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DOES AI VIBRANCY RESHAPE EMPLOYMENT STRUCTURES AND UNEMPLOYMENT? SHORT-RUN EVIDENCE FROM GLOBAL PANEL DATA

Aleksandra Kuzior
Silesian University of Technology
Poland
ORCID 0000-0001-9764-5320

Agnieszka Lopatka
University of Szczecin
Poland
ORCID 0000-0001-9775-640X

Yong Zhou
Sumy State University
Ukraine
ORCID 0009-0007-4479-979X

Judit Oláh
University of Debrecen, Hungary;
WSB University, Poland;
University of Johannesburg, South Africa
ORCID 0000-0003-2247-1711

Abstract: *This study examines whether national AI vibrancy affects employment structures and unemployment, utilising panel data for 36 countries (2017–2023) from the Stanford AI Vibrancy Index and World Bank indicators. Fixed- and random-effects models, along with Hausman tests and clustered standard errors, were applied. Results reveal no significant short-term effect of AI vibrancy on industrial or service employment, nor on unemployment. GDP per capita showed a modest positive effect on industry ($\beta = 0.046$, $p < 0.10$) and, in some models, on services ($\beta = 0.045$, $p \approx 0.06$). Labour force participation correlated positively with service employment ($\beta = 0.322$, $p < 0.10$) and negatively with unemployment ($\beta = -0.006$, $p < 0.01$). Strong time effects reflect pandemic-related labour shifts: industrial jobs declined, service employment grew, and unemployment spiked temporarily. Overall, labour dynamics appear driven more by global shocks and demographics than by AI vibrancy.*

Keywords: *artificial intelligence, AI vibrancy, employment structures, unemployment, labour force participation, panel data analysis.*

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INTRODUCTION

Whether AI vibrancy is reshaping employment structures and unemployment is a highly topical issue, as international organisations warn of profound shifts underway in the global workforce. The International Monetary Fund estimates that AI could affect roughly 40 per cent of jobs worldwide, with around half of those roles benefiting from increased productivity. At the same time, the remainder might face reduced labour demand or job displacement, particularly in advanced economies (Cazzaniga et al., 2024). This underscores the dual nature of AI: a force for both augmentation and disruption.

Evidence from the International Labour Organisation adds nuance to this picture. While occupational exposure to generative AI is widespread, covering an estimated 24 per cent of global employment, jobs are more likely to be transformed than eliminated. Only a small minority, around 3.3 per cent, falls into the highest-risk category where AI could fully replace human tasks (Harrington, 2025). Still, the shift toward task transformation presents challenges, especially in administrative and clerical roles, where generative AI is acquiring capabilities once performed by human workers, a trend with potential gender implications. ILO reports highlight that women's jobs are disproportionately exposed to such transformation (Le Poidevin, 2025).

The World Bank notes that the impact of AI will vary across different development contexts. Low-income countries appear less exposed overall, owing to limited digital infrastructure and labour markets dominated by manual or interpersonal work, which are less amenable to AI automation. However, these economies also risk falling behind, as they may lack the capacity and policy frameworks to harness AI's potential (Demombynes et al., 2025).

These institutional findings underscore that AI's influence on employment is neither uniform nor immediate. Instead, it manifests unevenly across countries, sectors, and worker groups, with transformation often occurring within tasks rather than at the level of entire occupations. For a study examining AI vibrancy and aggregate labour outcomes from 2017 to 2023, such context highlights why large-scale employment shifts may not yet be observable, and why empirical analysis must account for complex institutional and structural mediators.

The relationship between AI, labour markets, and employment structures has attracted growing attention as digitalisation accelerates. Early contributions stressed the transformative capacity of AI and automation, with expectations that industrial employment would decline, services would expand, and unemployment might rise if labour could not adjust swiftly (Acemoglu & Restrepo, 2018; Autor & Salomons, 2018; Brynjolfsson & McAfee, 2014; Frey & Osborne, 2017; Sarker, 2022). Empirical findings reveal a more nuanced picture, with technological progress exerting complex and heterogeneous impacts across sectors, skill groups, and regions (Bessen, 2019; Fan, 2025).

A growing body of studies analyses how AI adoption interacts with human capital, competencies, and labour productivity. Research on emerging economies reveals that the macroeconomic effects of AI on labour markets may differ significantly from developed countries, with Bangladesh showing limited realization of AI's expected economic benefits due to insufficient AI robot integration across manufacturing and service sectors (Sarker, 2022). Research shows that the integration of AI reshapes tasks more than entire occupations, requiring employees to adapt by developing new skills while organisations adjust to maintain productivity (Bîrcă, 2025; Cramarenco et al., 2023; Istudor et al., 2024; Głód et al., 2025; Cham et al., 2022). This task-level transformation is evident in sector-specific applications, where AI technologies such as machine learning, robotics, and IoT significantly improve operational performance in warehouses and logistics (Angammana & Jayawardena, 2022), while real-time monitoring technologies enhance efficiency in industrial operations by reducing non-productive time (Aneke & Oboho, 2024). Evidence confirms that AI increasingly complements knowledge-intensive jobs while challenging low- and medium-skilled roles, a shift which requires active reskilling strategies (Abid et al., 2024; Androniceanu, 2025; Bian & Wang, 2024; Pisică & Zaharia, 2025). At the same time, global labour markets reveal significant skill mismatches, where digital transformation outpaces the preparedness of education systems and training institutions (Butum & Nicolescu, 2024; Jarząbek & Stolarska-Szeląg, 2024; Jarzębowski et al., 2024; Roshchyk et al., 2024; Vorontsova et al., 2021).

Broader structural and demographic factors further influence the dynamics of employment. Studies confirm that productivity growth, output fluctuations, and employment exhibit complex bi-directional linkages, often amplifying labour market adjustment pressures (Butkus et al., 2024; Yurchyk et al., 2024). Other work highlights the differentiated exposure of groups such as youth, women, and persons with disabilities, whose participation in labour markets is mediated by urbanisation, inclusiveness, and targeted support policies (Bal-Domańska et al., 2025; Jarząbek & Stolarska-Szeląg, 2024; Moutik, 2025). Migration and remittance flows further shape labour supply and employment trajectories, particularly in transition economies (Denissova, 2025; Oliinyk et al., 2024; Peković, 2025; Privara, 2025).

The effects of digitalisation extend beyond employment levels to employee well-being, organisational performance, and governance structures. Studies indicate that digital transformation reshapes job satisfaction, stress levels, and work–life balance, while also introducing ethical challenges in law enforcement, traffic enforcement, and public sector decision-making (Haley, 2025; Haley & Burrell, 2025; Hernik et al., 2025; Mujtaba et al., 2025; Trembeczki et al., 2025; Welch, 2025). Similar challenges emerge in sectors such as agriculture and health, where digital competitiveness, governance, and AI-enabled systems drive both opportunities and vulnerabilities (Ernawati et al., 2025; Kuzior et al., 2024; Dobrovolska & Kolomiiets, 2024; Maró et al., 2024). The literature also shows that leadership, organisational politics, and employee engagement play a crucial role in mediating the adoption of AI and sustaining firm performance (Hussein et al., 2024; Kuzior et al., 2022; Liu et al., 2024; Mihajlovic et al., 2025; Urbański et al., 2024; Vuong, 2025).

Parallel streams of research highlight the impact of digitalisation on finance and economic sectors, where AI and fintech applications reshape employment opportunities and organisational strategies (DingYi et al., 2024; Hossain, 2025; Kozhushko, 2023; Lipták et al., 2023; Parajuli et al., 2024; Zada et al., 2024; Chandran & Ittimani Tholath, 2025). Similar dynamics emerge in influencer marketing and public services, where AI-enabled platforms transform competencies, infrastructure, and employment prospects (Pilelienė & Bogoyavlenska, 2025; Szedmák et al., 2025; Virlanuta et al., 2024; Wang et al., 2025). The broader socio-economic implications of AI adoption for equity, inclusiveness, and empowerment have also been addressed, with findings pointing to both opportunities for gender empowerment and risks of new forms of exclusion (Moutik, 2025; Yarovenko et al., 2024; Skrynnyk et al., 2022).

The COVID-19 pandemic created further complexity by accelerating digital transformation while triggering sharp disruptions in employment and unemployment. Real-time survey evidence confirms that the shock had unequal effects across groups and occupations (Adams-Prassl et al., 2020). The pandemic exacerbated uncertainty in worker behaviour, migration patterns, and public health determinants, making labour market dynamics more volatile (Denissova, 2025; Dobrovolska & Kolomiiets, 2024; Trembeczki et al., 2025; Yekimov et al., 2022). Studies highlight that resilience to such shocks depends on both digital readiness and labour market institutions, which can buffer or amplify the employment impact of crises (Jarzębowski et al., 2024; Ualtayev et al., 2024).

The literature reveals a multifaceted landscape in which AI influences employment not through simple substitution, but via gradual task transformation, productivity linkages, and broader socio-economic and institutional contexts. While expectations of large-scale displacement remain prevalent, empirical evidence highlights the importance of complementary skills, labour market rigidities, and global shocks in mediating outcomes. These insights provide a foundation for testing whether AI vibrancy at the national level has exerted measurable effects on employment structures and unemployment in recent years.

This study aims to examine whether national-level AI vibrancy influences labour market structures and outcomes, specifically employment in industry, employment in services, and unemployment. By applying panel data methods to 36 countries from 2017 to 2023, the research aims to determine whether AI vibrancy has measurable short-run effects on sectoral employment shares and unemployment, after controlling for economic development, labour force participation, and time-specific shocks.

Based on theoretical expectations of technological change and labour reallocation:

- H1: Higher AI vibrancy is associated with a reduction in the share of employment in industry.
- H2: Higher AI vibrancy is associated with an increase in the share of employment in services.
- H3: Higher AI vibrancy is associated with higher unemployment rates, reflecting short-term displacement effects.

METHODS

The study employs annual panel data for 36 countries from 2017 to 2023. Dependent variables include employment in industry (as a percentage of total employment), employment in services (as a percentage of total employment), and unemployment (as a percentage of the total labour force), all drawn from the World Bank's World Development Indicators (World Bank, n.d.). The key explanatory variable is the AI Vibrancy Score, sourced from Stanford University's Global AI Vibrancy Tool (Stanford University, n.d.), which measures national-level AI activity and ecosystem strength. GDP per capita (in constant 2015 US dollars) and labour force participation rate (as a percentage of the population aged 15–64) are included as control variables, also sourced from the World Bank database.

Variable transformations were applied based on Box–Cox tests to address differences in scale and non-normal distributions. The AI Vibrancy Score was transformed using a logarithmic specification, GDP per capita by square-root transformation, and unemployment through an inverse-root transformation. Employment shares and labour force participation were maintained at their current levels. These transformations ensured more stable variance and reduced skewness in the data.

The empirical analysis proceeded in two stages. In the first stage, two-way fixed effects models were estimated, incorporating country and year effects. This specification controls time-invariant country characteristics (institutional frameworks, labour market traditions, or long-standing industrial structures) and global shocks standard to all countries (e.g., the COVID-19 pandemic). This step provides a baseline assessment of whether AI vibrancy exerts any measurable short-run effect on employment outcomes once unobserved heterogeneity is accounted for.

In the second stage, the analysis compared fixed effects (FE) and random effects (RE) estimators for each outcome variable. The FE estimator is robust when regressors are correlated with unobserved country-specific factors, whereas the RE estimator is more efficient if such correlation is absent. The Hausman test was applied to determine the appropriate specification. Where the test rejected the RE assumption, two-way FE models were retained as consistent estimators (as was the case for industry and services employment). Where the test failed to reject, the RE estimator was considered valid and was preferred for efficiency (as in the unemployment model).

All models were estimated with clustered standard errors at the country level to ensure robust inference, correcting for heteroscedasticity and serial correlation within panels. This specification provides more reliable significance tests in the presence of intra-country correlation over time. By combining two-way FE baselines with FE–RE comparisons, the modelling strategy provides a rigorous framework to isolate the role of AI vibrancy in shaping labour market outcomes while accounting for structural determinants and exogenous shocks.

RESULTS

The descriptive statistics (Table 1) highlight apparent differences in scale and distribution across variables. The AI Vibrancy Score (x1) shows extreme dispersion: although the mean is 18.46, the standard deviation is more than four times larger (85.63), with values ranging from 0.34 to 1363. The skewness (15.36) and very high kurtosis (238.22) indicate severe positive skew and heavy tails. This suggests that most countries in the sample have low AI vibrancy, while a few exhibit very high values. Therefore, a transformation of x1 is necessary to normalise its distribution, stabilise variance, and reduce the influence of extreme outliers. The GDP per capita (x2) also exhibits substantial variation, with values ranging from below USD 2,000 to above USD 110,000. Although skewness (0.68) and kurtosis (0.18) are not extreme, the extensive range and cross-country heterogeneity justify a transformation for meaningful comparison and to mitigate heteroscedasticity. Labour force participation (x3) shows mild negative skew but remains within acceptable ranges.

By contrast, the labour market variables are relatively well-behaved. Employment in industry (y1) and services (y2) has moderate dispersion, with low skewness and kurtosis close to normality. Transformations are not strictly necessary for these variables. However, the unemployment rate (y3) is positively skewed (skew = 3.48, kurtosis = 14.25), indicating that while most countries maintain relatively low unemployment rates, some face very high levels.

For robustness, applying a log or square root transformation to unemployment may improve its distributional properties.

Transformations are strongly recommended for the AI Vibrancy Score (x1) and GDP per capita (x2), and are advisable for the unemployment rate (y3). The employment shares and labour force participation can be used in their raw percentage form without modification.

Table 1. Descriptive statistics of variables (2017–2023, 36 countries, N = 252) [Source: authors' calculations in R Studio]

Variable	AI Vibrancy Score	GDP per capita (constant 2015 US$)	Employment in industry (% of total employment)	Employment in services (% of total employment)	Labour force participation rate, total (% ages 15–64)	Unemployment, total (% of total labour force)
Code	x1	x2	y1	y2	x3	y3
Mean	18,46	39151,7	22,13	71,74	73,74	6,38
Std. Dev.	85,63	24860,4	4,91	11	7,06	4,89
Median	11,18	40501,4	20,53	73,88	74,69	4,99
Min	0,34	1788,7	9,19	31,02	54,37	2,15
Max	1363	110426	34,6	89,73	85,5	34,01
Skewness	15,36	0,68	0,06	–1,59	–0,83	3,48
Kurtosis	238,22	0,18	–0,32	3,23	0,14	14,25

The estimated Box–Cox parameter (λ) is centred around zero, with the 95% confidence interval spanning zero (Figure A1, Appendix A). The Box–Cox plot for GDP per capita also shows that the optimal λ is close to zero, with the confidence interval encompassing zero but excluding one (Figure A2, Appendix A). This suggests that a log transformation of GDP per capita is statistically justified. The Box–Cox likelihood function for unemployment rate indicates that the preferred λ is between -1 and 0, with zero in the confidence interval (Figure A3, Appendix A). Box–Cox transformation tests were conducted for the AI Vibrancy Score, GDP per capita, and unemployment rate to improve the statistical properties of these variables and address issues of skewness. The results indicate that the estimated transformation parameter for the AI Vibrancy Score is $\lambda \approx 0.03$ (95% CI: –0.04 to 0.10), which is statistically indistinguishable from zero, confirming that a logarithmic transformation is appropriate. For GDP per capita, the optimal parameter is $\lambda \approx 0.50$ (95% CI: 0.36 to 0.64), rejecting both the log ($\lambda = 0$) and linear ($\lambda = 1$) specifications, which suggests that a square-root transformation provides the best normalisation. For unemployment, the estimated λ is –0.73 (95% CI: –0.94 to –0.51), with both the log and untransformed forms firmly rejected; this implies that an inverse-root transformation best corrects distributional irregularities. Accordingly, the AI Vibrancy Score is used in its logarithmic form, GDP per capita in the square root form, and unemployment in the inverse root form. At the same time, employment shares and labour force participation are retained in their original scales as their distributions are approximately symmetric.

The diagnostic statistics confirm (Table 2) that the chosen transformations substantially reduced skewness and excess kurtosis. The AI Vibrancy Score became nearly symmetric after log transformation; GDP per capita achieved approximate normality under square-root transformation; and unemployment distribution was normalised through the Box–Cox inverse-root transform.

Table 2. Descriptive statistics before and after transformation [Source: authors' calculations in R Studio]

Variable	Mean	Std. Dev.	Skewness	Kurtosis
AI Vibrancy Score (raw)	18.46	85.63	15.36	238.22
AI Vibrancy Score (log)	2.25	0.97	–0.17	2.58
GDP per capita (raw)	39,151.71	24,860.40	0.68	0.18
GDP per capita (√)	186.45	66.37	–0.10	–0.57
Unemployment rate (raw)	6.38	4.89	3.48	14.25
Unemployment rate (Box–Cox λ≈–0.73)	0.95	0.13	0.02	–0.11

The results for employment in industry (y1) suggest that AI vibrancy (log-transformed, lagged) does not exert a statistically significant effect on the industrial employment share. However, the estimated coefficient is negative (–0.22). This indicates that, while higher levels of AI vibrancy might reduce industry employment, the evidence is not robust within this panel. By contrast, GDP per capita (square-root transformed) has a positive and significant effect on industry employment, implying that higher income levels are associated with a larger share of industrial jobs. Labour force participation shows a negative and significant effect, suggesting that as more of the working-age population participates in the labour market, the share of industry employment declines. The year dummies indicate a systematic decline in industry employment after 2019, consistent with global shocks such as the COVID-19 pandemic and subsequent economic restructuring.

For employment in services (y2), the coefficients display almost the mirror image of the industrial results. AI vibrancy is again statistically insignificant, with a small negative estimate. GDP per capita exerts a negative but non-significant influence. At the same time, labour force participation has a strong positive effect, indicating that increases in participation rates tend to expand the relative size of the service sector. The year dummies after 2019 show positive and significant effects, highlighting a structural shift towards services during and after the pandemic years. The findings reveal that the main drivers of service sector expansion are labour supply dynamics and year-specific shocks rather than AI vibrancy.

For unemployment (y3, transformed via the Box–Cox method), the results show that AI vibrancy, GDP per capita, and labour force participation do not exert statistically significant direct effects. Instead, unemployment dynamics appear strongly shaped by time effects. The year 2020 was marked by a significant rise in unemployment, reflecting the global impact of the COVID-19 pandemic. Elevated levels persist in 2021, while in 2022 and 2023, unemployment shows significant declines compared with the baseline, likely reflecting recovery policies and labour market adjustments. The model's explanatory power is relatively high ($R^2 = 0.44$), indicating that macroeconomic shocks, as captured by time-fixed effects, are more important determinants of unemployment than structural variables in this dataset.

The panel fixed-effects regressions suggest that the impact of AI vibrancy on labour market outcomes is limited in the short term. Rather than directly reshaping sectoral employment or unemployment, AI vibrancy may influence labour markets indirectly or over longer horizons. In contrast, labour force participation and income levels have stronger and more consistent associations with employment structures. Year effects are crucial in explaining short-term fluctuations, particularly during the pandemic period, underscoring the importance of global shocks in shaping labour market outcomes in the 2017–2023 window.

Table 3. Two-way fixed effects regression results [Source: authors' calculations in R Studio]

Variable	Industry Employment (y1)	Services Employment (y2)	Unemployment (y3_tr)
Lagged AI Vibrancy (x1_tr, t–1)	–0.223 (0.153)	–0.056 (0.161)	–0.007 (0.007)
GDP per capita (x2_tr)	0.046** (0.020)	–0.034 (0.021)	–0.001 (0.001)
Labour force participation (x3)	–0.198** (0.082)	0.322*** (0.087)	–0.004 (0.004)
Year 2019	–0.481** (0.209)	0.511** (0.219)	–0.015 (0.009)
Year 2020	–0.592*** (0.215)	0.609*** (0.226)	0.039*** (0.009)
Year 2021	–0.769*** (0.225)	0.806*** (0.237)	0.033*** (0.010)
Year 2022	–0.879*** (0.244)	0.963*** (0.257)	–0.023** (0.011)
Year 2023	–0.957*** (0.255)	1.113*** (0.268)	–0.033*** (0.011)
R^2 (within)	0.196	0.295	0.442
Observations	216	216	216
Countries	36	36	36

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Clustering of standard errors at the country level is necessary because the dataset is a panel with repeated observations for each country. In such contexts, the error terms will likely be correlated within countries over time (serial correlation) and may exhibit heteroskedasticity across units. If standard errors are not adjusted, the inference would be biased, leading to underestimated standard errors and overstated statistical significance. The estimates remain unbiased by clustering at the group (country) level, but the inference becomes robust to arbitrary within-country correlation and heteroskedasticity, providing more reliable significance levels (Table 4).

The results for employment in industry show that the lagged AI Vibrancy Score has a negative but statistically insignificant effect on the share of industrial employment, suggesting no robust direct relationship in the short run. GDP per capita has a positive influence on industry employment, with the coefficient being marginally significant at the 10% level ($p = 0.076$). This weakens the evidence that higher income levels are associated with a larger share of the industrial workforce. Labour force participation is negative but insignificant under clustered inference. The most consistent effects are observed in the year dummies: from 2019 onwards, the industrial employment share declines significantly, with extreme reductions during 2020–2023. This points to structural labour market shifts, likely linked to the COVID-19 pandemic and broader post-2019 global economic shocks.

In the case of employment in services, the lagged AI Vibrancy Score again exhibits no significant impact, and the same holds for GDP per capita. Labour force participation is positively associated with service sector employment, with significance at the 10% level ($p = 0.072$), implying that higher participation rates tend to reinforce the relative size of the service sector. As with the industry model, the year effects dominate: all post-2019 years display substantial and statistically significant increases in service employment shares, underscoring a reallocation of labour towards services in the wake of structural shocks.

For unemployment (transformed), neither AI vibrancy, GDP per capita, nor labour force participation show statistically significant associations. This confirms that structural variables are less relevant in explaining unemployment variation over this short horizon. Instead, unemployment dynamics are strongly driven by year-specific shocks. Compared with the 2018 baseline, 2019 shows a modest decline, while 2020 and 2021 display sharp increases in unemployment, consistent with pandemic-induced disruptions. By 2022 and 2023, unemployment falls again, indicating labour market recovery. These results indicate that macroeconomic shocks and policy responses account for a greater proportion of unemployment fluctuations than structural variables during the studied period.

The evidence suggests that the short-term effects of AI vibrancy on employment structure and unemployment are negligible. Instead, labour market outcomes are primarily shaped by economic development (as measured by GDP per capita) and exogenous shocks (captured by year fixed effects). When robust clustered inference is applied, labour force participation plays a role in reinforcing service employment but does not significantly affect unemployment.

Table 4. Two-way fixed effects regressions with clustered standard errors [Source: authors' calculations in R Studio]

Variable	Industry Employment (y1)	Services Employment (y2)	Unemployment (y3_tr)
Lagged AI Vibrancy (x1_tr, t–1)	–0.223 (0.189)	–0.056 (0.166)	–0.007 (0.007)
GDP per capita (x2_tr)	0.046* (0.026)	–0.034 (0.025)	–0.001 (0.001)
Labour force participation (x3)	–0.198 (0.168)	0.322* (0.178)	–0.004 (0.004)
Year 2019	–0.481** (0.183)	0.511** (0.166)	–0.015*** (0.004)
Year 2020	–0.592** (0.202)	0.609*** (0.192)	0.039*** (0.011)
Year 2021	–0.769** (0.248)	0.806*** (0.276)	0.033*** (0.009)
Year 2022	–0.879** (0.310)	0.963*** (0.344)	–0.023** (0.010)
Year 2023	–0.957*** (0.285)	1.113*** (0.332)	–0.033*** (0.011)
R^2 (within)	0.196	0.295	0.442
Observations	216	216	216
Countries	36	36	36

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant.

Under the FE model (Table 6), the lagged AI Vibrancy Score shows a negative but statistically insignificant effect on industry employment (–0.22). This suggests that AI developments are not measurably reshaping industrial employment shares in the short run. In contrast, GDP per capita (square-root transformed) is positive and statistically significant at the 5% level, pointing to a tendency for more prosperous countries to maintain relatively higher industrial employment. Labour force participation has a negative and significant effect, indicating that greater overall engagement of the working-age population is associated with a smaller proportion of jobs in industry. Strong negative coefficients for 2019–2023 highlight a structural decline in industrial employment after 2019, consistent with pandemic-driven disruptions and subsequent economic restructuring.

The RE model (Table 5), by contrast, produces somewhat different results: GDP per capita becomes negative and significant (–0.020, $p < 0.05$), and the AI vibrancy effect is slightly larger in magnitude (–0.28, marginally significant at the 10% level). Including an intercept (32.8) reflects the RE model's assumption that unobserved heterogeneity is uncorrelated with regressors, which the Hausman test invalidates. These differences confirm that RE would yield misleading conclusions about the role of economic development in shaping industry employment, reinforcing the choice of FE.

The Hausman test strongly rejects the null hypothesis that the random effects estimator is consistent ($\chi^2 = 21.95$, df = 8, p = 0.005). This indicates that regressors are correlated with unobserved country-specific effects, meaning the random effects model would yield biased estimates. Therefore, the fixed effects (FE) specification is preferred for interpreting the relationship between AI vibrancy, GDP per capita, labour force participation, and industry employment.

The Hausman test ($\chi^2 = 31.55$, df = 8, $p < 0.001$) decisively rejects the null hypothesis that the random effects estimator is consistent. This means that regressors correlate with unobserved country-specific heterogeneity, so the FE is preferred for inference.

Table 5. Fixed Effects vs Random Effects estimates for industry employment (y1) [Source: authors' calculations in R Studio]

Variable	FE Estimate	RE Estimate
Lagged AI Vibrancy (x1_tr, t–1)	–0.223 (0.153)	–0.284 (0.154).
GDP per capita (x2_tr)	0.046** (0.020)	–0.020** (0.010)
Labour force participation (x3)	–0.198** (0.082)	–0.078 (0.070)
Year 2019	–0.481** (0.209)	–0.441** (0.216)
Year 2020	–0.592*** (0.215)	–0.678*** (0.219)
Year 2021	–0.769*** (0.225)	–0.595*** (0.223)
Year 2022	–0.879*** (0.244)	–0.654*** (0.227)
Year 2023	–0.957*** (0.255)	–0.822*** (0.238)
Intercept	–	32.801*** (4.732)
R^2 (within)	0.196	0.166
Observations	216	216
Countries	36	36
Hausman χ^2 (df=8)	21.95 (p = 0.005)	–

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

In the FE specification (Table 6), the lagged AI Vibrancy Score does not significantly affect service employment, suggesting no short-run measurable role of AI in shaping the relative importance of services. GDP per capita is negative but not statistically significant, implying that income levels do not systematically influence service employment once country-specific effects are controlled for. In contrast, labour force participation exerts a strong and positive effect ($p < 0.01$), indicating that higher participation rates are associated with a larger service employment share. The year dummies are consistently positive and significant after 2019, highlighting a pronounced shift toward services, particularly in 2020–2023, consistent with structural labour reallocation in the aftermath of the COVID-19 shock.

In contrast, the RE model (Table 6) produces materially different results. Here, GDP per capita is positive and highly significant ($p < 0.01$), suggesting that richer countries tend to have larger service sectors. Labour force participation remains strongly positive and significant, consistent with the findings of FE. However, the year dummies have smaller magnitudes than under FE, and AI vibrancy is again insignificant. A large, significant intercept (37.7) reflects the RE assumption that unobserved heterogeneity is uncorrelated with the regressors, an assumption rejected by the Hausman test. These results reinforce that the FE estimator is a consistent and reliable model for explaining service employment shares. They suggest that short-term AI vibrancy has no direct effect, while labour force participation and post-2019 shocks are the key drivers of service sector expansion. The comparison with RE also underlines the risks of misspecification: RE would misleadingly attribute part of the structural increase in services to GDP per capita, whereas FE isolates the stronger role of demographic participation and global shocks.

Table 6. Fixed Effects vs Random Effects estimates for services employment (y2) [Source: authors' calculations in R Studio]

Variable	FE Estimate	RE Estimate
Lagged AI Vibrancy (x1_tr, t–1)	–0.056 (0.161)	0.091 (0.167)
GDP per capita (x2_tr)	–0.034 (0.021)	0.050*** (0.015)
Labour force participation (x3)	0.322*** (0.087)	0.328*** (0.085)
Year 2019	0.511** (0.219)	0.417* (0.231)
Year 2020	0.609*** (0.226)	0.793*** (0.236)
Year 2021	0.806*** (0.237)	0.499** (0.242)
Year 2022	0.963*** (0.257)	0.506** (0.252)
Year 2023	1.113*** (0.268)	0.698*** (0.265)
Intercept	–	37.718*** (6.078)
R^2 (within)	0.295	0.302
Observations	216	216
Countries	36	36
Hausman χ^2 (df=8)	31.55 ($p < 0.001$)	–

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

The Hausman test (Table 7) yields a χ^2 of 1.22 (df = 8, p = 0.996), providing no evidence to reject the null hypothesis that the random effects estimator is consistent. This contrasts with the results for industry and services, where FE was the preferred option. Here, the test suggests that regressors are not correlated with unobserved country-specific heterogeneity, meaning both FE and RE are valid, but RE is more efficient.

In the FE model (Table 7), none of the structural regressors, AI vibrancy, GDP per capita, or labour force participation, is a significant predictor of unemployment. Instead, year dummies drive the results: 2020 and 2021 show significant increases in unemployment, while 2022 and 2023 display significant declines relative to the baseline. This suggests that unemployment dynamics in the 2017–2023 period were primarily shaped by global shocks (most notably the COVID-19 pandemic) and subsequent recovery, rather than by long-term structural factors.

The RE model (Table 7) produces broadly consistent conclusions with slightly different emphasis. The coefficient for labour force participation is negative and statistically significant (–0.005, $p < 0.05$), suggesting that higher participation rates are associated with lower unemployment in the pooled sample. The year dummies show the same pattern as in FE: sharp increases in 2020–2021 followed by declines in 2022–2023. Importantly, AI vibrancy and GDP per capita remain insignificant, reinforcing the interpretation that unemployment fluctuations were driven more by cyclical and exogenous shocks than by structural changes in technology or income.

Given the Hausman test result, the RE model is the statistically preferred unemployment specification. FE and RE highlight that AI vibrancy had no measurable short-run effect on unemployment in this period. At the same time, labour supply factors and external shocks, notably the pandemic, were the dominant influences on labour market outcomes.

The clustered FE/RE results (Table 8) strengthen the earlier conclusion: AI vibrancy does not exert a measurable short-run effect on employment outcomes, whereas macro shocks and labour force dynamics are the dominant explanatory factors. Sectoral reallocation is evident, with industry declining and services expanding after 2019, while unemployment patterns align closely with pandemic and post-pandemic trajectories.

Table 7. Fixed Effects vs Random Effects estimates for unemployment (y3, transformed) [Source: authors' calculations in R Studio]

Variable	FE Estimate	RE Estimate
Lagged AI Vibrancy (x1_tr, t–1)	–0.007 (0.007)	–0.008 (0.006)
GDP per capita (x2_tr)	–0.001 (0.001)	0.000 (0.0003)
Labour force participation (x3)	–0.004 (0.004)	–0.005** (0.003)
Year 2019	–0.015* (0.009)	–0.016* (0.009)
Year 2020	0.039*** (0.009)	0.039*** (0.009)
Year 2021	0.033*** (0.010)	0.033*** (0.009)
Year 2022	–0.023** (0.011)	–0.024** (0.009)
Year 2023	–0.033*** (0.011)	–0.033*** (0.010)
Intercept	–	1.376*** (0.166)
R^2 (within)	0.442	0.410
Observations	216	216
Countries	36	36
Hausman χ^2 (df=8)	1.22 (p = 0.996)	–

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

For industry employment, the results indicate that AI vibrancy has no statistically significant effect on the industrial share of employment in the short term, as the coefficient is negative but insignificant. GDP per capita exerts a positive effect, marginally significant at the 10% level, suggesting a tendency for higher-income countries to maintain relatively larger industrial employment shares. Labour force participation shows a negative but insignificant coefficient when clustered standard errors are applied. The most robust findings come from the year dummies. All years from 2019 to 2023 are significantly negative, indicating a systematic decline in industry employment that accelerated during and after the COVID-19 pandemic.

For service employment, the lagged AI vibrancy score again remains insignificant, reinforcing that AI vibrancy has not yet translated into measurable structural effects on sectoral labour allocation. GDP per capita also proves insignificant under clustered inference, but labour force participation is positively associated with service employment, with marginal significance ($p < 0.1$). The most pronounced effects are again observed in the time dummies: service employment rose significantly after 2019, with the most substantial increases occurring from 2020 to 2023, reflecting a structural reallocation of labour away from industry and into services during the pandemic.

For unemployment, estimated under the RE model with clustered errors, the coefficients for AI vibrancy and GDP per capita remain insignificant. However, labour force participation has a significant adverse effect, suggesting that higher participation rates may reduce unemployment in the medium term. Year effects dominate the model: unemployment fell modestly in 2019, spiked significantly in 2020 and 2021 during the height of the pandemic, and then declined in 2022 and 2023, consistent with economic recovery and stabilisation. This confirms that unemployment dynamics are primarily driven by macroeconomic shocks and recovery cycles, rather than AI vibrancy or income levels.

Table 8. Regression results with clustered standard errors [Source: authors' calculations in R Studio]

Variable	Industry Employment (y1, FE)	Services Employment (y2, FE)	Unemployment (y3_tr, RE)
Lagged AI Vibrancy (x1_tr, t–1)	–0.223 (0.189)	–0.056 (0.166)	–0.008 (0.007)
GDP per capita (x2_tr)	0.046* (0.026)	–0.034 (0.025)	0.000 (0.0003)
Labour force participation (x3)	–0.198 (0.168)	0.322* (0.178)	–0.005** (0.002)
Year 2019	–0.481** (0.183)	0.511** (0.166)	–0.016*** (0.004)
Year 2020	–0.592*** (0.202)	0.609*** (0.192)	0.039*** (0.012)
Year 2021	–0.769*** (0.248)	0.806*** (0.276)	0.033*** (0.009)
Year 2022	–0.879*** (0.310)	0.963*** (0.344)	–0.024** (0.009)
Year 2023	–0.957*** (0.285)	1.113*** (0.332)	–0.033*** (0.010)
Intercept	–	–	1.376*** (0.117)
R^2 (within)	0.196	0.295	0.410
Observations	216	216	216
Countries	36	36	36

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

The models estimated with AI Vibrancy in contemporaneous form (without lag) (Table 9) confirm that the index has no significant effect on labour market outcomes across industry, services, or unemployment. The Hausman test rejects random effects in favour of fixed effects for industry employment, but AI Vibrancy remains insignificant. Global shocks, rather than technological change, explain the declines observed from 2020 to 2023.

The Hausman test again supports the use of fixed effects for service employment, and AI Vibrancy shows no measurable influence. Instead, service expansion after 2019 is driven by structural reallocation during the pandemic. GDP per capita shows a marginal positive effect, while labour force participation is positive but not robustly significant. For unemployment, the Hausman test indicates that random effects are consistent. AI Vibrancy is again insignificant, while labour force participation is strongly negative, confirming that higher participation reduces unemployment. Year dummies capture the pandemic shock (2020–2021) and subsequent recovery (2022–2023). When AI Vibrancy is included without lag, it does not exert a significant short-run influence on employment structures or unemployment. Labour force participation and time-specific shocks remain the primary drivers of labour market dynamics from 2017 to 2023.

The results do not provide empirical support for the stated hypotheses that higher AI vibrancy reduces industrial employment (H1), increases service employment (H2), or raises unemployment (H3). Across all specifications, both lagged and contemporaneous, AI vibrancy coefficients remain statistically insignificant, indicating no measurable short-run impact of AI vibrancy on labour market structures or unemployment in the 36-country sample. Instead, labour force participation shows partial significance, GDP per capita exerts only marginal effects, and year dummies powerfully capture the structural shifts associated with the COVID-19 pandemic. These findings suggest that recent labour market dynamics are primarily shaped by demographic participation and global shocks. At the same time, the transformative effects of AI vibrancy are not yet detectable within the short observation window of 2017–2023.

Table 9. Regression results (contemporaneous AI vibrancy, clustered SEs) [Source: authors' calculations in R Studio]

Variable	Industry Employment (y1, FE)	Services Employment (y2, FE)	Unemployment (y3_tr, RE)
AI Vibrancy (x1_tr)	–0.356 (0.223)	0.191 (0.141)	–0.002 (0.005)
GDP per capita (x2_tr)	–0.015 (0.024)	0.045* (0.024)	0.000 (0.0003)
Labour force participation (x3)	–0.101 (0.198)	0.332 (0.204)	–0.006*** (0.002)
Year 2018	0.090 (0.072)	0.037 (0.076)	–0.024*** (0.004)
Year 2019	–0.251 (0.199)	0.409** (0.193)	–0.038*** (0.007)
Year 2020	–0.486** (0.191)	0.756*** (0.192)	0.015 (0.013)
Year 2021	–0.591** (0.274)	0.570* (0.290)	0.007 (0.008)
Year 2022	–0.572* (0.331)	0.567 (0.350)	–0.047*** (0.008)
Year 2023	–0.726** (0.333)	0.761** (0.354)	–0.054*** (0.009)
Intercept	—	—	1.456*** (0.133)
R^2 (within)	—	—	0.410
Observations	216	216	216
Countries	36	36	36

Signif. codes: '***' – 0.001; '**' – 0.01; '*' – 0.05; '.' – 0.1; 'no symbol' – insignificant

The absence of significant effects of AI vibrancy on industrial employment, service employment, and unemployment can be explained by several economic factors. First, the relatively short observation period of 2017–2023 may be insufficient to capture the long-run impact of technological change, as structural transformations in labour markets typically evolve over decades rather than a few years (Acemoglu & Restrepo, 2018). During this period, employment outcomes were significantly influenced by the global COVID-19 shock, which triggered abrupt shifts in sectoral employment and unemployment, overshadowing any incremental effects of AI adoption (Adams-Prassl et al., 2020).

Moreover, the AI Vibrancy Index reflects national-level readiness and activity but does not measure sector-specific adoption. Many firms, particularly in industry, may not yet have integrated AI at a scale that would influence aggregate employment patterns. Even in economies with high AI vibrancy, adoption remains concentrated in a few firms or sectors, limiting its measurable impact at the macro level. In addition, AI deployment has tended to complement rather than substitute human labour, enhancing productivity and efficiency without leading to immediate job destruction or creation on a scale visible in employment statistics (Brynjolfsson & McAfee, 2014; Bessen, 2019).

Additionally, early-phase AI adoption tends to complement, rather than substitute for, labour, augmenting productivity rather than immediately eliminating jobs. Empirical work supports the idea that AI initially transforms tasks instead of entire occupations (Autor & Salomons, 2018). Moreover, labour market rigidities, such as stringent employment protection legislation, intense collective bargaining, and limited retraining capacities, often dampen the short-run responsiveness of employment to technological advancements. These rigidities can slow the adoption of adaptive technologies, such as AI, as firms face high costs or procedural hurdles when adjusting their workforce. A recent theoretical contribution by Fan (2025) further supports this dynamic: it shows that workers' limited mobility across occupation groups, with substitutability declining as the skill gap widens, constrains the labour market's ability to absorb rapid technological progress, even when automation begins to affect neighbouring job categories (Fan, 2025). Finally, mismatches between innovation and workforce skills slow down diffusion: firms may develop AI capabilities without deploying them broadly enough to influence national employment patterns (Frey & Osborne, 2017).

DISCUSSION

The empirical findings of this study suggest that AI vibrancy has not yet exerted a significant short-run effect on employment in industry, employment in services, or unemployment across the 36-country sample during 2017–2023. Instead, labour market dynamics were strongly shaped by macroeconomic shocks such as the COVID-19 pandemic and by demographic participation, with year dummies capturing sharp declines in industry employment (–0.592 in 2020; –0.957 in 2023), increases in services (0.609 in 2020; 1.113 in 2023), and temporary rises in unemployment (0.039 in 2020; 0.033 in 2021). These results diverge from early theoretical expectations that AI adoption would accelerate labour displacement and restructuring (Acemoglu & Restrepo, 2018; Autor & Salomons, 2018; Frey & Osborne, 2017), but align with more recent evidence highlighting that AI adoption often complements rather than substitutes labour in its initial stages (Bîrcă, 2025; Cramarenco et al., 2023; Bessen, 2019).

The absence of measurable short-run effects can be attributed to the aggregate and national-level nature of AI vibrancy, which may not adequately capture sector-specific adoption. This aligns with arguments that AI diffusion is concentrated in particular industries and among leading firms, thereby limiting its impact on broader labour market structures (Brynjolfsson & McAfee, 2014; Fan, 2025). Furthermore, the results support findings that labour market rigidities, institutional arrangements, and skill mismatches delay the visible impact of technological change (Istudor et al., 2024; Jarząbek & Stolarska-Szeląg, 2024; Butum & Nicolescu, 2024). The positive role of labour force participation in reducing unemployment ($\beta = –0.006$, $p < 0.01$) also echoes studies emphasising the importance of human capital and reskilling in mitigating technological shocks (Abid et al., 2024; Androniceanu, 2025; Pisică & Zaharia, 2025).

At the same time, the strong year effects in this study highlight how exogenous global crises can temporarily overshadow the influence of technological trends. Evidence from the literature confirms that the COVID-19 pandemic disrupted labour markets far more dramatically than technological change during this period, with unequal impacts across demographic groups and sectors (Adams-Prassl et al., 2020; Denissova, 2025; Trembeczki et al., 2025). The results suggest that while AI vibrancy is an important indicator of digital readiness, its measurable effects on employment structures and unemployment may only materialise in the longer run, once adoption deepens and interacts with institutional frameworks and workforce skills.

Limitations. This study has several limitations that should be acknowledged. First, the analysis is based on a relatively short time span (2017–2023), which may not fully capture the long-run effects of AI vibrancy on labour market outcomes, especially given the gradual diffusion of technological change. Second, the AI Vibrancy Score is an aggregate index at the national level and does not reflect sector-specific adoption of AI technologies, which could mask heterogeneous impacts across industries. Third, the results may be influenced by unobserved institutional and policy factors that are not explicitly modelled, such as labour market regulations, social protection systems, or targeted innovation policies. Fourth, the findings are significantly shaped by the COVID-19 pandemic, representing an extraordinary global shock that may dominate the short-term dynamics of employment and unemployment during the observation period. Finally, the study is limited by data availability; additional controls, such as productivity, education, or technological investment indicators, could provide a more nuanced understanding of the relationship between AI vibrancy and labour market structures.

CONCLUSIONS

This study examined whether national-level AI vibrancy exerts measurable short-run effects on labour market outcomes, specifically employment in industry, employment in services, and unemployment, across 36 countries from 2017 to 2023. The analysis sought to test the hypotheses that higher AI vibrancy reduces industrial employment, increases service employment, and raises unemployment.

The study employed panel data econometric methods, utilising annual indicators from Stanford University's Global AI Vibrancy Tool and the World Bank's World Development Indicators. After performing Box–Cox transformations to stabilise distributions, two-way fixed effects and random effects models were estimated, with the appropriate specification selected using Hausman tests. Standard errors were clustered at the country level for heteroscedasticity and serial correlation.

The empirical results provide no support for the stated hypotheses. Across all specifications, AI vibrancy coefficients remained statistically insignificant, whether included contemporaneously or with a one-year lag. In contrast, GDP per capita showed a weakly positive effect on industrial employment (estimate 0.046, $p < 0.10$) and on service employment in some specifications (0.045, $p \approx 0.06$), while labour force participation exhibited a positive association with service employment (0.322, $p < 0.10$) and a negative association with unemployment (–0.006, $p < 0.01$). The most consistent and significant results emerged for the year dummies: industrial employment declined sharply from 2020 onwards (–0.592 in 2020; –0.957 in 2023), while service employment rose (0.609 in 2020; 1.113 in 2023). Unemployment increased significantly during 2020–2021 (0.039 2020; 0.033 in 2021) before falling in 2022–2023 (–0.023; –0.033). These findings suggest that recent labour market dynamics were primarily driven by global shocks, notably the COVID-19 pandemic, and demographic participation, rather than by AI vibrancy.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

Policy implications follow directly from these results. Since AI vibrancy does not yet appear to affect employment structures or unemployment in the short run, policymakers should not expect immediate labour market disruptions from AI readiness at the national level. Instead, greater attention should be paid to resilience against macroeconomic shocks, strengthening labour force participation, and supporting sectoral reallocation during crises. However, investments in workforce reskilling and AI-related competencies remain essential, as the absence of effects in 2017–2023 may reflect delayed adoption and diffusion. In the medium to long term, the transformative potential of AI is likely to emerge, and proactive policy measures today can help smooth the adjustment, minimise displacement, and ensure that the benefits of AI are broadly shared.

REFERENCES

Abid, U., Faisal, M., & Al-Esmael, B. (2024). Exploring the moderating role of technological competence and artificial intelligence in green HRM. *Polish Journal of Management Studies*, 29(2), 7-22. https://doi.org/10.17512/pjms.2024.29.2.01.

Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation and work. National *Bureau of Economic Research working paper series*, No. 24196. https://www.nber.org/system/files/working_papers/w24196/w24196.pdf

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real-time surveys. *Journal of Public Economics*, *189*, 104245. https://doi.org/10.1016/j.jpubeco.2020.104245

Androniceanu, A. (2025). The impact of artificial intelligence on human resources processes in public administration. *Administratie si Management Public*, 44, 75-93. https://doi.org/10.24818/amp/2025.44-05

Angammana, J. S. K., & Jayawardena, M. (2022). Influence of artificial intelligence on warehouse performance: The case study of the Colombo area, Sri Lanka. *Journal of Sustainable Development of Transport and Logistics*, *7*(2), 80–110. https://doi.org/10.14254/jsdtl.2022.7-2.6

Autor, D., & Salomons, A. (2018). *Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share*. Brookings Papers on Economic Activity. *BPEA Conference Drafts*, March 8–9, 2018, https://www.brookings.edu/wp-content/uploads/2018/03/1_autorsalomons.pdf

Bal-Domańska, B., Kusideł, E., & Brudz, M. (2025). Equal opportunities: Youth inclusiveness in the Polish labour market in the context of urbanisation. *Economics and Sociology*, 18(2), 206-220. doi:10.14254/2071-789X.2025/18-2/11

Bessen, J. (2019). *AI and Jobs: The Role of Demand*. National Bureau of Economic Research working paper series, No. 24235. https://www.nber.org/system/files/working_papers/w24235/w24235.pdf

Bian, X., & Wang, B. (2024). Exploring the Influence of Artificial Intelligence Usage on Ethical Decision Making Among Public Sector Employees: Insights into Moral Identity and Service Motivation. *Business Ethics and Leadership*, *8*(3), 133–150. https://doi.org/10.61093/bel.8(3).133-150.2024

Bîrcă, A. (2025). The Assessment of Employees' Competences on the Labour Market in the Context of the Development of Artificial Intelligence Systems. *Montenegrin Journal of Economics*, *21*(3). https://doi.org/10.14254/1800-5845/2025.21-3.4

Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* W. W. Norton & Company. URL: https://books.google.pl/books?hl=en&lr=&id=WiKwAgAAQBAJ&oi=fnd&pg=PA1&ots=4-YsZiYvbb&sig=s9-II78mfcdZtyKni5H4ZIHna7M&redir_esc=y#v=onepage&q&f=false

Butkus, M., Dargenytė-Kacilevičienė, L., Matuzevičiūtė, K., Ruplienė, D., & Šeputienė, J. (2024). Simultaneous, endogenous, and bi-directional relationship between output, labour productivity, and employment: a 3SLS estimation of the employment version of Okun equation. *Journal of Business Economics and Management*, *25*(5), 1030–1051. https://doi.org/10.3846/jbem.2024.22425

Butum, L. C., & Nicolescu, L. (2024). Global Skills and Abilities for Economic Fresh Graduates in Romania. Analysis of Employers' Demand for Global Competences Through Online Ads. *European Journal of Interdisciplinary Studies*, *16*(2), 1–24. https://doi.org/10.24818/ejis.2024.09

Cazzaniga, M., Jaumotte, F., Li, L., Melina, G., Panton, A. J., Pizzinelli, C., Rockall, E. J., & Tavares, M. M. (2024). Gen-AI: Artificial intelligence and the future of work (*IMF Staff Discussion Note* No. 2024/001). International Monetary Fund. https://doi.org/10.5089/9798400262548.006

Cham, T. H., Cheah, J. H., Memon, M. A., Fam, K. S., & László, J. (2022). Digitalization and its impact on contemporary marketing strategies and practices. *Journal of Marketing Analytics*, *10*(2), 103-105. https://doi.org/10.1057/s41270-022-00167-6

Chandran K. R., P., & Ittimani Tholath, D. (2025). Digital insurance acceptance among older adults in the context of AI. *Insurance Markets and Companies*, *16*(1), 131–145. https://doi.org/10.21511/ins.16(1).2025.11

Cramarenco, R. E., Burcă-Voicu, M. I., & Dabija, D. C. (2023). The impact of artificial intelligence (AI) on employees' skills and well-being in global labor markets: A systematic review. *Oeconomia Copernicana, 14*(3), 731-767. https://doi.org/10.24136/oc.2023.022

Demombynes, G., Langbein, J., & Weber, M. (2025). *AI's impact on jobs may be smaller in developing countries*. World Bank Blogs. https://blogs.worldbank.org/en/investinpeople/AI-impact-on-jobs-may-be-smaller-in-developing-countries

Denissova, O. (2025). Migration Processes in the Labor Market Associated With the Uncertainty of Behavior of the Employed Population During and After the Pandemic. *Montenegrin Journal of Economics, 21*(3). https://doi.org/10.14254/1800-5845/2025.21-3.6

DingYi, W., Yamaoka, Y., Sartamorn, S., Oe, H. (2024). Can citizen Internet banking in China become a champion in the digital transformation era?. *Financial Markets, Institutions and Risks, 8*(1), 16–30. https://doi.org/10.61093/fmir.8(1).16-30.2024

Dobrovolska, O., & Kolomiiets, S. (2024). The Impact of Digitalisation on Social Determinants of Public Health. *Health Economics and Management Review, 5*(3), 128-142. https://doi.org/10.61093/hem.2024.3-09

Ernawati, Syarif, M. and Asri, M. (2025). The Impact of Governance and Digital Competitiveness on Agriculture Sectors Amid Global Uncertainty. *AGRIS on-line Papers in Economics and Informatics*, Vol. 17, No. 2, pp. 51-62. ISSN 1804-1930 DOI 10.7160/aol.2025.170204.

Fan, T. (2025, April 5). *The labor market incidence of new technologies*. arXiv.org https://doi.org/10.48550/arXiv.2504.04047. https://arxiv.org/abs/2504.04047

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Głód, G., Głód, W. Wolniak, R., and Jonek-Kowalska, I. (2025). The quality of IT systems and the competencies and training of employees in the process of implementing a new cost accounting standard in the hospital. *Administratie si Management Public*, 44, 94-113. https://doi.org/10.24818/amp/2025.44-06

Haley, P. (2025). Artificial Intelligence and Ethical Dimensions of Automated Traffic Enforcement: Implications for Public Health, Healthcare Equity, and Social Justice. *Health Economics and Management Review, 6*(2), 32–49. https://doi.org/10.61093/hem.2025.2-03

Haley, P., & Burrell, D. N. (2025). Integrating Artificial Intelligence into Law Enforcement: Socioeconomic and Ethical Challenges. *SocioEconomic Challenges, 9*(2), 60–77. https://doi.org/10.61093/sec.9(2).60-77.2025

Harrington, S. (2025). *What ILO's Global Index tells us about GenAI and jobs | The People Space*. The People Space: Digital HR publication for the future of work. https://www.thepeoplespace.com/ideas/articles/what-ilos-global-index-tells-us-about-genai-and-jobs

Hernik, J., Sagan, A., Jarecki, W., & Grinberga-Zalite, G. (2025). Digital transformation in business process management: The role of employee engagement. *Human Technology*, *21*(1), 203–221. https://doi.org/10.14254/1795-6889.2025.21-1.10

Hossain, M. B., Rahman, M. U., Čater, T., & Vasa, L. (2025). Determinants of SMEs' strategic entrepreneurial innovative digitalization: examining the mediation role of human capital. European *Journal of Innovation Management, 28*(7), 2733-2760. https://doi.org/10.1108/EJIM-02-2024-0176

Hussein, A.M.A., Montaser, M. A., Suliman, S., & Mkheimer, I. (2024). Leadership in the digital era: Exploring the nexus between leadership styles and job satisfaction. The mediating role of perceived organizational politics in Jordanian insurance companies. *Insurance Markets and Companies*, *15*(1), 58–69. https://doi.org/10.21511/ins.15(1).2024.05

Istudor, N., Socol, A.G., Marinaș, M.C. & Socol, C. (2024). Analysis of the Adequacy of Employees' Skills for the Adoption of Artificial Intelligence in Central and Eastern European Countries. *Amfiteatru Economic,* 26(67), pp. 703-720. DOI: https://doi.org/10.24818/EA/2024/67/703

Jarząbek, K., & Stolarska-Szeląg, E. (2024). Influence of education on improving the employment prospects of individuals with disabilities. *Journal of International Studies*, 17(3), 38-50. doi:10.14254/2071-8330.2024/17-3/2

Jarzębowski, S., Bozhenko, V., Didorenko, K., Tkachenko, O., Blyznyukov, A., Melnyk, M., & Cieslik, J. (2024). The Impact of Digitalisation on the Competitiveness of European Countries. *SocioEconomic Challenges, 8*(3), 238-261. https://doi.org/10.61093/sec.8(3).238-261.2024

Kozhushko, I. (2023). Transformation of Financial Services Industry in Conditions of Digitalization of Economy. *Financial Markets, Institutions and Risks, 7*(4), 189–200. https://doi.org/10.61093/fmir.7(4).189-200.2023

Kuzior, A., Marszałek-Kotzur, I., Kurovska, Y., & Chvankin, Y. (2024). The Role of Digital Economy in Transformation of Public Health: Modeling and Analysis. *Health Economics and Management Review, 5*(4), 91-109. https://doi.org/10.61093/hem.2024.4-06

Kuzior, A., Ober, J., & Karwot, J. (2022). Employee Attitudes towards Employee Evaluation Systems in the Utility Sector: A Case Study of Sewage and Water Supply Ltd., Rybnik, Poland. *Sustainability*, *14*(19), 12436. https://doi.org/10.3390/su141912436

Le Poidevin, O. (2025). AI poses a bigger threat to women's work than men's, says report | Reuters. https://www.reuters.com/business/world-at-work/ai-poses-bigger-threat-womens-work-than-mens-says-report-2025-05-20/

Lipták, K., Horváthné Csolák, E., & Musinszki, Z. (2023). The digital world and atypical work: Perceptions and difficulties of teleworking in Hungary and Romania. *Human Technology*, *19*(1), 5–22. https://doi.org/10.14254/1795-6889.2023.19-1.2

Liu, Y., McDowell, S., Xue, C., & Zhang, J. (2024). Environmental, social, and governance performance: The role of Chinese employee stock ownership plans. *Environmental Economics*, *15*(2), 132–148. https://doi.org/10.21511/ee.15(2).2024.10

Maró, Z. M., Borda, Á. J. & Balogh, J. M. (2024). Challenges and Trends in Agricultural Employment: The Case of Hungary. *AGRIS on-line Papers in Economics and Informatics*, Vol. 16, No. 16, pp. 109-128. ISSN 1804-1930. DOI 10.7160/aol.2024.160409.

Mihajlovic, I., Brkic, V. S., Perisic, M., Milosevic, I., & Arsic, S. (2025). Effects of employees' attitudes towards digital transformation factors on smes'sustainability and financial performance. *Transformations in Business and Economics*, 24 (2 (65)), 242–266. https://www.transformations.knf.vu.lt/65/article/effe

Moutik, I. (2025). Artificial Intelligence as a Driver for Women's Empowerment in Agriculture: A Theoretical Ecosystem for Inclusive Leadership and Sustainable Development. *Business Ethics and Leadership, 9*(2), 200-210. https://doi.org/10.61093/bel.9(2).200-210.2025

Mujtaba, B. G., Vardarlier, P., Salamzadeh, Y., & Topaloglu, E. (2025). Employee Stress Caused by Socioeconomic Challenges: Task and Relationship Management as a Buffer to Mitigate the Stress Outcomes. *SocioEconomic Challenges*, *9*(2), 190–206. https://doi.org/10.61093/sec.9(2).190-206.2025

Oliinyk, O., Mishchuk, H., & Bilan, Y. (2024). Leadership and its role in intellectual migration and creativity development. *Creativity Studies, 17*(2), 379-394. https://doi.org/10.3846/cs.2024.21186

Parajuli, D., Adhikari, G. M., & Bhattarai, G. (2024). Drivers of Intention to Adopt Fintech: A Study in the Urban Sector. *Financial Markets, Institutions and Risks, 8*(3), 80–97. https://doi.org/10.61093/fmir.8(3).80-97.2024

Peković, D. (2025). Impact of remittances on employment: Evidence from posttransition countries. Journal of International Studies, 18(1), 145–155. doi:10.14254/2071-8330.2025/18-1/9

Pilelienė, L., & Bogoyavlenska, Y. (2025). Artificial intelligence in influencer marketing: Current researchscape, trends and insights from a bibliometric review. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 20*(2), 583-611. https://doi.org/10.24136/eq.3783

Pisică, A. I., & Zaharia, R. M. (2025). What Artificial Intelligence Means to Us – Students' Insights. *European Journal of Interdisciplinary Studies*, *17*(1), 142–152. https://doi.org/10.24818/ejis.2025.09

Privara, A. (2025). Wired for stability: The role of infrastructure and Fintech in migrant employment. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, *20*(1), 285–325. https://doi.org/10.24136/eq.3573

Roshchyk, I., Mishchuk, H., Bilan, Y., & Brezina, I. (2024). Determinants of demand for young professionals with tertiary education amidst migration resulting from the war in Ukraine. *Intellectual Economics*, *18*(2), 402–428. https://doi.org/10.13165/IE-24-18-2-08

Sarker, P. K. (2022). Macroeconomic effects of artificial intelligence on emerging economies: Insights from Bangladesh. *Economics, Management and Sustainability*, *7*(1), 59–69. https://doi.org/10.14254/jems.2022.7-1.5

Skrynnyk, O., Lyeonov, S., Lenska, S., Litvinchuk, S., Galaieva, L. & Radkevych, O. (2022). Artificial Intelligence in Solving Educational Problems. *Journal of Information Technology Management*, *14*(Special Issue: Digitalization of Socio-Economic Processes), 132–146. https://doi.org/10.22059/jitm.2022.88893

Stanford University. (n.d.). *Global AI vibrancy tool - AI index*. Stanford University Human-Centered Artificial Intelligence. https://aiindex.stanford.edu/vibrancy

Szedmák, B., Varga, L., & Szabó, RZ (2025). Digital Transformation of Public Services: The Case of the Document Management Application. *International Journal of Public Administration*, 1–18. DOI: 10.1080/01900692.2025.2520522

Trembeczki, E., Tvaronavičienė, M., Besenyő, J., & Kobolka, I. (2025). Effects of the COVID-19 crisis on work-life balance, mental health, and perceived health status among Hungarian defense employees: a cross-sectional study. *Journal of Business Economics and Management*, *26*(3), 599–620. https://doi.org/10.3846/jbem.2025.24189

Ualtayev, MD, Ualtayeva, AS, Kaliyeva, SA, & Vasa, L. (2024). Problems and prospects for legal regulation of innovations in digital and information technologies of the labour market in Kazakhstan. *Transformations in Business & Economics*, *23*(3), 325-344.

Urbański M., Haque, A. U., Kaur, H., Yamoah, F. A., & Kot, M. (2024). Gender dynamics in knowledge hiding and occupational stress on employee performance. *Economics and Sociology*, 17(4), 29-42. doi:10.14254/2071-789X.2024/17-4/2

Virlanuta, F. O., Barbuta-Misu, N., Bacalum, S., David, S., & Moisescu, F. (2024). Digitalisation of public services in Romania. A correlational study. *Transformations in Business and Economics*, *23*(2 (63)), 21–35. https://www.transformations.knf.vu.lt/62/article/digi

Vorontsova, A., Vasylieva, T., Lyeonov, S., Artyukhov, A., & Mayboroda, T. (2021). Education expenditures as a factor in bridging the gap at the level of digitalization. *2021 11th International Conference on Advanced Computer Information Technologies (ACIT)*, 242–245. https://doi.org/10.1109/acit52158.2021.9548338

Vuong, T. (2025). The role of artificial intelligence in team performance and employee engagement. *Polish Journal of Management Studies*, 31(2), 244-257. https://doi.org/10.17512/pjms.2025.31.2.15.

Wang, C., Yan, G. and Yang, J., 2025. Navigating Employment Transformations: Liberalism vs. Statism in the Era of Industry 4.0. *Amfiteatru Economic*, 27(68), pp. 145-161. https://doi.org/10.24818/EA/2025/68/145

Welch, N. (2025). Exploring Underrepresented Employee Perceptions of AI Receptivity Through Leaders' Stakeholder Engagement. *Business Ethics and Leadership, 9*(2), 108–119. https://doi.org/10.61093/bel.9(2).108-119.2025

World Bank. (n.d.). *World Bank Open Data*. World Bank Open Data. https://data.worldbank.org/indicator

Yarovenko, H., Kuzior, A., Norek, T., & Lopatka, A. (2024). The future of artificial intelligence: Fear, hope or indifference?. *Human Technology*, *20*(3), 611–639. https://doi.org/10.14254/1795-6889.2024.20-3.10

Yekimov, S., Nianko, V., Perevozova, I., Mykhailyshyn, L., & Kalinina, S. (2022). Human Resources Management of a machine-building enterprise in the post covid-19 pandemic environment. *AIP Conference Proceedings*, *2467*, 040007. https://doi.org/10.1063/5.0092486

Yurchyk, H., Mishchuk, H., Bilan, S., & Scare, M. (2024). Social expenditure multiplier: Assessment of economic effect and optimal values. *Economics and Sociology, 17*(1), 182–195. doi:10.14254/2071-789X.2024/17-1/12

Zada, M., Khan, S., Mehmood, S., & Contreras-Barraza, N. (2024). Generative artificial intelligence in FinTech: Applications, environmental, social, and governance considerations, and organizational performance: The moderating role of ethical dilemmas. *Oeconomia Copernicana*, *15*(4), 1303–1347. https://doi.org/10.24136/oc.3323

Authors' Note

All correspondence should be addressed to
Aleksandra Kuzior
Silesian University of Technology,
Akademicka, 2A, 44-100, Gliwice, Poland
Aleksandra.Kuzior@polsl.pl

Appendix A

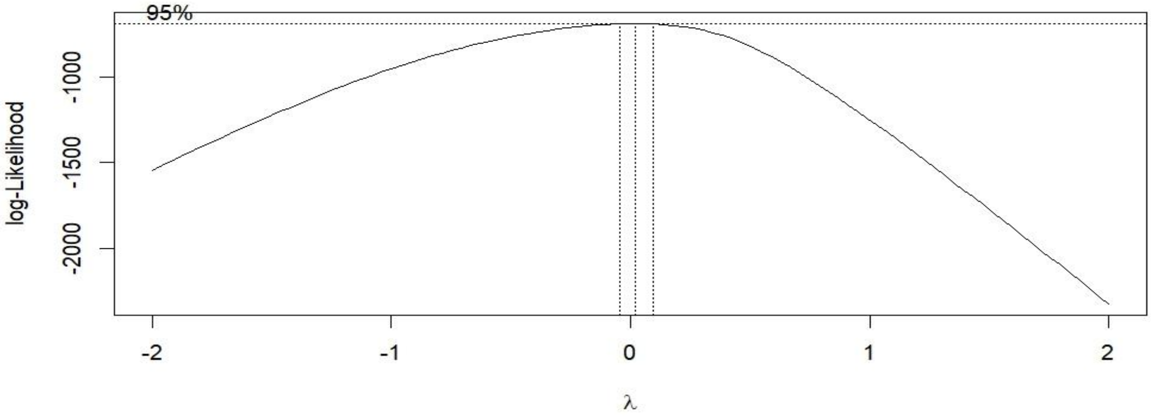

Figure A1. Figure A1. Box–Cox transformation plot for AI Vibrancy Score (x1)
[Source: authors' calculations in R Studio]

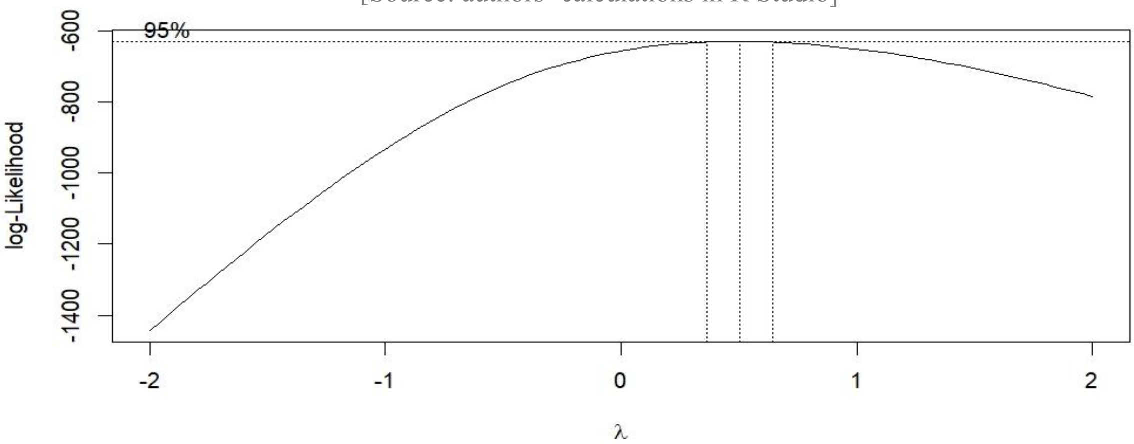

Figure A2. Box–Cox transformation plot for GDP per capita (x2)
[Source: authors' calculations in R Studio]

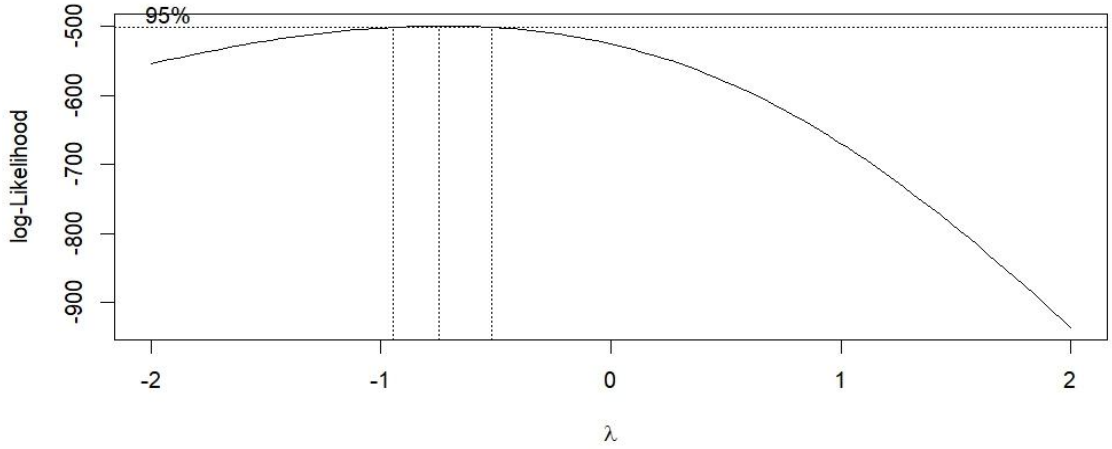

Figure A3. Box–Cox transformation plot for Unemployment rate (y3)
[Source: authors' calculations in R Studio]