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Artificial Intelligence Readiness and Employment: A Global Panel Analysis

Abstract. *Artificial Intelligence (AI) is a major technological advancement, whose capabilities and rapid penetration into diverse sectors are reshaping jobs and raising fears about the displacement of human workers. The impact of AI on labour markets is mixed. It is anticipated that both creation and substitution effects will occur. The AI Readiness (AIR) Index, as proposed by Oxford University, captures the contribution of government, technology (including human capital), and infrastructure in preparing a country's economy for the challenges posed by AI. In this paper, we examine the impact of AI on the employment of highly educated workers. We test the impact of the AIR Index on employment using a global panel analysis on a sample of 78 countries and data covering the period 2019-2022. The results indicate that higher AI readiness scores are associated with a positive impact on the employment of highly educated workers. Insufficient AI literacy is an obstacle that could result in worker displacement. Policies enhancing AI literacy could assist human workers in adapting to the new intelligence, thereby facilitating their transition to an AI-driven environment.*

Keywords: *panel analysis, artificial intelligence, technological change, Artificial Intelligence Readiness, employment, labour markets.*

JEL Classification: O3, O33, J2, J20.

1. Introduction

The quick uptake of AI has given rise to concerns about the displacement of human workers and the occurrence of substantial AI-driven changes in employment and labour markets are foreseen (Georgieff and Hyee, 2022; Qian, 2023; Xiaowen et al., 2024). However, there is no consensus among scholars (Xiaowen et al., 2024)

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about the net impact of AI on labour markets: both substitution and creation effects are anticipated (Qian, 2023). In contrast to previous technological advancements, which typically had a negative impact on low-skilled/low-educated or middle-skilled/middle-educated workers, AI is likely to also impact on the employment of high-skilled/highly educated workers (Acemoglu and Restrepo, 2019; Webb, 2020; Jongwanich et al., 2022; Lane and Saint-Martin, 2023; OECD, 2023; Cazzaniga et al., 2024). Studies and cross-country surveys have indicated that the workforce in more developed countries is less likely to be affected by AI advancement than in less developed countries, and more developed countries exhibit superior AI readiness scores (Green and Lamby, 2023; Lane and Saint-Martin, 2023; OECD, 2023; Cazzaniga et al., 2024). Nevertheless, no existing studies have tested the extent to which AI readiness influences the impact of AI on employment. The objective of this paper is to address this gap in the literature by examining the impact of AI on employment using the AI Readiness Index as an explanatory variable. The paper aimed at testing the impact of AI on employment of highly educated workers using the AI Readiness Index proposed by Oxford University on a sample of 78 countries and data covering the period from 2019 to 2022. The findings confirmed that higher scores for AI readiness had a positive impact on the total employment of highly educated workers and revealed the differential contributions of the AI readiness pillars and components to employment.

2. Literature review

Early definitions referred to AI as capability of an intelligent machines to mimic the brain and to simulate any aspect of learning or any feature of the human intelligence (McCArthy et al., 1955). The integration of AI has enabled machines to undertake a range of tasks that require learning, thinking, decision-making, and problem-solving abilities. This has resulted in the development of machines that are capable to "emulate human actions and execute tasks intelligently, mirroring people's activities" (Shabbir and Anwer, 2018). The term "AI" is defined by recent research as "the examination of how digital computers and algorithms perform tasks and solve complex problems that would normally require or exceed the human intelligence" (Giuggioli and Pellegrini, 2022). This definition encompasses the gradual evolution of AI towards an imitation of human intelligence (Shabbir and Anwer, 2018) and human cognitive function (DiCuonzo et al., 2023). It is anticipated that generative AI systems will develop the capacity for self-awareness and consciousness, representing a substantial advancement in their cognitive capabilities (Sehn-Kalb and Mehta, 2023).

The outstanding capabilities of AI, together with its rapid diffusion and extensive applicability to diverse sectors and activities (Cazzaniga et al., 2024), have given rise to concerns about the displacement of workers (Webb, 2020). Furthermore, AI is expected to reshape job functions (Cazzaniga et al., 2024). It is critical to acknowledge that the relationship between AI and employment is more intricate than that observed in previous technological advancements, (robotics, software, ICT) and depends, among other things, on the magnitude of the AI adoption within the economy (Georgieff and Hyee, 2022).

Earlier studies (Autor et al., 2003) suggest that previous technological advances mostly contributed to automation of routine tasks, whereas non-routine tasks, encompassing both non-routine skilled and non-routine cognitive tasks, seemed to escape to automation. Computers and robots have facilitated the automation of routine cognitive tasks related to calculation, information search, while industrial robots have contributed to the automation of routine manual tasks (Raj and Seamans, 2019; Webb, 2020). Recent studies indicate that these technologies have mainly affected low-skilled and medium-skilled occupations, which are most exposed to robots (Webb, 2020); this has resulted in the displacement of human workers or, at the very least, the limitation of human intervention in the execution of routine tasks (Georgieff and Hyee, 2022).

In contrast to earlier technological transformations, the deployment of AI-powered tools has a significant influence on both routine and non-routine tasks. Artificial intelligence is based on computer software that employs sophisticated algorithmic techniques (Georgieff and Hyee, 2022) to automate non-routine cognitive tasks that typically performed by medium and high-skilled/highly educated workers. Consequently, in contrast to other technologies, AI is expected to impact a diverse range of occupations: high-skilled and older workers are at the greatest risk of displacement (Webb, 2020), while low-skilled workers engaged in manual and non-routine tasks appear to be less vulnerable to replacement (Xiaowen et al., 2024). The substitution and displacement effects may be observed when AI assumes tasks that were previously performed by human workers (Georgieff and Hyee, 2022; Jongwanich et al., 2022; Cazzaniga et al., 2024). Nevertheless, it is not possible for AI to fully replace the human factor, as it lacks social intelligence (Georgieff and Hyee, 2022) and the capabilities to replicate the human capacity for tacit knowledge (Jarrati et al., 2022); therefore, the substitution effect will be limited in the case of jobs that require creativity or social intelligence (Georgieff and Hyee, 2022), jobs which are usually performed by highly educated workers. In the short term, any technological advancement (including AI) has resulted in the displacement of workers and a decrease in labour demand can be observed (Acemoglu and Restreppo, 2019), particularly in the case of occupations and tasks that are susceptible to automation. In the long run, there is an instalment effect (technology creates new tasks that reinsert workers in various activities) which, when combined with the technology-led increase in productivity, will result in a job creation effect and an increase in labour demand (Acemoglu and Restreppo, 2019; OECD, 2023); this is particularly evident for high-skilled/highly educated workers (Jongwanich et al., 2022).

The task-based approach of Autor et al. (2003) argues that individual occupations are bundles of tasks (Cazzaniga et al., 2024) and some of these tasks could be replaced or complemented by AI technology (Acemoglu and Restrepo, 2022; Moll et al., 2022). To obtain more precise results on the impact of AI on jobs and workers, recent studies employ new variables, such as: a) the index of "exposure to AI" defined as the degree of overlap between required human skills and AI (Felten et al., 2021), which provides an indication of the substitutability of the human factor by AI in performing tasks specific to a job (Cazzaniga et al., 2024) and b) the index of potential "AI complementarity" which has developed around the specific factors of work context and skills associated with occupations and reflects the degree of shielding from AI-driven job displacement (Pizzinelli et al., 2023; Cazzaniga et al., 2024) or the degree to which human workers could be complemented or replaced by AI in the case of different occupations. Occupations that are least exposed to AI include: high-skilled/highly educated occupations requiring reasoning in response to novel situations, occupations requiring interpersonal skills, as well as physical/manual occupations, agriculture/forestry/fishery workers (Lane and Saint-Martin, 2023; OECD, 2023).

Cazzaniga et al. (2024) combined the exposure to AI with AI complementarity and introduced the conceptual distinction between "jobs" and "workers" into a complex methodological framework to obtain more precise results on the impact of AI on labour markets (jobs, employment and workers). Their findings indicate that "AI adoption may destroy some jobs (and displace associated workers)", but the magnitude of the effects depends on the characteristics of the workers and characteristics of the job (Cazzaniga et al., 2024) and their adaptability to AI. For high-skilled / highly-educated young workers, the results are mixed as they are "exposed to both potential labour market disruptions and opportunities in occupations likely to be affected by AI" (Cazzaniga et al., 2024), while older workers who may have less adaptability to new technologies (including AI) are rather exposed to displacement and unemployment (Cazzaniga et al., 2024), regardless of their education level.

Fast AI adoption in various industries reveals that the possession of skills and knowledge to develop and maintain AI systems, to adopt, use, and interact with AI applications, becomes a critical factor (OECD, 2023) to mitigate workers displacement and to stimulate AI driven employment creation. *AI literacy* is quantifying the capability (skills, competences, abilities, knowledge) of a human individual to the ability to know and to understand AI technology (concepts and techniques), to use, apply, and monitor AI tools in different contexts and activities and to evaluate and create AI tools using advanced thinking skills within an ethical context (Ng et al., 2021).

The *AI Readiness* describes an organisation's capability to adopt and implement AI systems (Tehrani et al., 2024) requires changes in terms of decision-making processes and personnel for effective adoption of artificial intelligence. The main components of the AI readiness include: 1) infrastructure and mechanisms, 2) technology, and 3) AI literacy, namely specific AI skills, capabilities and knowledge (Tehrani et al., 2024). The AI readiness framework (Holmstrom, 2022) can be evaluated at various levels: organisational (Holmstrom, 2022; Tehrani et al., 2024), industry (AI Singapore Insights, 2024), and governmental (Oxford Insights, 2023). Given the impact of governance frameworks (legal conditions, incentives for AI adoption, AI ethics, technology and innovation policies, etc.) on the activities of individual workers and companies across various industries, it is evident that government policy and government AI readiness play a pivotal role in determining an organisation's capacity to adopt AI. These factors are also likely to influence the extent of AI-driven employment changes.

Oxford University has developed an *AI Readiness Index* that consists of 3 pillars (Hankins et al., 2023): 1) *Government Pillar* which captures "the strategic vision for how it develops and governs AI, supported by appropriate regulation and attention to ethical risks"; 2) *Technology Pillar* which captures the size and maturity of the AI tools provided by the country's technology sector along with the country's innovation capacity and good levels of human capital with the necessary AI skills and AI literacy and 3) *Data and Infrastructure Pillar* that captures the availability of quality data and the availability of the necessary infrastructure to power the adoption of AI. Empirical evidence (Hankins et al., 2023) indicates that more developed economies tend to exhibit higher scores for the AI readiness index. Several studies (OECD, 2023; Lane and Saint-Martin, 2023; Cazzaniga et al., 2024) indicate that net AI-driven job creation is predominantly observed in more developed countries, where higher AI readiness scores are also evident. Studies and cross-country survey have indicated that the workforce in more developed countries, where higher AI readiness scores are also observed, is less likely to be affected by AI advancement than in less developed countries (Green and Lamby, 2023; Lane and Saint-Martin, 2023; OECD, 2023; Cazzaniga et al., 2024). None of the studies addressed the question of whether AI readiness exerted an influence on the magnitude and nature of the impact of AI on employment. Therefore, the impact of AI on employment using the AI Readiness Index as an explanatory variable will be examined in this paper.

3. Model specification

3.1 Model Description and Hypothesis

The advent of artificial intelligence (AI) represents a profound technological advance that will have far-reaching implications for many economic sectors and will undoubtedly lead to substantial shifts in the employment and labour markets. The primary objective of our research is to examine the impact of AI on the employment of highly educated workers (with advanced qualifications and skills). In light of the aforementioned objective, the following research hypotheses are proposed:

H1: The employment of highly educated workers is positively affected by AI. A potential substitution effect must also be considered: the employment rate of highly educated workers will increase compensating for the decrease in the employment rate of low educated/low skilled labour force. This estimated substitution effect can only be compensated for by educational attainment.

H2: Government actions and public policies that promote AI and Information and Communication Technologies (ICT) developments, focusing on better governance, digital capacity, and adaptability, have a positive impact on the employment rate of highly educated workers.

H3: The advancement of the AI technology sector (that includes AI human capital and AI innovation capacity) has a positive impact on the employment rate of highly educated workers.

H4: The Data and AI infrastructure (including digital infrastructure, data availability, and data representativeness) have a positive impact on the employment rate of highly educated workers.

H5: The estimated positive impact of AI readiness varies considerably between the employment rates of highly educated males and females.

In order to test the aforementioned research hypotheses, the following variables were selected for inclusion in the present study:

Dependent variables:	**Details**:	**Data source**:
- Employment rate (total) of highly educated workers - Employment rate (male) of highly educated workers - Employment rate (female) of highly educated workers	Employment of graduates in the first stage of tertiary education (not leading to an advanced research qualification) and the second stage of tertiary education (leading to an advanced research qualification). The rate is calculated by dividing the number of people employed (total, male, and female) by the total number of people employed.	International Labor Organization (ILO)
Explanatory variables:	**Details**:	**Data source**:
- AI (artificial intelligence) Readiness Index - AI Readiness Index Pillar 1: Government - AI Readiness Index Pillar 2: Technology Sector - AI Readiness Index Pillar 3: Data and Infrastructure - AI Governance and Ethics (Pillar 1) - AI Digital Capacity (Pillar 1) - AI Adaptability (Pillar 1) - AI Sector Size (Pillar 2) - AI Innovation Capacity (Pillar 2) - AI Human Capital (Pillar 2) - AI Infrastructure (Pillar 3) - AI Data Capacity (Pillar 3) - AI Data Representativeness (Pillar 3)	AI Readiness Index is a composite index elaborated by taking into consideration three pillars (Government, Technology Sector and Data and Infrastructure) described by 9 indicators (3 indicators for each pillar): AI governance and ethics, AI digital capacity, AI adaptability, AI sector size, AI innovation capacity, AI human capital, AI infrastructure, AI data availability, and AI data representativeness.	Oxford Insights (OI)

Due to the very limited number of observations, we used the data panel research framework. We gradually developed our study on the impact of AI on the employment rate of highly educated workers, from general to specific, by using the following panels and equations:

Level A - General Impact of AI on the employment rate of highly educated workers:

$$\mathrm{EMPLOYMENT_{it}} = \mathrm{a_1} \times \mathrm{AI\ Readiness\ Index}_{it} + \mathrm{C} + \varepsilon_{\mathrm{it}} \quad (1)$$

$$\mathrm{EMPLOYMENT\ MALE_{it}} = \mathrm{a_2} \times \mathrm{AI\ Readiness\ Index}_{it} + \mathrm{C} + \varepsilon_{\mathrm{it}} \quad (2)$$

$$\mathrm{EMPLOYMENT\ FEMALE_{it}} = \mathrm{a_3} \times \mathrm{AI\ Readiness\ Index}_{it} + \mathrm{C} + \varepsilon_{\mathrm{it}} \quad (3)$$

Level B - Specific Impact of AI on the Employment Rate of highly educated workers:

$$\mathrm{EMPLOYMENT_{it}} = a_1 \times \text{AI Government}_{it} + b_1 \times \text{AI Technology Sector}_{it} + c_1 \times \text{AI Data and Infrastructure}_{it} + C + \varepsilon_{it} \quad (4)$$

$$\mathrm{EMPLOYMENT\ MALE_{it}} = a_2 \times \text{AI Government}_{it} + b_2 \times \text{AI Technology Sector}_{it} + c_2 \times \text{AI Data and Infrastructure}_{it} + C + \varepsilon_{it} \quad (5)$$

$$\mathrm{EMPLOYMENT\ FEMALE_{it}} = a_3 \times \text{AI Government}_{it} + b_3 \times \text{AI Technology Sector}_{it} + c_3 \times \text{AI Data and Infrastructure}_{it} + C + \varepsilon_{it} \quad (6)$$

Level C – Specific determinants of the impact of AI on the employment rate of highly educated workers:

AI Pillar 1 components:

$$\mathrm{EMPLOYMENT_{it}} = a_1 \times \text{AI Governance and Ethics}_{it} + b_1 \times \text{AI Digital Capacity}_{it} + c_1 \times \text{AI Adaptability}_{it} + C + \varepsilon_{it} \quad (7)$$

$$\mathrm{EMPLOYMENT\ MALE_{it}} = a_2 \times \text{AI Governance and Ethics}_{it} + b_2 \times \text{AI Digital Capacity}_{it} + c_2 \times \text{AI Adaptability}_{it} + C + \varepsilon_{it} \quad (8)$$

$$\mathrm{EMPLOYMENT\ FEMALE_{it}} = a_3 \times \text{AI Governance and Ethics}_{it} + b_3 \times \text{AI Digital Capacity}_{it} + c_3 \times \text{AI Adaptability}_{it} + C + \varepsilon_{it} \quad (9)$$

AI Pillar 2 components:

$$\mathrm{EMPLOYMENT_{it}} = a_4 \times \text{AI Sector Size}_{it} + b_4 \times \text{AI Innovation Capacity}_{it} + c_4 \times \text{AI Human Capital}_{it} + C + \varepsilon_{it} \quad (10)$$

$$\mathrm{EMPLOYMENT\ MALE_{it}} = a_5 \times \text{AI Sector Size}_{it} + b_5 \times \text{AI Innovation Capacity}_{it} + c_5 \times \text{AI Human Capital}_{it} + C + \varepsilon_{it} \quad (11)$$

$$\mathrm{EMPLOYMENT\ FEMALE_{it}} = a_6 \times \text{AI Sector Size}_{it} + b_6 \times \text{AI Innovation Capacity}_{it} + c_6 \times \text{AI Human Capital}_{it} + C + \varepsilon_{it} \quad (12)$$

AI Pillar 3 components:

$$\mathrm{EMPLOYMENT_{it}} = a_7 \times \text{AI Infrastructure}_{it} + b_7 \times \text{AI Data Capacity}_{it} + c_7 \times \text{Data Representativeness}_{it} + C + \varepsilon_{it} \quad (13)$$

$$\mathrm{EMPLOYMENT\ MALE_{it}} = a_8 \times \text{AI Infrastructure}_{it} + b_8 \times \text{AI Data Capacity}_{it} + c_8 \times \text{AI Data Representativeness}_{it} + C + \varepsilon_{it} \quad (14)$$

$$\mathrm{EMPLOYMENT\ FEMALE_{it}} = a_9 \times \text{AI Infrastructure}_{it} + b_9 \times \text{AI Data Capacity}_{it} + c_9 \times \text{Data Representativeness}_{it} + C + \varepsilon_{it} \quad (15)$$

3.2 The analysis

The data sample included a panel of 78 countries and a period of 4 years (2019 – 2022), for a total number of 312 observations. Data for employment were collected from International Labour Organization (ILO) database (available at: https://genderdata.worldbank.org/en/indicator/sl-tlf-zs) and for AI Readiness Index – composition, scores and reports are based on Oxford Insights database and reports (available at: https://oxfordinsights.com/ai-readiness/ai-readiness-index/). To ensure the integrity of the data set, countries lacking complete data were excluded. Therefore, our panel is a long panel (more countries than years), is a balanced panel (data covers all countries included in the panel), and is a fixed panel (data cover all years included in the panel). The countries included in the panel are the following: Argentina, Armenia, Australia, Austria, Belgium, Bulgaria, Bosnia and Herzegovina, Belarus, Bolivia, Brazil, Brunei Darussalam, Bhutan, Botswana, Canada, Switzerland, Chile, Colombia, Costa Rica, Cyprus, Czech Republic, Germany, Denmark, Dominican Republic, Ecuador, Egypt, Spain, Estonia, Finland, France. Georgia, Greece, Guatemala, Honduras, Croatia, Hungary, Indonesia, India, Ireland, Iran, Iceland, Israel, Italy, Jamaica, Jordan, Republic of Korea, Saint Lucia, Lithuania, Luxembourg, Latvia, Republic of Moldova, Mexico, North Macedonia, Malta, Montenegro, Mongolia, Netherlands, Norway, Panama, Peru, Poland, Portugal, Romania, Russian Federation, Rwanda, Salvador, Serbia, Slovakia, Slovenia, Sweden, Thailand, Trinidad and Tobago, Turkey, Ukraine, United States of America, Vietnam, South Africa, Zambia. Our panel is representative because it encompasses more than 60% of all highly educated workforce global employment. Furthermore, the structure of the panel ensures the representativeness of the results across all types of economies: developed countries, emerging countries, less developed countries, etc.

Table 1. Panel Descriptive Statistics

	EMPL_TOTAL	EMPL_MALE	EMPL_FEMALE	AI_READINESS	PILLAR1_GOV	PILLAR2_TECHSECT	PILLAR3_DATAINFR	P1_1_GOVANDETHICS
Mean	1.184639	1.180195	1.1805	1.835265	1.840824	1.738656	1.877881	1.836682
Median	1.184401	1.18002	1.180384	1.847842	1.874915	1.736549	1.887373	1.848104
Maximum	1.195831	1.186144	1.18665	2.01351	2.017793	2.020302	2.032268	2.043205
Minimum	1.176151	1.176137	1.176145	1.262641	1.261025	1.176091	1.357681	1.176091
Std. Dev.	0.004059	0.00198	0.002314	0.103676	0.126176	0.125869	0.101969	0.129387
Skewness	0.191368	0.423803	0.099038	-0.927665	-0.805891	-1.021728	-1.031585	-1.649081
Kurtosis	2.495031	3.07736	2.164074	5.509896	3.644679	6.595262	5.262895	8.939679
Jarque-Bera	5.219247	9.417472	9.594078	126.6438	39.17488	222.321	121.9057	600.0496
Probability	0.07356	0.00902	0.00825	0.00000	0.00000	0.00000	0.00000	0.00000
	P1_2_DIGITAL_CAPACITY	P1_3_ADAPTABILITY	P2_1_SIZE	P2_2_INNOVATION_CAPACITY	P2_3_HUMAN_CAPITAL	P3_1_INFRASTRUCTURE	SER01	P3_3_DATA_REPRESENTATIVENESS
Mean	1.870752	1.841099	1.607117	1.777871	1.791261	1.81317	1.830202	1.94668
Median	1.879893	1.856856	1.621948	1.777201	1.816222	1.810786	1.904137	1.958186
Maximum	2.060698	2.014259	2.060698	2.033489	1.990593	2.036505	2.045908	2.058805
Minimum	1.393048	1.176091	1.176091	1.176091	1.176091	1.176091	1.176091	1.583879
Std. Dev.	0.102691	0.115483	0.174594	0.136339	0.138619	0.139688	0.224259	0.076328
Skewness	-0.646695	-3.082535	-0.509946	-1.453808	-1.811952	-1.407844	-1.97051	-1.212396
Kurtosis	4.006715	18.3264	3.408758	8.34977	8.470401	7.96018	6.106487	4.87079
Jarque-Bera	34.92232	3547.787	15.69439	481.9655	559.7535	422.9093	327.3646	121.9331
Probability	0.000000	0.000000	0.000391	0.000000	0.000000	0.000000	0.000000	0.000000

Source: Authors' estimations, based on the data sample.

The descriptive statistics are shown in Table 1 above. In accordance with the results, all variables included in the panel data have the skewness and kurtosis exhibits some type of nonnormality (the probability of Jarque-Bera test is less than 0.01 and the value of the test is significantly different from 0 indicating the clear rejection of null hypothesis of normality). However, this is a common situation of panel data series, with very few of them matching a normal distribution. The test and the use of fixed and random effects are recommended in this case.

Stationarity is a very important property of the panel data for valid inference and forecasting. To test the stationarity of the panel data, the following recommended tests for the "level" were used: Levin, Lin and Chu test, ADF - Fisher Chi-square test and PP - Fisher Chi-square test. The aforementioned tests were performed, but their results indicate that all variables included in the research did not exhibit a unit root (the p-values rejected the presence of a unit root in the time series data) and they are not significant for panels with data covering a 4 years-period.

In line with the initial research hypothesis, a panel data analysis was conducted on three levels for all three categories of high-educated workers (total, male, and female). **Level 1 of analysis** contains 3 data panels testing the impact of AI readiness on the employment of highly educated workers (total and by gender). **Level 2 of analysis** contains 3 data panels testing the impact of main pillars of AI readiness (AI government, AI technology, and AI data and infrastructure) on the employment of highly educated workers (total and by gender). **Level 3 of analysis** contains 9 data panels testing the impact of the components of each pillar on the employment of highly educated workers (total and by gender). To ensure the reliability of the findings, there was conducted a comprehensive examination of all 15 the data panel models, encompassing both cross-sectional and period fixed and random effects. Random-effect adjustments control for individual-specific factors that vary across cross-sectional units, but are constant over time. For panel data fixed effects, there were used redundant FE tests (likelihood ratio); for panel-data random effects, there were used Correlated RE (Hausman test). The results only confirmed the presence of cross-sectional fixed effects, for all data panel models.

4. Results and discussion

Following the research goal and hypothesis, the research on the impact of AI on highly-educated employment is developed in three stages. The first stage is an impact assessment of the overall AI readiness in the employment. The second stage is an impact assessment of the main pillars of AI readiness in the employment (AI governance, AI technology sector and AI data and infrastructure). The third stage is an impact assessment of each decomposed pillar of AI readiness in employment.

Table 2. Results for the analysis of the impact of AI readiness on the highly educated employment (Adv. Empl.)

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
AI_READINESS	0.00034*	0.000	0.0003*	0.141	0.0002*	0.000
C	1.184	0.000	1.180	0.000	1.180	0.000
Model statistics	**Panel 1**		**Panel 2**		**Panel 3**	
Adj. R-squared	0.999		0.99845		0.99763	
F-statistic	3259.507		2567.051		1677.348	
Prob(F-statistic)	0.000		0.000		0.000	
DW Test stat.	1.722		1.981		1.684	
FE / RE adj.	Cross-section FE		Cross-section FE		Cross-section FE	

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

The results of the first stage are illustrated in Table 2. Based on these results, a direct proportional and statistically significant impact of AI readiness was found on the employment of highly educated workers. These results are confirmed for all three categories: total, male, and female employment. However, the results indicate that the direct proportional impact of AI readiness on the employment of highly educated workers is more pronounced for male workers than for female workers. The results substantiated the research hypothesis and yielded the anticipated findings.

The second stage of our research is dedicated to an in-depth examination of the three fundamental pillars of AI readiness. The objective is to examine the impact of AI governance, the AI technology sector, and AI data and infrastructure on the employment of workers with high levels of education. The results are presented in tabular form in Table 3. In accordance with the findings of our investigation, the following observations were made. The impact of **AI Governance (Pillar 1)** on the employment of highly educated workers is found to be directly proportional and statistically significant. In light of these findings, it becomes evident that public policies and government support play a pivotal role in shaping the future trajectory of the labour market, particularly in the context of AI-driven transformations. The impact of the **AI Technology Sector (Pillar 2)** is inversely proportional, but not statistically significant with regard to total employment. However, when considered in relation to specific categories, namely male and female employment, the impact becomes significant. These findings suggest that the advancement of the AI technology sector can lead to a decline in the employment of workers with high levels of education. The impact of **AI Data and Infrastructure (Pillar 3)** on total employment is inversely proportional but not statistically significant. Nevertheless, the impact is significant by category (male and female employment).

Table 3. Results for the analysis of the impact of AI readiness pillars on the highly educated employment (Adv. Empl.)

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
PILLAR1_GOV	0.00042*	0.004	0.00046*	0.0000	0.0006*	0.000
PILLAR2_TECHSECT	0.000022	0.922	-0.00024*	0.013	-0.0004*	0.029
PILLAR3_DATA and INFR.	-0.00016	0.423	-0.00036*	0.012	-0.0002	0.437
C	1.184*	0.000	1.180*	0.000	1.180*	0.000
Model statistics	**Panel 1**		**Panel 2**		**Panel 3**	
Adj. R-squared	0.999		0.99809		0.99738	
F-statistic	4462.676		2030.458		1482.016	
Prob(F-statistic)	0.000		0.000		0.000	
Durbin-Watson stat.	1.688		2.022		1.635	

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

It is therefore evident that in order to achieve a more favourable positive impact on employment, AI developments should be concentrated on the uptake of AI in a variety of fields (healthcare, engineering, education, etc.). The developments of ICT sector and the investments in data and infrastructure development should continue to support the AI readiness, but, for the employment of highly educated workers, practical use and its applications of AI are also important. To gain a deeper insight into the influence of AI readiness on the employment of highly educated workers, we proceeded to examine the impact of the constituent elements of each pillar.

The results pertaining to the Pillar 1 components, namely AI governance and ethics, AI digital capacity, and AI adaptability, are summarised in Table 4. Our findings indicate that there is a direct and statistically significant impact of AI governance and AI ethics on the employment of workers with high levels of education, regardless of gender. However, our results suggest that this relationship is inverse when considering overall employment. A similar pattern emerges with regard to the impact of AI digital capacity. In this case, the results indicate an inversely proportional impact on total and female employment, while the impact on male employment is directly proportional. In light of these findings, it can be concluded that there are inconsistencies in the impact of both components. The adaptability of AI has a directly proportional and statistically significant effect on the employment rate of workers with a high level of education (all categories).

Table 4. Results for the analysis of the impact of AI readiness Pillar 1 components on the highly educated employment (Adv. Empl)

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
P1_1_ GOVANDETHICS	-0.0002*	0.030	0.00003*	0.6422	0.0003*	0.014
P1_2_DIGITAL_ CAPACITY	-0.0002*	0.025	0.00004*	0.6653	-0.0005*	0.000

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
P1_3_ ADAPTABILITY	0.0007*	0.000	0.00009*	0.3384	0.0005*	0.000
C	1.1840*	0.000	1.17990*	0.0000	1.180*	0.000
Model statistics	**Panel 1**		**Panel 2**		**Panel 3**	
Adj. R-squared	0.999		0.99860		0.99752	
F-statistic	3085.961		2764.653		1564.044	
Prob(F-statistic)	0.000		0.000		0.000	
Durbin-Watson stat.	1.779		1.986		2.070	

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

Pillar 2 describes the AI technological sector and looks at the AI sector size, AI innovation capacity, and AI human capital. The results of the estimated impact on the employment of highly educated workers are summarised in Table 5. Our findings indicate that the size of the AI sector exerts a direct proportional impact on total employment and an inverse proportional (though not statistically significant) impact on male and female employment. Innovation capacity exerts a direct influence on total and male employment, while exerting an inverse influence on female employment. The AI human capital component of the artificial intelligence readiness index has an inverse impact on total employment of highly educated men and a direct proportional impact on female employment. The analysis of the Pillar 2 components (AI sector size, AI innovation capacity, and AI human capital) indicates that an increase in the intensity of AI entrepreneurship and innovation would have a positive impact on employment for workers with higher levels of education. This would provide a significant incentive for all workers to pursue continuous improvement in their education and digital skills.

Table 5. Results for the analysis of the impact of AI readiness Pillar 2 components on the highly educated employment (Adv. Empl)

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
P2_1_SIZE	0.00021*	0.042	-0.00009	0.1010*	-0.0001*	0.276
P2_2_ INNOVATION_ CAPACITY	0.00041*	0.003	0.00033	0.0002*	-0.0005*	0.000
P2_3_HUMAN _CAPITAL	-0.00052*	0.003	-0.00032	0.0004*	0.0005*	0.001
C	1.18449*	0.000	1.18033	0.0000*	1.180*	0.000
Model statistics	**Panel 1**		**Panel 2**		**Panel 3**	
Adj. R-squared	0.999		0.99881		0.99687	
F-statistic	4255.805		3251.798		1238.283	
Prob(F-statistic)	0.000		0.000		0.000	
Durbin-Watson stat.	1.776		1.993		2.048	

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

Pillar 3 is decomposed into AI infrastructure, AI data availability, and AI data representativeness. The results are presented in Table 6. Our findings indicate that the impact of the AI Readiness Pillar 3 on the employment of workers with high levels of education (across genders) can be quantified as follows: The impact of AI infrastructure on male and female employment is directly proportional and statistically significant. However, this result is not statistically significant for total employment. The impact of AI data availability on all categories of high-educated employment is directly proportional and statistically significant. This impact is less significant for male employment, but more intense. The impact of AI data representativeness on total high-educated employment is directly and positively related. However, this impact is negative but not significant for male employment and positive but not significant for female employment.

Table 6. Results for the analysis of the impact of AI readiness Pillar 3 components on the highly educated employment (Adv. Empl.)

Variable	Adv. Empl. Tot		Adv. Empl. Male		Adv. Empl. Fem.	
	Coeff.	Prob.	Coeff.	Prob.	Coeff.	Prob.
P3_1_INFRASTRUCTURE	-0.00006	0.625	0.00025*	0.0008	0.0000*	0.999
P3_2_DATA_AVAILABILIT Y	0.00029*	0.024	0.00011**	0.1073	-0.0005**	0.008
P3_3_DATA_REPRESENTA TIVENESS	0.00006*	0.815	-0.00003	0.8314	0.0005	0.325
C	1.18410*	0.000	1.18050*	0.0000	1.180*	0.000
Model statistics	**Panel 1**		**Panel 2**		**Panel 3**	
Adj. R-squared	0.998		0.99729		0.99888	
F-statistic	1694.623		1431.448		3466.199	
Prob(F-statistic)	0.000		0.000		0.000	
Durbin-Watson stat.	1.675		1.945		2.054	

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

The results are robust, and the presence of autocorrelation is either absent or minimal (weak positive autocorrelation), with no impact on the (Durbin-Watson tests yield values slightly less than 2 or very close to 2). The F-statistic test yielded values exceeding 2 in all models, thereby confirming their statistical significance (the probability was also less than 0.01 for all models). The elevated adjusted R-squared values substantiate a profound interconnection between the explanatory and dependent variables incorporated into our models. In light of these findings, it can be concluded that AI readiness and its constituent elements are highly pertinent in explaining the employment of workers with higher education/qualifications. Furthermore, the high statistical significance of the intercept (across all models) provides evidence that other potential explanatory factors may be relevant in understanding the employment rate of highly educated workers.

Table 7. The impact of AI Readiness on employment of highly educated workers (synthesis)

AI Readiness drivers for highly educated employment	Estimated impact on employment	Statistical sign.
Artificial Intelligence Readiness	Directly proportional (+)	Significant for total, male and female employment
AI Governance	Directly proportional (+)	Significant for total, male and female employment
AI Technological sector	Inversely proportional (-)	Not for total, only for male and female employment
AI Data and infrastructure	Inversely proportional (-)	Not for total, only for male and female employment
AI Governance and ethics	Directly proportional (+)	Significant for male and female employment
AI Digital capacity	Inversely proportional (-)	Significant for total and female employment
AI Adaptability	Directly proportional (+)	Significant for total, male and female employment
AI Size	Inversely proportional (-)	Significant for total, male and female employment
AI Innovation capacity	Directly proportional (+)	Significant for total, male and female employment
AI Human capital	Inversely proportional (-)	Significant for total, male and female employment
AI Infrastructure	Directly proportional (+)	Significant for male and female employment, not for total.
AI Data availability	Directly proportional (+)	Significant for total, male and female employment
AI Data representativeness	Directly proportional (+)	Significant for total employment only

Source: Authors' estimations, based on the data sample; * - 1% statistical significance.

In Table 7, we present a summary of the estimated impact of the primary AI readiness drivers on high-educated employment. As can be observed, with the exception of a few instances, all AI readiness drivers have a directly proportional impact that is also statistically significant for all three categories of workers included in the analysis (total, male, and female). The estimated impact on high-educated male and female employment differs only slightly (this research hypothesis was only partially confirmed).

It is beyond dispute that the future of work will be shaped by a significant rise in the utilisation of automation, particularly AI-driven automation (Gordon and Gunkel, 2024). This may result in a reduction of the need for human involvement (as AI can accomplish the tasks that humans used to accomplish) and fewer jobs for human workers (Gomes and Lins de Morales, 2024). Recent work suggests that this negative impact is likely to be experienced by human workers situated on the receiving end of these technological innovations (Gordon and Gunkel, 2024). Nevertheless, some of the displaced human workers may relocate, but it is possible that others lose their employment (Gomes and Lins de Morales, 2024). It is therefore imperative that policy makers design strategies to mitigate the detrimental effects of job insecurity/displacement by narrowing the distance between the experience of job loss and the advent of new employment prospects (Gordon and Gunkel, 2024). Based on our findings, this is contingent upon the formulation of education and training policies that enhance AI literacy and AI skills. However, there is a lack of consensus among governments with regard to the specific AI skills that should be prioritised (Rigley et al., 2024) in their skills policies. Recent findings (Rigley et al., 2024) on selected countries, ranked by 2022 scores for the Government AI Readiness Index (GAIRI) and the Global AI Index (GAI), have revealed the correlation between higher AI readiness scores and a more comprehensive approach to AI literacy in government strategy to upskill individuals, while policies focusing on specific expertise or advanced AI knowledge and skills has been found to correlate with lower AI readiness scores. This second option is particularly evident in countries where a select few highly educated elites are able to shape and define the future of AI technologies (Rigley et al., 2024), but it contributes to widening the AI divide and, in the context of the AI skills gap, it is probable that human workers will be displaced.

5. Conclusions

The implementation of AI has the effect of reducing costs for companies (lower salaries, fewer employees, higher productivity), creating incentives for its rapid penetration of various industries and consequently impacting both employment and education. High-skilled/highly educated workers are the most vulnerable to the effects of AI, either in terms of substitution or creation (Webb, 2020; Acemoglu and Restrepo, 2019; Acemoglu and Restrepo, 2022; Jongwanich et al., 2022). The results of our study confirm that there is a direct proportional impact of AI readiness on the employment of highly educated workers, both men and women (and total). The study also supported the hypothesis that certain aggregated factors may exert an inverse impact, such as AI data and infrastructure. This indicates that the further applications of AI in diverse fields (including engineering, economics, healthcare, the public sector, and financial services) are of greater consequence for the employment of highly educated workers than the mere development of ICT capacity and infrastructure. Furthermore, the findings indicated that the discrepancies between male and female employment rates among highly educated workers are not statistically significant. This phenomenon may be attributed to the fact that, at this level of education, gender-based disparities tend to be less pronounced during the selection process.

Based on our findings, continuous improvement in human workers' education and AI related/digital skills is expected to have positive impact on employment. Given the growing prevalence of AI in future employment, it is imperative that both professors and students receive comprehensive training in AI technology. This will enable them to ensure adequate AI literacy by developing the essential knowledge, skills, and competencies to thrive in an AI-centric workforce (Tomescu and Boeru, 2024; Covrig et al., 2023).

It is recommended that the educational system, particularly university education, become more aligned with the latest advancements in AI and AI-based applications. This would enhance AI literacy and skills among graduates, enabling them to keep pace with the rapid adoption of AI by various industries and the evolving needs of AI-driven work environments and economies. Educational and training systems and educational policies tailored to foster AI literacy represent the most sustainable means of addressing AI-driven employment and labour markets changes and challenges and transforming them into opportunities. The entire landscape of education and training (either formal, informal, or nonformal) should undergo a significant transformation to equip learners with AI skills and to deliver AI literacy, therefore to mitigate the potential impact of anticipated worker displacement. Our findings illustrate the pivotal role of the education system in fostering a deeper comprehension and seamless integration of AI advancements into our endeavours and professional roles. AI will have a profound impact on value-added processes, production, technology, and communication in the economic sphere. It is therefore important to highlight the added value of initiatives that facilitate the upskilling and reskilling of individuals throughout their professional careers. These initiatives should be seen as a valuable addition to the formal university education and professional training that employees receive, with the aim of increasing the number of skilled workers who are able to use AI effectively in complex environments (Bodea et al., 2024). This approach can help to mitigate the displacement of human workers and to facilitate their access to new employment opportunities.

The limitations of our study can be attributed to three primary factors. Firstly, the panel data analysis included a relatively limited number of years (4 years only). Secondly, a number of countries with significant global influence were not included due to a lack of available data (China, the UK, and Japan are the most notable examples). Thirdly, the AI Readiness index proposed by Oxford Insight is constrained in terms of the indicators it encompasses, in comparison to the alternative indicator for AI Readiness proposed by UNCTAD. Subsequent iterations of this research will address these limitations by incorporating additional years and countries, examining the influence of other facets of AI on employment, extending the investigation to encompass educational processes, and undertaking a sector-specific analysis (focusing on the sectors most impacted by AI).

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