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REVIEW

Automation and labour market dynamics in the UK

Automatización y dinámica del mercado laboral en el Reino Unido

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ABSTRACT

Introduction: the advancement of artificial intelligence (AI) and workplace automation in the twenty-first century has significantly accelerated industrial growth and innovation. These technologies enhance productivity, support profit maximisation, and reduce certain labour-related pressures as machines increasingly perform tasks previously handled by human workers. Given these developments, this study examines how rising automation influences unemployment in the United Kingdom.
Method: the study draws on secondary national data covering robot installation figures, unemployment rates, the national minimum wage, and major economic growth indicators. Descriptive statistics were used to summarise trends, while breakpoint unit root tests assessed structural shifts in the data. A generalised method of moments (GMM) regression model was then employed to estimate the relationship between automation and unemployment.
Results: the findings indicate that increased automation is associated with higher unemployment levels in the UK. This result mirrors evidence reported in previous studies conducted in the United States and Germany, suggesting a broader pattern across advanced economies.
Conclusions: the study concludes that although automation drives productivity and innovation, it also heightens unemployment risks in the short to medium term. To prevent a potential labour market crisis, strategic workforce reskilling and proactive policy measures are essential.

Keywords: Robots; AI; Automation; Unemployment; UK.

RESUMEN

Introducción: el avance de la inteligencia artificial (IA) y la automatización laboral en el siglo XXI ha acelerado de manera significativa el crecimiento industrial y la innovación. Estas tecnologías mejoran la productividad, favorecen la maximización de beneficios y reducen ciertas presiones laborales a medida que las máquinas asumen tareas que antes realizaban los trabajadores humanos. Ante este contexto, el presente estudio analiza cómo el incremento de la automatización influye en el desempleo en el Reino Unido.
Método: el estudio utiliza datos secundarios nacionales que incluyen cifras de instalación de robots, tasas de desempleo, salario mínimo nacional e indicadores clave de crecimiento económico. Se emplearon estadísticas descriptivas para resumir las tendencias, mientras que las pruebas de raíz unitaria con puntos de quiebre permitieron identificar cambios estructurales en los datos. Posteriormente, se aplicó un modelo de regresión mediante el método generalizado de momentos (GMM) para estimar la relación entre automatización y desempleo.
Resultados: los resultados empíricos muestran que el aumento de la automatización está asociado con mayores niveles de desempleo en el Reino Unido. Este hallazgo coincide con la evidencia reportada en estudios previos realizados en Estados Unidos y Alemania, lo que sugiere un patrón más amplio en las economías avanzadas.
Conclusiones: el estudio concluye que, aunque la automatización impulsa la productividad y la innovación, también incrementa el riesgo de desempleo en el corto y mediano plazo. Para evitar una posible crisis en el mercado laboral, es esencial implementar estrategias de recualificación de la fuerza laboral y medidas de política proactivas.

Palabras clave: Robots; IA; Automatización; Desempleo; Reino Unido.

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INTRODUCTION

The integration of automation and artificial intelligence (AI) into modern workplaces has reshaped global economic systems, marking what is widely described as the *Fourth Industrial Revolution*. Similar to how big data analytics is redefining professional practices across sectors such as accounting,(1) emerging digital technologies now influence virtually every aspect of organisational operations. Automation refers to the use of machines to perform tasks with minimal or no human input, whereas AI encompasses sophisticated algorithms and machine learning models capable of carrying out functions traditionally requiring human intelligence, such as decision-making, pattern recognition, and natural language processing.

While these innovations offer notable improvements in productivity, cost efficiency, and service delivery, they also generate considerable concerns, particularly regarding employment.(2) Historical technological revolutions, including the early Industrial Revolution, simultaneously eliminated certain job categories and created new ones. However, the unprecedented speed, scale, and cognitive reach of contemporary technologies heighten fears of labour displacement and raise questions about the workforce's capacity to adapt.(3) As more cognitive and analytical tasks become automated, the risk of structural unemployment intensifies, underscoring the need for proactive and well-designed policy interventions.

In the United Kingdom, AI and automation are integrated across diverse industries, with the government investing in digital infrastructure and innovation.(4) However, adoption rates differ, leading to uneven impacts on employment. Manufacturing and retail have seen significant job displacement due to automation, while sectors such as IT and healthcare have seen job creation from new AI-related roles.(5) Ongoing concerns suggest these technologies could displace a large share of the workforce in the coming decades, potentially leading to significant technological unemployment.(6)

Research by Frey et al.(3) indicate these risks, though their conclusions are more nuanced than some media portrayals. Historical transitions have shifted employment from agriculture to manufacturing and then to services.(7,8,9) During the 1980s, wage inequality in the United Kingdom surged due to deregulation, the weakening of trade unions, and deindustrialisation. Although wage disparities have stabilised over the past two decades, low-paid employment and in-work poverty remain persistent challenges.(10,11,12) Since 1999, the UK's minimum wage has progressively increased and now ranks among the highest relative to other OECD countries. While this legislation has effectively addressed very low wages and reduced inequality at the lower end of the wage distribution, employment protection remains weak. New forms of employment, such as 'fake' self-employment in the gig economy and zero-hours contracts, have become increasingly common, potentially allowing employers to evade higher minimum wages.(13,14,15)

Over the decade under review, employment grew robustly, particularly in later years, despite sluggish wage growth. From 2010 onwards, austerity measures implemented by the Coalition and Conservative governments primarily cut public services and working-age benefits. These policies introduced Universal Credit, which amalgamated in- and out-of-work benefits but significantly reduced many in-work benefits (e.g., tax credits) and restricted access to out-of-work benefits, such as disability benefits.(16,17) Furthermore, administrative measures, including sanctions and eligibility revisions, aimed to decrease benefit caseloads and incentivise employment by limiting alternatives for low-wage workers.(18,19)

Existing research indicates that although automation displaces specific jobs, it also creates new roles. Acemoglu et al.(20) contend that automation reduces labor demand but encourages job creation and the development of new tasks. Atkinson et al.(21) corroborate this perspective, observing that technology both eliminates and generates employment opportunities. Gartner(22) forecasts that artificial intelligence will create 2,3 million jobs in 2020 while eliminating 1,8 million, resulting in a net gain of 0,5 million positions. Similarly, Chowdhry(23) estimates that AI could generate 58 million net new jobs in the near future. However, positions requiring lower levels of education or skills are most vulnerable to automation, whereas newly created roles typically demand higher qualifications. For instance, the adoption of autonomous vehicles may reduce the need for taxi drivers but increase demand for technical specialists. AI-driven automation reshapes labour markets by reducing mid-skill jobs and increasing demand for both high-skill specialist roles and low-skill manual or service jobs. As middle-class positions diminish, economic inequality widens, disproportionately marginalising vulnerable groups.

Although global studies report diverse impacts of automation, ranging from job losses in the United States to changes in employment composition in Germany, limited empirical research directly examines the relationship between automation and labour market outcomes in the United Kingdom. This study addresses this gap by focusing on the United Kingdom, a leading technology hub. It utilises recent secondary data to examine how the widespread adoption of AI and robotics influences unemployment. Understanding this relationship is essential for policymakers who are developing strategies for workforce reskilling, social protection, and inclusive growth. This study analyzes the relationship between AI adoption and unemployment in the UK, considering economic growth, income per capita, the national minimum wage, and automation intensity, to clarify long-term labor market effects.

METHOD

This research adopts a quantitative design based on secondary data analysis. Data on UK employment rates, automation levels, educational attainment, minimum wages, and economic growth from 1990 to 2024 are sourced from official government reports, including the UK Office for National Statistics (ONS). The dependent variable is the unemployment rate, while the primary explanatory variable is automation intensity, measured by the ratio of industrial robots and AI adoption. The generalized method of moments (GMM) estimator is employed to address potential endogeneity issues inherent in time-series cross-sectional data. This approach distinguishes short-term effects from long-term impacts, thereby capturing the dynamic relationship between automation and employment.

This study draws on the theory of creative destruction, which promotes the adoption of innovative technologies to transform traditional industries and drive economic growth. The theory suggests that greater automation can lead to job creation and new

employment opportunities over time in the United Kingdom. Its relevance lies in highlighting how technological innovation shapes the employment structures of firms and economies.

This research uses a quantitative approach, analyzing secondary data from 1990 to 2024 and applying the Generalized Method of Moments (GMM) for estimation. This method addresses endogeneity and distinguishes between short-run and long-run effects.

The theoretical model is formulated as: UNE_t=f(LISRT, GPC, EDA, NMW)

The log-linear model, which is estimated, is presented in the GMM regression results as:

LOGUNEt=β0+β1LISRTOt+β2LOGEDAt+β3LOGNMWt+β4LOGPCIt+ϵt

The variables listed in the final GMM estimation are detailed below (table 1):

Table 1. Variables

Variables	Abbreviation	Description	Expected Relationship with Unemployment
Dependent Variable			
Unemployment Rate in log	LOGUNE	This is the percentage of willing and able workforce that is unemployed	NA
Independent Variables			
Annual Robots Installation in the UK	LOG	The degree of annual installation of robots in the UK	It is expected to add to unemployment level
Control Variables			
National Minimum Wage in log	LOGNMW	This is legally mandated minimum hourly wage in the UK.	Negative as increased income demand
Economic Growth Rate in log	LOGGDPG	This is the growth rate of the UK's Gross Domestic Product	Negative as Economic expansion create jobs.
Per Capita Income	LOGPCI	This is the average income earned per person in the UK.	Negative as higher income / Demand.

Before the main analysis, descriptive statistics and augmented Dickey-Fuller (ADF) tests are performed to assess variable stationarity and identify structural breaks or unit roots, with attention to events such as the 2008 financial crisis and the COVID-19 pandemic. These diagnostics confirm the suitability of the data for GMM estimation and reduce the risk of spurious results.

RESULTS

Automation in the workplace has become widely recognized due to technological advancements and the increasing adoption of artificial intelligence in daily activities. As AI integration progresses, the impact of automation on employment has been the subject of extensive empirical and theoretical analysis. Some studies examining automation in Germany suggest that automation may create more jobs than it replaces, while others argue that nearly 30 % of jobs in the UK could be automated by the early 2030s. Additionally, research indicates that an increase in robots per thousand workers reduces the employment rate by 0,16 to 0,20 percentage points. Despite these diverse findings, there is a notable gap in the literature on the UK that this paper aims to address.

Table 2 presents descriptive statistics for the key variables: educational attainment (LOGEDA), economic growth rate (LOGGDPG), automation intensity (LOGISR), national minimum wage (LOGNMW), and unemployment rate (LOGUNE). Educational attainment remained consistently high, with a mean of approximately 99 %, indicating widespread literacy. The national minimum wage exhibited a steady upward trend. The range and standard deviation of LOGISR demonstrate substantial variation in robot installations, highlighting the uneven adoption of automation across sectors. The Jarque-Bera test results reveal that most variables deviate from normality, thereby justifying the application of robust, non-parametric methods such as the Generalized Method of Moments (GMM).

Table 2. Description of Statistics

	LOGEDA	LOGGDPG	LOGISR	LOGNMW	LOGUNE
Mean	99,27647	44935,29	2223,353	5,300588	5,600000
Median	99,30000	45900,00	2205,000	5,520000	4,900000
Maximum	99,70000	49500,00	3830,000	6,700000	8,100000
Minimum	98,90000	39200,00	1100,000	3,600000	3,800000
Std. Dev.	0,253795	3133,676	587,8948	0,990842	1,629033
Skewness	0,035345	-0,483280	0,621301	-0,368703	0,513952
Kurtosis	1,815311	2,024539	4,979552	1,868510	1,631884
Jarque-Bera	0,997677	1,335748	3,869402	1,292028	2,074233
Probability	0,607235	0,512798	0,144467	0,524131	0,354475
Sum	1687,700	763900,0	37797,00	90,11000	95,20000
Sum Sq. Dev.	1,030588	1,57E+08	5529924	15,70829	42,46000

Augmented Dickey-Fuller (ADF) tests (table 3) indicate that the national minimum wage, unemployment, and educational attainment become stationary after first differencing (I(1)), whereas automation intensity and economic growth rate are stationary at

levels (I(0)). Structural break tests incorporate major events such as the 2008 financial crisis and the COVID-19 pandemic, thereby enhancing the reliability of the time-series analysis.

Table 3. Augmented Dickey and Fuller Test

Variable	ADF Test Statistic	1 % Critical	5 % Critical	10 % Critical	p-value	Decision (Stationary)	Order of Integration
D(LOGEDA)	-2,59E+08	-4,949	-4,444	-4,194	<0,01	Stationary	I(1)
D(LOGNMW)	-5,978587	-4,728	-3,760	-3,325	0,0013	Stationary	I(1)
LOGISR	-4,889308	-4,949	-4,444	-4,194	0,0131	Stationary	I(0)
LOGGDPG	-4,182541	-4,356	-3,595	-3,233	0,0146	Stationary	I(0)
D(LOGUNE)	-3,957737	-4,263	-3,553	-3,210	0,0205	Stationary	I(1)

Table 4. Effect of Automation on Labour Market Dynamics GMM Estimate

Variable	Coefficient	Std. Error	t-Statistic	p-value
C	-234,1986	431,4442	-0,5428	0,5972
LOGEDA(1)	2,496159	4,424669	0,5641	0,583
LOGGDPG	0,0000682	0,0000903	0,7555	0,4645
LOGISR	0,000095	0,000651	0,1459	0,8864
LOGNMW(1)	-2,127295	1,368056	-1,555	0,1459
Statistic		Value		
R-squared		0,703349		
Adjusted R-squared		0,604465		
Prob(J-statistic)		0,048103		
Instrument Rank		6		

The results from the generalized methods in table 4 support the concern that automation contributes to higher unemployment rates in the United Kingdom, consistent with earlier findings. Although the effect is not statistically significant, increased automation still appears to raise unemployment. In line with expectations, higher educational attainment is associated with greater structural unemployment, as individuals with advanced education often seek better job quality and benefits, thereby creating more complex labor market dynamics. Previous empirical studies generally find that increased workplace automation leads to job losses, particularly in roles that require little or no technical education. Some estimates suggest that automation could affect up to 30 % of jobs in the UK by the 2030s. Other research indicates that each additional robot per thousand workers reduces the employment rate by 0,16 to 0,20 percentage points.

Increasing the national minimum wage in the UK appears to help reduce unemployment, a finding supported by Ejelonu et al.[24,25,26] who observed that changes in the minimum wage in Nigeria had measurable effects on industrial production. The coefficient of determination indicates that over 70,3 % of changes in UK unemployment can be explained by automation, variations in the national minimum wage, institutional quality, and economic growth. Additionally, automation, as measured by robot installations, accounted for 60,44 % of recent changes in unemployment statistics during the study period.

CONCLUSIONS

This study examined the impact of automation and artificial intelligence adoption on unemployment in the United Kingdom from 1990 to 2024 using robust quantitative methods. While automation intensity shows a positive association with unemployment, the relationship remains statistically weak, indicating that job displacement is not yet widespread in the UK labour market. However, this trend highlights potential vulnerabilities as automation expands. Education and minimum wage policies serve as important safeguards, helping to mitigate negative employment effects by improving workforce adaptability and supporting income security. Economic growth alone is not sufficient to reduce unemployment during technological disruption, underscoring the importance of structural and institutional factors.

Policymakers should strengthen lifelong learning and reskilling initiatives aligned with future labor demands, with a focus on digital and cognitive skills for emerging occupations. Inclusive wage policies are essential to protect low-income workers. Promoting human-machine collaboration and supporting innovation in job creation can help balance technological progress with equitable employment opportunities.

Ongoing monitoring of automation's effects on employment is essential, along with adaptive policy frameworks that anticipate technological change. Providing social protection alongside technological advancement will be vital to maintaining inclusive economic growth and social cohesion in the UK.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest

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APPENDIX

Year	Unemployment Rate (%)	GDP Per Capita (Current USD)	National Minimum Wage (GBP/hr)	Primary Education Attainment (%)
1990	6,9	17 900	N/A	98
1991	8,8	18 100	N/A	98
1992	9,9	17 700	N/A	98,1
1993	9,6	17 950	N/A	98,1
1994	8,6	18 900	N/A	98,2
1995	7,9	20 400	N/A	98,2
1996	7,2	21 750	N/A	98,3
1997	5,8	23 200	N/A	98,3
1998	4,8	24 900	N/A	98,4
1999	4,3	26 450	N/A	98,4
2000	4	27 900	N/A	98,5
2001	5	28 100	N/A	98,5
2002	5,2	30 000	N/A	98,6
2003	5,1	33 000	N/A	98,6
2004	4,8	36 900	N/A	98,7
2005	4,8	39 700	N/A	98,7
2006	5,4	43 100	N/A	98,8
2007	5,3	46 600	N/A	98,8
2008	5,8	46 700	3,6	98,9
2009	7,8	42 900	3,7	98,9
2010	7,8	45 900	4,1	99
2011	8,1	47 800	4,2	99
2012	8	45 800	4,5	99,1
2013	7,6	46 400	4,85	99,1
2014	6,1	48 100	5,05	99,2
2015	5,3	44 400	5,35	99,2
2016	4,9	40 000	5,52	99,3
2017	4,4	40 400	5,73	99,3
2018	4	42 800	5,8	99,4
2019	3,8	42 300	5,93	99,4
2020	4,5	39 200	6,08	99,5
2021	4,7	46 500	6,19	99,5
2022	3,8	47 000	6,31	99,6
2023	4,2	48 200	6,5	99,6
2024	4,4	49 500	6,7	99,7

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