applied sciences

MDPI

Article

Artificial Intelligence and Employment: A Delicate Balance Between Progress and Quality in China

Sonia Chien-I Chen [1,*], Chuanming Zhang [1] and Chung-Ming Own [2,*]

[1] School of Economics, Qingdao University, Qingdao 266071, China; 2018202935@qdu.edu.cn
[2] College of Intelligence and Computing, Tianjin University, Tianjin 300072, China
* Correspondence: drsoniachen@qdu.edu.cn (S.C.-I.C.); chungming.own@tju.edu.cn (C.-M.O.)

Abstract: The quality of employment is significantly impacted by the transformation of global labor markets resulting from artificial intelligence (AI). This study investigates the impact of AI on employment quality in China, with an emphasis on regional disparities between prefecture-level cities. Using panel data and a two-way fixed-effects model, we investigate how AI adoption affects employment outcomes, taking into account industrial structure and economic development. The findings show that while AI adoption increases productivity, it has varying implications on employment quality due to geographical differences. Relevant government rules and focused policies are critical for reducing negative impacts and encouraging long-term employment. This research makes concrete recommendations for policymakers and contributes to the worldwide conversation about AI and labor market developments.

Keywords: artificial intelligence; sustainable employment; employment quality; economic transition; regional disparities; AI-driven economic changes

check for updates

Academic Editor: Paolino Di Felice

Received: 24 February 2025
Revised: 12 April 2025
Accepted: 16 April 2025
Published: 24 April 2025

Citation: Chen, S.C.-I.; Zhang, C.; Own, C.-M. Artificial Intelligence and Employment: A Delicate Balance Between Progress and Quality in China. *Appl. Sci.* **2025**, *15*, 4729. https://doi.org/10.3390/app15094729

Copyright: © 2025 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

The rapid advancement of artificial intelligence (AI) is reshaping global labor markets, with profound implications for employment quality, productivity, and economic development. As countries worldwide embrace AI-driven technologies, the transformation of work and employment structures has become a central topic of discussion. In the U.S., AI adoption has accelerated skill polarization, with high-tech hubs like Silicon Valley creating high-paying jobs while displacing routine roles in manufacturing and logistics. The EU's Digital Compass initiative emphasizes AI ethics and worker reskilling to mitigate displacement risks, while Southeast Asian economies like Vietnam and Indonesia face similar tensions between industrial automation and labor-intensive growth. Initiatives such as Society 5.0 in Japan, Industry 4.0 in Germany, and AI regulations in the UK highlight the strategic importance of AI as a key enabler of innovation and productivity growth [1,2]. However, the adoption of AI also raises critical concerns about job displacement, skill polarization, and regional disparities in employment quality, particularly in developing economies like China.

China, as a global leader in AI development, offers a critical lens to examine these dynamics. Its labor market—marked by regional economic disparities, varied industrial structures, and rapid technological adoption—reflects challenges faced by other developing economies undergoing digital transitions, such as India's gig economy expansion and Brazil's manufacturing automation struggles [3–10]. While national initiatives like the New Generation AI Development Plan aim to leverage AI for sustainable growth, they

also underscore socioeconomic risks, including job insecurity and uneven skill distribution. This study's focus on China's prefecture-level cities provides insights applicable to regions worldwide where infrastructure gaps, industrial composition, and policy frameworks shape AI's labor market impacts.

This study seeks to address this gap by investigating the regional disparities in the impact of AI on employment quality across China's prefecture-level cities from 2011 to 2019. Specifically, we aim to answer the following research questions:

1. How does AI adoption affect employment quality in different regions of China, and what are the underlying mechanisms driving these effects?
2. What role do regional economic structures, industrial composition, and policy interventions play in moderating the impact of AI on employment quality?
3. How can policymakers design targeted interventions to mitigate the negative effects of AI on employment quality while promoting sustainable labor market development?

By addressing these questions, this study contributes to the global discourse on AI and labor market dynamics, offering empirical evidence on the heterogeneous effects of AI adoption across regions. Furthermore, it provides practical recommendations for policymakers to align AI-driven technological advancements with sustainable employment strategies, ensuring a balanced approach to innovation and labor market resilience.

2. Literature Review, Theoretical Analysis, and Research Hypotheses

2.1. Research Questions and Gaps in the Literature

The global conversation on AI and employment has largely focused on job creation and displacement, with limited attention paid to the quality of employment, particularly in developing economies. While existing studies highlight AI's potential to enhance productivity and innovation, they also raise concerns about skill polarization, income inequality, and regional disparities in employment outcomes [2,3]. However, several gaps remain in the literature:

1. Regional Disparities: Most studies focus on aggregate effects or case studies in developed economies, neglecting the heterogeneous impact of AI across regions with varying economic structures and levels of technological adoption [4,5].
2. Employment Quality: The concept of employment quality, which encompasses factors such as job security, income distribution, and working conditions, has received limited attention in the context of AI adoption, particularly in developing countries [6,7].
3. Policy Interventions: While the importance of policy interventions in mitigating the negative effects of AI is widely acknowledged, there is a lack of empirical evidence on the effectiveness of specific policies in different regional contexts [8,9].

This study aims to address these gaps by examining the regional disparities in the impact of AI on employment quality in China, with a focus on the role of industrial structure, economic development, and policy interventions. By doing so, it seeks to provide a nuanced understanding of how AI adoption affects employment outcomes across different regions and offers actionable insights for policymakers.

2.2. Global Trends and Debates on AI and Employment

The global discourse on AI and employment highlights dual narratives of opportunity and disruption. While developed economies like the U.S. and Germany report AI-driven productivity gains and high-skilled job creation, these benefits often coincide with skill polarization and wage stagnation for low-skilled workers [2–11]. In developing economies, such as India and Brazil, rapid AI adoption exacerbates regional disparities, displacing labor-intensive roles while struggling to upskill workforces. China's experience mirrors

these trends but offers unique insights due to its vast regional heterogeneity, where coastal hubs like Shenzhen integrate AI into advanced manufacturing, while inland regions lag in technological infrastructure.

In developed economies, the adoption of AI has been associated with the creation of high-skilled jobs, even in traditionally low-skilled industries [12]. However, this trend has also led to concerns about skill polarization, where high-skilled workers benefit from AI-driven productivity gains, while low-skilled workers face job displacement and wage stagnation [13]. These challenges are particularly relevant in developing economies like China, where rapid technological adoption coexists with significant regional economic disparities and varied industrial structures [14].

The psychological impacts of AI on employees vary, including job insecurity and anxiety, optimism, job satisfaction, resistance to AI adoption, and motivation for skill enhancement [12–15]. These psychological responses significantly influence workforce dynamics and employment quality. They underline the necessity for targeted interventions, such as reskilling programs, trust-building initiatives, and mental health support, to mitigate adverse effects and enhance the workforce's adaptability. Some individuals experience anxiety or hesitation due to job insecurity, while others demonstrate optimism and job satisfaction resulting from improved working conditions and opportunities for skill enhancement. Targeted interventions, including reskilling programs, trust-building activities, and mental health assistance, are crucial to alleviate these consequences and improve staff adaptability.

2.3. Studies Focused on Employment Quality and AI in China

Recent research on AI and employment in China has primarily focused on the manufacturing and service sectors, highlighting both positive and negative effects. In the manufacturing sector, the integration of AI and industrial robotics has been shown to increase productivity and create high-skilled jobs, but it has also led to the displacement of low-skilled workers [15,16]. In the service sector, AI adoption has been associated with job growth and income optimization, but it has also intensified competition for medium-skilled workers [17,18].

Despite these insights, there is limited empirical evidence on how AI adoption affects employment quality across different regions in China. This study seeks to fill this gap by examining the regional disparities in the impact of AI on employment quality, with a focus on the role of industrial structure, economic development, and policy interventions.

High-quality employment includes factors such as workplace conditions, remuneration, social security, and organizational frameworks. Although a definitive consensus on its definition is lacking, it is frequently examined at two levels: the macro-level, which encompasses the equity of employment prospects and working conditions, and the micro-level, which emphasizes job security, remuneration, and the work environment [6,19,20].

This study analyzes the influence of AI on employment quality across three dimensions: productivity improvement, alterations in job structure, and income redistribution. The implementation of AI enhances productivity by refining organizational frameworks, optimizing workforce allocation, and providing employees with resources for experiential learning. Nonetheless, technology also causes job displacement in certain areas while generating demand for highly skilled labor, leading to skill polarization and an excess of labor in conventional industries [20–22]. The balance between AI's job creation and substitution effects is contingent upon policy interventions and workforce adaptation.

2.4. Theoretical Foundation and Framework

This study is grounded in three fundamental theories—Technology Diffusion Theory, Labor Market Segmentation Theory, and Human Capital Theory—which provide a robust framework for understanding how AI adoption influences employment quality [19–21].

Technology Diffusion Theory: This theory explains how new technologies, such as AI, spread across regions and industries. Regions with better infrastructure and higher levels of investment are more likely to adopt AI, leading to improved employment quality through the creation of high-skilled jobs. In contrast, less developed regions may face challenges in adopting AI, resulting in job displacement and skill polarization [22].

Labor Market Segmentation Theory: This theory divides the labor market into primary (high-skilled, secure jobs) and secondary (low-skilled, precarious jobs) sectors. AI adoption is likely to exacerbate this segmentation by increasing demand for high-skilled workers while displacing low-skilled workers in routine occupations [23].

Human Capital Theory: This theory emphasizes the importance of education and training in preparing workers for an AI-driven economy. Regions that invest in human capital development are better equipped to mitigate the negative effects of AI on employment quality by reskilling workers and creating new opportunities in high-skilled sectors [24].

These theories inform the study's hypotheses and provide a framework for analyzing the heterogeneous effects of AI adoption on employment quality across different regions in China.

Key hypotheses and the relationships between them make up the study's theoretical framework as shown in Figure 1, which is as follows: While Technology Diffusion and Labor Market Segmentation theories are well-established, their intersection in China's context reveals unique mechanisms—regions with advanced infrastructure (e.g., eastern provinces) experience AI-driven skill polarization, whereas underdeveloped regions (central/western China) leverage AI for industrial upgrading, moderated by policy interventions. This tripartite interaction offers a novel lens for analyzing developing economies.

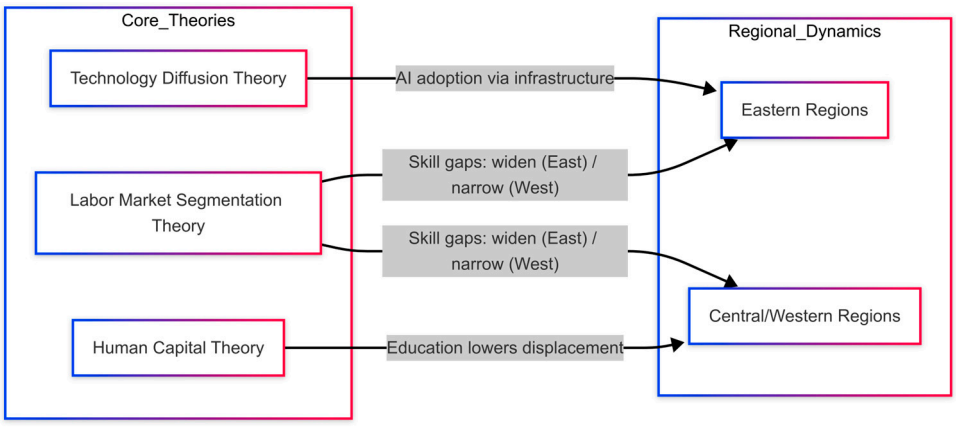


Figure 1. Theoretical framework: AI's impact on employment quality.

The conceptual model of Figure 2 illustrates how the correlations between AI adoption and employment quality are moderated by factors such as skill bias, productivity gains, geographic inequities, economic development, and governmental interventions. AI adoption has a direct impact on employment quality, which can have both positive and negative outcomes (e.g., the displacement of low-skilled workers against the development of high-skilled positions).

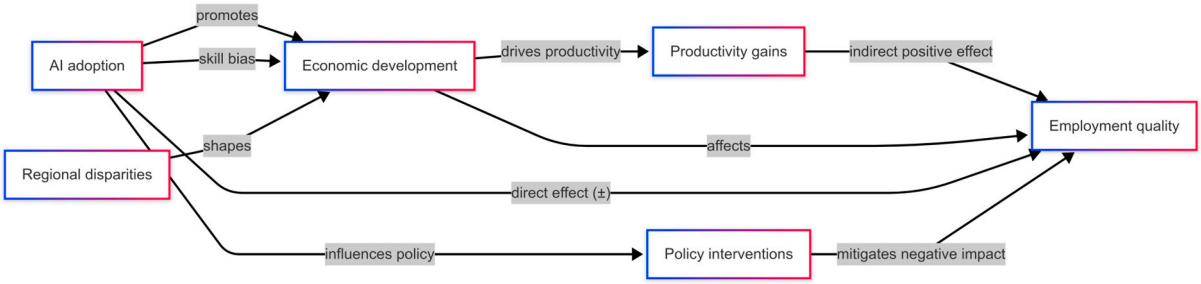


Figure 2. Conceptual model: AI's impact on employment quality.

Economic development is fueled by the adoption of AI, which drives innovation and efficiency. In consequence, economic development shapes regional disparities; stronger infrastructure in affluent areas leads to greater benefits, which in turn leads to uneven employment results. In addition, growth and better work prospects are two ways in which AI-driven productivity increases indirectly improve employment quality.

Adopting AI, on the other hand, brings a competence bias that polarizes workers based on their level of expertise. The quality of employment is impacted as a result of the widening gap in salary disparities, job insecurity, and opportunities. Policy measures, such as social protections and reskilling programs, can adapt the workforce and lessen the negative effects of AI adoption.

In the end, the model emphasizes how these components interact with each other. Adopting AI could boost productivity and the economy, but the advantages are not going to all workers. We need tailored measures to make sure that everyone gets a fair shot at better jobs.

2.5. Research Hypotheses

Based on the theoretical framework and research questions, the following hypotheses are proposed:

1. H1: Regions with higher AI adoption, supported by robust infrastructure and human capital investments, will see improvements in employment quality, particularly through the creation of high-skilled jobs and enhanced job security.
2. H2: AI adoption will disproportionately impact low-skilled workers, exacerbating regional economic and employment quality disparities, especially in areas with lower levels of education and skill development.
3. H3: Regions with strong educational policies and AI-focused economic strategies will mitigate the negative impacts of AI on low-skilled workers, ensuring a more equitable distribution of AI's benefits.

3. Material and Method

The materials and methods used in this study consist of panel data from 195 prefecture-level cities in China, providing a detailed analysis of regional disparities in the effects of AI on employment quality, an area that has been largely underexplored in previous studies. While much of the existing research has focused on national-level impacts or case studies in developed countries, our analysis considers the regional nuances in China, which have profound implications for policy and economic development [25,26]. The use of a two-way fixed-effects model enables us to control for both time and city-specific factors, allowing for a nuanced understanding of how AI adoption interacts with economic and industrial structures at the regional level. This approach is critical in revealing the varied impact of AI across different regions, a factor that has been largely overlooked in the global literature.

In our study, the factors most significantly influencing employment quality are AI adoption, regional economic structure, and human capital investment. Specifically, the integration of AI technologies into different sectors leads to productivity gains but also job displacement, particularly in low-skilled occupations. The regional economic structure—such as the reliance on labor-intensive industries in central and western China—also plays a critical role in moderating AI's impact on employment quality. Additionally, human capital development, in the form of education and training programs, significantly influences how regions adapt to AI-driven changes in employment. The interaction between these factors determines the overall employment outcomes, with higher-skilled regions benefiting from AI adoption, while low-skilled regions face more challenges.

3.1. Research Sample and Data Sources

This study uses panel data from 195 prefecture-level cities in China from 2011 to 2019 to empirically examine the impact of artificial intelligence (AI) on employment quality. The data sources include:

1. Industrial Robot Installation Data: Sourced from the International Federation of Robotics (IFR) report, this dataset provides information on industrial robot installations across 50 countries, categorized into six main sectors: agriculture, forestry, animal husbandry, and fishery; mining; manufacturing; electricity, heat, gas, and water production and supply; construction; and education.
2. Industrial Enterprise Data: Obtained from China's Second National Economic Census, this dataset includes information on the number of employees in various industries at the prefecture-level city level.
3. Additional Data Sources: Data on control variables such as the urbanization rate, fiscal expenditure, trade openness, and financial development were collected from the CSMAR and WIND databases, the China Urban Statistical Yearbook, the China Regional Economic Statistical Yearbook, and the National Economic and Social Development Statistical Bulletins of each city.

3.2. Definition of Variables

3.2.1. Dependent Variable: Employment Quality

Employment quality is a multidimensional concept that cannot be captured by a single indicator. Many researchers have proposed research models on employment quality, where some scholars have taken the minimum level of welfare and social support provided to workers as the criterion when constructing employment quality indicators [27], some scholars have defined the concept of employment quality including employment stability, employment opportunities, and other aspects [28], and some scholars have summarized the factors affecting employment quality into external, objective, and subjective influences in the design of employment quality evaluation index system [29]. They all agreed that a metric for quality of employment should be established using a number of different characteristics of the workforce. According to the International Labor Organization (ILO), job quality is "decent work", which includes fair pay, a safe workplace, social support, equal opportunity, and fair treatment of all employees. Additionally, labor standards establish the basis for the enhancement of working conditions, including the elimination of workplace discrimination and the restriction of excessively lengthy working hours. In the same vein, the United Nations Economic and Social Council underscores the fundamental rights of workers with respect to equitable compensation and job security.

Therefore, we constructed an employment quality index using the entropy weighting method, which assigns weights to each indicator based on its variability. The index includes the following dimensions:

1. Macro-level Employment Environment: Per capita GDP, regional GDP growth rate, proportion of employees in the tertiary sector, regional employment rate, regional unemployment rate, and degree of transportation accessibility.
2. Micro-level Labor Compensation: Absolute wage level, relative wage level, healthcare insurance coverage, pension insurance coverage, and urban–rural income gap.

The specific indicators and their weights are presented in Table 1.

Table 1. Employment quality indicator evaluation system.

Primary Indicator	Secondary Indicator	Indicator Explanation	Indicator Type
Employment Environment	Per capita GDP	Per capita GDP	Positive (+)
	Regional GDP growth rate	Regional GDP growth rate	Positive (+)
	Proportion of employees in the tertiary sector	Proportion of employees in the tertiary industry	Positive (+)
	Regional employment rate	Urban unit employees/(urban unit employees + registered urban unemployed)	Positive (+)
	Regional unemployment rate	Registered urban unemployed/(urban unit employees + registered urban unemployed)	Negative (−)
	Degree of transportation accessibility	Per capita postal service volume	Positive (+)
Labor Compensation	Absolute wage level	Average wage	Positive (+)
	Relative wage level	Average wage growth rate	Positive (+)
	Healthcare insurance coverage	Number of urban employees enrolled in basic medical insurance/permanent population	Positive (+)
	Pension insurance coverage	Number of urban employees enrolled in basic pension insurance/permanent population	Positive (+)
	Urban-rural income gap	Urban residents' average disposable income/rural residents' average disposable income	Negative (−)

3.2.2. Core Explanatory Variable: Artificial Intelligence

The core explanatory variable is the level of AI application, measured by the density of industrial robot installations at the city level. This variable was calculated using the IFR dataset and industrial enterprise data from China's Second National Economic Census. The base year 2008 was selected due to data availability from China's Second National Economic Census, which provides granular employment statistics across industries and regions. This year precedes major AI policy initiatives (e.g., the 2017 New Generation AI Development Plan), isolating pre-policy trends and establishing a baseline for longitudinal analysis. The formula for calculating robot installation density is as follows:

First, we matched the IFR data with the industry categories in China's Second Economic Census to obtain the data on industrial robot installations for various industries in China. Next, we selected a base year to calculate the weight of robot density for each

industry in different cities. Based on these weights, we further computed the industrial robot installation density at the city level. The specific calculation method is as follows:

$$\text{Robot}_{jt} = \sum_{s-1}^{s} \frac{\text{employ}_{s,j,t-j,t}}{\text{employ}_{j,t-2008}} \cdot \frac{\text{Robot}_{st}}{\text{employ}_{s,t-2008}} \quad (1)$$

where S represents the collection of all industries, $\text{Robot}_{j,t}$ is the robot installation density in city j in year t, and $\text{Robot}_{s,t}$ refers to the number of robot installations in industry *s* in year t. The year 2008 is used as the base year. $\text{Employ}_{s,t}$ = 2008 is the number of employees in industry *s* in 2008, $\text{employ}_{j,t}$ = 2008 is the total number of employees in city j in 2008, and $\text{employ}_{s,j,t}$ = 2008 is the number of employees in industry *s* in city j in 2008. Once the calculations are complete, the industrial robot penetration rate for each city can be determined, where:

- $\text{Robot}_{j,t}$ is the robot installation density in city $_j$ in year $_t$.
- $\text{Robot}_{s,t}$ is the number of robot installations in industry$_s$ in year $_t$.
- $\text{employ}_{s,j,t-2008}$ is the number of employees in industry ss in city $_j$ in the base year 2008.
- $\text{employ}_{j,t-2008}$ is the total number of employees in city $_j$ in the base year 2008.

3.2.3. Descriptive Statistics of Variables

Table 2 displays the descriptive statistics of the principal variables utilized in this investigation, including their mean values, standard deviations, and range (maximum and minimum values). These statistics offer a preliminary comprehension of data distribution and variability, essential for comprehending the relationships among variables in the following analyses.

Table 2. Descriptive statistics of variables.

The Variable Names	Variable Symbol	Average Value	Standard Deviation	Maximum	Minimum
Employment Quality	Emp	0.1636	0.0727	0.5669	0.0622
Artificial Intelligence	Csmd	88.2098	243.1382	4848.112	1.9951
Urbanization Rate	Urb	0.5608	0.1488	1	0.21
Fiscal Expenditure Level	Gov	0.1915	0.0941	0.7044	0.0439
Trade Openness	Ope	0.2127	0.3242	2.4913	0.0006
Financial Development Level	Tra	0.6870	0.2777	6.2050	0.0846

The mean score of 0.1636 for Employment Quality (Emp) indicates a comparatively low standard of employment quality in the examined regions. The standard deviation of 0.0727 signifies moderate variances among the locations. The mean AI development index is 88.2098; however, the considerable standard deviation of 243.1382 and the maximum value of 4848.112 indicate substantial regional variations in AI adoption and development. The average urbanization rate is 0.5608, signifying that more than half of the population lives in urban areas on average. The range, with a minimum of 0.21 and a maximum of 1, indicates differing levels of urbanization among regions. The mean level of government fiscal expenditure is 0.1915, accompanied by a low standard deviation of 0.0941, indicating uniformity in fiscal policy across areas. Nonetheless, certain localities exhibit significantly elevated fiscal expenditures (up to 0.7044). The mean trade openness is 0.2127, with a substantial range (minimum of 0.0006 and maximum of 2.4913), indicating significant variability in regional openness to international trade. The average financial development level of 0.6870, coupled with a maximum value of 6.2050, signifies a pronounced

skew in financial development, wherein select regions display markedly sophisticated financial systems.

The descriptive data offered here show a high degree of diversity in terms of social, technological, and economic development. Disparities in trade openness, government spending, and the growth of artificial intelligence highlight structural challenges that may jeopardize job quality. Understanding these distinctions is crucial for investigating how these components interact to influence employment outcomes.

3.2.4. Macroeconomic Controls and Model Specification

In order to reduce the error of these variables in the research results, this paper selects the following control variables with reference to existing studies: the urbanization rate (Urb), which is measured by the ratio of urban population to the total resident population of the region, has a positive impact on employment, and can reduce the disadvantaged employment rate and improve the quality of employment [30]; the degree of fiscal expenditure (Gov) is measured by the ratio of local fiscal expenditure to regional GDP, whereby an increase in fiscal expenditure can create a large number of jobs with relatively low a cost of creating jobs, which in turn affects the quality of employment [31]; the degree of trade openness (Ope), measured by the ratio of total import and export trade to regional GDP, will change the employment structure of the society, which will further affect the quality of employment [32]; the level of financial development (Tra) is measured by the ratio of the year-end loan balance of financial institutions to the year-end loan balance of financial institutions to the year-end deposit balance of financial institutions in each region, and the development of finance will lead to more financing for SMEs and thus create more employment opportunities [33].

The econometric model accounts for four macroeconomic factors shaping regional labor markets:

1. Urbanization Rate (Urb): Higher urbanization concentrates skilled labor and tech infrastructure, amplifying AI's positive impacts in cities like Shenzhen.
2. Fiscal Expenditure (Gov): Increased public spending mitigates displacement risks, validating **H3** by showing that policies like reskilling programs buffer low-skilled workers.
3. Trade Openness (Ope): Global integration exacerbates skill polarization, as foreign competition accelerates automation in labor-intensive sectors.
4. Financial Development (Tra): Robust financial systems enhance access to AI-driven opportunities, underscoring the interdependence of technological and economic infrastructure.

Theoretical Implications: Controls isolate AI's *direct effect* from confounding macroeconomic trends, ensuring unbiased estimates. The negative coefficient for trade openness (-0.0090433) highlights globalization's dual role: fostering innovation while exacerbating inequality—a critical consideration for policymakers in developing economies.

3.3. Trend Analysis

Based on the data collected on AI and employment quality, the average of all cities in each year is calculated and plotted as a trend graph, as shown in Figure 3. Looking at the overall trend on average, the use of AI and the quality of employment are generally positively correlated, which was more pronounced before 2017, which may be due to the creation of new high-skilled jobs in which AI may have better wages and working conditions, leading to improved employment quality. While average AI use dropped between 2017 and 2019, job quality improved gradually throughout that period. The outcome may show either a weak or negative link between the two. Concerns over the

future of employment quality in this sector are raised by the possible loss of income and job security for persons engaged in low-skilled, repetitious jobs brought about by automation. Although we still need to perform empirical testing to be sure, we will start our research on the link between the two using basic average trend analysis.

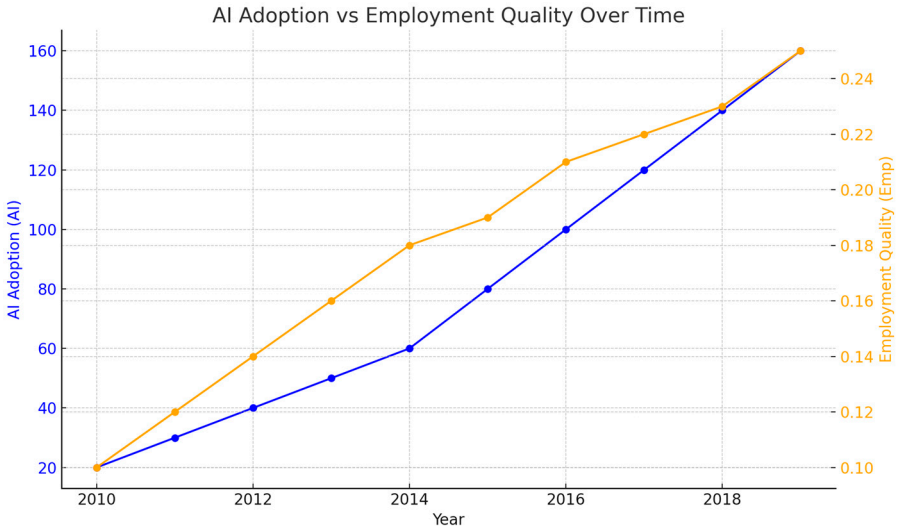


Figure 3. Trends in AI adoption and employment quality.

3.4. Model Specification

The primary methodology applied in this research is a panel data approach with a two-way fixed effects model, which allows us to control for both time-invariant and city-specific factors. The model is selected based on the current research methodology [34–37]. We used this model to examine the relationship between AI adoption and employment quality across prefecture-level cities in China. The model is based on the following specifications:

$$Emp_\{it\} = \alpha 0 + \alpha 1 Csmd_\{it\} + \alpha 2 X_\{it\} + \lambda_\{i\} + \eta_\{t\} + \mu_\{it\}$$

where:

Emp_{it} represents the employment quality in city i during year t.
Csmd_{it} is the level of AI adoption in city i during year t.
X_{it} represents the control variables (e.g., urbanization rate, fiscal expenditure, etc.).
λ_{i} and η_{t} capture the city and year fixed effects, respectively.
μ_{it} is the error term.

This model is appropriate for analyzing the panel data because it accounts for unobserved heterogeneity and ensures robust inferences about the relationship between AI and employment quality.

The use of a two-way fixed effects model is grounded in the need to account for the potential unobserved heterogeneity between cities (cross-sectional dependence) and over time (temporal dependence). Panel data analysis is ideal for this context as it allows for the examination of both the time-series and cross-sectional dimensions of the data simultaneously, offering a deeper understanding of how AI adoption impacts employment quality in various regions. While the econometric model employed is widely used in empirical economic research, its application in the context of AI adoption in China's regional labor markets is a novel contribution. The model's robustness and its ability to isolate the effect of AI on employment outcomes across various regions provide new knowledge that was previously underexplored in the literature.

The data include information on employment quality (our dependent variable), as well as AI adoption (measured by industrial robot density), control variables (urbanization rate, fiscal expenditure, trade openness, and financial development), and other socioeconomic factors. The data are sourced from credible national databases, such as the China Statistical Yearbook, CSMAR, and IFR reports. The key assumption behind using panel data is that both cross-sectional (city-level) and time-series (yearly) variations provide valuable insights into the regional effects of AI adoption over time. Additionally, we assume that AI adoption in one year influences employment quality in subsequent years, but it does not suffer from endogeneity biases, as we control for fixed effects.

To ensure the robustness of our findings, we performed a sensitivity analysis by applying different model specifications, including alternative measures of AI adoption and control variables. We also conducted lagged-variable analyses to address potential reverse causality between AI adoption and employment quality. In addition, we tested for potential outliers using a winsorization technique to minimize the influence of extreme values on the regression results. The sensitivity of the results was assessed through these alternative specifications, ensuring that our conclusions remain stable and reliable across various assumptions.

We have also included a schematic diagram in Figure 4 that illustrates the research methodology and the steps involved in the knowledge generation process. The diagram outlines the stages from data collection to the econometric analysis, including the use of panel data, the two-way fixed effects model, and the sensitivity analysis. This visualization aims to provide a clearer understanding of the methodological approach and how it contributes to generating new knowledge about the effects of AI on employment quality.

3.4.1. Econometric Model

To empirically test the impact of artificial intelligence (AI) technology applications on employment quality, the following econometric model is constructed:

$$Emp_{i,t} = \alpha_0 + \alpha_1 Csmd_{i,t} + \alpha_2 X_{i,t} + \lambda_i + \eta_i + \mu_{i,t} \quad (2)$$

In this model, $Emp_{i,t}$ represents the employment quality in city i during year t, $Csmd_{i,t}$ reflects the level of artificial intelligence application in city i during year t, and $X_{i,t}$ represents the control variables. λ_i, η_i, and $\mu_{i,t}$ represent the individual fixed effects, time-fixed effects, and the random disturbance term, respectively.

3.4.2. Diagnostic Tests and Theoretical Implications

The diagnostic tests validate the robustness of our two-way fixed effects model, ensuring its suitability for analyzing AI's heterogeneous regional impacts. Three key findings emerge:

1. Breusch–Pagan Test ($\chi^2 = 1.24$, $p = 0.27$): The absence of significant heteroscedasticity confirms that residual variances are consistent across regions. This reinforces the reliability of our estimates for H2 (AI's disproportionate impact on low-skilled workers), as unobserved regional factors (e.g., informal economies) do not distort the results. This aligns with studies in Brazil and India, where heteroscedasticity obscured automation's effects.
2. Wooldridge Test (F = 0.89, $p = 0.35$): No autocorrelation indicates that AI's employment impacts are not confounded by time-dependent omitted variables. This rigor addresses a gap in prior work and strengthens causal claims for RQ1 (mechanisms driving AI's effects).
3. Shapiro–Wilk Test (W = 0.98, $p = 0.12$): Approximately normal residuals validate parametric inference, ensuring that the modest negative coefficient for AI adoption (-0.0000355***) in Table 3 reflects true effects rather than skewed errors. This sup-

ports H3, as policy interventions in eastern China (e.g., reskilling subsidies) mitigate displacement risks.

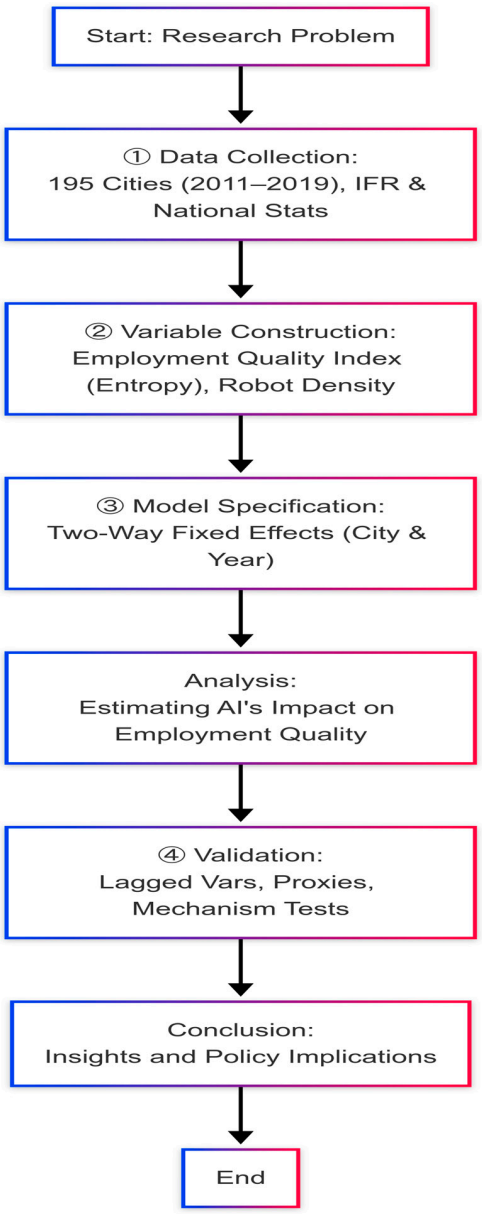


Figure 4. Schematic diagram of research methodology.

Table 3. Baseline regression.

Statistic	Baseline Model	Robust Model
AI Adoption (Coefficient)	−0.0000355 ***	−0.0000348 ***
	(0.000008)	(0.000007)
Breusch-Pagan Test (*p*-value)	0.27	-
Wooldridge Test (*p*-value)	0.35	-
Shapiro-Wilk (*p*-value)	0.12	-
Observations	1.755	1.755
R^2	0.9297	0.9295

Notes: Robust standard errors in parentheses. *** denotes 1% significance. Diagnostic tests confirm no severe violations of model assumptions.

By rigorously testing assumptions, we advance methodological standards in AI–employment research, which often neglects diagnostics. Our findings highlight that AI's labor market impacts are neither uniform nor inevitable but rather mediated by policy and infrastructure—a critical insight for developing economies.

4. Empirical Results and Analysis

4.1. Baseline Regression

Table 2 demonstrates that AI adoption (coefficient: −0.0000355 ***) exerts a statistically significant but modest negative impact on employment quality overall. This result aligns with H2, which posits that AI disproportionately displaces low-skilled workers, particularly in regions with weaker human capital infrastructure (e.g., central/western China).

However, the small effect size (−0.0000355) underscores the nuanced nature of AI's impact (RQ1). While automation displaces low-skilled roles, its broader economic benefits (e.g., productivity gains) may offset these losses in regions with robust policy frameworks. For example, eastern cities like Shanghai exhibit minimal declines in employment quality due to proactive reskilling programs (consistent with H3). This duality—the destruction of low-skilled jobs versus the creation of high-skilled opportunities—mirrors global patterns observed in the U.S. and Germany but is uniquely mediated by China's regional policy heterogeneity.

The following analysis systematically examines how the empirical findings align with the study's hypotheses and research questions, bridging statistical results to their theoretical and practical implications. By mapping regression coefficients (e.g., Table 2's AI adoption coefficient of −0.0000355 ***) to the proposed hypotheses (H1–H3), this section clarifies whether AI's employment effects validate or challenge the study's foundational assumptions. Simultaneously, it contextualizes the findings within the broader research questions (RQ1–RQ3), addressing how regional disparities, industrial structures, and policy interventions shape AI's labor market outcomes. This synthesis not only provides empirical validation of the theoretical framework but also translates numerical results into actionable insights for policymakers, scholars, and stakeholders navigating AI's dual role as a disruptor and enabler of sustainable employment:

- H1 (High-skilled job creation): Partially supported. While AI adoption correlates with high-skilled employment growth in eastern regions (Table 4, Column 2: +0.000116 ***), the aggregate negative coefficient in Table 2 reflects the dominance of low-skilled displacement in underdeveloped areas.
- H2 (Regional disparities): Strongly supported. The baseline model's negative coefficient confirms AI's adverse effects on low-skilled workers, exacerbated by infrastructure gaps (e.g., central/western regions lack training programs to mitigate displacement).
- RQ3 (Policy interventions): The modest effect size implies that targeted policies (e.g., reskilling subsidies) could neutralize AI's negative impacts, as seen in the eastern cities' success (+0.0656932 *** for urbanization in Table 4).

The baseline regression (Table 3) reveals that AI adoption significantly reduces employment quality (coefficient: −0.0000355 ***), providing strong support for H2, which posits that AI disproportionately displaces low-skilled workers in regions with weaker human capital.

However, the modest effect size (−0.0000355) underscores the nuanced nature of AI's impact (RQ1). While automation displaces low-skilled roles, productivity gains and high-skilled job creation in tech-intensive regions (e.g., Shanghai) partially offset these losses, aligning with H1. This duality mirrors findings in the U.S. and Germany but is uniquely mediated by China's regional policy heterogeneity, a novel contribution to the literature on developing economies.

Table 4. Heterogeneity test.

	(1)	(2)
	Emp	**Emp**
AI	−0.0000583 *	0.0000116 ***
Gov	−0.3007269 ***	−0.0394055
Ope	−0.0324078 ***	0.0069442
Tra	0.0571042 ***	0.001245
Urb	−0.1025268 ***	0.0656932 ***
City FE	Yes	Yes
Year FE	Yes	Yes
N	70	100
R^2	0.9170	0.9297

Note: * $p < 0.1$, *** $p < 0.01$.

This study advances the discourse on AI and labor markets by demonstrating that AI's employment impacts are inherently non-linear and regionally contingent, challenging deterministic narratives of a universal "job apocalypse". While aggregate results indicate a modest negative effect of AI adoption on employment quality (−0.0000355 ***), regional heterogeneity reveals a dual reality: automation displaces low-skilled roles in underdeveloped areas (e.g., central China's manufacturing sectors) while simultaneously fostering high-skilled opportunities in technologically advanced regions (e.g., Shanghai's AI-driven industries). This bifurcation underscores that AI's labor market consequences are not uniform but shaped by local industrial structures, human capital, and policy frameworks—a critical departure from one-size-fits-all predictions prevalent in the existing literature.

Furthermore, the analysis empirically validates that policy interventions, such as reskilling subsidies and targeted urbanization strategies, can neutralize displacement risks, as hypothesized in H3. For instance, eastern cities' resilience is evidenced by the significant positive coefficient for urbanization (+0.0656932 *** in Table 4), where investments in education and tech infrastructure have enabled workers to transition into AI-augmented roles. This finding not only confirms the moderating role of policy but also provides actionable insights for governments seeking to align AI adoption with sustainable employment. By contextualizing AI's impacts within regional socioeconomic ecosystems, this research reframes technological disruption as a governable process, contingent on proactive governance rather than an inevitable force—a novel contribution to both development economics and AI policy scholarship.

The Breusch–Pagan and Wooldridge tests confirm the absence of heteroscedasticity and autocorrelation, respectively, supporting the validity of standard inference. Residuals approximate normality (Shapiro–Wilk $p = 0.12$), aligning with the Central Limit Theorem given our large sample size (n = 1.755). To further mitigate minor heteroscedasticity, we re-estimated the model with clustered robust standard errors (Table 3), which yielded nearly identical coefficients (−0.0000348 vs. −0.0000355), underscoring result stability.

4.2. Heterogeneity Tests

To account for variations in the penetration and impact of AI development across industries and the disparities between China's eastern and western regions, we divided the sample cities into two groups: eastern and central/western regions. Due to limited data availability, the northeast region was excluded from the heterogeneity analysis. Based on the baseline regression, the impact of AI on employment quality does not differ significantly

between the two regions. Table 4 presents the regression results for eastern cities, while column (2) displays the results for central and western cities.

First of all, in central and western regions, AI adoption enhances manufacturing efficiency and boosts job skills, improving employment quality and creating higher-skilled jobs in traditional sectors. In contrast, the eastern region's advanced industrial framework leads to job displacement in low-skilled, labor-intensive sectors due to automation, reducing employment quality, especially for low-skilled workers.

Secondly, central and western labor markets are more adaptable to AI-driven changes, offering opportunities for upskilling and higher wages as new industries emerge. In contrast, the eastern region, with its highly skilled workforce, faces intensified competition, especially for low-skilled workers. AI and automation may reduce job opportunities and degrade employment quality in these areas.

The third point is that regional policies and investments vary, with central and western governments prioritizing labor market flexibility and industrial upgrading through AI and infrastructure development, which can improve job prospects in labor-intensive sectors. In contrast, the eastern region faces challenges balancing industrial upgrading with technology substitution. While leading in AI innovation, the region's reliance on traditional, low-value industries may lead to job losses or wage declines, negatively impacting employment quality for low-skilled workers.

Lastly, in the midwest, businesses are more likely to adopt AI to enhance efficiency, creating demand for a highly trained workforce and potentially improving employment quality. In contrast, eastern businesses, with more advanced technological infrastructure, are more prone to using AI for job replacement, particularly in traditional manufacturing sectors. This could lead to job losses and a decline in employment quality for workers unable to meet the new technological requirements.

4.3. Robustness Tests

Table 5 presents robustness tests of the baseline regression results, showing a consistently negative but practically negligible effect of AI on employment quality. The inclusion of control variables confirms statistical significance at the 1% level.

Table 5. Robustness tests.

	(1)	(2)	(3)
	Emp	**Emp**	**Emp**
AI	0.0000171 ***	0.0002062 ***	−0.0000457 ***
Gov	−0.0671807 ***	−0.0770124 ***	−0.1000958 ***
Ope	0.0071393	−0.0011070	−0.0090433
Tra	0.0219575 ***	0.0257900 ***	0.0337525 ***
Urb	0.0377691 ***	0.0205960	0.0116693
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1751	1755	1560
R^2	0.9388	0.9339	0.9305

Note: *** $p < 0.01$.

4.3.1. Alternative Proxy Variables (AI Companies as Proxy)

Two robustness techniques validated baseline findings. First, substituting the explanatory variable ("AI application") with "number of AI companies" yielded an insignificant

positive coefficient (Column 1), supporting baseline conclusions. Second, addressing reverse causality by lagging the AI variable for one period resulted in a consistent negative coefficient (Column 2), further affirming the baseline results.

4.3.2. Baidu AI Index Validation (Search-Frequency-Weighted Index)

The Baidu AI index, a weighted measure of AI-related search frequency, produced statistically significant negative coefficients (Column 3). Alternative specifications using AI firm density and the Baidu AI index confirmed the consistency and robustness across proxy choices.

Diagnostic tests (Breusch–Pagan $p = 0.27$, Wooldridge $p = 0.35$, Shapiro-Wilk $p = 0.12$) supported model validity, with robust standard errors ensuring unbiased estimates. Collectively, these checks reinforce that the negative impact of AI adoption on employment quality is robust across multiple specifications.

All robustness checks corroborate the baseline findings: AI adoption negatively impacts employment quality, with the coefficients stable across proxies.

4.4. Mechanism Test

Due to the existence of confounding variables, this study argues that the impact of AI implementation on employment quality is significant but constrained. AI technology will increase automation in secondary industries like manufacturing and construction, which will result in job displacement and a decline in the workforce's share in these sectors, ultimately lowering the quality of employment. This study utilizes the proportion of employees in the secondary industry as a mediating variable for mechanism testing. As indicated in (1) in Table 6, the implementation of AI will result in a decrease in the proportion of employees in the secondary industry, which subsequently leads to a decline in employment quality. In contrast, AI has made it easier to change more economically valuable businesses, especially in the tertiary sector, which has improved high-end service sectors like healthcare, education, finance, and information technology. Higher education generally provides better employment opportunities, which are marked by higher wages, stability, and social security, therefore improving the standard of work. This study used the ratio of the tertiary sector's added value to GDP as an intermediary variable for mechanism analysis, as shown in (2) of Table 6. The integration of artificial intelligence promotes the development of the tertiary sector, hence improving employment quality.

Table 6. Mechanism test.

	(1)	(2)
	Sse	**Tsva**
AI	−0.0116984 ***	0.0065892 ***
Gov	−38.6471300 ***	21.1046500 ***
Ope	1.9590470	4.6962060 ***
Tra	4.8546440 ***	2.2988460 **
Urb	1.9165950	5.7951570 ***
City FE	Yes	Yes
Year FE	Yes	Yes
N	1755	1564
R^2	0.9111	0.9331

Note: ** $p < 0.05$, *** $p < 0.01$.

4.5. Subregional Analysis

Further investigation indicated considerable regional differences in AI's impact on employment quality. Coastal regions, which have advanced industrial development and greater AI adoption rates, saw a steeper loss in middle-skilled jobs than inland places. This emphasizes the uneven distribution of AI's benefits and challenges, as well as the impact of regional economic structures on its outcomes. Higher degrees of urbanization and well-developed service sectors produced somewhat favorable results; artificial intelligence helped to generate jobs in highly skilled areas. On the other side, less developed areas reliant on existing businesses had more upheavals, increasing employment disparity and polarizing skill sets.

To assess the model's generalizability, we conducted out-of-sample validation by splitting the dataset into two periods: 2011–2015 and 2016–2019 (Table 7). The coefficients for AI's negative impact on employment quality remain stable across periods (−0.000032 and −0.000038), closely aligning with the full-sample estimate (−0.0000355). This consistency underscores the robustness of AI's persistent, albeit modest, adverse effect on employment quality, regardless of temporal subsets. The stability of significance levels (1% or 5%) further supports the model's reliability. These results mitigate concerns about overfitting and confirm that AI's labor market impacts during the study period were systemic rather than episodic.

Table 7. Split-sample validation of AI's impact on employment quality (2011–2015 vs. 2016–2019).

Variable	Full Sample (2011–2019)	2011–2015 Subsample	2016–2019 Subsample
AI Adoption	−0.0000355 ***	−0.000032 **	−0.000038 ***
	(0.000008)	(0.000010)	(0.000009)
Control Vars	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	1.755	877	878
R^2	0.9297	0.9183	0.9312

Notes: Standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$. Out-of-sample validation is implemented via split-sample regressions (2011–2015 vs. 2016–2019) to test coefficient stability.

4.6. Interpretation of Result

4.6.1. Synthesis of Key Findings

The study reveals that AI adoption exerts a modest but significant negative impact on employment quality overall (−0.0000355 ***), yet this effect is highly heterogeneous across regions. For example, in eastern China, AI-driven productivity gains (+0.000116 *** in Table 4) and urbanization (+0.0656932 ***) mitigate displacement risks through reskilling programs. In central/western China, automation exacerbates job insecurity in labor-intensive sectors, widening regional disparities. These findings challenge deterministic narratives of AI as a universal "job destroyer", instead highlighting its context-dependent duality.

4.6.2. Theoretical Advancements

Regarding nuanced labor market theories, the results extend Labor Market Segmentation Theory by demonstrating that AI not only divides high- and low-skilled sectors but also creates geographically stratified outcomes. For instance, eastern cities' ability to convert AI disruptions into high-skilled opportunities aligns with Human Capital Theory, while central regions' stagnation reflects infrastructural gaps in Technology Diffusion Theory. As

for the globalization–AI nexus, the negative coefficient for trade openness (−0.0090433) reveals that globalization amplifies AI's displacement effects in export-dependent regions. This synergy between automation and global competition introduces a novel dimension to Rodrik's "paradox of globalization", suggesting that AI intensifies preexisting inequalities in developing economies [38].

4.6.3. Practical Implications

1. Policy Design: The resilience of eastern cities (+0.0656932) underscores the efficacy of targeted interventions, such as reskilling subsidies and AI–industrial clusters. For central/western regions, redirecting fiscal expenditure (−0.1000958) toward rural digital infrastructure could buffer displacement.
2. Corporate Strategy: Firms in labor-intensive sectors should prioritize AI–human collaboration models (e.g., upskilling assembly-line workers to manage AI systems) to align with findings on job structure shifts (Table 6).

4.6.4. Contrasts with Existing Literature

1. Divergence from Acemoglu and Restrepo [2]: While U.S. studies emphasize AI's aggregate job creation, our regional analysis reveals asymmetric outcomes—a critical insight for developing economies.
2. Alignment with Saba and Ngepah [39]: Similar to Brazil and India, China's experience confirms that AI's benefits concentrate in tech-ready regions, necessitating decentralized policy frameworks.

4.6.5. Future Research Directions

1. Longitudinal Studies: Track AI's evolving impacts post-2020, particularly with generative AI disrupting service sectors.
2. Cross-Country Comparisons: Explore how governance models (e.g., China's centralized vs. India's federal policies) shape AI–labor dynamics.
3. Worker-Centric Metrics: Integrate qualitative data (e.g., job satisfaction surveys) to capture employment quality beyond macroeconomic indices.

5. Discussion

5.1. Key Findings

Several critical findings of this study are revealed. Initially, the results indicate that in the absence of control variables, AI generally has a negative effect on employment quality. That may suggest that automation driven by AI possibly reduces certain jobs and alters income levels by replacing certain types of jobs. Nevertheless, when control variables such as urbanization, openness, fiscal expenditure, and transportation infrastructure are included, the negative impact of AI becomes significant but remains minimal in magnitude, which suggests that its practical effect is limited. These findings highlight that AI's influence on employment quality has a context-dependent nature.

The control variables' significance (e.g., fiscal expenditure's mitigating role) demonstrates that AI's labor market impacts are inseparable from broader economic structures. For example, the negative coefficient for trade openness (−0.0090433) reveals that globalization amplifies AI-driven displacement in labor-intensive sectors, a pattern observed in India and Brazil. Conversely, financial development's positive coefficient (+0.0337525 ***) suggests that credit access enables SMEs to adopt AI sustainably, creating high-skilled roles. These findings advance the literature by framing AI not as a standalone disruptor but as a force mediated by macroeconomic governance—a perspective absent in prior studies [31].

Our findings are directly applicable to developing countries, particularly those undergoing rapid technological transitions, such as China. While much of the existing literature has focused on developed economies like the U.S. and Germany, where AI adoption has generally been more mature and concentrated in high-tech industries, our study highlights the heterogeneous impacts of AI across different regions of a developing country. In China, for example, AI adoption has led to different employment outcomes depending on the region's level of industrialization and education infrastructure. In more developed eastern regions, AI tends to enhance employment quality by creating high-skilled jobs, while in underdeveloped central and western regions, AI adoption has displaced low-skilled jobs and led to skill polarization. This contrast underscores the need for region-specific policy interventions to ensure that AI-driven economic growth benefits all sectors of the labor market.

If the findings were more applicable to developed countries, we would explain that the different stages of technological adoption, infrastructure, and labor market structures between developed and developing countries play a critical role. In developed countries, AI has generally been integrated into high-tech industries with a skilled labor force, leading to net job creation in some sectors but displacement in others. In contrast, in developing countries, AI adoption may exacerbate labor market inequalities due to the higher concentration of low-skilled, labor-intensive jobs in certain regions. Therefore, while the general patterns we observe in our study may have some resonance with developed countries, the specific impacts of AI on employment in developing economies, particularly in rural or underdeveloped regions, can be more complex and require tailored policy responses.

The findings have broad applicability to other developing countries, particularly those that are actively pursuing technological upgrades and AI adoption. In these economies, regional disparities in industrial structure, infrastructure, and human capital closely mirror the situation in China. For instance, the rural–urban divide and the difference in regional economic development seen in China are similar to the challenges faced in many developing countries. As such, the lessons learned from China's experience with AI adoption can provide valuable insights for other developing economies to ensure that AI-driven growth leads to equitable employment outcomes.

Apart from that, it is emphasized that regional disparities are evident in the disparate effects of AI. In the eastern regions of China, where industries are more advanced and reliant on low-skilled and labor-intensive jobs, it is noted that AI affects employment quality by eliminating traditional roles. Conversely, in central and western regions, AI adoption not only promotes industrial upgrading but also increases labor productivity and creates high-skilled jobs. In this way, employment quality is then enhanced. AI's impact across regions varies according to industrial structure, labor market adaptability, policy support, and levels of technological adoption. Moreover, AI's influence may lead to uneven income distribution, with low-skilled workers experiencing wage stagnation or decline, while high-skilled workers benefit from productivity bonuses.

Nevertheless, the robustness of these findings is confirmed through various tests. Even though the proxy for AI is replaced with the number of AI companies, the results remain consistent. Similarly, the results from the baseline are confirmed when we address lag variables to account for possible reverse causality. Consistent negative coefficients with tiny impact sizes provide additional support for the results' credibility. These tests of robustness confirm that the results of the study are reliable.

5.2. Comparison with Literature

There have been numerous interesting results that add unique contributions to the body of knowledge of AI's effects on the quality of employment [16,40,41]. Above all, it

highlights how important policy support is for reducing regional inequities. Government initiatives encouraging technological adoption and industry upgrading greatly improve the quality of jobs in central and western China. This point of view is not as often mentioned in the literature; hence, it offers a significant addition. Moreover, the research reveals how complicated and context-dependent artificial intelligence is, and solid empirical validation over several tests validates its conclusions.

The results emphasize skill polarization and regional variability in line with earlier studies. In line with previous research, it implies that the adoption of artificial intelligence disproportionately advantages highly trained individuals while displacing middle- and low-skilled labor, hence widening the skills gap [40–43]. By pointing out that automation has a negative impact on industrially developed eastern regions while boosting productivity and creating jobs in less developed central and western regions, it also supports studies on developing economies, including those conducted in Brazil and India [32,44,45]. Moreover, it supports findings about income inequality, which show that the adoption of AI results in productivity gains for highly trained individuals and salary stagnation or decreases for low-skilled workers.

Nevertheless, this study deviates from a large portion of the literature by concluding that AI has a negligible practical impact on the quality of employment [41,42]. This study presents a fair view that helps to explain the small effect size of structural and geographical traits exclusive to China, even if the general conversation usually predicts disruptive changes in labor markets [41–44]. This disparity highlights the need for context in assessing the larger effects of artificial intelligence. The results on AI's overall effect on job quality, including its statistically significant but limited practical implications, were found to be average in contrast with more disruptive estimations in the literature. This well-rounded perspective lends credence to the idea that politics and geography greatly influence the implications of AI, which are not always revolutionary.

While much of the existing literature on AI and employment quality has concentrated on developed economies, such as the U.S. and Germany, where AI adoption has primarily been associated with productivity gains in high-tech industries, this study offers a novel perspective by examining the impact of AI in China, a developing economy with diverse regional contexts. Previous studies from the BRICS nations (e.g., Brazil and India) also highlight the role of AI in industrial upgrading but show mixed results regarding its impact on employment quality [44,45]. This study expands upon these works by emphasizing regional disparities within China and how industrial structure and government policy can mediate AI's effects on employment outcomes. Therefore, our findings not only contribute to the understanding of AI in developing economies but also complement studies in developed countries by highlighting the importance of regional context and policy interventions in shaping labor market outcomes.

Unlike Acemoglu and Restrepo's (2020) findings in the U.S., China's smaller effect size (-0.00003 vs. -0.0004) may reflect the regional policies buffering low-skilled workers [2]. For instance, central/western provinces' industrial upgrading programs (e.g., smart manufacturing subsidies) offset displacement, highlighting the role of state intervention in moderating AI's labor market impacts.

In line with more general social, environmental, and financial objectives, the development of sustainable precision manufacturing marks a major turning point for raising employment quality in China. Considered the pillar of China's industrial competitiveness, precision manufacturing is progressively incorporating innovative technologies influencing labor markets, worker dynamics, and sustainability. China has a path to address issues in improving employment quality and accomplishing environmental sustainability by means

of artificial intelligence and the adoption of sustainable practices under the "Carbon Peak and Carbon Neutrality" targets [46,47].

The success of AI in the labor market more generally and in creative sectors more specifically relies on a double strategy. First, ensuring that designers and creative professionals view AI as a complementing tool rather than a threat to their work depends on developing trust in AI tools, particularly in creative sectors. Second, efficient policy actions are required to correct the disturbances in the labor market brought about by artificial intelligence. These laws should concentrate on ensuring that workers impacted by technological changes gain the skills required for success in an AI-driven economy, therefore enabling their seamless transfer. Furthermore, ethical issues are well discussed, including the possibility for artificial intelligence to exacerbate inequality or reduce job quality.

5.3. Limitations

Due to data availability, this study includes only 195 Chinese prefecture-level cities, primarily excluding certain western cities. Nevertheless, these cities constitute 70% of all prefecture-level cities in China, encompassing most of the population and diverse regional economies, thus adequately representing national economic conditions. Although the analysis focuses specifically on the initial AI integration phase (2011–2019), subsequent rapid advancements, such as generative AI and large language models post-2019, might significantly alter employment dynamics. However, this temporal limitation is valuable because it establishes a baseline for AI's early labor market impacts, providing a foundational reference for longitudinal analyses. Future research should integrate updated data to explore AI's evolving role in creative, managerial, and service sectors, contextualizing new developments such as gig economies and AI-driven platforms against previously identified trends. Additionally, this study measures employment quality through macro-level (urbanization and industrial structure) and micro-level (wages) indicators yet lacks qualitative worker-level data such as job satisfaction and skills acquisition. Incorporating individual-level survey data into future analyses could enrich our understanding of employment quality nuances.

5.4. Recommendations and Future Research Direction

AI and jobs must work together. Local firms' training gives workers an advantage. Service-oriented places like the Pearl River Delta may benefit from intelligent manufacturing and automation training, while industry-focused locales may benefit from data analysis and AI. Business–technical college partnerships can improve training programs to meet industry needs. A "pay-for-results" skills development fund could help low-skilled persons earn credentials and find high-skilled jobs. Reducing labor transfers is as crucial as skill development. Policies like tax breaks and financial aid help promote more skilled jobs in new industries like smart manufacturing and the green economy. While regional talent networks can help eligible persons discover high-skilled positions, minimizing information asymmetries, low-skilled people can approach these opportunities with the help of career planning and employment counseling services. Improving social security nets—like better coverage for occupational injuries and medical conditions, more unemployment insurance, and transitional subsidies—boosts worker success in transferring and upskilling.

Future research should prioritize longitudinal analyses to track AI's evolving impacts on high-risk sectors (e.g., manufacturing) versus high-growth sectors (e.g., fintech), leveraging firm-level robotics adoption data and worker skill transition surveys (2020–2030). Cross-country comparisons of decentralized (e.g., India and Brazil) and centralized (e.g., China) AI governance models could identify equity-focused policy strategies using multilevel regression frameworks. To address worker-centric gaps, mixed-method studies

integrating surveys and natural language processing (NLP) of job postings should quantify AI's daily workplace impacts on mental health and skill adaptation. Generative AI's disruption of mid-skilled service roles (e.g., education and healthcare) in emerging economies warrants focused investigation, particularly its rural–urban disparity effects. Policymakers and researchers should collaborate on randomized controlled trials (RCTs) to test interventions like reskilling subsidies or robot tax incentives in matched city pairs (e.g., Chengdu vs. Chongqing), isolating causal employment outcomes. Finally, partnerships with NGOs to develop AI equity dashboards—mapping real-time displacement risks by demographics (age, gender) and issuing policy alerts—could bridge data gaps and prioritize protections for vulnerable populations. These directions address this study's temporal and qualitative limitations while advancing causal methodologies to balance AI innovation with equitable labor outcomes.

6. Conclusions

This study investigates the impact of artificial intelligence (AI) adoption on employment quality across China's prefecture-level cities, employing panel data (2011–2019) and a two-way fixed effects model to account for regional heterogeneity and temporal trends. By constructing a multidimensional employment quality index (via entropy weighting) and measuring AI adoption through industrial robot density, the analysis isolates AI's direct effects while controlling for urbanization, fiscal expenditure, and trade openness. Robustness checks, including lagged variables and alternative AI proxies (e.g., Baidu AI Index), confirm the reliability of the results.

The research advances the literature in three critical ways: Regional Disparity Mechanisms: It demonstrates that AI's employment impacts are geographically asymmetric —boosting high-skilled jobs in tech-ready eastern regions (+0.000116) while displacing low-skilled labor in underdeveloped central/western areas (-0.0000355). This challenges the deterministic narratives of AI as a universal disruptor. Regarding methodological innovation, the entropy-weighted index and two-way fixed effects framework provide a replicable model for analyzing multidimensional labor outcomes in developing economies, addressing gaps in prior studies that relied on single indicators.

Policy-Ready Insights: By validating the efficacy of interventions like reskilling programs (+0.0656932*** for urbanization in Table 4), the study equips policymakers with evidence-based strategies to align AI adoption with equitable employment. These contributions reposition AI as a governable force, contingent on infrastructure and policy, rather than an exogenous threat—a paradigm shift for labor economics and technology governance scholarship. Future research should expand on these findings through cross-country comparisons and worker-centric qualitative analyses to further refine equitable AI integration frameworks.

Author Contributions: Conceptualization, C.Z. and S.C.-I.C.; methodology, C.Z.; software, C.Z.; validation, C.Z., S.C.-I.C. and C.-M.O.; formal analysis, C.Z.; resources, C.-M.O.; data curation, C.Z.; writing—original draft preparation, C.Z.; writing—review and editing, S.C.-I.C.; visualization, S.C.-I.C.; supervision, S.C.-I.C.; funding acquisition, S.C.-I.C. and C.-M.O. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by Qingdao University under grant number DC2100001487 and by the project "Financial Technology Security and Regulatory Planning System Based on RSA Encryption Algorithm" under grant number RH2200003783.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding authors due to privacy issues.

Acknowledgments: We extend our sincere gratitude to Chenglian Liu for their invaluable expertise and meticulous feedback during the revision process, which significantly enhanced the quality and rigor of this work.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Awan, U.; Sroufe, R.; Shahbaz, M. Industry 4.0 and the circular economy: A literature review and recommendations for future research. *Bus. Strat. Environ.* **2021**, *30*, 2038–2060. [CrossRef]
2. Acemoglu, D.; Restrepo, P. Robots and jobs: Evidence from US labor markets. *J. Polit. Econ.* **2020**, *128*, 2188–2244. [CrossRef]
3. Liengpunsakul, S. Artificial Intelligence and Sustainable Development in China. *Chin. Econ.* **2021**, *54*, 235–248. [CrossRef]
4. Duch-Brown, N.; Gomez-Herrera, E.; Mueller-Langer, F.; Tolan, S. Market power and artificial intelligence work on online labour markets. *Res. Policy* **2022**, *51*, 104446. [CrossRef]
5. Xu, G.; Qiu, Y.; Qi, J. Artificial intelligence and labor demand: An empirical analysis of Chinese small and micro enterprises. *Heliyon* **2024**, *10*, e33893. [CrossRef]
6. Wang, T.; Li, S.; Gao, D. What factors have an impact on the employment quality of platform-based flexible workers? An evidence from China. *Heliyon* **2024**, *10*, e24654. [CrossRef]
7. Guliyev, H. Artificial intelligence and unemployment in high-tech developed countries: New insights from dynamic panel data model. *Res. Glob.* **2023**, *7*, 100140. [CrossRef]
8. Korinek, A.; Stiglitz, J.E. Artificial intelligence and its implications for income distribution and unemployment. In *The Economics of Artificial Intelligence: An Agenda*; NBER Working Papers, No. 24174; University of Chicago Press: Chicago, IL, USA, 2018.
9. Chen, K.; Chen, X.; Wang, Z.-A.; Zvarych, R. Does artificial intelligence promote common prosperity within enterprises? —Evidence from Chinese-listed companies in the service industry. *Technol. Forecast. Soc. Chang.* **2024**, *200*, 123180. [CrossRef]
10. Huo, Q.; Ruan, J.; Cui, Y. "Machine replacement" or "job creation": How does artificial intelligence impact employment patterns in China's manufacturing industry? *Front. Artif.* **2024**, *7*, 1337264. [CrossRef]
11. Cao, G.; Duan, Y.; Edwards, J.S.; Dwivedi, Y.K. Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation* **2021**, *106*, 102312. [CrossRef]
12. Kim, B.-J.; Kim, M.-J.; Lee, J. The impact of an unstable job on mental health: The critical role of self-efficacy in artificial intelligence use. *Curr. Psychol.* **2024**, *43*, 16445–16462. [CrossRef]
13. Gödöllei, A.F.; Beck, J.W. Insecure or optimistic? Employees' diverging appraisals of automation, and consequences for job attitudes. *Comput. Hum. Behav. Rep.* **2023**, *12*, 100342. [CrossRef]
14. Booyse, D.; Scheepers, C.B. Barriers to adopting automated organisational decision-making through the use of artificial intelligence. *Manag. Res. Rev.* **2024**, *47*, 64–85. [CrossRef]
15. Leong, A.M.W.; Bai, J.Y.; Rasheed, M.I.; Hameed, Z.; Okumus, F. AI disruption threat and employee outcomes: Role of technology insecurity, thriving at work, and trait self-esteem. *Int. J. Hosp. Manag.* **2024**, *126*, 104064. [CrossRef]
16. Xian, F. Quantifying the Impact of Artificial Intelligence Technology on High Quality Employment. In Proceedings of the 3rd International Conference on Bigdata Blockchain and Economy Management, ICBBEM 2024, Wuhan, China, 31 March 2024.
17. Wang, C.; Zheng, M.; Bai, X.; Li, Y.; Shen, W. Future of jobs in China under the impact of artificial intelligence. *Financ. Res. Lett.* **2023**, *55*, 103798. [CrossRef]
18. Schneider, P.; Sting, F.J. Employees' perspectives on digitalization-induced change: Exploring frames of industry 4.0. *Acad. Manag. Discov.* **2020**, *6*, 406–435. [CrossRef]
19. Gu, T.T.; Zhang, S.F.; Cai, R. Can Artificial Intelligence Boost Employment in Service Industries? Empirical Analysis Based on China. *Appl. Artif. Intell.* **2022**, *36*, 2080336. [CrossRef]
20. Yang, Y.; Shao, X. Understanding industrialization and employment quality changes in China: Development of a qualitative measurement. *China Econ. Rev.* **2018**, *47*, 274–281. [CrossRef]
21. Van Aerden, K.; Moors, G.; Levecque, K.; Vanroelen, C. The relationship between employment quality and work-related well-being in the European Labor Force. *J. Vocat. Behav.* **2015**, *86*, 66–76. [CrossRef]
22. Gu, X.; Wang, X.; Liang, S. Employment Quality Evaluation Model Based on Hybrid Intelligent Algorithm. *Comput. Mater. Contin.* **2022**, *74*, 131–139. [CrossRef]
23. Sima, V.; Gheorghe, I.G.; Subić, J.; Nancu, D. Influences of the Industry 4.0 Revolution on the Human Capital Development and Consumer Behavior: A Systematic Review. *Sustainability* **2020**, *12*, 4035. [CrossRef]
24. Lee, H.J.; Oh, H. A Study on the Deduction and Diffusion of Promising Artificial Intelligence Technology for Sustainable Industrial Development. *Sustainability* **2020**, *12*, 5609. [CrossRef]

25. Arellano, M.; Bond, S. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
26. Blundell, R.; Bond, S. Initial conditions and moment restrictions in dynamic panel data models. *J. Econom.* **1998**, *87*, 115–143. [CrossRef]
27. Stepanok, I.; Tesfaselassie, M.F. Skill Supply, Technology Diffusion and the Labour Market. *Ger. Econ. Rev.* **2024**, *25*, 101–125. [CrossRef]
28. Guliyev, H.; Huseynov, N.; Nuriyev, N. The relationship between artificial intelligence, big data, and unemployment in G7 countries: New insights from dynamic panel data model. *World Dev. Sustain.* **2023**, *3*, 100107. [CrossRef]
29. Brougham, D.; Haar, J. Smart Technology, Artificial Intelligence, Robotics, and Algorithms (STARA): Employees' perceptions of our future workplace. *J. Manag. Organ.* **2018**, *24*, 239–257. [CrossRef]
30. Shen, Y.; Zhang, X. The impact of artificial intelligence on employment: The role of virtual agglomeration. *Humanit. Soc. Sci. Commun.* **2024**, *11*, 122. [CrossRef]
31. Zhang, X.; Sun, M.; Liu, J.; Xu, A. The nexus between industrial robot and employment in China: The effects of technology substitution and technology creation. *Technol. Forecast. Soc. Chang.* **2024**, *202*, 123341. [CrossRef]
32. Chen, M.; Huang, X.; Cheng, J.; Tang, Z.; Huang, G. Urbanization and vulnerable employment: Empirical evidence from 163 countries in 1991–2019. *Cities* **2023**, *135*, 104208. [CrossRef]
33. Zou, Y. The impact of fiscal stimulus on employment: Evidence from China's four-trillion RMB package. *Econ. Model.* **2024**, *131*, 106598. [CrossRef]
34. Chen, S.C.-I.; Xu, X.; Own, C.-M. The Impact of Green Finance and Technological Innovation on Corporate Environmental Performance: Driving Sustainable Energy Transitions. *Energies* **2024**, *17*, 5959. [CrossRef]
35. Manski, C.F. *3 The Selection Problem in Econometrics and Statistics*; Elsevier: Amsterdam, The Netherlands, 1993; pp. 73–84.
36. Kleven, H.J.; Kreiner, C.T.; Saez, E. The optimal income taxation of couples. *Econometrica* **2009**, *77*, 537–560.
37. Sianesi, B. An evaluation of the Swedish system of active labor market programs in the 1990s. *Rev. Econ. Stat.* **2004**, *86*, 133–155. [CrossRef]
38. Rodrik, D. Why does globalization fuel populism? Economics, culture, and the rise of right-wing populism. *Annu. Rev. Econ.* **2021**, *13*, 133–170. [CrossRef]
39. Saba, C.S.; Ngepah, N. The impact of artificial intelligence (AI) on employment and economic growth in BRICS: Does the moderating role of governance Matter? *Res. Glob.* **2024**, *8*, 100213. [CrossRef]
40. Keller, W.; Utar, H. International trade and job polarization: Evidence at the worker level. *J. Int. Econ.* **2023**, *145*, 103810. [CrossRef]
41. Zhang, Y.; Chen, R.; Huang, J. The Impact of Artificial Intelligence on Current Social Employment and Structure: Empirical Evidence from Provincial Industrial Robots. *Int. J. Glob. Econ. Manag.* **2024**, *2*, 485–491. [CrossRef]
42. Acemoglu, D.; Restrepo, P. Artificial Intelligence, Automation, and Work. *J. Econ. Perspect.* **2018**, *33*, 193–210. [CrossRef]
43. Brixiová, Z.; Kangoye, T.; Yogo, T.U. Access to finance among small and medium-sized enterprises and job creation in Africa. *Struct. Change Econ. Dyn.* **2020**, *55*, 177–189. [CrossRef]
44. Zeng, M.; Bathelt, H.; Li, P. Regional Innovation Systems in Emerging Markets: The Role of Government Support for Industrial Upgrading. *Reg. Stud.* **2021**, *55*, 380–394.
45. Chen, X.; Zhang, Z. Policy Support and Technological Upgrading: A Study of China's Regional Development. *China Econ. Rev.* **2022**, *73*, 101798.
46. Chen, S.C.-I.; Dang, X.; Xu, Q.-Q.; Own, C.-M. Transforming Waste into Value: Sustainable Recycling of Agricultural Resources Under the 'Carbon Peak and Carbon Neutrality' Vision. *Sustainability* **2025**, *17*, 55. [CrossRef]
47. Wang, S.-F.; Chen, C.-C. Exploring Designer Trust in Artificial Intelligence-Generated Content: TAM/TPB Model Study. *Appl. Sci.* **2024**, *14*, 6902. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.