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Posted Date: 11 July 2024

doi: 10.20944/preprints202407.0906.v1

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Impact and Regulations of AI on Labor Markets and Employment in USA

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Abstract: This study investigates the impact of AI regulations and adoption on labor markets and employment in the USA. In order to achieve the study's objective, a robust econometric approach was employed using Principal Components Analysis (PCA) to address multicollinearity among the variables. The regression analysis incorporated principal components representing overall AI adoption and education (PC1), AI innovation and academic output (PC2), economic growth (PC3), and unemployment and AI strategies (PC4). The analysis utilized heteroskedasticity-robust standard errors to ensure reliable coefficient estimates and tested for stationarity to confirm the stability of the time series data. Data were collected from 2010 to 2022, encompassing key AI-related and economic indicators. The results reveal that higher AI adoption and education levels initially lead to job displacement, negatively impacting labor market metrics. Similarly, AI innovation and economic growth driven by AI do not immediately translate into job creation, reflecting transitional challenges. However, the strategic implementation of AI significantly mitigates these adverse effects and enhances employment conditions. The study finds that comprehensive AI strategies, robust regulatory frameworks, and effective workforce retraining and upskilling programs are essential for supporting labor market stability and promoting employment growth. Based on the findings, the study recommended that there is the need to develop and implement comprehensive AI strategies that include robust regulatory frameworks to support workforce transitions. Policies should focus on retraining and upskilling programs to help displaced workers adapt to new AI-driven roles.

Keywords: Artificial Intelligence (AI); Labor Markets; Employment; AI Adoption; AI Innovation; Economic Growth; AI Strategies

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Introduction

Artificial Intelligence (AI) is a transformative technology with profound implications for various facets of society, including the labor market. AI encompasses a broad array of technologies that enable machines to perform tasks that typically require human intelligence, such as learning, problem-solving, and decision-making. The rapid advancements in AI have led to its integration into numerous industries, revolutionizing the way businesses operate and reshaping job functions and structures (Joni, 2024; Webb, 2019).

In the United States, AI adoption has been accelerating, driven by significant investments from both the private and public sectors. Major tech companies, startups, and academic institutions are at the forefront of AI research and development, leading to innovations that are rapidly disseminated across industries (Loong et al., 2021). The proliferation of AI technologies has been particularly notable in sectors such as manufacturing, healthcare, finance, and transportation, where AI-driven automation and data analytics are enhancing productivity and efficiency (Zarifhonarvar, 2024).

 doi:10.20944/preprints202407.0906.v1

The regulatory landscape for AI in the USA is evolving, with policymakers grappling to keep pace with technological advancements. Regulations focus on ensuring ethical AI use, protecting data privacy, and mitigating the risks of job displacement due to automation. Government initiatives, such as the National AI Initiative Act, aim to coordinate AI research, development, and policy across federal agencies (Shuhratovna, 2023). However, there is a continuous debate on the adequacy of these regulations in addressing the rapid advancements and the socio-economic impacts of AI (Groshen & Holzer, 2019).

The impact of AI on industries is profound and multifaceted. AI technologies are enhancing operational efficiency, enabling predictive maintenance, and optimizing supply chains (Unuriode et al., 2024). However, these advancements come with the challenge of displacing jobs, particularly those involving routine and manual tasks. On the other hand, AI is creating new opportunities and job roles that require advanced technical skills, such as AI specialists, data scientists, and cybersecurity experts. The duality of AI's impact necessitates a nuanced understanding of its benefits and challenges (Carbonero et al., 2023).

The labor market in the USA is undergoing significant transformation due to AI-driven automation. While AI increases productivity and generates new employment opportunities, it also poses the risk of job displacement, particularly in low-skilled sectors (Bian, 2024). Policymakers must address these challenges by fostering an environment that supports workforce re-skilling and up-skilling, ensuring that workers can transition to new roles created by AI. Effective regulation is crucial to balance the benefits of AI with its potential to disrupt traditional labor markets (Braunerhjelm et al., 2023).

Several studies have explored the impact of AI on labor markets, providing valuable insights into the opportunities and challenges posed by this technology. For instance, Joni (2024) highlights the dual impact of AI on job creation and displacement, while Webb (2019) examines how AI could reduce wage inequality by increasing the demand for high-skilled jobs. Other researchers, such as Loong et al. (2021) and Zarifhonarvar (2024), have focused on the regulatory responses needed to mitigate the adverse effects of AI on employment (Duch-Brown et al., 2022; Sokolić, 2022).

Despite extensive research, significant gaps remain in understanding the comprehensive impact of AI on labor markets and the effectiveness of current regulations. Many studies have focused on specific sectors or short-term effects, leaving a gap in longitudinal analyses and cross-sector comparisons. Additionally, there is a need for more empirical research on the socio-economic impacts of AI and the effectiveness of regulatory frameworks in mitigating these impacts. This study aims to fill these gaps by providing a detailed analysis of the impact and regulations of AI on labor markets and employment in the USA, drawing on a broad range of data sources and methodologies (Felten et al., 2019; Laukes, 2024). By addressing these gaps, this research will contribute to a more nuanced understanding of how AI is reshaping labor markets and inform policymakers on effective strategies to manage this transition. This is crucial for ensuring that the benefits of AI are broadly shared, and the risks are mitigated, thereby promoting inclusive economic growth and stability in the labor market (Ernst et al., 2019; Yan, 2024).

Objectives of the Study

The following are the objectives of the study:

1. To examine the impact of AI regulations on the labor markets and employment in USA
2. To examine the impact of AI on the labor markets and employment in USA

Literature Review

Impact of AI Regulations on the Labor Markets and Employment

The regulation of AI in the USA is a critical factor in shaping its impact on labor markets and employment. Joni (2024) emphasizes that AI regulations are essential in managing the dual nature of AI's influence on job creation and displacement. These regulations are designed to ensure that AI technologies are implemented ethically and that their benefits are maximized while minimizing adverse effects on the workforce (Joni, 2024). Moreover, the effectiveness of these regulations is pivotal in balancing innovation with protection for workers who may be at risk of job displacement due to AI automation.

Groshen and Holzer (2019) argue that current AI policies in the USA are still evolving and often lag behind the rapid pace of technological advancement. They stress the need for comprehensive regulatory frameworks that address both the ethical implications of AI and its economic impact on the labor market. Similarly, Zarifhonarvar (2024) points out that while AI has the potential to transform labor markets positively, inadequate regulations can lead to significant disruptions and increased inequality, necessitating proactive policy measures to safeguard against these risks.

Loong et al. (2021) provide a comparative perspective by examining AI regulations in other countries, highlighting that the USA can learn from the regulatory frameworks of countries like China, which have implemented robust AI policies to mitigate labor market disruptions. They suggest that the USA adopt similar strategies to ensure that AI deployment does not exacerbate existing labor market inequalities. Furthermore, Braunerhjelm et al. (2023) discuss how labor market regulations can promote innovation and technological change, emphasizing that well-designed regulations can foster a conducive environment for AI-driven growth while protecting workers.

Impact of AI on the Labor Markets and Employment

The impact of AI on labor markets in the USA has been extensively studied, with researchers highlighting both opportunities and challenges. Webb (2019) explores the potential of AI to reduce wage inequality by creating high-skilled jobs that command higher wages. He posits that while AI can displace routine jobs, it simultaneously generates demand for new skill sets, thus reshaping the labor market dynamics. Shuhratovna (2023), who identifies the creation of new job roles as a significant positive outcome of AI integration, echoes this sentiment, although she cautions that the transition requires substantial investment in workforce training and education.

Unuriode et al. (2024) provide empirical evidence on the displacement effects of AI, noting that sectors heavily reliant on manual labor are most at risk. They argue that the negative impacts can be mitigated through strategic policy interventions that promote re-skilling and job transition programs. Similarly, Carbonero et al. (2023) discuss the potential for AI to exacerbate existing labor market inequalities, particularly in developing regions. Their findings highlight the need for inclusive policies that ensure the benefits of AI are widely distributed across different socio-economic groups.

Duch-Brown et al. (2022) examine the influence of AI on online labor markets, emphasizing that AI can both disrupt and enhance these markets. They suggest that AI can lead to greater efficiency and productivity but also warn of the potential for increased market power among a few dominant players, which could negatively impact competition and worker conditions【. In contrast, Sokolić (2022) highlights the positive implications of AI, such as improved job matching and the creation of more flexible work arrangements, which can benefit workers by providing more opportunities and better work-life balance.

Research Gaps and the Need for This Particular Study

Several studies have provided valuable insights into the impact of AI on labor markets. Felten et al. (2019) investigate the occupational impact of AI, identifying a trend towards labor market polarization, where high-skilled and low-skilled jobs are less affected, while middle-skilled jobs face the highest risk of automation. This polarization is a critical issue that policymakers need to address to prevent a widening skills gap and ensure equitable economic growth.

Laukes (2024) delves into the changing skill requirements driven by AI, noting that the demand for advanced technical skills is rapidly increasing. This study underscores the importance of aligning

 doi:10.20944/preprints202407.0906.v1

educational curricula with industry needs to prepare the workforce for future job roles. Similarly, Ernst et al. (2019) discuss the broader economic implications of AI, suggesting that while AI can drive significant productivity gains, it also necessitates substantial policy adjustments to manage its impact on employment and income distribution.

Zhou (2023) provides a comprehensive review of the current research on AI's labor market impacts, highlighting gaps in existing studies and calling for more empirical research to inform policy decisions. Zhou's work emphasizes the need for longitudinal studies that track the long-term effects of AI on employment and wages, which are crucial for developing effective regulatory frameworks.

Despite the extensive research conducted, significant gaps remain in understanding the full impact of AI on labor markets and the effectiveness of current regulatory responses. Many studies have focused on short-term effects and specific sectors, leaving a gap in comprehensive analyses that consider the broader, long-term implications of AI adoption. Furthermore, there is a need for more empirical research that evaluates the effectiveness of different regulatory approaches in mitigating the adverse effects of AI on employment.

This study aims to address these gaps by providing a detailed analysis of the impact and regulations of AI on labor markets and employment in the USA. By examining a broad range of data sources and employing robust methodologies, this research will offer new insights into how AI is reshaping labor markets and inform policymakers on effective strategies to manage this transition. Ultimately, this study seeks to contribute to a more nuanced understanding of AI's socio-economic impacts, ensuring that the benefits of AI are widely shared and that potential risks are effectively mitigated (Yan, 2024; Zhou, 2023).

Theoretical Framework

The theoretical foundation of this study is grounded in two key theories: Technological Displacement Theory and Human Capital Theory. These theories provide a comprehensive framework for understanding the multifaceted impact of AI on labor markets and employment in the USA. Technological Displacement Theory explains how AI-driven automation can lead to job displacement, particularly in routine and manual occupations, while also creating new employment opportunities in advanced technical fields. Human Capital Theory, on the other hand, emphasizes the critical role of education and skills development in enhancing workforce adaptability and productivity in response to technological changes.

Technological Displacement Theory

Technological Displacement Theory provides a crucial framework for understanding the impact of AI on labor markets. This theory posits that technological advancements, such as AI, lead to the displacement of workers by automating tasks previously performed by humans. According to Joni (2024), AI technologies are particularly adept at replacing routine, manual, and repetitive tasks, which makes jobs in these categories highly susceptible to automation. Webb (2019) supports this view by demonstrating that the displacement effect is most pronounced in mid-skill jobs, leading to a polarization of the labor market where high-skill and low-skill jobs become more prevalent, while mid-skill jobs decline.

This displacement, however, is not entirely negative. Technological Displacement Theory also suggests that while some jobs are lost, new opportunities are created in areas that require higher cognitive skills and technical expertise. This dynamic is evident in the growing demand for AI specialists, data scientists, and cybersecurity experts, as highlighted by Shuhratovna (2023). She notes that these new roles often come with higher wages and better working conditions, which can offset the negative impacts of job displacement if workers are adequately trained and re-skilled. Nonetheless, the transition period can be challenging for workers displaced by AI, emphasizing the need for supportive policies and programs to facilitate their movement into new roles.

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Human Capital Theory

Human Capital Theory offers another essential perspective on the impact of AI on labor markets. This theory emphasizes the importance of education and skills in enhancing worker productivity and adaptability in the face of technological change. According to Groshen and Holzer (2019), investing in human capital through education and training is crucial for preparing the workforce to meet the demands of an AI-driven economy. Zarifhonarvar (2024) extends this argument by suggesting that continuous learning and skill development are vital for workers to remain competitive in an ever-evolving job market.

Human Capital Theory underscores the role of educational institutions and employers in facilitating the development of relevant skills. Loong et al. (2021) highlight the importance of aligning educational curricula with industry needs to ensure that graduates possess the skills required for AI-related jobs. They argue that partnerships between academia and industry can help bridge the skill gap and enhance the employability of the workforce. This collaboration is essential for creating a pipeline of skilled workers who can thrive in an AI-dominated labor market.

Furthermore, Human Capital Theory posits that investment in human capital leads to higher productivity and economic growth. Braunerhjelm et al. (2023) illustrate this by showing how countries that prioritize education and skill development tend to have more resilient labor markets and better economic outcomes in the face of technological advancements. This theory suggests that policymakers should focus on enhancing the quality and accessibility of education and training programs to equip workers with the skills needed for the future.

Integration of Theories

Integrating Technological Displacement Theory and Human Capital Theory provides a comprehensive understanding of the impact of AI on labor markets. While Technological Displacement Theory explains the immediate effects of AI on job displacement and creation, Human Capital Theory offers a long-term perspective on how workers can adapt to these changes. Together, these theories highlight the need for a dual approach that combines technological adoption with robust education and training programs.

Ernst et al. (2019) advocate for policies that support both technological innovation and human capital development. They argue that such an integrated approach can mitigate the adverse effects of AI on employment while maximizing its potential benefits for economic growth and productivity. Yan (2024), who emphasizes that successful adaptation to AI requires not only regulatory measures to manage displacement but also significant investments in human capital to ensure a skilled and adaptable workforce, echoes this view.

In essence, the theoretical foundation for this study rests on the interplay between Technological Displacement Theory and Human Capital Theory. Understanding how AI displaces certain jobs while creating new ones, and recognizing the critical role of education and training in facilitating this transition, provides a robust framework for analyzing the impact and regulations of AI on labor markets and employment in the USA. This integrated approach is essential for developing effective policies that support workers and ensure that the benefits of AI are broadly shared across society (Zhou, 2023; Carbonero et al., 2023).

Methods

Data Collection

The data for this study were collected from a variety of reputable sources to ensure a comprehensive analysis of the impact and regulations of AI on labor markets and employment in the USA. Primary data sources included databases and reports available at Our World in Data, which provide detailed metrics on research and development activities, including AI investments and technology adoption trends (Our World in Data, 2024). Additional data were gathered from the U.S. Bureau of Labor Statistics (BLS), National Center for Education Statistics (NCES), and legislative databases to capture variables related to employment, education, and regulatory measures.

Sample Population

The sample population for this study encompasses data from the years 2010 to 2022. This period was chosen to capture the rapid advancements in AI technologies and their corresponding impacts on the labor market. The span of over a decade provides a longitudinal perspective, enabling the identification of trends and patterns in AI adoption, labor market changes, and policy implementations.

Measures

The study utilizes several key variables to measure the impact of AI on labor markets and employment, as well as the effectiveness of AI regulations. These variables are categorized into three main groups: Artificial Intelligence, Labor Markets and Employment, and Policy and Regulation of AI.

Table 1. Measurements of Variables.

Variables	Definitions	Acronym	Measurements
Artificial Intelligence	Annual private investment in artificial intelligence	AI Investment	This measures the total amount of private sector investment in AI technologies each year.
	Share of artificial intelligence jobs among all job postings	AI Job Share	This variable captures the proportion of job postings that require AI-related skills.
	Share of companies using artificial intelligence technology	AI Tech Use	This measures the percentage of companies that have integrated AI technologies into their operations
Labor Markets and Employment	Unemployment Rate	Unemployment Rate	This is the percentage of the labor force that is unemployed and actively seeking employment.
	Educational Attainment	Education Level	This variable measures the highest level of education achieved by individuals in the workforce.
Policy and Regulation of AI	Countries with national artificial intelligence strategies	AI Strategies	This variable identifies whether a country has implemented a national strategy for AI

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			development and regulation.
	Employer of new AI PhDs	New AI PhDs Employers	This measures the sectors and industries that employ new AI PhD graduates.
	Annual granted patents related to artificial intelligence, by industry	AI Patents by Industry	This variable tracks the number of AI-related patents granted each year, categorized by industry.
Controlled Variables	Annual GDP Growth	Annual GDP Growth	The year-over-year percentage change in the Gross Domestic Product
	Inflation Rate	Inflation Rate	The annual percentage change in the Consumer Price Index
	Annual patent applications	Patent Applications	The total number of patent applications filed each year, sourced from patent offices and industry reports.

Analytical Approach

The analytical approach for this study includes several statistical techniques to examine the impact and regulations of AI on labor markets and employment in the USA. These methods ensure a comprehensive analysis by addressing various aspects of the data and their relationships.

Descriptive Statistics

Descriptive statistics are used to summarize and describe the main features of the collected data. This includes measures such as mean, median, standard deviation, and range for each variable. Descriptive statistics provide a clear overview of the data distribution and highlight any initial patterns or anomalies. For instance, the mean annual private investment in AI, the average unemployment rate, and the typical share of AI-related job postings were calculated to understand general trends over the period from 2010 to 2022.

Correlation Analysis

Correlation analysis is performed to identify the strength and direction of the relationships between variables. This analysis helps in understanding how AI adoption, measured by investment and job share, is correlated with labor market outcomes like unemployment rates and educational attainment. Pearson correlation coefficients were computed for each pair of variables to determine if there are significant associations that warrant further investigation.

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Stationary Tests Results

Stationary tests, such as the Augmented Dickey-Fuller (ADF) test and the Phillips-Perron (PP) test, are conducted to ensure that the time series data are stationary. Stationarity is crucial for accurate modeling and forecasting. These tests help determine whether the mean, variance, and autocorrelation of the variables are constant over time. Non-stationary data can lead to spurious regression results, so differencing or other transformations may be applied to achieve stationarity.

Model Specification Tests

Model specification tests are used to validate the chosen econometric model. The Ramsey RESET test were applied to check for model misspecification, ensuring that the functional form of the model is appropriate. This step is critical to confirm that the model accurately represents the underlying relationships between the variables without omitting important predictors or including unnecessary ones.

Multicollinearity Check

Multicollinearity occurs when two or more independent variables in a regression model are highly correlated, which can distort the estimation of coefficients. Variance Inflation Factor (VIF) and tolerance tests were conducted to detect multicollinearity. If high multicollinearity is detected, it may be necessary to exclude or combine variables, or use techniques such as principal component analysis to mitigate its effects.

Heteroskedasticity Test

Heteroskedasticity refers to the presence of non-constant variance in the error terms of a regression model, which can lead to inefficient estimates and affect hypothesis testing. The Breusch-Pagan test and White test were used to detect heteroskedasticity. If heteroskedasticity is found, robust standard errors or other corrective measures were applied to ensure reliable estimates.

Least Squares Regression

The core analytical technique for this study is the Least Squares Regression method. Ordinary Least Squares (OLS) regression were used to estimate the relationships between the dependent variable (labor market outcomes) and independent variables (AI adoption, regulatory measures, and control variables). The OLS method minimizes the sum of the squared differences between observed and predicted values, providing the best linear unbiased estimates (BLUE) of the model coefficients. This approach allows for testing hypotheses about the impact of AI and its regulations on employment and economic indicators

Data Quality Measures

Ensuring data quality is paramount in this study. Several measures were implemented to maintain the integrity and reliability of the data. Data sources were carefully selected based on their credibility and relevance. Cross-validation techniques were employed to verify the consistency of data from multiple sources. Any discrepancies identified during the data collection process were thoroughly investigated and resolved. Additionally, data were cleaned and pre-processed to handle missing values and outliers, ensuring that the analysis is based on accurate and representative datasets (Our World in Data, 2024; BLS, 2024).

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Results

Descriptive Statistics

The descriptive statistics provide an overview of the central tendencies and dispersion of the variables in the dataset, offering insights into the characteristics of AI adoption, economic indicators, and labor market outcomes over the sample period.

The mean value of AI Job Share is approximately 0.92, indicating that on average, about 0.92% of job postings were related to AI. The AI Tech Use has a mean of 21.54%, suggesting a moderate level of AI technology adoption among companies. The unemployment rate's mean is 6.10%, which is relatively high, reflecting the economic fluctuations during the sample period. The Education Level, with a mean of 99.32%, indicates a highly educated workforce, essential for AI-related roles.

Skewness and Kurtosis

Examining the skewness and kurtosis values reveals the distribution shapes of the variables. Most notably, AI Investment exhibits a highly negative skewness (-2.98) and high kurtosis (10.31), indicating a distribution with a long left tail and a peaked shape, respectively. This suggests that while AI investment is generally low, there are a few instances of very high investment.

The Inflation Rate also shows significant positive skewness (1.82) and kurtosis (5.85), suggesting a distribution with a long right tail and a more peaked shape compared to a normal distribution. These skewness and kurtosis values imply that economic variables have experienced extreme values during certain periods, reflecting economic instability or significant policy changes.

Variability and Dispersion

The standard deviation values indicate the variability within the dataset. AI Tech Use and AI Patents by Industry show high standard deviations (25.10 and 68.81, respectively), highlighting considerable variability in AI adoption rates and innovation across different industries. This high variability suggests that while some industries have aggressively adopted AI technologies, others lag significantly.

The standard deviation of the Unemployment Rate (2.09) and Annual GDP Growth (1.70) reflects economic volatility during the study period, encompassing periods of both growth and recession. The Education Level shows minimal variability (standard deviation of 0.36), indicating consistent educational attainment across the observed years, which is crucial for maintaining a skilled labor force capable of adapting to AI advancements.

Table 2. Descriptive Statistics Results.

	AI Job Share	AI Tech Use	Unemployment Rate	Education Level	AI Strategies	New AI PhDs Employers	AI Patents by Industry	Annual GDP Growth	Inflation Rate	AI Investment	Patent Applications
Mean	0.917206	21.53846	6.098615	99.32308	0.307692	109.0000	83.23077	2.259231	2.434818	9.558965	2.480130
Median	0.810827	9.000000	5.350000	99.40000	0.000000	101.0000	58.00000	2.458000	1.812210	10.20776	2.930855
Maximum	2.054984	59.00000	9.608000	99.70000	1.000000	195.0000	211.0000	5.800000	8.002800	11.14779	2.955476
Minimum	0.000000	0.000000	3.633000	98.80000	0.000000	0.000000	0.000000	-2.214000	0.118627	0.000000	0.000000
Std. Dev.	0.771495	25.10516	2.089793	0.358594	0.480384	54.57411	68.80789	1.699600	1.993244	2.925911	1.100924
Skewness	0.026694	0.459556	0.338106	-0.139172	0.833333	-0.143052	0.599342	-0.791094	1.824089	-2.975519	-1.917220
Kurtosis	1.518134	1.384928	1.690493	1.280819	1.694444	2.457562	2.174808	6.041092	5.846816	10.30768	4.678643
Jarque-Bera	1.191004	1.870497	1.176540	1.642907	2.427887	0.203718	1.147134	6.365428	11.59902	48.10920	9.490416
Probability	0.551286	0.392488	0.555287	0.439792	0.297024	0.903157	0.563512	0.041473	0.003029	0.000000	0.008693
Sum	11.92368	280.0000	79.28200	1291.200	4.000000	1417.000	1082.000	29.37000	31.65263	124.2666	32.24170
Sum Sq. Dev.	7.142456	7563.231	52.40684	1.543077	2.769231	35740.00	56814.31	34.66368	47.67625	102.7314	14.54441
Observations	13	13	13	13	13	13	13	13	13	13	13

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Correlation Analysis

Stationary Tests

The stationary tests, including Levin, Lin & Chu t*, Im, Pesaran and Shin W-stat, ADF Fisher Chi-square, and PP Fisher Chi-square, consistently indicate that the series in the dataset (AI Investment, AI Patents by Industry, AI Job Share, AI Strategies, AI Tech Use, Annual GDP Growth, Education Level, Inflation Rate, New AI PhDs Employers, Patent Applications, and Unemployment Rate) are stationary. The tests reject the null hypothesis of a unit root with p-values of 0.0000, confirming that the variables' mean and variance remain constant over time.

The Levin, Lin & Chu t* test, assuming a common unit root process, and the Im, Pesaran and Shin W-stat test, allowing for individual unit root processes, both support stationarity. Similarly, the ADF and PP Fisher Chi-square tests, which account for autocorrelation and heteroskedasticity, corroborate these findings. The consistent stationarity across tests ensures the data's statistical properties are stable, making them suitable for econometric analysis. This stationarity is crucial for reliable regression models and statistical analyses, ensuring valid insights into the relationships between AI adoption, technological advancement, economic growth, and labor market outcomes. Thus, the results affirm the robustness and reliability of subsequent analyses based on these data.

Table 3. Correlation Analysis Results.

	1	2	3	4	5	6	7	8	9	10	11
1. AI Investment	1.000000										
2. AI Patents by Industry	0.432953	1.000000									
3. AI Job Share	-0.280644	0.250271	1.000000								
4. AI Strategies	-0.306038	-0.166199	0.794670	1.000000							
5. AI Tech Use	-0.299420	0.121924	0.939079	0.890304	1.000000						
6. Annual GDP Growth	0.064941	-0.148030	0.032861	-0.106958	-0.027396	1.000000					
7. Education Level	-0.075195	0.397619	0.903667	0.680980	0.850114	0.009630	1.000000				
8. Inflation Rate	-0.802335	-0.429652	0.494836	0.522805	0.575820	0.230967	0.349874	1.000000			
9. New AI PhDs Employers	0.727740	0.499206	0.388282	0.292436	0.401190	0.160702	0.489270	-0.318818	1.000000		
10. Patent Applications	0.605715	0.542505	-0.585809	-0.643709	-0.629061	-0.414103	-0.401587	-0.874328	0.094596	1.000000	
11. Unemployment Rate	0.221392	-0.489986	-0.731329	-0.302524	-0.530129	-0.322714	-0.660260	-0.303819	-0.232385	0.328697	1.000000

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Table 4. Stationary Tests Results.

Group unit root test: Summary				
Series: AI Investment, AI Patents by Industry, AI Job Share, AI Strategies, AI Tech Use, Annual GDP Growth, Education Level, Inflation Rate, New AI PhDs Employers, Patent Applications, Unemployment Rate				
Sample: 2010 2022				
Exogenous variables: Individual effects				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0 to 1				
Newey-West automatic bandwidth selection and Bartlett kernel				
Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-7.43360	0.0000	10	96
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.75940	0.0000	10	96
ADF - Fisher Chi-square	79.2402	0.0000	10	96
PP - Fisher Chi-square	129.624	0.0000	10	100

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Multicollinearity Check

Multicollinearity occurs when independent variables in a regression model are highly correlated, leading to unreliable coefficient estimates and inflated standard errors. To address this issue, Principal Components Analysis (PCA) was utilized to transform the original correlated variables into a set of uncorrelated principal components.

The PCA results show that the first four principal components explain approximately 95.4% of the total variance, with eigenvalues of 5.068817, 3.006559, 1.314526, and 1.103700, respectively. This indicates that a significant amount of information from the original variables is captured by these four components. The remaining components explain minimal variance, suggesting that they contain less useful information and can be disregarded in the analysis.

In addition, the loadings provide insights into how much each original variable contributes to each principal component. For instance, AI Job Share, AI Strategies, and AI Tech Use have high loadings on the first principal component (PC1), reflecting their interconnectedness and joint contribution to the explained variance. Conversely, variables such as Annual GDP Growth and Education Level have higher loadings on subsequent components, indicating their unique contributions. By transforming the original variables into principal components, multicollinearity is effectively mitigated. The principal components are uncorrelated by design, ensuring that the regression model using these components will not suffer from multicollinearity. This transformation allows for more reliable coefficient estimates and better model interpretation.

In summary, using PCA to address multicollinearity reveals that the first four principal components capture most of the variance in the original dataset. The transformation mitigates multicollinearity, allowing for more accurate and robust regression analysis. This approach ensures that the relationships between AI investment, technological adoption, and economic indicators can be reliably examined without the distortions caused by multicollinearity. Thus, PCA proves to be an effective technique for enhancing the validity of econometric models in this context.

Table 5. Multicollinearity Test Results.

Principal Components Analysis

Sample: 2010 2022

Included observations: 13

Computed using: Ordinary correlations

Extracting 11 of 11 possible components

Eigenvalues: (Sum = 11, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	5.068817	2.062258	0.4608	5.068817	0.4608
2	3.006559	1.692033	0.2733	8.075376	0.7341
3	1.314526	0.210826	0.1195	9.389902	0.8536
4	1.103700	0.894318	0.1003	10.49360	0.9540
5	0.209382	0.073141	0.0190	10.70298	0.9730
6	0.136241	0.052782	0.0124	10.83922	0.9854
7	0.083459	0.034916	0.0076	10.92268	0.9930
8	0.048543	0.032894	0.0044	10.97123	0.9974
9	0.015649	0.007580	0.0014	10.98687	0.9988
10	0.008069	0.003012	0.0007	10.99494	0.9995
11	0.005057	---	0.0005	11.00000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8	PC 9	PC 10	PC 11
AI Investment	-0.207189	0.436140	0.176469	0.375158	0.027182	-0.175765	-0.169939	-0.247517	0.441171	-0.102531	0.517735
AI Patents by Industry	0.001541	0.490427	-0.055912	-0.456960	0.339868	0.269348	0.217524	0.102907	0.452142	-0.136116	-0.280384
AI Job Share	0.419190	0.154132	-0.074800	-0.060659	-0.181326	-0.048972	-0.254622	0.442058	0.237440	0.644838	0.153392

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AI Strategies	0.375190	0.003412	-0.242998	0.358961	-0.388175	0.180167	0.536686	-0.334997	0.256321	0.046291	-0.141711
AI Tech Use	0.419049	0.102101	-0.155062	0.132023	0.160904	0.276900	0.100784	0.378986	-0.266875	-0.470358	0.472956
Annual GDP Growth	0.069451	-0.050948	0.848227	0.040917	0.008662	-0.006651	0.461020	0.215457	-0.017253	0.102708	0.038604
Education Level	0.369758	0.254500	-0.077045	-0.049230	0.235638	-0.796260	0.171653	-0.110314	-0.195821	-0.062752	-0.129140
Inflation Rate	0.323953	-0.346353	0.065823	-0.071611	0.614489	0.191832	-0.067058	-0.467847	0.088491	0.270675	0.216248
New AI PhDs Employers	0.101851	0.479156	0.171463	0.415008	0.147367	0.311544	-0.273431	-0.126047	-0.409120	0.165761	-0.392582
Patent Applications	-0.349618	0.288666	-0.227960	-0.189122	0.015106	0.082169	0.432578	-0.117498	-0.407290	0.435951	0.377967
Unemployment Rate	-0.293059	-0.186616	-0.256752	0.532219	0.468144	-0.101694	0.228898	0.411960	0.167023	0.162734	-0.155329

doi:10.20944/preprints202407.0906.v1

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Heteroskedasticity Test

The Breusch-Pagan-Godfrey test results indicate no significant evidence of heteroskedasticity in the regression model. The F-statistic of 1.166380 with a p-value of 0.3937, along with the Obs*R-squared value of 4.788729 and a p-value of 0.3097, suggests that we fail to reject the null hypothesis of homoskedasticity. Additionally, the Scaled Explained Sum of Squares value and its associated p-value of 0.8563 further confirm the absence of heteroskedasticity. Examining the coefficients of the regression model, the constant term is statistically significant (p = 0.0072), indicating a robust intercept. The principal components (PC1 to PC4) reveal mixed results. PC1 is not significant, suggesting its minimal impact on heteroskedasticity. In contrast, PC2 (p = 0.0387), PC3 (p = 0.0062), and PC4 (p = 0.0058) are statistically significant, highlighting their relevance in explaining the variance of the residuals.

The overall model fit, reflected by an R-squared of 0.368364 and an adjusted R-squared of 0.052546, indicates that the model explains a moderate portion of the variability. The Durbin-Watson statistic of 2.502485 suggests no autocorrelation in the residuals, supporting the model's reliability. In essence, the absence of heteroskedasticity, confirmed by multiple test statistics, underscores the robustness of the regression model. The significant principal components indicate that while some factors are crucial in explaining residual variance, the model overall is well-specified and reliable for further analysis.

Table 6. Heteroskedasticity Test Results.

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.166380	Prob. F(4,8)	0.3937
Obs*R-squared	4.788729	Prob. Chi-Square(4)	0.3097
Scaled explained SS	1.329933	Prob. Chi-Square(4)	0.8563

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Sample: 2010 2022
Included observations: 13
HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.244619	0.068265	3.583379	0.0072
PC1	-0.031101	0.022189	-1.401635	0.1986
PC2	0.059704	0.024175	2.469696	0.0387
PC3	0.053398	0.014517	3.678285	0.0062
PC4	-0.108369	0.029045	-3.731027	0.0058

R-squared	0.368364	Mean dependent var	0.244619
Adjusted R-squared	0.052546	S.D. dependent var	0.308350
S.E. of regression	0.300140	Akaike info criterion	0.714587
Sum squared resid	0.720672	Schwarz criterion	0.931875

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Log likelihood	0.355186	Hannan-Quinn criter.	0.669924
F-statistic	1.166380	Durbin-Watson stat	2.502485
Prob(F-statistic)	0.393706		

Regression Analysis

The regression analysis aims to examine the impact of AI regulations and adoption on labor markets and employment. The model uses principal components (PC1 to PC4) derived from AI-related variables to mitigate multicollinearity and provides insights into the significant factors affecting the labor market.

The constant term (C) has a coefficient of 6.098615, highly significant with a p-value of 0.0000, indicating a strong baseline level of labor market and employment metrics. This intercept reflects the inherent conditions of the labor market when all principal components are zero. Principal Component 1 (PC1), representing overall AI adoption and education, has a negative coefficient (-0.588407) and is statistically significant (p = 0.0000). This suggests that higher AI adoption and education levels are associated with a reduction in labor market and employment metrics, possibly due to initial job displacement as the workforce adapts to new technologies.

Principal Component 2 (PC2), indicating AI innovation and academic output, also shows a significant negative impact (-0.374688, p = 0.0016) on labor markets. This highlights that while AI innovation drives technological progress, it may initially disrupt employment, reflecting transitional challenges in integrating new AI advancements. Principal Component 3 (PC3), associated with economic growth, similarly shows a significant negative effect (-0.515510, p = 0.0000) on the labor market. This could imply that economic growth driven by AI does not immediately translate into job creation, likely due to increased productivity and efficiency reducing the need for labor in certain sectors.

Conversely, Principal Component 4 (PC4), representing unemployment and AI strategies, has a positive and significant coefficient (1.068594, p = 0.0001). This indicates that effective AI strategies can mitigate the adverse impacts on employment and help transition the workforce, leading to improved labor market conditions.

Model Fit and Diagnostics

The R-squared value of 0.939320 and adjusted R-squared of 0.908980 indicate that the model explains a substantial proportion of the variance in labor market and employment metrics. The high F-statistic (30.95977) and significant p-value (0.000064) confirm the overall model's robustness. However, the Durbin-Watson statistic (1.475998) suggests potential autocorrelation, warranting further investigation.

In summary, the regression analysis reveals that while AI adoption, innovation, and economic growth initially pose challenges to the labor market, strategic implementation of AI can counteract these effects and enhance employment conditions. These findings underscore the importance of developing comprehensive AI strategies to support workforce transitions and capitalize on the benefits of AI advancements for the labor market. The model's high explanatory power highlights its reliability, but attention to potential autocorrelation is necessary to refine the analysis further.

Table 7. Regression Results.

Dependent Variable: Labour Market & Employment

Method: Least Squares

Sample: 2010 2022

Included observations: 13

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed

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bandwidth = 3.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.098615	0.178220	34.21954	0.0000
PC1	-0.588407	0.064194	-9.166017	0.0000
PC2	-0.374688	0.080256	-4.668680	0.0016
PC3	-0.515510	0.058119	-8.869919	0.0000
PC4	1.068594	0.145068	7.366151	0.0001

R-squared	0.939320	Mean dependent var	6.098615
Adjusted R-squared	0.908980	S.D. dependent var	2.089793
S.E. of regression	0.630481	Akaike info criterion	2.199055
Sum squared resid	3.180049	Schwarz criterion	2.416343
Log likelihood	-9.293857	Hannan-Quinn criter.	2.154392
F-statistic	30.95977	Durbin-Watson stat	1.475998
Prob(F-statistic)	0.000064	Wald F-statistic	518.1025
Prob(Wald F-statistic)	0.000000		

PC1: Represents overall AI adoption and education; PC2: Represents AI innovation and academic output; PC3: Represents economic growth; PC4: Represents unemployment and AI strategies.

Discussions

The regression analysis indicates that AI adoption, innovation, and economic growth initially pose challenges to the labor market. Specifically, higher AI adoption and innovation negatively impact labor markets due to initial job displacement and the transitional period required for the workforce to adapt to new technologies. However, strategic AI implementation, as reflected in PC4, positively impacts employment conditions, suggesting that well-planned AI strategies can mitigate adverse effects and promote labor market stability.

These findings align with those of Webb (2019), who highlighted the disruptive nature of AI on employment, particularly in the short term, as industries transition towards greater automation. Webb's study emphasized the displacement of routine jobs and the need for policies that facilitate worker retraining and skill development to ease the transition (Webb, 2019). This is consistent with our findings, where strategic AI implementation significantly mitigates the negative impacts on employment.

Contrastingly, Joni (2024) found that AI adoption could lead to substantial long-term benefits for the labor market, including the creation of new job categories and increased productivity, which ultimately drive employment growth. This perspective aligns with the positive coefficient of PC4 in our study, suggesting that while initial disruptions are inevitable, the long-term benefits of AI, if strategically managed, can enhance employment conditions (Joni, 2024).

Furthermore, Loong et al. (2021) examined the regulatory landscape and its role in shaping AI's impact on employment. Their study concluded that robust regulatory frameworks are crucial for maximizing AI's positive effects on the labor market. They found that countries with comprehensive AI strategies and regulations experienced smoother transitions and better employment outcomes. This supports our finding that effective AI strategies (PC4) are vital for positive labor market impacts, underscoring the role of regulation in facilitating these transitions (Loong et al., 2021).

In comparison, Zarifhonarvar (2024) focused on the economic implications of AI and highlighted the importance of economic growth driven by AI investments. However, similar to our findings, Zarifhonarvar noted that economic growth does not immediately translate into job creation, as productivity gains often reduce the demand for labor initially. This reflects our results where economic growth (PC3) negatively impacts employment in the short term (Zarifhonarvar, 2024).

In conclusion, the comparative analysis underscores the complex interplay between AI adoption, innovation, economic growth, and labor market outcomes. While initial disruptions are common, strategic AI implementation and robust regulatory frameworks can significantly mitigate these effects and enhance employment conditions. This alignment with existing literature highlights the necessity for comprehensive AI strategies to support workforce transitions and harness AI's long-term benefits for the labor market. The consensus among studies emphasizes the critical role of policy and strategy in navigating the challenges posed by AI advancements, ensuring that their benefits are maximized while minimizing their disruptive impacts.

Conclusions

The primary objective of this study was to investigate the impact of AI regulations and adoption on labor markets and employment in the USA. By analyzing how AI innovation, adoption, and strategic implementation affect employment, this study aimed to provide a comprehensive understanding of the transitional challenges and potential benefits associated with AI advancements.

To achieve this objective, the study employed a robust econometric approach using Principal Components Analysis (PCA) to address multicollinearity issues among the variables. The regression analysis incorporated principal components representing overall AI adoption and education (PC1), AI innovation and academic output (PC2), economic growth (PC3), and unemployment and AI strategies (PC4). The analysis utilized heteroskedasticity-robust standard errors to ensure reliable coefficient estimates and tested for stationarity to confirm the stability of the time series data.

The findings reveal that AI adoption, innovation, and economic growth initially pose challenges to the labor market, leading to job displacement and transitional unemployment. However, strategic AI implementation significantly mitigates these adverse effects, highlighting the importance of well-planned AI strategies in promoting labor market stability and employment growth. The study underscores the necessity for comprehensive AI policies that facilitate workforce transitions and harness the long-term benefits of AI advancements.

The regression results indicate that higher AI adoption and education levels (PC1) are associated with a reduction in labor market and employment metrics due to initial job displacement. Similarly, increased AI innovation and academic output (PC2) negatively impact employment, reflecting the transitional challenges in integrating new AI technologies. Economic growth driven by AI (PC3) does not immediately translate into job creation, suggesting that productivity gains may reduce labor demand in the short term. Conversely, effective AI strategies (PC4) have a positive impact on employment conditions, demonstrating that strategic implementation of AI can support workforce transitions and enhance labor market outcomes.

In conclusion, this study provides valuable insights into the complex dynamics between AI adoption, innovation, economic growth, and labor markets. The critical role of strategic AI implementation and robust regulatory frameworks in facilitating smooth workforce transitions and enhancing employment conditions cannot be overstated. Policymakers and stakeholders must prioritize the development of comprehensive AI strategies to navigate the challenges and capitalize on the benefits of AI advancements for sustainable economic and employment growth.

Practical Implications

The findings of this study offer several practical implications for policymakers, businesses, and educators aiming to navigate the complex landscape of AI adoption and its impact on labor markets and employment. The critical insights derived from the regression analysis underscore the necessity of strategic interventions to mitigate the initial disruptions caused by AI technologies.

Firstly, policymakers must recognize the importance of developing comprehensive AI strategies that include robust regulatory frameworks. The positive impact of strategic AI implementation on employment highlights the need for policies that support workforce retraining and upskilling. By

 doi:10.20944/preprints202407.0906.v1

facilitating smooth transitions, these policies can help displaced workers adapt to new roles created by AI advancements. This aligns with the findings of Loong et al. (2021), who emphasized the role of regulatory frameworks in enhancing employment outcomes during technological transitions.

Furthermore, businesses must invest in AI not only for innovation but also for developing human capital. The negative impacts of AI adoption and innovation on employment, as shown by PC1 and PC2, indicate that businesses should prioritize employee training programs. This investment can help employees acquire new skills that are relevant in an AI-driven economy. The alignment with Joni's (2024) findings suggests that businesses that integrate AI while supporting their workforce can achieve sustainable growth and improved labor market outcomes.

Additionally, educational institutions play a crucial role in preparing the future workforce for an AI-dominated job market. The high correlation between education levels and positive labor market outcomes underscores the importance of enhancing educational curricula to include AI and related technologies. Educators should focus on equipping students with the skills needed to thrive in AI-enhanced industries. This approach resonates with Webb's (2019) emphasis on education and skill development as critical components of successful AI integration.

Moreover, the study's insights on economic growth driven by AI, which does not immediately translate into job creation, suggest that economic policies should balance AI investment with initiatives that promote job creation. Policymakers should encourage industries to adopt AI in a manner that complements human labor rather than replaces it entirely. This can be achieved through incentives for businesses that demonstrate a commitment to augmenting their workforce with AI technologies, rather than merely automating jobs.

In conclusion, the practical implications of this study highlight the need for a multi-faceted approach to managing AI adoption. Policymakers, businesses, and educators must collaborate to develop strategies that mitigate the short-term disruptions of AI while maximizing its long-term benefits. By fostering a supportive environment for workforce transition and skill development, stakeholders can ensure that AI advancements lead to sustainable economic growth and improved employment conditions. This comprehensive approach is essential for navigating the complexities of AI's impact on the labor market and capitalizing on its potential to drive future prosperity.

Implications for Artificial Research

The findings of this study provide significant implications for future artificial intelligence (AI) research, emphasizing the need to address both the technological advancements and their socio-economic impacts. These implications suggest new directions for researchers aiming to understand and enhance the integration of AI into various sectors while mitigating its adverse effects on labor markets.

Firstly, the study highlights the importance of examining the transitional impacts of AI adoption on employment. The negative effects of AI adoption and innovation on labor market metrics indicate that future research should focus on identifying strategies to minimize job displacement during the initial phases of AI implementation. This includes studying the effectiveness of different retraining and upskilling programs, as well as exploring policies that support workers through these transitions. Researchers like Webb (2019) have already begun to address these areas, but there is a need for more detailed longitudinal studies that track the long-term impacts of such interventions.

Moreover, the positive impact of strategic AI implementation on employment conditions, as revealed by the regression analysis, underscores the necessity for research into best practices for AI strategy development. Scholars should investigate how different industries can formulate and execute AI strategies that not only drive technological innovation but also promote inclusive growth. Comparative studies across industries and regions could provide valuable insights into how context-specific factors influence the success of AI strategies, aligning with findings from Joni (2024) and Loong et al. (2021).

Additionally, the study's findings suggest that the relationship between AI-driven economic growth and employment requires further exploration. The observation that economic growth does not immediately translate into job creation indicates that AI research should delve deeper into the

 doi:10.20944/preprints202407.0906.v1

dynamics between productivity gains and labor demand. Researchers should aim to uncover the conditions under which AI-driven growth can lead to job creation, identifying factors that can help balance productivity improvements with employment opportunities. This aligns with Zarifhonarvar's (2024) emphasis on understanding the nuanced economic impacts of AI.

Furthermore, the role of education in supporting AI-related employment emerges as a critical area for future research. The strong correlation between education levels and positive labor market outcomes suggests that AI research should include a focus on educational policies and curricula. Studies should evaluate the effectiveness of current educational programs in preparing students for AI-enhanced job markets and propose innovations to enhance these programs. This direction supports Webb's (2019) call for integrating AI and technological skills into educational systems.

Lastly, there is a need for interdisciplinary research that bridges AI technology and social sciences. The complex interplay between AI adoption, regulatory frameworks, and labor market outcomes requires a holistic approach that incorporates insights from economics, sociology, and public policy. By fostering collaboration across disciplines, researchers can develop comprehensive models that better predict and manage the socio-economic impacts of AI.

In summary, the implications for AI research derived from this study emphasize the need for a multifaceted approach that addresses both technological and socio-economic dimensions. Future research should focus on strategies to mitigate job displacement, best practices for AI strategy development, the relationship between economic growth and employment, the role of education, and interdisciplinary collaboration. These directions will help ensure that AI advancements contribute positively to labor markets and broader societal well-being.

Limitations and Future Work

Limitations

Despite the comprehensive analysis, this study has several limitations that should be acknowledged. Firstly, the sample size of 13 years, while providing a decade-long perspective, may not capture long-term trends and cyclical variations in AI adoption and labor market dynamics. A longer time series could offer more robust insights into the impacts of AI over different economic cycles.

Secondly, the study relies on principal components derived from a set of AI-related and economic variables. While PCA effectively addresses multicollinearity, it may also obscure the nuanced effects of individual variables. The aggregation of variables into principal components can sometimes mask specific relationships that might be crucial for a more detailed understanding of AI's impact on labor markets.

Thirdly, the study's scope is limited to the USA, which may not fully represent global trends in AI adoption and its labor market impacts. Different countries have varying levels of AI maturity, regulatory frameworks, and labor market structures, which can lead to different outcomes. Thus, the findings may not be generalizable to other contexts without further comparative research.

Lastly, the study primarily focuses on quantitative data, which, while useful for identifying trends and correlations, does not capture the qualitative aspects of AI adoption. Factors such as organizational culture, employee perceptions, and the social implications of AI are equally important and require a qualitative approach to understand fully.

Future Work

Building on the limitations identified, future research should consider expanding the dataset to include a longer time series. This would help in capturing more comprehensive trends and assessing the long-term impacts of AI on labor markets. Additionally, incorporating a broader range of countries in the analysis would provide a more global perspective and allow for comparative studies to understand how different regulatory and economic contexts influence AI's impact on employment.

Future work should also explore the individual effects of specific AI-related variables that were aggregated in this study. By examining variables such as AI job share, AI strategies, and AI tech use

 doi:10.20944/preprints202407.0906.v1

in more detail, researchers can uncover more precise relationships and provide targeted recommendations for policy and strategy.

Moreover, integrating qualitative research methods would enrich the understanding of AI's impact on labor markets. Case studies, interviews, and surveys can provide deeper insights into how AI adoption affects employees, organizational practices, and societal outcomes. This qualitative data can complement the quantitative findings and offer a more holistic view of the implications of AI.

Finally, interdisciplinary research involving economists, sociologists, and technologists is crucial for addressing the multifaceted nature of AI's impact. Collaborative efforts can lead to the development of comprehensive models and frameworks that better capture the complex interactions between AI adoption, economic growth, and labor market dynamics.

In conclusion, while this study provides valuable insights into the impact of AI on labor markets and employment, addressing its limitations and pursuing the proposed future research directions will enhance the understanding and management of AI's socio-economic implications. This comprehensive approach will help policymakers, businesses, and educators develop strategies that maximize the benefits of AI while mitigating its challenges.

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