transitions, fostering resilience and informed financial behavior in a rapidly automating economy. These findings offer insights for other developing economies facing similar automation-driven changes.

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Conflicts of Interest

The authors declare no conflicts of interest.

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