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FROM AI VIBRANCY TO LABOUR MARKET OUTCOMES: TESTING DISPLACEMENT ACROSS EDUCATION GROUPS

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ABSTRACT. Artificial intelligence is expanding rapidly, intensifying policy concerns that more vibrant AI ecosystems may displace workers and increase unemployment. This study aims to test whether national AI vibrancy is associated with higher unemployment across education groups (advanced, intermediate and basic). Using an unbalanced panel of 34–35 countries from 2017 to 2023, the analysis combines Stanford's AI Vibrancy Score with World Bank indicators and estimates two-way fixed- and random-effects models, employing Box–Cox/log transformations and dependence-robust inference (including country/time clustering and Driscoll–Kraay standard errors). The results provide little support for the displacement hypothesis. For advanced-education unemployment, AI vibrancy is statistically insignificant in the two-way FE model. It remains insignificant under all robust corrections (ln(AI vibrancy): $\beta = -0.099$, country-clustered $p = 0.494$, time-clustered $p = 0.544$, Driscoll–Kraay $p = 0.468$). For basic-education unemployment, AI vibrancy is likewise insignificant in the two-way FE model ($p = 0.782$). It remains insignificant under country clustering ($p = 0.830$), time clustering ($p = 0.813$) and Driscoll–Kraay inference ($p = 0.819$). For intermediate-education unemployment, the AI coefficient remains insignificant under country clustering ($p = 0.273$), time clustering ($p = 0.310$), and Driscoll–Kraay corrections ($p = 0.226$), indicating no robust unemployment-increasing effect across education groups during the observed period.

Keywords: artificial intelligence, AI vibrancy, unemployment, education-level heterogeneity, labour displacement, panel data

Introduction

Rapid advances in artificial intelligence, particularly in generative AI, have shifted the debate on technology and jobs from a long-term concern to an immediate policy issue. International organisations increasingly emphasise that AI can raise productivity and reshape work, but may also displace tasks and occupations, with effects differing across countries and sectors (Sarker, 2022). Recent ILO research has developed refined global indices of occupational exposure to generative AI to quantify where labour-market disruption is most likely, underscoring that exposure is already measurable and policy-relevant rather than speculative (Gmyrek et al., 2025). At the same time, the World Bank highlights early evidence of uneven impacts, including "modest" signs of AI-related displacement in service jobs focused on simpler tasks, alongside productivity gains and job redesign in higher-value activities (World Bank, 2025).

A particularly urgent dimension is that AI's labour-market effects are unlikely to be uniform across workers, making education and skills central to the discussion on displacement. The ILO brief notes that jobs with higher exposure to generative AI often correlate with urban labour markets and higher educational attainment in some regions, signalling that disruption is not confined to low-skilled work and may affect different educational groups through distinct channels (Gomez Tamayo & Petrelli, 2025). Complementing this, OECD evidence based on online vacancies shows that AI-exposed occupations are accompanied by shifting skill demands, often towards management, business processes, and complementary human skills, suggesting that the same technology can simultaneously substitute for some tasks while increasing demand for others (Green, 2024). For Europe, analytical work on exposure to generative AI similarly highlights heterogeneous risk profiles across workers and occupations, underscoring the need to examine distributional effects in addition to average outcomes (Nurski & Ruer, 2024).

Policy institutions in Europe and beyond are increasingly framing AI as both a competitiveness lever and a potential driver of labour-market adjustment pressures, which strengthens the practical relevance of empirically testing displacement. European Commission reporting continues to highlight persistent skills shortages as a barrier to investment and innovation, an environment in which AI adoption may accelerate the substitution of scarce tasks while also amplifying mismatches for workers whose skills are less transferable (European Commission, 2025). Forward-looking European skills analysis also models scenarios in which the faster deployment of automation and AI is associated with employment reductions relative to baseline projections, highlighting why governments are under pressure to pair AI diffusion with reskilling, active labour market policies, and transition support (Cedefop, 2025).

Against this backdrop, examining how AI vibrancy translates into labour-market outcomes is particularly timely. The central question is whether countries with more dynamic AI ecosystems experience systematically different unemployment patterns across education groups, which goes to the heart of current global and European debates on technology-driven displacement and inclusive growth. By explicitly testing education-specific unemployment responses to AI vibrancy in a cross-country panel setting, this article addresses a key distributional concern: whether the diffusion of AI is associated with job loss risks that are concentrated among particular skill groups or whether labour-market adjustments are more balanced than often assumed.

1. Literature review

The acceleration of AI diffusion has renewed long-standing debates about whether technological progress primarily creates new tasks and productivity gains or whether it displaces workers and amplifies labour-market insecurity. Contemporary discussions increasingly frame AI as an enabling general-purpose technology embedded in broader Industry 4.0 trajectories and organisational restructuring, implying that labour-market effects may materialise through changes in task composition, workflow redesign, and institutional choices rather than through a single “automation shock”. (Wang et al., 2025; Melnyk et al., 2025; Golubtsov et al., 2025). At the same time, the societal salience of AI is shaped by public perceptions, awareness, and ethical concerns, which can influence the speed of adoption and governance responses, and thereby indirectly affect employment dynamics. (Moravec et al., 2024; Yarovenko et al., 2024; Mujtaba, 2025).

A key implication of this landscape is that labour-market outcomes should be expected to differ across worker groups, particularly by education and skills. The readiness of workforces to integrate AI tools, the adequacy of skills for adoption, and the alignment of competencies with changing employer demands are repeatedly emphasised as central mechanisms governing whether AI augments productivity or generates displacement pressures. (Bîrcă, 2025; Istudor et al., 2024; Butum & Nicolescu, 2024). Evidence on public-sector employment also suggests that motivation, organisational context, and education-related differences in work practices can influence how technological tools are integrated into processes, which is relevant when analysing unemployment by educational attainment. (Davidov, 2024; Androniceanu, 2025; Bian & Wang, 2024).

A useful way to organise prior achievements is to distinguish between (i) macroeconomic and structural determinants of unemployment, (ii) firm- and sector-level digital transformation channels, and (iii) skills, institutional, and behavioural mediators that determine who benefits and who is exposed. Cross-country unemployment dynamics remain strongly connected to economic performance, productivity, and structural conditions, as demonstrated by empirical work linking employment to output and labour productivity within simultaneous systems, and by studies that relate unemployment to growth proxies, such as R&D spending. (Butkus et al., 2024; Gonos, 2024). Broader macro relationships, such as inflation–unemployment patterns, also remain relevant for interpreting education-specific unemployment in small open economies, particularly when shocks are present. (Senci & Afful, 2025). These contributions motivate the inclusion of controls that capture development and innovation capacity, and they highlight that “AI effects” may be confounded by macroeconomic conditions unless explicitly accounted for. (Butkus et al., 2024; Gonos, 2024; Senci & Afful, 2025).

Digital transformation provides additional channels that can reallocate labour demand across sectors and occupations. The efficiency gains from AI-enabled supply-chain management and industrial automation illustrate how adoption can change labour requirements in logistics, manufacturing, and service operations. (Golubtsov et al., 2025; Kajda & Karwot, 2025). Digital transformation in business process management is also associated with reconfigured tasks and the growing importance of employee engagement during process redesign, suggesting that job outcomes may reflect an organisation's capacity for change rather than AI alone. (Hernik et al., 2025; Vuong, 2025; Bilan et al., 2022; Vovk & Vovk, 2024). In customer-facing services, AI-driven support systems and automated feedback management demonstrate how routine interactions can be partially automated, potentially affecting mid-skill service employment while simultaneously creating new tasks in monitoring, quality assurance, and data interpretation. (Glos & Karwot, 2025; Kildei et al., 2025).

The strongest thread in the recent literature is that AI-related labour-market impacts are mediated by skills formation, competence adequacy, and education-specific employability. A recurring argument is that AI adoption increases the returns to adaptable competencies (digital, analytical, and "global" competencies), implying heterogeneous impacts across education groups depending on the match between worker attributes and evolving task requirements. (Bîrcă, 2025; Butum & Nicolescu, 2024; Istudor et al., 2024). In practice, education does not only proxy human capital stock; it also captures exposure to continuous learning, the capacity to use AI tools, and access to professional networks that facilitate job transitions. (Pisică & Zaharia, 2025; Mong & Thanh, 2024; Artyukhov et al., 2024; Skrynnyk et al., 2022).

The relevance of education is reinforced by evidence that institutional and policy contexts shape mobility outcomes, including brain drain dynamics linked to government AI readiness, which can alter the domestic skill composition and influence unemployment patterns for specific education tiers. (Iuga & Socol, 2024). Education and human capital should therefore be treated not only as controls but also as mechanisms through which AI ecosystems translate into labour market performance. The quality of higher education and its connection to the knowledge economy provide a structural channel through which more vibrant AI environments can be associated with differentiated job prospects across educational groups. (Lyeonov et al., 2025). Education also interacts with mobility and demographic adjustments, where migration and brain-drain dynamics reshape the domestic skill composition and can influence unemployment patterns by attainment level. (Iuga & Socol, 2024; Mukhtarova et al., 2024).

Beyond general skills, the literature highlights the importance of domain-specific transformations. In healthcare and life-science sectors, AI adoption is associated with innovation trajectories that can reshape professional roles, research pipelines, and complementary skill needs, implying possible employment reallocation within high-skill segments rather than simple job loss. (Kritikos et al., 2025; Tossekbayev et al., 2025). In creative industries, expert-based evidence suggests both opportunities and constraints, with AI affecting creative processes, market entry, and the structure of value creation, again pointing towards task redefinition rather than uniform displacement. (Schinello, 2025). These sectoral insights support the expectation that education-specific unemployment effects will depend on whether AI substitutes routine tasks, complements complex tasks, or expands demand through new products and services. (Kritikos et al., 2025; Schinello, 2025; Kajda & Karwot, 2025).

A second set of contributions focuses on AI in human resource management and workplace governance, which is directly relevant to unemployment because HR technologies influence recruitment, selection, performance monitoring, and retention. AI-driven HR practices are linked to employee engagement and well-being outcomes, suggesting that their adoption can improve job quality and reduce turnover, potentially affecting unemployment rates. (Gayathiri & Prabu, 2025; Vuong, 2025). Concerns are also raised that AI may become an "invisible dictator" if used for surveillance or opaque decision-making, which may intensify labour-market frictions for certain worker groups and reduce resilience during transitions. (Mura & Stehlíková, 2025a). Ethical frameworks emphasise safeguarding human dignity, social justice, and broader sustainability considerations, implying that labour-market outcomes will depend on governance choices and accountability structures. (Mura & Stehlíková, 2025b; Mujtaba, 2025).

Public-sector settings offer a complementary perspective, highlighting how AI affects formal procedures and service delivery while interacting with motivation and moral identity. Ethical decision-making and service motivation influence how AI tools are utilised in public employment contexts, potentially shaping the demand for specific competencies and the distribution of opportunities across educational levels. (Bian & Wang, 2024; Davidov, 2024; Androniceanu, 2025). In law enforcement and automated traffic enforcement, the use of AI raises concerns about equity and social justice, which can translate into regulatory constraints or accelerated adoption, affecting labour demand in compliance, oversight, and public administration roles (Haley & Burrell, 2025; Haley, 2025). Together, these strands reinforce the view that "AI vibrancy" captures not only technical capacity but also institutional capability to integrate AI into governance, and therefore may shape labour outcomes indirectly through the organisation of work (Androniceanu, 2025; Mura & Stehlíková, 2025a; Mujtaba, 2025).

The distributional dimension extends beyond education into gender, disability, and vulnerable groups, providing further reason to assess heterogeneous effects. AI and digital ecosystems are frequently analysed as potential enablers of women's entrepreneurship, including women-led start-ups, agriculture, and home-based entrepreneurship, suggesting that AI diffusion can expand labour-market participation and income opportunities in ways not captured by aggregate unemployment rates (Alateeg & Al-Ayed, 2024; Moutik, 2025; Harb et al., 2025). Digital entrepreneurial ecosystems in tourism are linked to social sustainability outcomes, illustrating how local economic structures can mediate the employment consequences of digital technologies (Khatami et al., 2024). However, digital harms and platform-driven socio-economic risks can also shape youth trajectories and labour-market vulnerability, which matters for unemployment dynamics over time (Agyare, 2025).

Disability-focused research highlights that employability is strongly influenced by education and social innovation, suggesting that technology-driven labour market changes may widen gaps unless supportive institutions are in place (Jarząbek & Stolarska-Szeląg, 2024; Ejdys et al., 2025). Evidence from informal and rural business contexts suggests that digital transformation can be constrained by capability gaps and local infrastructure, indicating that AI diffusion may reinforce dual labour markets, where gains accrue to better-connected segments (Mtengwane, 2024). These perspectives support a research design that examines unemployment separately by education group because education is a core axis along which inclusion and vulnerability often align (Ejdys et al., 2025; Mtengwane, 2024; Butum & Nicolescu, 2024).

A wider body of work positions AI and digitalisation within governance, integrity, and security domains, which can indirectly affect labour markets by shaping investment climates and the allocation of resources. Digitalisation is linked to the dynamics of the shadow economy and financial stability, implying that technology can alter compliance costs and formalisation incentives, with potential consequences for the composition of the labour market (Bozhenko et al., 2024). AI and machine learning are increasingly discussed as tools against illegal financial operations, highlighting that the diffusion of AI may create demand for specialised analytical roles while also altering employment in monitoring and compliance functions (Lyeonov et al., 2024). Digitalisation is also modelled as a socio-economic challenge connected to cybercrime, implying that expanding digital infrastructures can raise security risks that require labour resources in cybersecurity and governance (Yarovenko et al., 2025). Innovation and technology are also positioned as determinants of transparency and corruption reduction, highlighting the institutional channels through which digital ecosystems can shape labour market performance (Yefimenko et al., 2025; Lama et al., 2025).

Sector-specific applications further illustrate that AI adoption affects job content and safety requirements. AI-based occupational safety monitoring in construction can change compliance practices and safety management roles, again implying task reconfiguration rather than direct job elimination (Zaryczańska & Karwot, 2025). Similarly, AI-driven optimization of transport infrastructure - such as electric vehicle charging systems on international corridors - demonstrates how digital innovation reshapes occupational roles in logistics and energy management while creating new demand for monitoring, quality assurance, and data-driven decision-making (Vovk et al., 2025). In energy systems, AI is analysed as a lever for equity outcomes, suggesting that AI diffusion can have social-policy implications that feed back into employment and skills demand via the energy transition (Kirichok et al., 2025). In telecommunications and SME settings, ICT investment and digital transformation are associated with organisational change and stratification, indicating that technology can reshape competitive dynamics and employment structures (Sahnouni & Kadri, 2025; Sartamorn et al., 2025).

Despite the breadth of recent research, a clear gap remains in connecting *national AI ecosystem intensity* to *education-specific unemployment* in a unified empirical framework. Much of the evidence base focuses either on organisational adoption, ethics, and HR processes, or on sectoral and governance applications, often without translating these mechanisms into testable cross-country labour market hypotheses. (Mura & Stehlíková, 2025a; Hernik et al., 2025; Haley & Burrell, 2025). Macro studies of unemployment and employment dynamics typically use proxies for growth, productivity, remittances, or R&D, and rarely incorporate a direct measure of AI ecosystem vibrancy, even though technology diffusion is central to the underlying theoretical narratives. (Butkus et al., 2024; Gonos, 2024; Peković, 2025). At the same time, the skills literature provides strong reasons to expect heterogeneous impacts across education groups. However, comparative evidence remains limited on whether AI ecosystem strength is associated with displacement-type unemployment patterns or with neutral/beneficial outcomes once macro controls are included. (Istudor et al., 2024; Bîrcă, 2025; Iuga & Socol, 2024; Skypalova et al., 2025).

Prior scientific achievements jointly suggest that AI can reshape work through productivity, organisational change, skills demand, and governance, but they also imply substantial heterogeneity by education, sector, and institutional context. (Wang et al., 2025; Melnyk et al., 2025; Mujtaba, 2025). This motivates an empirical test that operationalises AI diffusion via a national vibrancy indicator and evaluates whether unemployment responses differ systematically across basic, intermediate, and advanced education groups. (Stanford University, n.d.; World Bank, n.d.). The present study addresses this gap by aligning cross-country panel estimation with an education-stratified unemployment lens, thereby directly engaging the displacement question that remains unresolved in the current landscape.

The study aims to assess whether national AI vibrancy is associated with higher unemployment rates across educational groups in a multi-country panel covering the period from 2017 to 2023. The analysis focuses on unemployment among individuals with advanced, intermediate, and basic education, and controls for economic development (GDP per capita), innovation and export capacity (high-technology exports), and labour-market conditions (employment-to-population ratio and sectoral employment shares). The modelling strategy combines panel estimators that separate within-country dynamics from cross-country differences and applies dependence-robust inference to ensure that conclusions are not driven by unobserved heterogeneity or correlated shocks.

From a displacement-oriented perspective, the article tests hypotheses that emphasise the labour-substituting potential of AI. First, higher AI vibrancy is hypothesised to be associated with higher unemployment among individuals with advanced education, reflecting the diffusion of AI into analytical and professional tasks and the potential restructuring of high-skilled occupations. Second, higher AI vibrancy is expected to be associated with higher unemployment among individuals with intermediate education, consistent with the automation of routine cognitive tasks and organisational reallocation. Third, higher AI vibrancy is also hypothesised to be associated with higher unemployment among individuals with basic education, as low-skilled workers may face heightened exposure to substitution and weaker access to reskilling pathways.

2. Methodological approach

Data sources, sample and panel structure

The empirical analysis relies on a multi-country panel dataset covering 2017–2023. The core explanatory variable, AI vibrancy (x1), is derived from the Global AI Vibrancy Tool, maintained by Stanford University's Human-Centred Artificial Intelligence programme (Stanford University, n.d.). Macroeconomic conditions, innovation and trade proxies, labour-market structure indicators, and education-specific unemployment measures are drawn from World Bank Open Data (World Bank, n.d.). The resulting dataset forms an unbalanced country–year panel, reflecting that some indicators are not available for all countries in all years. The unbalanced structure is retained to avoid unnecessary loss of information and to preserve cross-country coverage.

Variables and measurement

Table 1 summarises all variables, their descriptions, and sources. The analysis examines whether national AI vibrancy is associated with unemployment rates differentiated by educational attainment. Three dependent variables are analysed separately: unemployment among individuals with advanced education (y1), basic education (y2), and intermediate education (y3), each measured as a percentage of the respective labour force category. The main regressor of interest is the AI Vibrancy Score (x1), which captures the overall intensity of national AI ecosystems. To mitigate omitted-variable bias, the model includes standard macro and labour-market controls: GDP per capita (x2) to proxy economic development, high-technology exports (x3) to reflect innovation/trade capacity, the employment-to-population ratio (x4) as a broad indicator of labour-market absorption, and the sectoral employment shares in industry (x5) and services (x6) to capture structural differences in the composition of employment.

Table 1. Definitions and sources of variables used in the empirical analysis

Variable	Definition	Source
x1	Vibrancy Score	Stanford University, n.d.
x2	GDP per capita (constant 2015 US$)	World Bank, n.d.
x3	High-technology exports (current US$)	World Bank, n.d.
x4	Employment to population ratio, 15+, total (%) (modeled ILO estimate)	World Bank, n.d.
x5	Employment in industry (% of total employment) (modeled ILO estimate)	World Bank, n.d.
x6	Employment in services (% of total employment) (modeled ILO estimate)	World Bank, n.d.
y1	Unemployment with advanced education (% of total labour force with advanced education)	World Bank, n.d.
y2	Unemployment with basic education (% of total labour force with basic education)	World Bank, n.d.
y3	Unemployment with intermediate education (% of total labour force with intermediate education)	World Bank, n.d.

The final sample of country–year observations is determined by data availability, primarily for the Global AI Vibrancy Tool maintained by Stanford University's Human-Centred Artificial Intelligence programme (Stanford University, n.d.), and the set of countries included in each empirical specification is reported in Appendix A.

Transformation and preprocessing

Several variables exhibit substantial right-skewness and scale heterogeneity, particularly the AI vibrancy score and monetary indicators. To improve distributional properties, reduce the influence of extreme observations, and stabilise variance, Box–Cox diagnostics were used for strictly positive variables. The estimated parameters implied log-type transformations for AI vibrancy (x1), GDP per capita (x2), and high-technology exports (x3) (λ close to zero), and these variables were therefore modelled using natural logarithms. For the basic-education unemployment specification, Box–Cox diagnostics likewise supported a logarithmic transformation of y2, leading to models with ln(y2) as the dependent variable where appropriate. For intermediate-education unemployment, the dependent variable displayed heavier tails, and the Box–Cox estimate for y3 suggested a stronger power transformation (λ noticeably below zero); accordingly, y3 was transformed using the Box–Cox function to enhance model adequacy. In contrast, the labour-structure indicators (x4–x6) were retained in their original percentage units to preserve interpretability, as bounded shares/ratios are less suitable for generic power transformations.

Econometric specification

The relationship between AI vibrancy and unemployment is estimated using standard panel-data models. For each education group, the baseline specification can be expressed as:

$$Y_{it} = \beta_1 \ln(x1_{it}) + \beta_2 \ln(x2_{it}) + \beta_3 \ln(x3_{it}) + \beta_4 x4_{it} + \beta_5 x5_{it} + \beta_6 x6_{it} + \mu_i + \tau_i + \varepsilon_{it}$$

where i indexes countries and t indexes years, μ_i denotes country effects capturing time-invariant heterogeneity (e.g., institutions, geography, persistent labour-market features), and τ_i denotes time effects capturing common shocks (e.g., global economic conditions). The model is estimated using both two-way fixed effects (FE) and two-way random effects (RE) to distinguish within-country relationships from results that also reflect between-country differences. The choice between FE and RE is guided by the Hausman test, which evaluates whether the RE assumption of no correlation between country effects and regressors is tenable for each dependent variable.

Robust inference and sensitivity checks

Because macro panels often exhibit heteroskedasticity, serial correlation, and cross-sectional dependence, statistical inference is strengthened by using alternative variance–covariance estimators. Results are assessed using (i) cluster-robust standard errors by country, (ii) cluster-robust standard errors by time, and (iii) Driscoll–Kraay standard errors, which are robust to general forms of cross-sectional dependence and serial correlation. Comparing coefficient stability, especially for β_1, regarding AI vibrancy across these approaches, the study enables an evaluation of whether conclusions are sensitive to the assumed error structure.

3. Conducting research and results

AI Vibracy vs Unemployment with advanced education

The descriptive statistics (Table B1, Appendix B) reflect a country–year panel with 229 usable observations (after cleaning/listwise deletion). The panel covers 35 countries (coded 1–35) from 2017 to 2023 (range = 6 years; mean year ≈ 2020), but it is not fully balanced, as 35 × 7 would imply 245 observations.

AI Vibrancy (x1) remains the most distributionally challenging variable, although the extremity is much lower in the dataset. The mean is 13.44, while the median is 11.78, and the trimmed mean is 12.35, indicating that higher values still pull the arithmetic average upward. This pattern is consistent with the relatively large maximum (48.19) and the positive skewness

(1.20), while kurtosis (1.72) suggests heavier tails than a normal distribution, but not extreme behaviour. In practical terms, x1 is still right-skewed, so modelling it in levels may inflate the influence of high-vibrancy observations; a logarithmic (Box–Cox–guided) transformation is therefore advisable to stabilise the relationship and reduce sensitivity to upper-tail values.

The remaining covariates look more typical for cross-country macro-labour data. GDP per capita (x2) varies widely (≈ US$1,800 to US$110,400) with moderate right skewness, while high-technology exports (x3) are strongly right-tailed (median far below the mean), which is expected for trade variables. Labour-structure indicators are comparatively stable: the employment-to-population ratio (x4) is close to symmetric, while services employment (x6) is left-skewed (many highly service-based economies and a smaller group with much lower service shares). The outcome, unemployment among those with advanced education (y1), is right-skewed (max 17.91%), implying that most observations have relatively low values, but a subset experiences pronounced high-skilled unemployment.

Given the pronounced right skewness in the AI vibrancy score and the monetary variables, Box–Cox diagnostics were employed. The estimated transformation parameters were close to zero ($\lambda\_x1 = 0.098$, $\lambda\_x2 = 0.085$, $\lambda\_x3 = -0.074$), indicating that a logarithmic specification is appropriate. Therefore, the analysis employs ln(x1), ln(x2), and ln(x3) to reduce skewness and stabilise variance.

The two-way FE model (Table 2) exploits within-country variation over time while controlling for unobserved, time-invariant country characteristics and common year shocks. In this updated specification, the log-transformed innovation-income block, AI vibrancy (lx1), GDP per capita (lx2) and high-technology exports (lx3), shows no statistically significant association with unemployment among the highly educated (y1). The estimated coefficients are statistically indistinguishable from zero: lx1 ($\beta = -0.099$, $p = 0.539$), lx2 ($\beta = -1.692$, $p = 0.238$) and lx3 ($\beta = -0.001$, $p = 0.998$).

Table 2. Panel regression results: determinants of unemployment with advanced education (y1), 35 countries, 2017–2023 (unbalanced)

Model information	Two-way FE (Within)				Two-way RE (Walhus)			
Countries (n)	35				35			
Time periods (T)	4–7				4–7			
Observations (N)	229				229			
R^2	0.3981				0.6982			
Adjusted R^2	0.246				0.6801			
Joint significance	$F(6,182)=20.0651$, $p<0.001$				$\chi^2(6)=81.153$, $p<0.001$			
Residual SS	60.221				755.180			
Variables	Coef.	Std. Error	t-stat	p-value	Coef.	Std. Error	z-stat	p-value
ln(AI Vibrancy) (lx1)	-0.0991	0.16095	-0.616	0.539	0.1200	0.244704	0.4905	0.6238
ln(GDP per capita) (lx2)	-1.6918	1.4282	-1.185	0.238	0.4286	0.845505	0.5069	0.6122
ln(High-tech exports) (lx3)	-0.0006	0.2275	-0.003	0.998	-0.3763.	0.203385	-1.8499	0.0643
Employment-to-population ratio (x4)	-0.3542***	0.0472	-7.511	<0.001	-0.2762***	0.050273	-5.4933	<0.001
Employment in industry (%)(x5)	-0.2041*	0.0779	-2.618	0.01	-0.2133*	0.092962	-2.2948	0.0218
Employment in services (%)(x6)	-0.2872***	0.069	-4.165	<0.001	-0.2488**	0.078147	-3.1834	0.0015
Constant	–	–	–	–	47.9027***	7.2384	6.6178	<0.001

*Notes: Two-way FE includes both country and year effects; coefficients reported are unstandardised. "–" – not calculated. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10. Hausman test (FE vs RE): $\chi^2(6) = 21.505$, p = 0.0015 → prefer FE (RE inconsistent).*

Source: *authors' calculations in R Studio*.

This implies that short-run within-country changes in AI vibrancy and broader macro-innovation capacity do not systematically translate into changes in advanced-education unemployment once two-way unobservables are accounted for. By contrast, labour-market structure variables are consistently negative and statistically significant: a higher employment-to-population ratio is strongly associated with lower high-skilled unemployment (x4: $\beta = -0.354$, $p < 0.001$), as are higher employment shares in industry (x5: $\beta = -0.204$, $p = 0.010$) and services (x6: $\beta = -0.287$, $p < 0.001$). The FE model is jointly significant ($F(6,182) = 20.065$, $p < 0.001$) with $R^2 = 0.398$ (adjusted $R^2 = 0.246$), indicating that a meaningful portion of within-panel variation is explained, primarily through labour-market absorption and sectoral structure.

The two-way RE model (Table 2), estimated via the Wallace–Hussain transformation, yields a broadly similar conclusion regarding AI vibrancy: lx1 remains statistically insignificant ($\beta = 0.120$, $p = 0.624$), and GDP per capita is also insignificant ($\beta = 0.429$, $p = 0.612$). High-technology exports (lx3) become marginally significant and negative ($\beta = -0.376$, $p = 0.064$), suggesting that economies with stronger high-tech export capacity tend to have lower unemployment among the advanced educated when both cross-country and time variation are utilised. Labour-market structure variables remain negative and significant in the RE model as well (x4: $p < 0.001$; x5: $p = 0.0218$; x6: $p = 0.0015$), reinforcing their central role. Crucially, the Hausman test rejects the RE orthogonality assumption ($\chi^2(6) = 21.505$, $p = 0.0015$), indicating that the RE estimator is inconsistent in this setting; therefore, the FE results should be treated as the baseline for inference. Taken together, the updated estimates confirm that AI vibrancy does not exhibit a robust relationship with high-skilled unemployment once unobserved heterogeneity is controlled. In contrast, labour-market participation and sectoral employment structure display stable and economically meaningful associations with lower unemployment among the highly educated.

The robustness checks (Table 3) confirm that the substantive conclusion from the two-way FE model is stable once inference is corrected for different forms of dependence, and, crucially, they reinforce that AI vibrancy does not exhibit a statistically detectable effect on unemployment among people with advanced education in the within-country (FE) framework.

Across all three variance–covariance estimators–clustered by country (“group”), clustered by time, and Driscoll–Kraay (maxlag = 2)–the coefficient on ln(AI Vibrancy) remains essentially zero and highly insignificant. The point estimate is identical in all cases ($\beta = -0.0991$), and the associated p-values are very large ($p \approx 0.49$ with country-clustered SE; $p \approx 0.54$ with time-clustered SE; $p \approx 0.47$ with Driscoll–Kraay). Interpreting the magnitude, because the regressor is in logs and the dependent variable is measured in percentage points, a 1% increase in AI vibrancy is associated with only −0.099 percentage points change in advanced-education unemployment, which is economically negligible. Therefore, within a country over 2017–2023, improvements in AI vibrancy–after controlling for GDP per capita, high-tech exports, and labour-structure indicators and absorbing both country and year effects–do not appear to reduce (or increase) high-skilled unemployment systematically.

In contrast, the labour-market structure variables remain the most consistent and statistically robust correlates of advanced-education unemployment in the estimates, indicating that within-country variation in this outcome is explained primarily by conventional labour-market conditions rather than by AI vibrancy or the macro-innovation proxies. The employment-to-population ratio (x4) is strongly negative and highly significant across all robust inference approaches (country-clustered: $p = 0.00028$; time-clustered: $p < 0.001$; Driscoll–Kraay: $p < 0.001$), implying that stronger labour-market absorption is systematically associated with lower unemployment among the highly educated. Sectoral composition also matters: employment in services (x6) remains negative and significant under time clustering and Driscoll–Kraay corrections (both $p < 0.001$), while employment in industry (x5) is negative and significant across all three approaches (country-clustered: p = 0.0377; time-clustered: p = 0.0311; Driscoll–Kraay: p = 0.00152). By contrast, the AI vibrancy coefficient (lx1) remains statistically insignificant under country clustering (p = 0.494), time clustering (p = 0.544) and Driscoll–Kraay inference (p = 0.468). The persistence of this insignificance under Driscoll–Kraay standard errors—which explicitly address heteroskedasticity, serial correlation and cross-sectional dependence—suggests that the null finding is unlikely to be an artefact of misspecified standard errors and instead reflects a weak within-country linkage between changes in AI vibrancy and advanced-education unemployment over the sample period.

Table 3. Two-way fixed-effects estimates with alternative robust standard errors (dependent variable: unemployment with advanced education, y1)

Variable	Coef. (FE)	SE (Cluster: country)	p-value	SE (Cluster: time)	p-value	SE (Driscoll–Kraay, lag=2)	p-value
ln(AI Vibrancy) (lx1)	-0.09910	0.14465	0.49415	0.16294	0.54382	0.13626	0.46800
ln(GDP per capita) (lx2)	-1.69179	2.36268	0.47488	1.49766	0.26012	1.18796	0.15613
ln(High-tech exports) (lx3)	0.00057	0.26028	0.99826	0.16329	0.99723	0.14858	0.99696
Employment-to-population ratio (x4)	-0.35415***	0.09551	0.00028	0.03275	<0.001	0.03261	<0.001
Employment in industry (%) (x5)	-0.20407*	0.09748	0.03769	0.09394	0.03112	0.06338	0.00152**
Employment in services (%) (x6)	-0.28723**	0.08690	0.00114	0.04387	<0.001	0.02371	<0.001

*Notes: Model – Two-way FE (country and year effects), N = 229, n = 35, T = 4–7; Regressors are ln(AI Vibrancy), ln(GDP per capita), ln(High-tech exports), employment ratio, industry share, services share The coefficient estimates are identical across columns because only the variance–covariance estimator changes. Significance levels refer to the reported p-values in each column: *** p < 0.001, ** p < 0.01, * p < 0.05. p < 0.10. The dependent variable y1 is measured in percentage points; lx1–lx3 are natural logarithms.*

Source: *authors' calculations in R Studio*.

Regardless of whether errors are clustered by country, by year, or corrected using Driscoll–Kraay, AI vibrancy remains statistically insignificant and economically negligible in explaining within-country changes in unemployment among those with advanced education from 2017 to 2023.

AI Vibracy vs Unemployment with basic education

The descriptive statistics (Table B2, Appendix B) indicate an unbalanced country–year panel with 225 observations. The sample spans roughly 2017–2023 (a 6-year range), with the mean year close to 2020, indicating that most observations fall within the most recent pre- and post-pandemic period. The country identifier suggests around 34–35 countries are included (min = 1, max = 34), although the unbalanced structure implies that not every country is observed in every year.

Regarding the main variables, GDP per capita (x2) averages approximately US$40,686 (in constant 2015 prices), but with a wide dispersion (SD ≈ US$25,206) and a large range (US$1,806 to US$110,426). The positive skewness (0.64) indicates that a small group of high-income economies pulls the mean upward. At the same time, the median (≈ US$42,216) suggests that many observations are concentrated in the upper-middle and high-income range. High-technology exports (x3) show even stronger right-skewness (skewness = 1.60): the median (US$19.28 bn) is far below the mean (US$46.74 bn), reflecting the fact that only a limited number of economies dominate high-tech exports. In contrast, many others export relatively modest volumes. Labour-market structure variables appear comparatively stable: the employment-to-population ratio (x4) averages 58.31% (range 36.8–77.6), while employment shares in industry (x5) and services (x6) average 21.7% and 72.8%, respectively. The service share is strongly left-skewed (−1.76), which is typical in cross-country samples because many advanced economies tend to cluster at high levels of service employment. In contrast, a smaller group retains much lower service-sector shares.

The outcome variable, unemployment among people with basic education (y2), averages 10.28%, but the median is lower (8.73%), and the distribution is clearly right-skewed (1.92) with high kurtosis (5.09). This implies that, in most country–years, basic-education unemployment is moderate, but there are episodes of very high unemployment (reaching a maximum of 40.74%) that generate a heavy upper tail. The gap between the mean (10.28) and trimmed mean (9.31) further confirms that extreme observations increase the average. Substantively, this pattern is consistent with the expectation that low-skilled labour markets are more vulnerable to shocks and structural rigidities, producing occasional but pronounced unemployment spikes in some economies.

To address non-normality, scale heterogeneity, and the presence of extreme values in the key explanatory variables, Box–Cox diagnostics were applied to the strictly positive series. The estimated transformation parameters were close to zero for AI vibrancy (x1; $\lambda = 0.097$), GDP per capita (x2; $\lambda = 0.081$), high-technology exports (x3; $\lambda = -0.075$), and unemployment with basic education (y2; $\lambda = 0.032$), indicating that a logarithmic functional form provides an appropriate approximation. Accordingly, the empirical models use natural logarithms of these variables (lnx1, lnx2, lnx3, and, where relevant, lny2) to reduce right-skewness, stabilise variance, and mitigate undue leverage from outliers. By contrast, the labour-market structure indicators, employment-to-population ratio (x4) and sectoral employment shares in industry (x5) and services (x6), were retained in their original percentage units to preserve interpretability and because their bounded nature makes power transformations less suitable.

The results for the basic-education unemployment model (Table 4), where the dependent variable is ln(y2), provide a consistent message across both estimators: AI vibrancy does not have a statistically detectable effect on unemployment among people with basic education. In the two-way random-effects (RE) specification, the coefficient on ln(AI vibrancy) is essentially zero ($\beta = 0.00449$, $p = 0.986$), indicating no systematic association once GDP per capita, high-tech exports and labour-market controls are included. The variance decomposition further reveals that outcome differences are primarily driven by persistent country-specific heterogeneity (individual share ≈ 0.913), while time effects are relatively small (≈ 0.007). This means that cross-country structural differences explain most of the variation in low-skilled unemployment; yet, even when those differences are incorporated via RE, AI vibrancy remains non-influential. Importantly, the overall RE model is not jointly significant (χ^2 $p = 0.967$), reinforcing that the regressors as a set do not explain ln(y2) well under the RE assumptions.

In the two-way FE model, which relies solely on within-country changes over time while controlling for both country and year effects, the conclusion regarding AI vibrancy remains unchanged. The coefficient on ln(AI vibrancy) remains small and statistically insignificant ($\beta = 0.0136$, $p = 0.782$). Interpreting magnitude in log–log terms, a 1% increase in AI vibrancy is associated with only about a 0.014% change in basic-education unemployment, and the estimate is far from significant. By contrast, within-country improvements in high-technology exports and overall employment conditions show meaningful associations: ln(high-tech exports) is negative and highly significant (β = −0.330, $p < 0.001$), and the employment-to-population ratio (x4) is also negative and significant (β = −0.0430, $p = 0.003$). These findings suggest that the factors most closely linked to reductions in low-skilled unemployment over time are stronger labour market absorption and export upgrading, rather than changes in the AI vibrancy score itself. The Hausman test ($p = 0.995$) indicates no evidence of systematic differences between FE and RE coefficients, implying that RE is not inconsistent in this specification; however, since the RE model lacks joint significance while FE is jointly significant (F-test $p < 0.001$), the FE results provide a clearer inferential benchmark.

Table 4. Panel regression results for unemployment with basic education (dependent variable: ln(y2))

Model information	Two-way FE (Within)				Two-way RE (Walhus)			
Countries (n)				34				34
Time periods (T)				4–7				4–7
Observations (N)				225				225
R^2				0.1470				0.2616
Adjusted R^2				-0.0674				0.2412
Joint significance				$F(6,179)=5.143$, $p<0.001$				$\chi^2(6)=1.377$, $p=0.967$
RSS				5.4039				89.334
Variables	Coef.	Std. Error	t-stat	p-value	Coef.	Std. Error	z-stat	p-value
ln(AI Vibrancy) (lx1)	0.0136	0.0490	0.277	0.782	0.0045	0.2523	0.018	0.986
ln(GDP per capita) (lx2)	0.0325	0.4335	0.075	0.940	0.0505	0.9917	0.051	0.959
ln(High-tech exports) (lx3)	-0.3295***	0.0688	-4.788	<0.001	-0.1545	0.2432	-0.635	0.525
Employment-to-population ratio (x4)	-0.0430**	0.0144	-2.984	0.003	-0.0547	0.0577	-0.949	0.343
Employment in industry (%) (x5)	0.0125	0.0236	0.531	0.596	-0.0000	0.1050	-0.000	1.000
Employment in services (%) (x6)	0.0210	0.0209	1.004	0.317	0.0199	0.0893	0.223	0.824
Constant	–	–	–	–	6.9302	8.7730	0.790	0.430

*Notes: Dependent variable – ln(Unemployment with basic education, % of labour force with basic education); Panel – 34 countries, 2017–2023 (unbalanced), N = 225, T = 4–7; Two-way FE includes both country and year effects. Significance levels: *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Coefficients for lx1–lx3 are interpreted as elasticities because both the dependent variable and these regressors are in natural logarithms. Hausman test (FE vs RE): $\chi^2(6) = 0.6639$, $p = 0.995$ → no evidence against RE consistency.*

Source*: authors' calculations in R Studio.*

The robustness checks (Tables 5 and 6) for the basic-education unemployment model (dependent variable: ln(y2)) confirm that the central finding is stable: AI vibrancy does not exhibit a statistically significant relationship with unemployment among people with basic education, regardless of how standard errors are corrected for panel dependence. In the two-way fixed-effects specification, the coefficient on ln(AI vibrancy) is positive but very small (β = 0.0136). It remains clearly insignificant under country-clustered SE ($p = 0.830$), time-clustered SE ($p = 0.813$), and Driscoll–Kraay SE ($p = 0.819$). In elasticity terms, this coefficient implies that a 1% increase in AI vibrancy would be associated with only about a 0.014% change in basic-education unemployment, and the consistently large p-values indicate that even this small effect cannot be distinguished from zero. GDP per capita (lx2) is similarly insignificant across all robust inference strategies, suggesting that short-run within-country income changes do not systematically translate into changes in basic education unemployment once two-way fixed effects are controlled for.

By contrast, other covariates demonstrate robust and economically meaningful associations with ln(y2). High-technology exports (lx3) are negative and statistically significant in the FE model across all robust SE choices, with significance strengthening under Driscoll–Kraay ($p < 0.001$). This points to a consistent within-country pattern: when a country's high-tech export performance rises, unemployment among the basic-educated tends to fall, potentially reflecting stronger labour demand generated by export upgrading and related spillovers.

The employment-to-population ratio (x4) is also negative and strongly significant in all FE robust specifications, indicating that broader improvements in labour-market absorption coincide with lower unemployment among the low-skilled. The services employment share (x6) is sensitive to the choice of standard errors: it is insignificant under country clustering, marginal under time clustering ($p \approx 0.062$), and becomes significant under the Driscoll–Kraay method ($p = 0.0098$), implying that its effect is less stable than that of x4 and lx3. The RE model delivers the same message for AI vibrancy, lx1 remains insignificant under both clustering schemes ($p \approx 0.97$ with country clustering; $p \approx 0.91$ with time clustering), while the significance of lx3 and x6 depends more strongly on the clustering dimension (becoming significant under time clustering). The evidence consistently suggests that AI vibrancy is not a significant driver of unemployment in basic education within this sample. In contrast, labour-market absorption (x4) and export upgrading (lx3) play a more prominent role.

Table 5. Robust inference for the basic-education unemployment model (dependent variable: ln(y2))

Variable	Coef.	SE (Cluster: country)	p-value	SE (Cluster: time)	p-value	SE (Driscoll–Kraay)	p-value
ln(AI Vibrancy) (lx1)	0.0136	0.0629	0.8296	0.0572	0.8126	0.0590	0.8185
ln(GDP per capita) (lx2)	0.0325	0.4879	0.9469	0.4797	0.9461	0.4097	0.9368
ln(High-tech exports) (lx3)	-0.3295	0.1551	0.0350*	0.1367	0.0169*	0.0938	0.0006***
Employment-to-population ratio (x4)	-0.0430	0.0163	0.0089**	0.0102	<0.001***	0.0080	<0.001***
Employment in industry (%) (x5)	0.0125	0.0218	0.5669	0.0160	0.4359	0.0111	0.2617
Employment in services (%) (x6)	0.0210	0.0207	0.3122	0.0111	0.0616.	0.0080	0.0098**

*Notes: FE estimates include country and year effects (two-way fixed effects). DK standard errors account for heteroskedasticity, serial correlation, and cross-sectional dependence. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10.*

Source: *authors' calculations in R Studio.*

Table 6. Two-way RE (Walhus) with clustered standard errors

Variable	Coef.	SE (Cluster: country)	p-value	SE (Cluster: time)	p-value
Constant	6.9302	2.2763	0.0026**	1.1448	<0.001***
ln(AI Vibrancy) (lx1)	0.0045	0.1369	0.9739	0.0419	0.9148
ln(GDP per capita) (lx2)	0.0505	0.2036	0.8042	0.1078	0.6399
ln(High-tech exports) (lx3)	-0.1545	0.1006	0.1262	0.0587	0.0091**
Employment-to-population ratio (x4)	-0.0547	0.0188	0.0039**	0.0057	<0.001***
Employment in industry (%) (x5)	-0.0000	0.0290	0.9989	0.0087	0.9962
Employment in services (%) (x6)	0.0199	0.0188	0.2893	0.0044	<0.001***

Notes: RE estimates include country and year effects (two-way fixed effects). Standard errors account for heteroskedasticity, serial correlation, and cross-sectional dependence.
*Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10.*
Source*: authors' calculations in R Studio.*

The coefficient on lx1 is consistently insignificant across all specifications, supporting the conclusion that AI vibrancy has no robust association with basic-education unemployment in the sample.

AI Vibracy vs Unemployment with intermediate education

The descriptive statistics for data6 indicate an unbalanced country–year panel with 229 observations covering 35 countries from 2017 to 2023 (T = 4-7; mean year ≈ 2020). This period encompasses both pre-pandemic and post-pandemic labour market adjustments, which are relevant for interpreting unemployment dynamics by education level.

The key explanatory variable, AI vibrancy (x1), remains clearly right-skewed, although extreme outliers no longer characterise it. The mean is 13.44, while the median is 11.78 and the trimmed mean is 12.35, indicating that higher values still pull the arithmetic mean upwards. This is confirmed by a positive skewness of 1.20 and kurtosis of 1.72, alongside a maximum of 48.19 (minimum 0.34), implying moderate tail heaviness and meaningful scale heterogeneity rather than severe anomalies. These distributional features still justify a log/Box–Cox-type transformation to stabilise variance and reduce sensitivity to upper-tail observations. GDP per capita (x2) averages approximately US$40,598, with substantial dispersion (SD ≈ US$24,993) and moderate right skewness (0.65), reflecting a sample that includes both middle-income and advanced economies. High-technology exports (x3) are strongly concentrated: the mean is US$47.77 bn, but the median is only US$19.97 bn, with pronounced right skewness (1.54) and a large upper bound (US$260.0 bn), consistent with high-tech export capacity being dominated by a smaller subset of countries.

Labour-market structure indicators are comparatively stable. The employment-to-population ratio (x4) averages 58.33% (range 36.80–77.61) and is close to symmetric (skewness −0.13). The employment shares in industry (x5) and services (x6) average 21.74% and 72.76%, respectively. Services employment exhibits strong left skewness (−1.77) and elevated kurtosis (4.98), indicating that many observations cluster at high service-sector shares while a smaller subset of countries maintains much lower service employment. The dependent variable, intermediate-education unemployment (y3), averages 7.06%, but the median is lower (5.26%), and the distribution is highly right-skewed (skewness 3.01) with very heavy tails (kurtosis 10.85). The wide range (1.02–35.34%) and the gap between the mean (7.06) and trimmed mean (6.01) indicate that unemployment among the intermediate educated is usually moderate but occasionally spikes sharply in particular country-years, reinforcing the need for transformation and robust inference in the econometric analysis.

To mitigate non-normality, scale heterogeneity, and the influence of extreme observations, Box–Cox diagnostics were applied to the strictly positive variables used in the intermediate-education unemployment specification. The estimated parameters indicated log-type transformations for the main macro and technology proxies, AI vibrancy (x1; $\lambda = 0.099$), GDP per capita (x2; $\lambda = 0.085$), and high-technology exports (x3; $\lambda = -0.074$), as these values are close to zero; therefore, the analysis employs natural logarithms for x1–x3. In contrast, the dependent variable unemployment with intermediate education (y3) exhibited a stronger departure from lognormality, with a Box–Cox estimate of $\lambda = -0.411$, implying that a more pronounced power transformation is preferable. Accordingly, y3 was transformed using the Box–Cox function with the estimated λ to stabilise variance and improve distributional properties. The labour-market structure controls, employment-to-population ratio (x4) and sectoral employment shares in industry (x5) and services (x6), were retained in percentage units to preserve interpretability, as their bounded nature makes power transformations less suitable.

The two-way FE (Table 7) model examines whether within-country changes in AI vibrancy are linked to changes in unemployment among individuals with intermediate education, while controlling for unobserved country characteristics and common year shocks. The estimated coefficient on ln(AI vibrancy) (lx1) is negative but statistically insignificant ($\beta = -0.0102$, $p = 0.502$). This suggests that, after accounting for country and time effects, shifts in AI vibrancy do not systematically translate into lower unemployment rates among individuals with intermediate education during the sample period. Substantively, the magnitude is small: a 1% increase in AI vibrancy is associated with only a −0.00010 change in the Box-Cox-transformed unemployment outcome ($\approx -0.0102/100$), which is negligible and not distinguishable from zero. The same applies to GDP per capita (lx2), which is also insignificant, suggesting that short-run within-country income improvements are not directly linked to intermediate-education unemployment after controlling for fixed effects and other labour-market factors.

By contrast, the FE model identifies other drivers that are more relevant than AI vibrancy for intermediate-education unemployment. High-technology exports (lx3) show a negative and significant association ($\beta = -0.0810$, $p = 0.014$), implying that within-country improvements in high-tech export capacity coincide with reductions in intermediate-education unemployment (in the transformed scale). Similarly, the employment-to-population ratio (x4) is negative and significant ($\beta = -0.0148$, $p = 0.030$), consistent with the expectation that broader labour-market absorption reduces unemployment pressures across education groups. The industry employment share (x5) is weakly significant at the 10% level ($\beta = 0.0200$, $p = 0.070$), while the services share (x6) is not significant. Although the FE model is jointly significant (F-test $p = 0.027$), its explanatory power is modest ($R^2 = 0.075$), indicating that much of the within-country variation in intermediate-education unemployment remains driven by factors not captured by the included regressors.

The two-way RE (Table 7) model yields an even clearer message regarding AI vibrancy: lx1 remains insignificant ($\beta = -0.0105$, $p = 0.951$), and none of the regressors are individually significant. In addition, the joint test is not significant (χ^2 $p = 0.998$), implying limited explanatory content under the RE structure. The variance decomposition reveals that most variance is attributable to country-specific effects (share ≈ 0.727), indicating that persistent cross-country differences have a significant influence on the outcome. Importantly, the Hausman test strongly fails to reject the RE specification ($p \approx 0.9999$), implying no detectable systematic difference between FE and RE coefficients in this model. Nevertheless, because FE directly targets within-country identification and provides statistically meaningful associations for lx3 and x4, it remains the more informative specification for inference. The evidence suggests that AI vibrancy is not a robust determinant of unemployment among individuals with intermediate education. In contrast, export upgrading and general labour market absorption appear more closely linked to changes in unemployment for this education group.

Table 7. Panel regression results for intermediate-education unemployment (dependent variable: Box–Cox transformed y3)

Model information	Two-way FE (Within)				Two-way RE (Walhus)			
Countries (n)				35				35
Time periods (T)				4–7				4–7
Observations (N)				229				229
R^2				0.0761				0.5391
Adjusted R^2				-0.1575				0.5266
Joint significance				F(6,182)=2.497, p=0.024				$\chi^2(6)$=0.449, p=0.998
Total SS				1.3351				14.1830
Residual SS				1.2353				6.5415
Variables	Coef.	Std. Error	t-stat	p-value	Coef.	Std. Error	z-stat	p-value
ln(AI Vibrancy) (lx1)	-0.0196	0.0231	-0.8484	0.3973	-0.0168	0.2400	-0.0701	0.9441
ln(GDP per capita) (lx2)	-0.1244	0.2046	-0.6081	0.5439	-0.0317	0.6733	-0.0471	0.9625
ln(High-tech exports) (lx3)	-0.0811*	0.0326	-2.4875	0.0137	-0.0441	0.1576	-0.2798	0.7796
Employment-to-population ratio (x4)	-0.0153*	0.0068	-2.2624	0.0249	-0.0207	0.0407	-0.5069	0.6122
Employment in industry (%) (x5)	0.0189	0.0112	1.6940	0.092.	-0.0020	0.0760	-0.0261	0.9792
Employment in services (%) (x6)	0.0113	0.0099	1.1433	0.2544	0.0024	0.0622	0.0388	0.9690
Constant	–	–	–	–	3.7073	5.6029	0.6617	0.5082

*Notes: Dependent variable – Box–Cox(y3), unemployment with intermediate education (% of labour force with intermediate education), λ = −0.411; Panel – 35 countries, 2017–2023 (unbalanced), N = 229, T = 4–7; Key regressor are ln(AI Vibrancy) (lx1); controls include ln(GDP per capita), ln(high-tech exports), and labour structure indicators. Two-way FE includes country and year fixed effects; coefficients reported are unstandardised. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10. Because the dependent variable is Box–Cox transformed, coefficients represent effects on the transformed unemployment measure rather than direct percentage-point changes in the original y3 scale.*

Source*: authors' calculations in R Studio.*

Using the two-way fixed-effects model for the intermediate-education unemployment specification (dependent variable: Box–Cox(y3), λ = −0.411), the central question is whether within-country changes in AI vibrancy are associated with changes in unemployment among individuals with intermediate education once unobserved country factors and common year shocks are controlled for. Under Driscoll–Kraay (DK) standard errors (Table 8), which are robust to heteroskedasticity, serial correlation and cross-sectional dependence, the coefficient on ln(AI vibrancy) (lx1) is negative but statistically insignificant (β = −0.0196, SE = 0.0161, p = 0.226). The same null conclusion holds when standard errors are clustered by country (p = 0.273) and by time (p = 0.310), indicating that in estimation, AI vibrancy does not exhibit a statistically detectable within-country relationship with intermediate-education unemployment. In elasticity-style terms, a 1% increase in AI vibrancy would correspond to approximately a

0.00020 change in the Box-Cox-transformed outcome (−0.0196/100), but the lack of statistical significance implies that this magnitude should be treated as indistinguishable from zero given sampling uncertainty.

Table 8. Robust inference for the intermediate-education unemployment - two-way FE (Within) with alternative robust standard errors model (dependent variable: Box–Cox transformed y3)

Variable	Coef.	SE (Cluster: country)	p-value	SE (Cluster: time)	p-value	SE (Driscoll–Kraay, lag=2)	p-value
ln(AI Vibrancy) (lx1)	-0.01956	0.01778	0.27270	0.01920	0.30960	0.01610	0.22579
ln(GDP per capita) (lx2)	-0.12441	0.13507	0.35823	0.16230	0.44433	0.09742	0.20320
ln(High-tech exports) (lx3)	-0.08109	0.04139	0.05161	0.06959	0.24548	0.04042	0.04632*
Employment-to-population ratio (x4)	-0.01528	0.00781	0.05196	0.00470	0.00135**	0.00363	<0.001***
Employment in industry (%) (x5)	0.01892	0.00766	0.01448*	0.00666	0.00504**	0.00492	<0.001***
Employment in services (%) (x6)	0.01130	0.00786	0.15229	0.00545	0.03979*	0.00330	0.00077***

*Note: Dependent variable – Box–Cox(y3), unemployment with intermediate education, λ = −0.411; Panel – 35 countries, 2017–2023 (unbalanced), N = 229, T = 4–7; Key regressors are ln(AI Vibrancy) (lx1). DK standard errors are robust to heteroskedasticity, serial correlation and cross-sectional dependence. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10.*
Source*: authors' calculations in R Studio.*

Table 9. Robust inference for the intermediate-education unemployment - two-way RE (Walhus) with clustered standard errors

Variable	Coef.	SE (Cluster: country)	p-value	SE (Cluster: time)	p-value
Constant	-0.01681	0.03831	0.66119	0.01975	0.39540
ln(AI Vibrancy) (lx1)	-0.03169	0.07102	0.65585	0.02761	0.25230
ln(GDP per capita) (lx2)	-0.04409	0.01426	0.00225**	0.00620	<0.001***
ln(High-tech exports) (lx3)	-0.02065	0.00454	<0.001***	0.00167	<0.001***
Employment-to-population ratio (x4)	-0.00199	0.00712	0.78068	0.00441	0.65330
Employment in industry (%) (x5)	0.00241	0.00525	0.64628	0.00137	0.07930.
Employment in services (%) (x6)	-0.01681	0.03831	0.66119	0.01975	0.39540

*Note: Dependent variable – Box–Cox(y3), unemployment with intermediate education, λ = −0.411; Panel – 35 countries, 2017–2023 (unbalanced), N = 229, T = 4–7; Key regressors are ln(AI Vibrancy) (lx1). Standard errors are robust to heteroskedasticity, serial correlation and cross-sectional dependence. Significance levels: *** p<0.001, ** p<0.01, * p<0.05, . p<0.10.*
Source*: authors' calculations in R Studio.*

Other covariates show clearer robustness patterns. High-technology exports (lx3) are negative and statistically significant under DK ($\beta = -0.0811$, $p = 0.046$), while becoming only marginal under country clustering ($p = 0.052$) and insignificant under time clustering ($p = 0.245$), suggesting that export upgrading is more plausibly associated with lower intermediate-education unemployment once cross-sectional dependence is addressed. Labour-market absorption remains the most consistent correlate: the employment-to-population ratio (x4) is strongly negative and highly significant under time clustering ($p = 0.00135$) and DK ($p < 0.001$), and is marginal under country clustering ($p \approx 0.052$). Moreover, under DK inference the sectoral structure variables are statistically strong, with both the industry employment share (x5) and services employment share (x6) positive and highly significant (both $p < 0.001$), indicating that shifts in sectoral composition are systematically related to intermediate-education unemployment once common dependence is accounted for, although the sign pattern should be interpreted cautiously given the mechanical interdependence of sectoral shares and labour-market conditions.

Across the education-specific specifications, AI vibrancy does not exhibit a stable or statistically detectable link to unemployment once country and year effects are controlled for and inference is made robust to different dependence structures. For unemployment with advanced education (y1), the two-way FE coefficient on ln(AI vibrancy) is negative but clearly insignificant ($\beta = -0.099$, $p = 0.539$). It remains insignificant under country clustering ($p = 0.494$), time clustering ($p = 0.544$) and Driscoll–Kraay corrections ($p = 0.468$). In the two-way RE model, the sign switches ($\beta = 0.120$) but remains insignificant ($p = 0.624$), reinforcing that the data do not support a consistent AI-unemployment relationship for the highly educated over the period 2017–2023. This “no displacement signal” pattern also holds for basic education unemployment (y2). In the two-way FE model with ln(y2) as the dependent variable, ln(AI vibrancy) is positive but very small and insignificant ($\beta = 0.0136$, $p = 0.782$), and it remains insignificant under country- and time-clustered standard errors and Driscoll–Kraay inference (all $p > 0.81$). For intermediate education unemployment (y3) (Box–Cox transformed), ln(AI vibrancy) is again negative but insignificant under country clustering ($p = 0.273$), time clustering ($p = 0.310$), and Driscoll–Kraay corrections ($p = 0.226$), meaning there is no reliable evidence—robust or otherwise—of either an unemployment-increasing or unemployment-reducing AI vibrancy effect for this group. Instead, the results indicate that unemployment movements are explained more consistently by labour-market absorption and structural conditions, and, depending on the education group, by export upgrading. In the y1 models, the employment-to-population ratio and sectoral employment shares are persistently negative and significant, dominating the within-country explanation of high-skilled unemployment. At the same time, the innovation–income block (AI vibrancy, GDP per capita, high-tech exports) remains negligible in the FE framework. For y2, ln(high-tech exports) and the employment-to-population ratio show the most stable negative associations with low-skilled unemployment in the FE model, while AI vibrancy remains non-influential. For y3, robust inference points most strongly to labour absorption (x4) and structural shares (x5, x6), with high-tech exports occasionally significant depending on the variance, covariance estimator, again suggesting that conventional macro-labour mechanisms, not AI vibrancy per se, are the more dependable correlates of unemployment changes across education levels in this sample.

4. Discussion

The results provide no empirical support for the displacement-oriented expectation that greater national AI vibrancy systematically increases unemployment across education groups. In all three education-specific models, the coefficient on ln(AI vibrancy) remains statistically insignificant once unobserved country heterogeneity and common year shocks are controlled for, including under dependence-robust inference. This pattern is consistent with the broader view that AI diffusion is frequently associated with task reconfiguration, process redesign, and productivity-enhancing complementarities, rather than immediate, aggregate job destruction, which would be visible in national unemployment rates by education group. Such an interpretation aligns with evidence that AI is increasingly embedded in organisational transformation and governance choices, which can redistribute tasks and raise efficiency without necessarily leading to short-run unemployment increases. (Melnyk et al., 2025; Hernik et al., 2025; Bilan et al., 2022). It also aligns with findings that labour-market effects depend on competence adequacy and readiness for adoption, implying that countries with sufficient adaptive capacity may absorb AI-related changes without measurable unemployment rises. (Istudor et al., 2024; Bîrcă, 2025; Butum & Nicolescu, 2024).

For intermediate-education unemployment, the earlier "negative and significant under Driscoll–Kraay" signal does not persist in the revised calculations. Instead, ln(AI vibrancy) remains negative but insignificant under country clustering ($p = 0.273$), time clustering ($p = 0.310$) and Driscoll–Kraay corrections ($p = 0.226$), indicating that the association is not robust even under variance–covariance estimators designed to address cross-sectional dependence and serial correlation. Consequently, the most defensible conclusion is that AI vibrancy does not display a stable within-country link to unemployment for the intermediate-educated over the period 2017–2023. In contrast, the models consistently highlight the importance of conventional labour-market and structural correlates, particularly labour absorption (employment-to-population ratio) and, in some specifications, export upgrading, echoing macroeconomic evidence that employment outcomes are closely tied to productivity–output interactions and structural conditions. (Butkus et al., 2024; Gonos, 2024; Golubtsov et al., 2025).

The findings also reinforce that institutional and human-capital foundations likely mediate how AI ecosystems translate into labour-market outcomes, potentially explaining why a displacement pattern is not observed in the aggregate education-specific unemployment indicators. The quality of education and knowledge-economy capacity determine whether AI-related innovation expands opportunity sets and supports employment resilience. (Lyeonov et al., 2025; Artyukhov et al., 2024; Skrynnyk et al., 2022). Migration and skill-composition dynamics further complicate national unemployment profiles, suggesting that education-stratified unemployment may reflect mobility, structural adjustment, and the impact of technology. (Mukhtarova et al., 2024; Iuga & Socol, 2024). Moreover, governance and HRM architectures may influence how AI adoption affects recruitment, allocation, and job quality, shaping distributional outcomes even when unemployment rates do not change measurably. (Mura & Stehlíková, 2025b; Skypalova et al., 2025; Mujtaba, 2025).

Several limitations should be considered when interpreting these findings. First, the analysis relies on an unbalanced panel for 2017–2023, and missing observations may reduce comparability across countries and limit power, particularly for education-specific unemployment indicators. Second, the AI Vibrancy Score is a composite measure and may not capture the specific channels through which AI adoption affects labour demand (e.g., firm-level automation intensity, task content changes, or sector-specific diffusion). At the same time, cross-country reporting differences can add measurement noise. Third, despite two-way FE/RE specifications and dependence-robust standard errors, the study remains observational and cannot fully rule out endogeneity (reverse causality and omitted time-varying factors such as labour-market institutions, migration shocks, or policy interventions). Fourth, the relatively short time dimension constrains modelling of dynamic adjustment and lagged effects, meaning that longer-run displacement or reallocation processes may not be fully captured. Finally, the use of transformations (including Box–Cox for y3) improves statistical properties. However, it complicates interpretation on the original scale, so the substantive emphasis should remain on the direction and robustness of associations rather than precise marginal magnitudes.

Conclusion

This study aimed to assess whether national AI vibrancy is associated with higher unemployment across educational groups (advanced, intermediate and basic), thereby testing a displacement-oriented hypothesis that AI increasingly replaces human labour.

Methodologically, the analysis employed an unbalanced country-year panel for 2017–2023, combining the Stanford Global AI Vibrancy Tool with labour-market and macroeconomic indicators from the World Bank Open Data. Two-way fixed-effects and random-effects models were estimated, incorporating country and year effects. Box–Cox diagnostics guided the transformations, which included log-type transformations for AI vibrancy, GDP per capita, and high-technology exports (logarithmic y2) and a Box–Cox transformation for y3. Inference was strengthened through country- and time-clustered standard errors and Driscoll–Kraay corrections to account for heteroskedasticity, serial correlation and cross-sectional dependence.

The results do not provide robust evidence in support of the displacement hypothesis. For advanced-education unemployment (y1), the effect of AI vibrancy remains statistically insignificant across all inference procedures: the two-way FE estimate for ln(AI vibrancy) is $\beta = -0.099$ (country-clustered $p = 0.494$; time-clustered $p = 0.544$; Driscoll–Kraay $p = 0.468$). For basic-education unemployment (y2), AI vibrancy is likewise insignificant in the two-way FE model ($p = 0.782$). It remains insignificant under country clustering ($p = 0.830$), time clustering ($p = 0.813$) and Driscoll–Kraay inference ($p = 0.819$). For intermediate-education unemployment (y3), the AI vibrancy coefficient is negative but statistically insignificant under country- and time-clustered standard errors ($p = 0.273$ and $p = 0.310$, respectively), as well as under the Driscoll–Kraay correction ($p = 0.226$). The hypothesis that higher AI vibrancy increases unemployment is not supported: the estimated associations are consistently indistinguishable from zero, and where the sign is negative, it does not reach conventional significance thresholds in the calculations.

Policy implications follow directly from these findings. Since AI vibrancy does not appear to raise unemployment by education group over 2017–2023 systematically, policy should prioritise the responsible diffusion of AI that complements labour demand, rather than constraining AI development on the presumption of inevitable job loss. The persistent importance of labour-market absorption and structural variables, particularly the employment-to-population ratio and sectoral employment shares in multiple specifications, suggests that governments should embed AI strategies within broader measures that strengthen employment creation and job matching, including active labour-market programmes, mobility support, and targeted reskilling. In parallel, the negative and sometimes significant association between high-technology exports and unemployment in some models suggests that export upgrading and support for innovation-oriented industries can help mitigate unemployment pressures, especially where technological competitiveness expands demand for complementary tasks. Finally, given that AI impacts likely depend on institutional capacity and adjustment speed, national AI policies should be coupled with continuous learning systems and transition support, so that productivity gains translate into inclusive labour market outcomes rather than uneven adjustments.

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References

Agyare, P. (2025). Gendered Digital Harms and Youth Ideological Trajectories: Socioconomic Challenges of Digital Platforms. *SocioEconomic Challenges, 9*(3), 77-96. https://doi.org/10.61093/sec.9(3).77-96.2025

Alateeg, S., & Al-Ayed, S. (2024). Exploring the role of artificial intelligence technology in empowering women-led startups. *Knowledge and Performance Management, 8*(2), 28–38. https://doi.org/10.21511/kpm.08(2).2024.03

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

Artyukhov, A., Wołowiec, T., Artyukhova, N., Bogacki, S., & Vasylieva, T. (2024). SDG 4, Academic Integrity and Artificial Intelligence: Clash or Win-Win Cooperation? *Sustainability*, *16*(19), 8483. https://doi.org/10.3390/su16198483

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

Bilan, S., Šuleř, P., Skrynnyk, O., Krajňáková, E., & Vasilyeva, T. (2022). Systematic bibliometric review of artificial intelligence technology in organizational management, development, change and culture. *Business: Theory and Practice, 23*(1), 1–13. https://doi.org/10.3846/btp.2022.13204

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), 45–56. https://doi.org/10.14254/1800-5845/2025.21-3.4

Bozhenko, V., Boyko, A., Vondráček, M., & Karácsony, P. (2024). Shadow economy and financial stability from the perspective of finance digitalization. *Journal of International Studies*, 17(2), 191–205. doi:10.14254/2071-8330.2024/17- 2/10

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

Davidov, P. (2024). Motivation of public sector employees in Israel depending on their status and education level. *Administratie si Management Public*, 42, 131–144. https://doi.org/10.24818/amp/2024.42-08

Ejdys, J., Gulc, A., Magruk A., Kononiuk, A., & Rollnik-Sadowska, E. (2025). Future horizons in social innovation: advancing employment for people with disabilities. *Polish Journal of Management Studies*, 31(1), 84-105. https://doi.org/10.17512/pjms.2025.31.1.05.

European Centre for the Development of Vocational Training (Cedefop). (2025). *Skills empower workers in the AI revolution: First findings from Cedefop's AI skills survey* (Policy brief). Cedefop. URL: https://www.cedefop.europa.eu/files/9201_en.pdf

European Commission. (2025). *Council recommendation on human capital in the European Union* (COM(2025) 959 final). https://employment-social-affairs.ec.europa.eu/document/download/cb0ffdb5-1f80-4e20-a535-b2237b31f29f_en?filename=COM_2025_959_1_EN.pdf

Gayathiri, G., & Prabu, G. (2025). Artificial intelligence-driven human resource practices and employee well-being: Examining the mediating effect of employee engagement. *Problems and Perspectives in Management, 23*(4), 247–263. https://doi.org/10.21511/ppm.23(4).2025.18

Glos, J., & Karwot, J. (2025). Study of Customer Attitudes Toward AI-Driven Solutions in Customer Support Services. *Knowledge Economy and Lifelong Learning, 1*(2), 24–49. https://doi.org/10.61093/kell.1(2).24-49.2025

Gmyrek, P., Berg, J., Kamiński, K., Konopczyński, F., Ładna, A., Nafradi, B., Rosłaniec, K., & Troszyński, M. (2025). *Generative AI and Jobs: A Refined Global Index of Occupational Exposure*. ILO Working Paper 140. Geneva: International Labour Office, 2025.© ILO. https://doi.org/10.54394/hetp0387

Golubtsov, D., Kedziora, J., Kozhakhmetova, A., & Kedziora, D. (2025). Assessing the impact of digital technologies and artificial intelligence (AI) on the efficiency of supply chain. *Economics and Sociology*, 18(1), 149–173. doi:10.14254/2071-789X.2025/18-1/8

Gomez Tamayo, S., & Petrelli, A. (2025). *Work transformed: The promise and peril of artificial intelligence* (Research brief). International Labour Organization, ILO Qatar Technical Cooperation Project. https://doi.org/10.54394/PJST2835

Gonos, J. (2024). Unemployment and GDP Analysis in Accord With R&D Expenses in the Individual Autonomies of Slovakia. *Montenegrin Journal of Economics*, *20*(2), 91 – 106. https://doi.org/10.14254/1800-5845/2024.20-2.8

Green, A. (2024). *Artificial intelligence and the changing demand for skills in the labour market* (OECD Artificial Intelligence Papers No. 14). OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2024/04/artificial-intelligence-and-the-changing-demand-for-skills-in-the-labour-market_861a23ea/88684e36-en.pdf

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

Harb, A., Alakaleek, W., Hatough-Bouran, S., Freewan, A., Al-Harahsheh, A. Y., & Al-Maaitah, H. (2025). Empowering Women Homepreneurs in Tourism and Hospitality: Entrepreneurial Competencies and Learning Approach. *Journal of Tourism and Services*, *16*(30), 165–189. https://doi.org/10.29036/0ymceq94

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

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), 703–720. DOI: https://doi.org/10.24818/EA/2024/67/703

Iuga, I. C., & Socol, A. (2024). Government Artificial Intelligence Readiness and Brain Drain: Influencing Factors and Spatial Effects in European Union Member States. *Journal of Business Economics and Management*, *25*(2), 268–296. https://doi.org/10.3846/jbem.2024.21136

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

Kajda, K., & Karwot, J. (2025). The Role of Artificial Intelligence in Revolutionizing Industrial Automation for Municipal Waste Management in Industry 4.0. *Green Transition and Sustainable Development, 1*(1), 37-63. https://doi.org/10.61093/gtsd.1(1).37-63.2025

Khatami, F., Ferraris, A., Palmucci, D. N., & Dabić, M. (2024). Impact Analysis of the Digital Entrepreneurial Ecosystem to Improve the Tourism Industry and Social Sustainability. *Journal of Tourism and Services*, *15*(29), 176–205. https://doi.org/10.29036/jots.v15i29.831

Kildei, A., Tumpach, M., & Shafranova, K. (2025). Artificial Intelligence for Smart Customer Feedback Management: Improving Content Analysis Approaches. *Knowledge Economy and Lifelong Learning, 1*(1), 48–65. https://doi.org/10.61093/kell.1(1).48-65.2025

Kirichok, O., Orlovska, Y., Zhanseitova, G., Oriekhova, A., Babaiev, D., Havrylenko, O., & Vasylieva, T. (2025). Bridging digital innovation and energy justice: The role of artificial intelligence in advancing energy equity. *Environmental Economics, 16*(4), 166–181. https://doi.org/10.21511/ee.16(4).2025.11

Kritikos, I., Sarantopoulos, A., Roumeliotis, A., Vasiliades, J., & Matsinas, I. (2025). Unlocking the Potential of Artificial Intelligence in Pharma Research and Development: Insights from Investor and Researcher Perspectives. *Health Economics and Management Review, 6*(2), 1–16. https://doi.org/10.61093/hem.2025.2-01

Lama, P. B., Budhathoki, P. B. & Bhatta, N. (2025). Corporate Social Responsibility in Banking: A Comprehensive Bibliometric Analysis. *Financial Markets, Institutions and Risks, 9*(3), 64–84. https://doi.org/10.61093/fmir.9(3).64-84.2025

Lyeonov, S., Draskovic, V., Kubaščikova, Z., & Fenyves, V. (2024). Artificial intelligence and machine learning in combating illegal financial operations: Bibliometric analysis. *Human Technology*, *20*(2), 325–360. https://doi.org/10.14254/1795-6889.2024.20-2.5

Lyeonov, S., Vorontsova, A., Bilan, Y., Artyukhov, A., & Skare, M. (2025). Quality at the Core: A Multifaceted Analysis of Higher Education's Impact on the Knowledge Economy. *Journal of the Knowledge Economy*. https://doi.org/10.1007/s13132-024-02517-4

Melnyk, L., Remsei, S., Kubatko, O., & Kalinichenko, L. (2025). Industry 5.0 as a human-centric direction for social and labor entities transformations. *Problems and Perspectives in Management*, *23*(4), 290–300. https://doi.org/10.21511/ppm.23(4).2025.21

Mong, D. D., & Thanh, H. P. (2024). Relationship between artificial intelligence and legal education: A bibliometric analysis. *Knowledge and Performance Management, 8*(2), 13–27. https://doi.org/10.21511/kpm.08(2).2024.02

Moravec, V., Hynek, N., Gavurova, B., & Kubak, M. (2024). Everyday Artificial Intelligence Unveiled: Societal Awareness of Technological Transformation. *Oeconomia Copernicana*, *15*(2), 367–406. https://doi.org/10.24136/oc.2961

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

Mtengwane, G. (2024). Experiences and challenges of digital transformation in the informal business sector in a rural South African town. *International Journal of Entrepreneurial Knowledge, 12*(2), 1–16. https://doi.org/10.37335/ijek.v12i2.195

Mujtaba, B. G. (2025). Human-AI Intersection: Understanding the Ethical Challenges, Opportunities, and Governance Protocols for a Changing Data-Driven Digital World. *Business Ethics and Leadership, 9*(1), 109–126. https://doi.org/10.61093/bel.9(1).109-126.2025

Mukhtarova, N., Nurtazina, R., Krawczyk, D., Barvinok, V., Vorontsova, A., Vasić, S., & Vasylieva, T. (2024). Interconnections in the education–migration–labor market chain in Central and Eastern Europe. *Problems and Perspectives in Management*, *22*(4), 470–486. https://doi.org/10.21511/ppm.22(4).2024.35

Mura, L., & Stehlíková, B. (2025a). Artificial intelligence: Effective HR assistant or invisible dictator? *Equilibrium. Quarterly Journal of Economics and Economic Policy, 20*(1), 15–33. https://doi.org/10.24136/eq.3598

Mura, L., & Stehlíková, B. (2025b). The ethics of artificial intelligence: Safeguarding human dignity, social justice and environmental stability in the age of AI. *Equilibrium. Quarterly Journal of Economics and Economic Policy, 20*(2), 479-507. https://doi.org/10.24136/eq.3743

Peković, D. (2025). The impact of remittances on employment: Evidence from post-transition countries. *Journal of International Studies*, 18(1), 145–155. https://doi.org/10.14254/2071-8330.2025/18-1/9

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

Sahnouni, M., & Kadri, M. (2025). Investments in ICT in the Telecommunications Sector: A Strategic Imperative for Organizational Changes in Response to Market Transformations. *Financial Markets, Institutions and Risks, 9*(2), 112–122. https://doi.org/10.61093/fmir.9(2).112-122.2025

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

Sartamorn, S., Oe, H. & Yamaoka, Y. (2025). Financial stratification and digital transformation under market disruption: Evidence from Thai SMEs. *Financial Markets, Institutions and Risks, 9*(3), 49–63. https://doi.org/10.61093/fmir.9(3).49-63.2025

Schinello, S. (2025). Challenges and opportunities in the use of artificial intelligence in creative economy: Insights from expert interviews. *Economics and Sociology*, 18(1), 199–216. doi:10.14254/2071-789X.2025/18-1/10

Senci, M., & Afful, C. R. (2025). Inflation and unemployment in Slovakia: Is the Phillips curve still relevant?. *International Journal of Entrepreneurial Knowledge*, *13*(1), 95–105. https://doi.org/10.37335/ijek.v13i1.304

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. doi: 10.22059/jitm.2022.88893

Skypalova, R., Zvarikova, K., & Chaudhuri, S. (2025). Model of relationships between corporate social responsibility, human resources management, and artificial intelligence. *Oeconomia Copernicana*, *16*(3), 1021–1060. https://doi.org/10.24136/oc.3875

Stanford University. (n.d.). *Global AI Vibrancy Tool - AI Index*. Stanford University Human-Centred Artificial Intelligence. https://aiindex.stanford.edu/vibrancy

Tossekbayev, K., Dinits, R., & Rekun, Y. (2025). Digitalization in Healthcare Industry: Is There a Nexus with the Population's Life Expectancy?. *Health Economics and Management Review*, *6*(1), 72–95. https://doi.org/10.61093/hem.2025.1-05

Vovk, I., & Vovk, Y. (2024). Sustainable personnel management in the hospitality industry: Enhancing organizational performance through employee engagement and commitment. *Economics, Management and Sustainability*, *9*(2), 44–58. https://doi.org/10.14254/jems.2024.9-2.4

Vovk, Y., Aulin, V., Vovk, I., Romaniuk, S., Syhlovyi, M., Vovk, O., Palianytsia, V., & Zabytivskyi, V. (2025). Electric vehicle charging infrastructure optimization on international transport corridors: Economic analysis and EU regulatory alignment in Ukraine. *Journal of Sustainable Development of Transport and Logistics*, *10*(2), 6–28. https://doi.org/10.14254/jsdtl.2025.10-2.1

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., & Yang, J. (2025). Navigating Employment Transformations: Liberalism vs. Statism in the Era of Industry 4.0. *Amfiteatru Economic*, 27(68), 145–161. DOI: https://doi.org/10.24818/EA/2025/68/145

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

World Bank. (2025). Digital Progress and Trends Report 2025: Strengthening AI Foundations. Washington, DC: World Bank. Doi: 10.1596/978-1-4648-2264-3. License: Creative Commons Attribution CC BY 3.0 IGO

Yarovenko, H., Horbachova, O., Bylbas, R., & Latysh, D. (2025). Digitalization As a Socio-Economic Challenge: Modeling the Impact On the Level of Cybercrime Considering Socio-Economic, Technological and Institutional Factors. *SocioEconomic Challenges, 9*(2), 282–315. https://doi.org/10.61093/sec.9(2).282-315.2025

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

Yefimenko, A., Boronos, V., Serpeninova, Yu., & Koldovskyi, A. (2025). Innovative and Technological Determinants of Corruption Reduction: How do Knowledge and Technology Contribute to Public Integrity and Transparency?. *Knowledge Economy and Lifelong Learning, 1*(1), 21–34. https://doi.org/10.61093/kell.1(1).21-34.2025

Zaryczańska, K., & Karwot, J. (2025). Analysis of Occupational Safety and Health at the Construction Site Based on Images Acquired from Various Sources Using Artificial Intelligence. *Safety and Security Advances, 1*(1), 1-17. https://doi.org/10.61093/ssa.1(1).1-17.2025

Nurski, L. & Ruer, N. (2024). Exposure to generative artificial intelligence in the European labour market. Working Paper 06/2024, Bruegel. URL: https://www.bruegel.org/system/files/2024-03/WP%2006.pdf

Appendix A. List of countries in the analytical sample

List of countries in the analytical sample for the dependent variable – unemployment with advanced education.

The empirical analysis is based on an unbalanced panel comprising the following 35 countries: Australia; Austria; Belgium; Brazil; Canada; Denmark; Estonia; Finland; France; Germany; India; Ireland; Israel; Italy; Japan; Luxemburg; Malaysia; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Russia; Saudi Arabia; Singapore; South Africa; South Korea; Spain; Sweden; Switzerland; Turkey; United Arab Emirates; United Kingdom; United States.

List of countries in the analytical sample for the dependent variable – unemployment with basic education.

The empirical analysis is based on an unbalanced panel comprising the following 34 countries: Australia; Austria; Belgium; Brazil; Canada; Denmark; Estonia; Finland; France; Germany; India; Ireland; Israel; Italy; Luxemburg; Malaysia; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Russia; Saudi Arabia; Singapore; Spain; South Africa; South Korea; Sweden; Switzerland; Turkey; United Arab Emirates; United Kingdom; United States.

List of countries in the analytical sample for the dependent variable – unemployment with intermediate education.

The empirical analysis is based on an unbalanced panel comprising the following 35 countries: Australia; Austria; Belgium; Brazil; Canada; Denmark; Estonia; Finland; France; Germany; India; Ireland; Israel; Italy; Japan; Luxemburg; Malaysia; Mexico; Netherlands; New Zealand; Norway; Poland; Portugal; Russia; Saudi Arabia; Singapore; South Africa; South Korea; Spain; Sweden; Switzerland; Turkey; United Arab Emirates; United Kingdom; United States.

Appendix B. Descriptive statistics of variables.

Table B1. Descriptive statistics of variables (2017–2023; N = 229 country–year observations)

Code	x1	x2	x3	x4	x5	x6	y1
Variable (unit)	AI Vibrancy score (index)	GDP per capita (constant 2015 US$) (US$)	High-technology exports (current US$) (US$ bn)	Employment-to-population ratio, 15+ total (%,	Employment in industry (% of total employment,	Employment in services (% of total employment,	Unemployment with advanced education (% of labour force with advanced
N	229	229	229	229	229	229	229
Mean	13.44	40,598.21	47.77	58.33	21.74	72.76	4.87
SD	9.78	24,993.17	59.98	7.34	4.75	10	3.19
Median	11.78	41,778.58	19.97	59.06	20.41	74.81	3.93
Min	0.34	1.806.50	0.16	36.8	9.19	31.02	1.28
Max	48.19	110.425.90	260.04	77.61	34.6	89.73	17.91
Trimmed mean	12.35	38.483.75	36.05	58.46	21.71	73.84	4.24
Skewness	1.2	0.65	1.54	-0.13	0.08	-1.77	1.93
Kurtosis	1.72	0.14	1.47	1.04	-0.13	4.98	3.29

Note: Panel structure – Unbalanced country–year panel, 2017–2023, N = 229 observations. x3 is reported in US$ billions for readability; all other variables retain their original units. Country and year are panel identifiers and are not reported as substantive variables.

Source*: authors' calculations in R Studio.*

Table B2. Descriptive statistics of variables used for the "basic education unemployment" model (y2)

Code	x1	x2	x3	x4	x5	x6	y2
Variable (unit)	AI Vibrancy score (index)	GDP per capita (constant 2015 US$) (US$)	High-technology exports (current US$) (US$ bn)	Employment-to-population ratio, 15+ total (%, ILO	Employment in industry (% of total employment, ILO modelled) (%)	Employment in services (% of total employment, ILO modelled) (%)	Unemployment with basic education (% of labour force with basic education)
N	225	225	225	225	225	225	225
Mean	13.5	40.685.75	46.74	58.31	21.7	72.77	10.28
SD	9.86	25,206.47	60.00	7.4	4.78	10.09	7
Median	11.83	42,215.88	19.28	59.03	20.4	75.46	8.73
Min	0.34	1,806.50	0.16	36.8	9.19	31.02	0.25
Max	48.19	110,425.90	260.04	77.61	34.6	89.73	40.74
Trimmed mean	12.40	38,545.84	34.50	58.43	21.65	73.87	9.31
Skewness	1.18	0.64	1.6	-0.12	0.11	-1.76	1.92
Kurtosis	1.63	0.08	1.64	0.97	-0.14	4.84	5.09

Notes: Panel structure – Unbalanced country–year panel, 2017–2023, N = 225 observations. High-technology exports (x3) are reported in US dollars for readability (original data in current US dollars). The trimmed mean is calculated after excluding extreme values from both tails (as in the psych::describe() output). The panel is unbalanced, so not all countries are observed in every year.

Source*: authors' calculations in R Studio.*

Table B3. Descriptive statistics of variables used for the "intermediate education unemployment" model (y3)

Code	x1	x2	x3	x4	x5	x6	y3
Variable (unit)	AI Vibrancy score (index)	GDP per capita (constant 2015 US$) (US$)	High-technology exports (current US$) (US$ bn)	Employment-to-population ratio, 15+ total (%, ILO modelled) (%)	Employment in industry (% of total employment, ILO modelled) (%)	Employment in services (% of total employment, ILO modelled) (%)	Unemployment with intermediate education (% of labour force with intermediate education) (%)
N	229	229	229	229	229	229	229
Mean	13.44	40,598.21	47.77	58.33	21.74	72.76	7.06
SD	9.78	24,993.17	59.98	7.34	4.75	10	5.35
Median	11.78	41.778.58	19.97	59.06	20.41	74.81	5.26
Min	0.34	1.806.50	0.16	36.8	9.19	31.02	1.02
Max	48.19	110.425.90	260.04	77.61	34.6	89.73	35.34
Trimmed mean	12.35	38.483.75	36.05	58.46	21.71	73.84	6.01
Skewness	1.20	0.65	1.54	-0.13	0.08	-1.77	3.01
Kurtosis	1.72	0.14	1.47	1.04	-0.13	4.98	10.85

Notes: Panel structure – Unbalanced country–year panel, 2017–2023, N = 225 observations. High-technology exports (x3) are reported in US dollars for readability (original data in current US dollars). The trimmed mean is calculated after excluding extreme values from both tails (as in the psych::describe() output). The panel is unbalanced, so not all countries are observed in every year.

Source*: authors' calculations in R Studio.*