Strategic Workforce Transformation in the AI Era: Managing Employment Risk

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ABSTRACT

Artificial intelligence (AI) is increasingly reshaping work; however, its aggregate employment effects remain uncertain. This study examines whether AI adoption is associated with workforce digital capacity and employment outcomes across the 27 European Union countries during 2023–2025. Using Eurostat data, the analysis combines descriptive statistics, Principal Component Analysis (PCA), and separate annual cross-sectional regressions. A Workforce Preparedness Index (WPI) was constructed from digital skills, enterprise-provided ICT training, and the share of ICT specialists. PCA supported a one-component solution explaining 70.18% of total variance. In the 2023 cross-section, AI adoption was positively associated with ICT training (β =.509, p =.007) and ICT specialists (β =.440, p =.021). Workforce preparedness was positively associated with the employment rate (β =.480, p =.011), while ICT specialists showed the strongest relationship with employment (β =.527, p =.005). Robustness analyses indicated that the association between AI adoption and ICT specialists remained significant and strengthened across 2023–2025, whereas the positive association between ICT specialists and employment remained significant but weakened over time. By contrast, AI adoption was not significantly associated with unemployment (β = −.115, p =.567). The findings shift the analytical focus from AI-induced job displacement towards workforce transformation, suggesting that employment risk in the AI era may depend less on technological adoption alone than on the capacity of economies to develop complementary workforce capabilities.

KEYWORDS: *AI Adoption, Digital Skills, Labour Market, Employment Resilience, Workforce Transformation*

JEL CLASSIFICATION: *J21, J24, M53,O33*

1. INTRODUCTION

Companies increasingly integrate AI into data analysis, decision-making, production, customer services, and other organisational processes, as such an important question becomes difficult to avoid: what happens to employment when technologies become capable of performing tasks previously carried out by workers? This question is particularly relevant in Europe, where AI adoption is advancing but remains uneven across countries and enterprises, reflecting differences in resources, innovation capacity, organisational characteristics, and access to qualified human capital (Drago et al., 2025; Ionașcu, 2025; Rožman et al., 2023). Artificial intelligence adoption should therefore be understood not simply as the introduction of a new technology, but as a transformation that may reshape both work and the capabilities required from workers. Nevertheless, the consequences of this transformation for employment are far from straightforward. The same technology that can replace human tasks can also increase the value of human skills needed to use, complement, and manage it. On the one hand, AI may reduce labour demand by performing activities previously undertaken by employees. Acemoglu and Restrepo (2019) describe this mechanism through the

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displacement effect of automation, whereby tasks are transferred from labour to capital. With AI, this concern extends beyond traditional routine automation because these technologies can increasingly perform cognitive activities involving prediction, classification, language, and decision support. The employment question is therefore not only whether AI can substitute for workers, but also which tasks are displaced, which capabilities become more valuable, and how prepared the workforce is to adapt to this change.

On the other hand, technological change does not necessarily lead to lower employment. Automation may increase productivity, create new tasks, and increase the demand for workers whose skills complement technology. Georgieff and Hyee (2022), analysing 23 OECD countries, found no clear overall relationship between occupational AI exposure and employment growth. However, employment increased more strongly in AI-exposed occupations characterised by intensive computer use. Guarascio and Reljic (2025) also identified a positive association between AI exposure and employment growth in European countries, although these benefits were concentrated in economies with stronger innovation systems. These results suggest that the employment implications of AI may depend not only on technological exposure but also on the ability of workers and economies to adapt to technological change.

Considering these different perspectives, two possible processes can be identified. The first involves AI adoption, automation, displacement, and employment risk, while the second involves AI adoption, augmentation, workforce adjustment, and employment resilience. These processes are not necessarily contradictory. AI may replace certain tasks while simultaneously increasing the importance of other occupations and skills (Acemoglu & Restrepo, 2019; Cramarenco et al., 2023; Rademakers & Zierahn-Weilage, 2024). Consequently, important changes in the structure of work may occur without an immediate increase in aggregate unemployment. Starting from these considerations, the present study approaches the relationship from another perspective, namely: AI adoption is influencing workforce digital capacity and has labour-market outcomes.

Workforce digital capacity may represent an important element in understanding how economies respond to AI adoption. Firms introducing advanced technologies require employees who can use, supervise, integrate, and complement them. Therefore, technological adoption may be accompanied by investments in training and by a greater importance of specialised Information and Communication Technology (ICT) workers. Cramarenco et al. (2023) highlight continuous upskilling and reskilling as important responses to AI-related technological change. Muehlemann (2025) also found that sustained AI adoption among German establishments was associated with increased investment in apprenticeship training and, to a lesser extent, continuing training. Regarding specialised human capital, Fontanelli et al. (2025) found that ICT engineers represented the occupational category most strongly associated with firms' AI adoption.

Digital capabilities may also be important for employment. Männasoo et al. (2023), using data from 27 European countries, show that digital capabilities, education, and digital infrastructure contribute to employment outcomes. Đorđević et al. (2025) also identified positive relationships between several dimensions of digital competence and employment rates in European countries. These studies suggest that workforce capabilities may influence not only the adoption of technologies but also workers' ability to adjust to increasingly digital labour markets. Despite the increasing interest in AI and employment, the existing literature remains divided between several areas. A substantial number of studies focus on automation, occupational exposure, and possible job displacement. Other studies examine the skills and organisational resources associated with technological adoption, while another group analyses

digital skills and employment. Comparatively less attention has been paid to whether actual enterprise AI adoption is associated with the development of workforce capabilities that may support employment resilience. In particular, limited evidence simultaneously considers enterprise AI adoption, ICT training, ICT specialisation, broader digital skills, and employment outcomes across European countries.

An important distinction also has to be made between AI exposure and AI adoption. Occupational exposure indicates the extent to which tasks could potentially be affected by AI, while adoption reflects the actual use of these technologies by enterprises. Moreover, even when AI is adopted, its effects may not immediately appear in aggregate unemployment because employment is influenced by productivity, occupational mobility, demographic factors, institutional conditions, and the creation of new activities. Changes in training, skills, and occupational specialisation may therefore become visible before substantial changes occur in aggregate employment indicators.

Considering these aspects, the purpose of the present study is to investigate the relationships between AI adoption, workforce digital capacity, and employment outcomes across 27 European countries during 2023–2025. Workforce digital capacity is approached through general digital skills, enterprise-provided ICT training, and ICT specialisation. In this context, employment risk is considered not only from the perspective of jobs potentially replaced by AI but also from that of insufficient workforce adaptation to technological change.

In order to achieve our purpose, we start from the following research question:

RQ: How is AI adoption associated with workforce digital capacity and employment outcomes across European countries?

Since relationships identified in a single year may reflect temporary economic conditions, we also investigate whether the main associations remain visible over successive years:

RQ2: Are the relationships between AI adoption, ICT specialisation, and employment outcomes temporally robust across 2023–2025?

Therefore, the study shifts attention from AI-induced job displacement towards the broader process of workforce transformation. From this perspective, AI readiness does not depend only on technological infrastructure or enterprise adoption. It may also depend on whether countries possess the skills, training capacity, and specialised human capital necessary to complement technological change.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI Adoption and Employment Risk

The possible effects of technological change on employment have been discussed extensively in the economic literature. Automation may reduce labour demand when technologies perform tasks previously undertaken by workers. Acemoglu and Restrepo (2019) describe this mechanism as the displacement effect, through which automation reallocates tasks from labour to capital. AI may extend this process to a wider range of occupations because it can increasingly perform cognitive as well as routine tasks.

However, the same technological process may also generate opposite effects. Automation can increase productivity, reduce production costs, stimulate economic activity, and create new tasks in which labour maintains a comparative advantage. Consequently, the final employment effect depends on the balance between displacement, productivity gains, and the creation of new tasks. Previous empirical studies provide mixed results. Georgieff and Hyee (2022) found no clear overall relationship between occupational AI exposure and employment

growth across OECD countries. Yet, more AI-exposed occupations with high computer use experienced comparatively stronger employment growth. Guarascio and Reljic (2025) obtained similar evidence for Europe, showing that greater AI exposure was associated with stronger employment growth, particularly in countries characterised by stronger innovation systems. Rademakers and Zierahn-Weilage (2024) also argue that recent technological change has produced more evident changes in skills and workforce composition than in aggregate employment. At the same time, technological change may create difficulties for specific groups of workers. Giwa and Ngepah (2024), for example, identified a negative long-run relationship between AI investment and low-skilled employment in South Africa. Such findings indicate that employment gains and displacement can coexist because the consequences of AI are not necessarily distributed equally between occupations and skill groups. Recent management research similarly indicates that the labour-market consequences of AI extend beyond direct job displacement, involving changes in employment structures, occupational requirements and the skills demanded from workers (Craciun and Băluț Gaboroi, 2025; Moldoveanu, 2022).

It is also important to distinguish occupational AI exposure from actual AI adoption. Exposure measures identify tasks that could potentially be affected by AI but do not indicate whether enterprises have implemented these technologies. This distinction is particularly relevant in Europe, where the adoption of AI remains uneven between countries (Drago et al., 2025; Ionașcu, 2025).

Considering these previous studies, the relationship between actual AI adoption and aggregate unemployment remains uncertain. AI may substitute for some labour, while productivity improvements, new activities, and complementary employment may compensate for this effect. For this reason, we do not formulate a directional hypothesis regarding AI adoption and unemployment. Instead, their relationship is examined as a supplementary analysis. This allows us to focus on another aspect that may appear earlier than changes in aggregate unemployment: the transformation of workforce capabilities.

2.2 AI Adoption and Workforce Transformation

The adoption of AI requires more than access to technological infrastructure. Enterprises need employees capable of selecting appropriate applications, using new systems, interpreting their outputs, and integrating them into existing organisational processes. Consequently, human capital can be considered a complementary resource for technological adoption.

One way in which firms develop these capabilities is through training. Cramarenco et al. (2023), reviewing the literature on AI and employees' skills, identify upskilling and reskilling as important responses to technological change. They also highlight skill mismatch as a significant challenge in labour-market adaptation. Kazancı Yabanova (2025) similarly emphasises the growing role of workplace learning as technological developments modify employees' skill requirements. Evidence at the firm level supports this relationship. Muehlemann (2025), analysing German establishments between 2019 and 2023, found that sustained AI adoption was associated with greater apprenticeship activity among firms already involved in apprenticeship training and with a more moderate increase in continuing training. These results suggest that enterprises adopting AI may also increase their efforts to develop the human capital required to work with new technologies. At the country level, the proportion of enterprises providing ICT training may therefore reflect one aspect of workforce adjustment to technological change. ICT training is broader than AI-specific training, and the relationship does not necessarily imply that AI adoption causes firms to provide training. Nevertheless, countries where enterprise AI adoption is more widespread may also display greater organisational demand for technological skills. Technological transformation also

increases the importance of continuous learning and structured digital training, as organisations need to develop employee competencies alongside the adoption of new technologies (Bănescu et al., 2023; Benchouat & Ghezal, 2025).

Considering these aspects, we formulate our first hypothesis:

H1. Higher levels of AI adoption are positively associated with greater provision of ICT training by enterprises.

Apart from training, AI adoption may also be related to the presence of specialised ICT workers. Advanced technologies require expertise in areas such as software, data, systems integration, digital infrastructure, and cybersecurity. Therefore, enterprises with greater access to specialised human capital may be better prepared to introduce AI technologies. Fontanelli et al. (2025), using matched French firm-level data, found that ICT engineers were the occupational group most consistently associated with firms' AI adoption. Their results indicate that specialised technological expertise represents an important complementary resource for AI diffusion. Yu and Qi (2025) also associate enterprise AI application with human-capital upgrading and greater reliance on skilled labour.

However, the direction of this relationship may work both ways. ICT specialists can facilitate AI adoption, while greater use of AI may simultaneously increase the demand for employees capable of implementing and managing these systems. Since the present study uses observational country-level data, it cannot establish which mechanism comes first. We therefore focus on the expected association between the two variables.

Taking into account the previous arguments, we develop our second hypothesis:

H2. Higher levels of AI adoption are positively associated with a greater share of ICT specialists in the workforce.

2.3 Digital Workforce Capacity and Employment Resilience

The ability of workers to adapt to technological change depends considerably on their existing skills and their opportunities to develop new ones. In increasingly digital labour markets, workers without appropriate capabilities may experience greater difficulties in adjusting to new occupational requirements, while digitally skilled workers may be better positioned to complement technological systems. Previous studies indicate that digital skills are related to employment outcomes. Männasoo et al. (2023), using microdata for 27 European countries, found that digital capabilities, education, and digital infrastructure contribute to employment. Đorđević et al. (2025) also identified positive associations between several dimensions of digital competence and employment rates across European economies. Moreover, Georgieff and Hyee (2022) show that the more favourable employment patterns associated with AI exposure were particularly visible in occupations characterised by intensive computer use.

Digital skills alone may not fully describe the capacity of a workforce to respond to technological change. Training is also important because existing competencies may become insufficient as technologies develop (Cramarenco et al., 2023; Kazancı Yabanova, 2025). ICT specialists add another dimension by providing the advanced expertise necessary to implement, integrate, and maintain digital technologies. Therefore, general digital skills, ICT training, and ICT specialisation can be considered complementary elements of workforce digital capacity.

In the present study, these three dimensions are brought together in a Workforce Preparedness Index (WPI). This index is not considered an established measurement scale but rather a theoretically motivated composite measure whose empirical structure is subsequently assessed in the methodology. A workforce characterised by stronger general digital skills,

greater training activity, and more specialised ICT human capital may be better prepared to respond to technological change and, consequently, to participate in employment.

Considering these previous arguments, our third hypothesis is:

H3. Higher workforce preparedness is positively associated with higher employment rates.

Among these dimensions, ICT specialisation deserves separate consideration because ICT specialists are directly involved in the development, implementation, and maintenance of advanced digital technologies. Their contribution is not limited to the ICT sector. Specialists working in manufacturing, finance, professional services, public administration, and other activities may facilitate technological adoption throughout the economy. Fontanelli et al. (2025) demonstrate the importance of specialised ICT human capital for enterprise AI adoption. More generally, a greater availability of ICT specialists may help economies translate technological investment into productive activities and reduce constraints arising from shortages of appropriate expertise. Nevertheless, this relationship may also depend on national economic structures, innovation capacity, and sectoral composition. Therefore, it should be interpreted as an association rather than as evidence of causality.

Taking into account these aspects, we formulate our fourth hypothesis:

H4. A greater share of ICT specialists in the workforce is positively associated with higher employment rates.

Taken together, these hypotheses allow us to approach employment risk from a broader perspective. AI may generate displacement in some tasks and occupations, but the capacity to respond to this process depends partly on workforce capabilities. The proposed framework links AI adoption to workforce transformation, the development of digital workforce capacity, and, ultimately, employment resilience. These relationships are not intended to imply causal mediation, as the analysis relies on observational country-level data and some of the associations may be reciprocal. Instead, the framework reflects the relationships identified in the literature and provides a basis for examining whether higher levels of AI adoption are associated with stronger workforce capabilities and whether these capabilities, in turn, are associated with employment outcomes. From this perspective, employment risk in the context of AI may not refer exclusively to the possibility that technologies replace workers. It may also concern the capacity of workers and economies to adapt when technological adoption advances. Consequently, insufficient digital skills, limited training, or shortages of ICT specialists may represent important constraints on the ability of European labour markets to benefit from technological transformation.

3. METHODOLOGY

3.1 Research Design

In order to achieve the purpose of the study and considering the results of previous research, we conducted a quantitative cross-country comparative analysis using JASP Version 0.98.1 (released July 7, 2026) based on secondary data from 11 Eurostat datasets. The analysis covers the 27 European Union countries for the period 2023–2025. The database is organised at the country-year level, resulting in 81 observations. However, the main regression analyses are conducted separately for each year and should therefore be interpreted as cross-sectional analyses rather than as a pooled panel regression.

The variables were collected from Eurostat and refer to AI adoption, digital skills, ICT training, ICT specialists, employment and unemployment, together with several socioeconomic indicators. It is important to mention that data availability differs across

indicators. Digital skills are available for 2023 and 2025, while ICT training is available for two waves. No interpolation or automatic imputation was applied to the missing observations. This approach was adopted in order to preserve the original Eurostat values.

The study focuses on actual AI adoption rather than potential occupational exposure to AI. This distinction is important since exposure to AI does not necessarily result in employment displacement (Georgieff & Hyee, 2022). Moreover, recent evidence suggests that the labour-market effects of AI may depend on the timing of technological adoption, worker characteristics and broader economic conditions (Brynjolfsson et al., 2026). Therefore, the analysis examines AI adoption together with workforce capabilities rather than assuming a direct relationship between AI adoption and unemployment.

3.2 Variables

The variables were selected according to the conceptual framework of the study, which connects AI adoption, workforce transformation, digital capacity and employment outcomes (as shown in Table 1). AI Adoption measures the proportion of enterprises using artificial intelligence technologies and represents the main indicator of technological adoption. Digital Skills measure the general digital capabilities of individuals, while ICT Training reflects enterprises' efforts to develop employees' technological skills. ICT Specialists represent the more specialised component of digital human capital.

Table 1. Variable Operationalisation

Variable	**Role in study**	**Measurement / filter**
Country_Code	Identifier	EU-27 country code
Country	Identifier	EU-27 country name
Year	Time reference	Reference year for main cross-section
AI_Adoption	Independent variable	Enterprises using ≥1 AI technology; enterprises with 10+ persons employed
Digital_Skills	Workforce preparedness	Individuals 16–74 with basic or above-basic overall digital skills; all individuals
ICT_Training	Workforce preparedness	Enterprises providing ICT training to personnel; enterprises with 10+ persons employed
Employment_Rate	Employment-risk component	Total employment; age 20–64; sex total
Unemployment_Rate	Employment-risk component	Unemployment; age 15–74; sex total
Job_Vacancy_Rate_Q4	Employment-risk component	Job vacancy rate; all NACE A–S aggregate in supplied export; NSA; total size
Temporary_Employment	Employment-risk component	Temporary contract; age 20–64; sex total
ICT_Specialists	Preparedness / control	Employed ICT specialists
GDP_per_capita_PPS_Index	Control	GDP per capita in PPS; EU27_2020=100
GDP_Growth	Control	Real GDP growth rate, chain-linked volumes
Tertiary_Education	Control	Age 25–34; sex total; ISCED 5–8

Source: authors' own description of variables with Eurostat codes

These dimensions are particularly relevant because AI does not necessarily lead only to job substitution. In many occupations, technological adoption changes the content of jobs and increases the importance of reskilling and upskilling (Emerson et al., 2026). At the same time, recent evidence indicates that AI may generate employment losses in occupations where it substitutes human labour while supporting employment where it complements workers (Goldman Sachs Research, 2026). Employers themselves increasingly anticipate such adjustments, particularly for junior and administrative positions (the Chartered Institute of Personnel and Development, 2025). The Employment Rate is therefore used as the main labour-market outcome in the hypotheses, while the Unemployment Rate is examined as a supplementary indicator. Considering the mixed findings regarding AI and employment, unemployment alone may not adequately capture workforce transformation.

Finally, the Workforce Preparedness Index (WPI) combines Digital Skills, ICT Training and ICT Specialists. These three variables represent general digital competence, organisational investment in workforce development and specialised digital human capital. The index is constructed using Principal Component Analysis (PCA), following the use of PCA as a method for developing composite indicators from correlated variables (Pricop & Diaconu, 2025).

3.3 Construction of the Workforce Preparedness Index (WPI)

In order to assess the digital capacity of the workforce, we developed a Workforce Preparedness Index (WPI) using Principal Component Analysis (PCA). The index includes three variables: “Digital Skills”, “ICT Training”, and “ICT Specialists”. PCA was used to reduce the three related indicators to a smaller number of underlying dimensions and to construct a composite index (Hair et al., 2019). It allows correlated indicators to be combined into a smaller number of components and provides an empirical basis for constructing a composite index, an approach also applied in previous cross-country studies using Eurostat indicators (Pricop & Diaconu, 2025).

Before extracting the principal components, the suitability of the data was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett’s test of sphericity. The KMO value of.686 indicated an acceptable level of sampling adequacy, while Bartlett’s test was statistically significant ($\chi^2 = 70.330$, df = 3, $p < .001$), confirming that the correlations between the three variables were sufficient for PCA. The PCA identified a clear one-component structure. As presented in Table 2, all three indicators recorded high loadings on the first component: ICT Training (.876), Digital Skills (.830), and ICT Specialists (.807). The first component had an eigenvalue of 2.105 and explained 70.18% of the total variance, indicating that the three indicators capture a substantial common dimension of workforce digital preparedness.

Table 2. Principal Component Analysis

Variable	Component 1 Loading
ICT Training	0.876
Digital Skills	0.830
ICT Specialists	0.807
Eigenvalue	**2.105**
Variance explained	**70.18%**

Source: authors’ calculations based on Eurostat data

4. RESULTS

4.1 Descriptive Results

Before testing the proposed hypotheses, the main indicators were examined for the 2023–2025 period. As can be observed in table 3, the average level of AI adoption increased considerably, from 12.62% in 2023 to 20.05% in 2024 and 29.23% in 2025. During the same period, the average employment rate increased moderately, from 76.86% to 77.68%, while the unemployment rate remained relatively stable, increasing only slightly from 5.77% to 5.84%. The average share of ICT specialists also increased, from 5.09% in 2023 to 5.35% in 2025.

These results reveal two different dynamics during the analysed period. On the one hand, enterprise AI adoption expanded rapidly across the European Union. On the other hand, aggregate employment indicators changed only moderately. Therefore, at the descriptive level, the acceleration of AI adoption was not accompanied by a comparable deterioration in employment conditions. It is important to mention, however, that these trends are descriptive and cannot establish a causal relationship between AI adoption and labour-market outcomes. Due to differences in data availability across years, the main hypothesis testing was conducted for 2023, when the indicators required for AI adoption, ICT training, ICT specialists and the Workforce Preparedness Index were jointly available.

Table 3. Descriptive Statistics for the Main Indicators, Period 2023-2025

Descriptive Statistics

	AI_Adoption			Digital_Skills			ICT_Training			Employment_Rate			Unemployment_Rate			Job_Vacancy_Rate_Q4			Temporary_Employment		
	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025	2023	2024	2025
Valid	27	27	27	27	0	0	27	27	0	27	27	27	27	27	27	27	27	27	27	27	27
Missing	0	0	0	0	27	27	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0
Median	10.37	19.91	30.10	29.08		25.87	15.42	16.50		77.90	78.50	79.30	5.600	5.400	5.800	-0.1000	-0.1000	-0.1000	8.900	9.100	9.000
Mean (arithmetic)	12.62	20.05	29.23	33.02	NaN	24.59	16.36	16.87	NaN	76.86	77.33	77.68	5.767	5.811	5.844	0.2847	0.3000	0.2882	8.515	9.267	9.070
Std. Deviation	6.971	6.890	12.80	13.38		13.68	6.548	6.512		4.769	4.403	4.352	2.252	2.168	2.077	0.6663	0.7514	0.7052	5.402	5.189	5.090
Skewness	0.2123	0.5094	0.4625	2.622	0.000*	2.397	0.7735	0.5203	0.000*	-0.5257	-0.7771	-0.7528	1.157	0.7903	0.6200	1.520	1.511	1.679	0.5188	0.4442	0.4435
Std. Error of Skewness	0.4479	0.4479	0.4479	0.4478	0.000	0.4479	0.4479	0.4479	0.000	0.4479	0.4479	0.4479	0.4479	0.4479	0.4479	0.5497	0.5497	0.5497	0.4479	0.4479	0.4479
Kurtosis	-1.303	-0.2001	-0.1595	6.981	NaN#	5.596	-0.02265	-0.8553	NaN#	-0.1015	-0.1924	-0.1540	1.043	0.4378	-0.3532	0.6534	0.7756	1.687	-0.04560	0.80764	0.1270
Std. Error of Kurtosis	0.8721	0.8721	0.8721	0.8721	0.000	0.8721	0.8721	0.8721	0.000	0.8721	0.8721	0.8721	0.8721	0.8721	0.8721	1.063	1.063	1.063	0.8721	0.8721	0.8721
Minimum	3.300	3.880	7.790	23.54	∞	22.76	8.000	7.700	∞	68.30	67.10	67.60	2.880	2.900	2.800	-0.4800	-0.2000	-0.2000	1.700	1.500	1.700
Maximum	22.99	40.92	58.27	81.09	-∞	80.06	39.63	38.33	-∞	83.50	83.50	82.60	12.20	11.40	10.50	2.300	2.000	2.000	23.40	22.80	22.30

* All values are identical

Minimum (minimum) of an empty set is +∞, supremum (maximum) of an empty set is -∞

Source: JASP calculations

4.2 Hypothesis Testing: 2023 Cross-Sectional Analysis

Regarding H1, the results in table 4 indicate a positive and statistically significant relationship between AI adoption and ICT training. AI adoption explained 25.9% of the variation in enterprise-provided ICT training (R^2 =.259; F(1,25) = 8.730, p =.01). The standardised coefficient was positive (β =.51), while the unstandardized coefficient was B =.72, with a 95% confidence interval between.217 and 1.216.

Table 4. Hypothesis Testing

Hypothesis	Relationship	B	β	R^2	F	p	Decision
H1	AI Adoption → ICT Training	0.72	0.51	0.259	8.73	0.01	Supported
H2	AI Adoption → ICT Specialists	0.11	0.44	0.194	6.02	0.02	Supported
H3	WPI → Employment Rate	2.72	0.48	0.23	7.47	0.01	Supported
H4	ICT Specialists → Employment Rate	1.68	0.53	0.277	9.6	0.01	Supported

Source: authors' calculations based on JASP

Considering these results, H1 is supported, indicating that countries with higher levels of enterprise AI adoption also tend to record greater provision of ICT training. As for H2, AI adoption was also positively associated with the share of ICT specialists. The model explained 19.4% of the variation in ICT specialist employment (R^2 =.194; F(1,25) = 6.02, p =.021). The standardised coefficient was β =.44, while the unstandardized coefficient was B =.11, with a 95% confidence interval ranging from.017 to.199. Therefore, H2 is supported. This result suggests that stronger AI adoption is associated not only with training activities but also with a greater presence of specialised digital human capital. Regarding workforce preparedness, the results also support H3. The Workforce Preparedness Index was positively associated with the employment rate (β =.480, p =.011), explaining 23.0% of its cross-country variation (R^2 =.230; F(1,25) = 7.470, p =.011). The unstandardized coefficient (B = 2.724) indicates that higher workforce preparedness is associated with higher employment rates, although the cross-sectional design does not allow this relationship to be interpreted causally. Consequently, H3 is supported.

Finally, H4 received the strongest statistical support among the four models. ICT specialists were positively associated with the employment rate (β =.53, p =.01), while the model explained 27.7% of the variation in employment rates across the analysed countries (R^2 =.277; F(1,25) = 9.6, p =.01). The unstandardized coefficient was B = 1.683, with a 95% confidence interval between.564 and 2.802. Considering these results, H4 is supported. Taken together, all four hypotheses were supported for the 2023 cross-sectional analysis. The results reveal a consistent pattern in which AI adoption is associated with indicators of workforce transformation, while stronger digital workforce capacity is associated with more favourable employment outcomes. Nevertheless, these relationships should be interpreted as cross-country associations and not as evidence of causal mediation.

4.3 Temporal Robustness of the Main Relationships, 2023–2025

To assess whether the relationships identified in the 2023 cross-sectional analysis were specific to a single year, additional regressions were estimated separately for 2024 and 2025. The robustness analysis focused on the relationships between AI adoption and ICT specialists (H2), and between ICT specialists and the employment rate (H4). As presented in Table 5, both relationships remained positive and statistically significant throughout the entire 2023–2025 period.

Table 5. Robustness Results

Relationship	Year	β	R^2	Adj. R^2	F	p	Hypothesis Assessment
H2: AI Adoption → ICT Specialists	2023	0.44	0.19	0.162	6.02	0.02	Supported
	2024	0.59	0.34	0.315	13	0	Supported
	2025	**0.61**	**0.37**	**0.345**	**14.7**	**<.001**	**Supported**
H4: ICT Specialists → Employment Rate	2023	0.53	0.28	0.248	9.6	0.01	Supported
	2024	0.47	0.22	0.189	7.04	0.01	Supported
	2025	**0.39**	**0.15**	**0.118**	**4.48**	**0.04**	**Supported**

Source: authors' calculations based on Eurostat data using JASP

Regarding H2, the positive association between AI adoption and the share of ICT specialists strengthened over time. In 2023, AI adoption was positively associated with ICT specialists (β =.440, R^2 =.194, p =.021). The standardised coefficient increased to β =.59 in 2024 and further to β =.61 in 2025, while the explanatory power of the model increased from 19.4% in 2023 to 34.2% in 2024 and 37.0% in 2025. All three models were statistically significant, with F = 6.02, p =.021 in 2023, F = 13, p =.001 in 2024, and F = 14.700, p <.001 in 2025. Therefore, the robustness analysis provides consistent support for H2 across all three years. AI adoption should therefore be considered together with complementary digital capabilities. Recent European evidence indicates that technological adoption is closely connected with ICT skills, specialised human capital and broader digital maturity (Obreja, 2025).

For H4, the relationship between ICT specialists and the employment rate also remained positive and statistically significant throughout the analysed period. The association was strongest in 2023 (β =.53, R^2 =.28, p =.01), followed by β =.47, R^2 =.220, p =.01 in 2024 and β =.390, R^2 =.15, p =.04 in 2025. Thus, although the magnitude and explanatory power of the relationship gradually decreased, the coefficient remained positive and statistically significant in each year. Consequently, H4 also receives consistent support across the 2023–2025 robustness tests.

The robustness results strengthen the findings of the initial 2023 analysis. The positive relationship between AI adoption and ICT specialists is not only persistent but becomes stronger over time, whereas the positive relationship between ICT specialists and employment remains significant, although its magnitude weakens between 2023 and 2025. These results support the broader interpretation that the labour-market implications of AI adoption may be more visible through changes in digital workforce capacity than through immediate aggregate employment disruption. At the same time, because the models represent separate annual cross-sectional associations, the findings should not be interpreted as evidence of causality or longitudinal effects at the country level.

4.4 Additional Analysis of AI Adoption and Unemployment

Considering the broader debate regarding technological unemployment, an additional analysis examined whether AI adoption was directly associated with the unemployment rate. The

relationship was weak, negative and statistically insignificant (β = −.115, p =.567). Thus, AI adoption explained only 1.3% of the variation in unemployment rates across the 27 countries. Additional models did not provide evidence that workforce preparedness changed this relationship. The interaction between AI adoption and WPI was statistically insignificant (β = −.407, p =.551), indicating that WPI did not significantly moderate the relationship between AI adoption and unemployment in the 2023 sample. These supplementary findings do not support a direct aggregate unemployment effect of AI adoption. Rather, within the present dataset, the statistically significant relationships appear more clearly in workforce transformation and employment capacity than in immediate changes in unemployment.

5. DISCUSSION

The purpose of this study was to examine whether AI adoption is associated with changes in workforce digital capacity and whether these capabilities are related to employment outcomes across European Union countries. Taken together, the results indicate that AI adoption is more clearly associated with indicators of workforce transformation than with aggregate unemployment. This finding provides a different perspective on employment risk, shifting attention from the immediate displacement of workers towards the capacity of economies and organisations to adapt their workforce to technological change.

First, AI adoption was positively associated with enterprise-provided ICT training. The 2023 analysis showed a statistically significant relationship between the two variables (β =.509, p =.007), with AI adoption explaining 25.9% of the cross-country variation in ICT training. This result supports H1 and suggests that countries characterised by higher levels of enterprise AI adoption also tend to display stronger organisational investment in employees' ICT capabilities. This finding is consistent with the argument that technological adoption changes the skills required from workers and increases the need for continuous learning, reskilling and upskilling (Cramarenco et al., 2023; Muehlemann, 2025). AI adoption should therefore not be regarded exclusively as a process through which technology substitutes human tasks. It may simultaneously generate demand for new capabilities required to implement, use and complement these technologies. In this sense, workplace training becomes part of the adjustment mechanism associated with technological transformation.

Second, AI adoption was positively associated with the share of ICT specialists, supporting H2. More importantly, this relationship remained significant in each of the three annual cross-sectional analyses. The standardised coefficient increased from β =.440 in 2023 to β =.585 in 2024 and β =.609 in 2025, while the explained variance increased from 19.4% to 37.0%. The increase in coefficient magnitude should be interpreted descriptively, since differences between annual coefficients were not formally tested. Nevertheless, the persistence of the relationship across all three years provides additional support for the connection between technological adoption and specialised digital human capital.

This result is consistent with Fontanelli et al. (2025), who identify ICT-related occupations as particularly important for firm-level AI adoption. It also complements European evidence showing that AI diffusion is associated with differences in innovation capacity, human capital and labour-market characteristics (Drago et al., 2025; Ionașcu, 2025). As AI technologies become more widely integrated into enterprises, the availability of employees able to implement, maintain and complement these technologies may become increasingly relevant.

Third, workforce digital capacity was positively associated with employment outcomes. The Workforce Preparedness Index was significantly associated with the employment rate in 2023 (β =.480, p =.011), supporting H3. ICT specialists also displayed a significant positive

relationship with employment, supporting H4. In 2023, ICT specialists explained 27.7% of the variation in employment rates across the analysed countries (β =.527, p =.005).

The H4 relationship remained statistically significant in 2024 and 2025, although its magnitude declined from β =.527 in 2023 to β =.469 in 2024 and β =.390 in 2025. Therefore, ICT specialisation remained positively associated with employment throughout the analysed period, but its explanatory strength became more moderate. Since the differences between coefficients were not formally tested, the decline should not be interpreted as evidence of a statistically significant weakening over time. It nevertheless indicates that ICT specialisation is only one of several factors associated with employment conditions. These findings are broadly consistent with research suggesting that digital capacity may contribute to more favourable labour-market outcomes (Männasoo et al., 2023; Đorđević et al., 2025). They also support the view that the effects of technological change depend partly on whether workers possess capabilities that complement new technologies. The employment consequences of AI may therefore differ considerably between economies depending on their existing skills, training systems and availability of specialised human capital.

The fourth finding is particularly important for the central research question. AI adoption was not significantly associated with unemployment in the supplementary 2023 analysis (β = −.115, p =.567). Moreover, the interaction between AI adoption and WPI was also insignificant (**β = −.407, p =.551), providing no evidence that workforce preparedness moderated the relationship between AI adoption and aggregate unemployment in this cross-section. The absence of a significant direct association is consistent with the mixed evidence identified in previous research. Georgieff and Hyee (2022) show that greater exposure to AI does not automatically translate into lower employment, while Guarascio and Reljic (2025) identify positive employment developments associated with AI exposure in parts of the European economy. These findings can be understood within the broader framework proposed by Acemoglu and Restrepo (2019), according to which technological change generates both displacement effects and countervailing mechanisms related to new tasks and labour demand. At the same time, the absence of an aggregate unemployment relationship does not imply the absence of employment risks. AI-related adjustment may occur through changes in occupations, tasks, hiring patterns or entry-level opportunities before being reflected in national unemployment rates. Consequently, aggregate unemployment may be too broad an indicator to capture the early stages of workforce transformation.

5.1 From Employment Risk to Workforce Preparedness

Considering these results, employment risk in the AI era can be approached from a broader perspective. Much of the debate focuses on whether AI will eliminate jobs. The results of the present study suggest that another risk deserves similar attention: whether workers and organisations develop the capabilities required to adapt to technological transformation. From this perspective, employment risk can be understood not only as a risk of job displacement, but also as a risk of insufficient workforce adaptation. Countries in which AI adoption advances more rapidly than digital skills, workforce training and specialised human capital may face adjustment difficulties even without an immediate increase in unemployment. The concept of workforce preparedness therefore provides a complementary perspective to technological displacement. The relevant question is not only whether AI replaces labour, but also whether employees possess the competencies required to work with technologies that increasingly restructure tasks and organisational processes. This interpretation is particularly relevant for strategic workforce transformation because it connects technological investment with human-capital development.

5.2 Theoretical Contribution

The main theoretical contribution of the study consists in shifting the analytical focus from AI-induced job displacement towards AI-related workforce transformation. Previous research has extensively discussed automation and the possibility that technology may substitute human tasks (Acemoglu & Restrepo, 2019; Georgieff & Hyee, 2022). The present results suggest that an exclusive focus on unemployment may provide an incomplete representation of the employment implications associated with AI adoption. More specifically, AI adoption was more clearly associated with ICT training and ICT specialisation than with aggregate unemployment. At the same time, workforce preparedness and ICT specialisation were positively associated with employment rates. These findings support a conceptual distinction between two dimensions of employment risk: the potential risk of losing employment and the risk of insufficient workforce adaptation.

The Workforce Preparedness Index contributes to this perspective by integrating three complementary dimensions: existing digital skills, organisational investment in ICT training and specialised ICT human capital. The PCA results indicate that these indicators capture a common underlying dimension, with the first component explaining 70.18% of total variance and all three indicators displaying high component loadings. The statistically significant Bartlett test further supported the suitability of their combination. The study therefore proposes workforce preparedness as an additional analytical lens through which employment risk can be examined. Rather than treating technology and employment as a simple direct relationship, the proposed framework introduces workforce capacity as an important dimension linking technological transformation and labour-market resilience.

5.3 Managerial and Policy Implications

The results also have implications for companies, managers and policy makers. At the organisational level, investment in AI should not be separated from workforce development. The positive association between AI adoption and ICT training suggests that technological transformation and skills development increasingly occur together. Consequently, AI investment strategies should incorporate training, reskilling, upskilling and strategic workforce planning rather than treating human-capital development as a subsequent adjustment.

For managers, these findings emphasise that AI readiness is not exclusively a technological capability. Organisations may possess access to advanced technologies while lacking the human capabilities required to implement and complement them effectively. Workforce planning should therefore identify not only which activities may be automated, but also which competencies will become more important as AI is integrated into organisational processes.

For policy makers, national indicators of AI adoption should be interpreted together with measures of digital skills, ICT training and ICT employment. Policies aimed exclusively at accelerating technology adoption may be insufficient if they are not accompanied by measures supporting workforce adaptation. In this context, education systems, lifelong learning initiatives and cooperation between employers and training institutions may become increasingly important components of employment resilience. This interpretation is also consistent with the human-centreed perspective on digital transformation, according to which technological investment alone is insufficient when it is not accompanied by appropriate organisational and workforce capabilities (Ionescu, 2025).

Therefore, AI readiness is not only a technological capability; it is also a workforce capability.

5.4 Limitations and Future Research

Several limitations have to be considered when interpreting the results. First, the analysis covers the 27 European Union countries, which restricts the number of observations available within each annual cross-section. Second, the period analysed, 2023–2025, is relatively short in comparison with the speed and complexity of technological and labour-market change. Third, the variables are measured at country level and therefore cannot capture differences between industries, occupations, firms or individual workers. Aggregate employment stability may coexist with substantial changes within particular occupational groups. Future research could therefore extend the analysis using firm-level, occupational or individual-level data. Another important limitation is related to the empirical design. The main models are separate annual cross-sectional regressions rather than panel regressions. Consequently, the identified relationships represent associations between countries and cannot establish causal or within-country effects over time. The differences observed between the 2023, 2024 and 2025 coefficients were also not formally tested and should therefore be interpreted descriptively. The Workforce Preparedness Index is based on three indicators—Digital Skills, ICT Training and ICT Specialists. Although the PCA provides empirical support for combining these dimensions, future research could extend the index by incorporating additional indicators related to lifelong learning, AI-specific competencies, organisational learning or occupational adaptability.

Finally, the models may be affected by omitted variables. Economic development, industrial structure, innovation intensity, labour-market institutions, demographic characteristics and education systems may simultaneously influence AI adoption, workforce capacity and employment outcomes. Future studies using longer time periods and panel-data models could provide a more comprehensive assessment of these relationships.

6. CONCLUSION

Artificial intelligence is transforming the way organisations perform tasks and the capabilities expected from workers. Against this background, the present study examined the relationships between AI adoption, workforce digital capacity and employment outcomes across the 27 European Union countries during 2023–2025. The results provide a relatively consistent picture. AI adoption was positively associated with ICT training and ICT specialisation, while workforce preparedness and the share of ICT specialists were positively associated with employment rates. Moreover, the association between AI adoption and ICT specialists remained statistically significant across the three annual cross-sections, with its estimated magnitude increasing over the analysed period. The positive relationship between ICT specialisation and employment also remained significant, although its magnitude was lower in 2025 than in 2023. By contrast, no statistically significant direct association was identified between AI adoption and aggregate unemployment in the supplementary analysis. This finding does not imply that AI creates no employment risks. Rather, it indicates that these risks may not be adequately represented by a simple relationship between technological adoption and national unemployment rates.

The study therefore suggests that the employment challenge associated with AI should be approached not only from the perspective of displacement, but also from that of workforce preparedness. An economy may face employment-related vulnerabilities when technological adoption advances more rapidly than the skills, training systems and specialised human capital required to complement it. The findings should be interpreted cautiously due to the short period, small annual sample and cross-sectional research design. Nevertheless, they provide initial evidence that the strategic employment challenge posed by AI may lie less in immediate aggregate unemployment effects and more in whether economies develop the workforce

capabilities required to complement technological adoption. Managing employment risk in the AI era therefore requires managing workforce transformation.

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