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### Article

# Analysis of the adequacy of employees' skills for the adoption of artificial intelligence in Central and Eastern European ountries

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## ANALYSIS OF THE ADEQUACY OF EMPLOYEES' SKILLS FOR THE ADOPTION OF ARTIFICIAL INTELLIGENCE IN CENTRAL AND EASTERN EUROPEAN COUNTRIES

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#### Abstract

The adoption of Artificial Intelligence (AI) technologies is reshaping the labour market, involving the enhancement of employees' digital skills and the acquisition of a mix of hard and soft skills. In this study, our objective was to identify, in an original way, the potential for adaptation to AI among company personnel in Central and Eastern European countries (CEE) based on four criteria and 17 analysis variables. Given the complexity of the research, we used three specific research methods for Multiple-criteria decision-making to identify the most important variables that influence rapid adaptation to AI and to classify the countries in the sample according to their level of performance. Based on the results obtained, we argue that any skills development strategy for AI should target upskilling and reskilling programmes aimed at developing above-average hard and soft skills. While increasing the number of graduates specialising in educational fields related to AI is essential in the new stage of the industrial revolution, the potential of this resource is underutilised, both due to brain drain and slow technological progress, as well as the migration of technological start-ups. For larger countries, the development of technological enclaves to attract specialised human resources and technology companies is the only way to boost their technological revolution.

**Keywords:** Artificial Intelligence (AI), soft skills, hard skills, upskilling, reskilling, Multicriteria Decision Analysis (MCDM), Industry 5.0

JEL classification: J24, M51, O15

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#### Introduction

Artificial intelligence (AI) is considered a disruptive technology with significant impacts on both the economy and society, serving as a component of the Industry 4.0 revolution alongside other digital technologies, while also being a fundamental structure of Industry 5.0. Industry 4.0 involves the automation of routine tasks, the adoption of data-driven decision-making using large volumes of data analysed with AI algorithms and machine learning processes. The foundation of the new stage of the industrial revolution (Industry 5.0) consists in the integration of human intelligence and creativity with AI technologies, with the aim of personalising products, developing new products, optimise risk management, enhancing resource use efficiency, and improving competitiveness of the enterprises.

AI technologies are leading to a new digital revolution that allows companies to improve business strategies and adapt more quickly to customer demands (Păvăloaia and Necula, 2023). Advances in AI are accelerating globally, both for early-stage technologies for creating data analysis infrastructure and for mature technologies with the launch and widespread use of large language models (LLM), such as ChatGPT (Balland and Renda, 2023). Integration of AI systems and technologies within companies requires not only the acquisition and development of technical (hard) skills related to programming languages for machine learning or deep learning, such as Python or JavaScript, but also the accumulation and enhancement of soft skills by employees (Hart et al., 2021). Digital skills above a certain level of proficiency are essential for the successful adoption of AI within a company. These skills should be possessed not only by individuals specialised in programming or data analysis, but also by all other employees, as they inevitably interact with AI, either within their roles or through ongoing long-life learning. Therefore, even specialised employees must continuously improve their soft skills, just as non-specialised personnel must acquire certain hard skills to effectively collaborate with various AI technologies (Bodea et al., 2024).

Given that EU member states are at different stages of economic development, then AI adoption will be heterogeneous between countries. There is a high probability that the technological gaps of the CEE countries will become persistent due to structural factors, such as lower research and development expenditures, limited innovation capacity, poor utilisation of talents in their own economies, and the migration of graduates/specialists to countries leading in AI implementation.

The choice of this group of countries is justified by the existence of a common pattern of structural transformations and factors that contribute to closing the gaps, such as European funds, foreign direct investments, and export growth. Additionally, these countries have both common and contrasting characteristics concerning the impact on the preparation of human resources for AI, such as the generation of talents in the educational fields of Science, Technology, Engineering, and Mathematics (STEM), Information and Communications Technology (ICT), the presence of specialised workers in the ICT sector involved in the development of start-ups, on the one hand, and brain drain, a high proportion of individuals with limited digital skills, on the other. The adoption of AI technologies within companies requires ensuring compatibility with the skills possessed by the personnel, and technological progress depends on human resources. If enterprises invest in technological development but face a skills shortage or lack sufficient specialised employees, it may lead to a bottleneck in AI implementation. Similarly, if enterprises have

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constraints in financing such investments, although the labour market can provide sufficient skilled individuals, there will be untapped potential for higher AI skills.

The study was structured into three sections based on the following research questions, which also reflect the essence of the research objectives:

• Q1. What are the main transformations in skills and professional requirements in the context of adopting AI technologies at the company level?

• Q2. What are the evaluation criteria for the readiness of AI skills in CEE countries, and which ones are most relevant for adapting to new technologies?

• Q3. Which are the best performing CEE economies in terms of AI skills?

The first section aims to analyse the influence of AI technologies on workforce skills and professional training programmes through a review of specialised literature. The trends in the reshaping of the labour market and the characteristics of CEE countries concerning human capital, derived from the first part, will be used to establish both a suitable research methodology and the selection of evaluation criteria and relevant variables. The following section includes the research results presented to identify a pattern that CEE countries should follow to avoid further deviation from the global AI frontier.

#### 1. Literature review

In the 2030 Digital Compass Report (European Commission, 2021), the EU has set a goal to increase the number of IT specialists from 9 to 20 million by 2030, as investments in digital technologies are expected to significantly increase the demand for such professionals. However, current estimates suggest that the number of these specialists will reach a maximum of 12 million, due to the lower capacity to generate talents, especially in STEM fields, to capitalise on their potential, and to retain them in the European economy.

Brey and van der Marel (2023) estimated that European economies that have previously invested in human capital are more likely to adopt AI at the company level. Thus, human capital explains approximately 35% of AI adoption, and in firms where at least half of the employees have higher education, the percentage is 50%. European companies are still far from the global technological frontier, with 70% of them considering the lack of adequate digital skills as the most significant obstacle to investing in new digital technologies, including AI. However, the use of AI technologies has not yet generated a significant productivity gain (Parteka and Kordalska, 2023). According to Rammer et al. (2022), the field of AI will increase the competitiveness gap between companies, favouring the most innovative ones, specifically those with the financial, technological, and human resources to enable the adoption and implementation of the latest AI innovations. Igna and Venturini (2023) argued that the innovation of new technologies at the level of European companies is facilitated by the pre-existing high degree of digitalisation.

The LEADS report (2023) argued that most European economic sectors are in the initial stage of AI usage, which requires certain skills to develop, implement, and manage the lifecycle of new technologies. With the expansion of AI from testing to production, a four-

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fold increase in job demand for skills related to AI application development, data analysis, and implementation within European companies is estimated over the next five years.

The process of adopting AI technologies is influenced both by the companies' ability to finance their acquisition, integrate them into business processes, and innovate, as well as by the employees' level of acceptance. Using the Unified Theory of Acceptance and Use of Technology (UTAUT) model, Kwarteng et al. (2023) concluded that performance expectations, favourable organisational conditions, and competitive pressure significantly affect European managers' intentions to adopt digital technologies in companies. The UTAUT model was developed based on the Technology Acceptance Model (TAM), which is the most widely used to examine AI technology acceptance. Perceived usefulness, attitude, and anticipated effort of using technologies have a statistically significant and positive influence on the decision of economic agents to adopt AI (Kelly et al., 2023). Cao et al. (2021) extended the TAM/UTAUT models to include managers' attitudes and intentions regarding AI adoption, arguing the necessity of training courses for them as well. Chatterjee et al. (2021) confirmed the fundamental role of leadership in AI technology adoption, using an integrated TAM-TOE (Technology-Organisation-Environment) model. Gursoy et al. (2019) consider that AI technology adoption models, such as those mentioned above, do not offer the best results given the complexity of the decision-making process regarding new technologies. According to these models, improving employees' digital, hard, and soft skills supports AI acceptance, but their adoption by companies also depends on other factors, such as resistance to change, acquisition and implementation costs, and internal process organisation within companies.

To address the first research question, we structured the specialised literature on the implications of AI on workforce skills into two main research directions: the skills required by companies using AI and the typology of professional development programmes, as well as the characteristics of CEE countries from the perspective of human resource skills.

#### **1.1. Hard and soft skills**

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The innovative capacity of AI technologies involves continuous adaptation efforts, including at the level of specialised workers previously in the field of programming and integration of digital technology. Consequently, new hard skills emerge, such as knowledge of new programming languages, data processing, analysis, and interpretation using AI algorithms, the development of machine learning software, the design of intuitive interfaces to facilitate interaction between staff/customers and AI technologies, and the implementation of cybersecurity measures to protect AI systems. Soft skills enable efficient collaboration, communication, problem-solving, creativity, and adaptability to changes among company personnel, and some of these, such as creativity, empathy, emotional intelligence, or leadership, are less susceptible to automation through AI.

Evaluating employees' hard skills is a mandatory condition to prepare companies for AIcentred digital transformation (Aldoseri et al., 2024). Poláková et al. (2023) argued that problem-solving ability is essential in the context of rapid transformations, such as those specific to AI, as it refers to the ability to think in terms of multiple options and different facets of a problem. Marr (2022) emphasised not only the importance of communication through ICT, but also interpersonal communication, which allows the transmission of emotions, persuasion, or conflict resolution. Mingaleva and Vukovic (2020) explained the

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relevance of critical thinking in the context of the large volume of information and data processed using technologies. The World Economic Forum Report (2023) ranked the top soft skills that will be demanded in the labour market over the next 5 years, with the most important being analytical thinking, active learning, complex problem-solving, as well as creativity, initiative, and originality. The fastest-growing labour demand has targeted individuals specialised in AI and machine learning, and skill development in the AI field has become a priority alongside creativity and analytical thinking.

Santana and Díaz-Fernandez (2023) argued that employees with digital skills have a greater capacity to accept and use AI technologies. According to Lane et al. (2023), about half of employers in the industrial and financial sectors stated that the main barrier to adopting AI is the lack of relevant skills among workers. The results of a McKinsey survey (2023) show that firms using at least one AI technology predominantly hired software engineers (39% of the participating entities), data engineers (35%), AI data analysts (33%), and machine learning engineers (30%), confirming the increasing demand for hard skills in AI. Furthermore, according to the Stanford University Report (2023), specific skills related to AI technologies and systems include natural language processing, machine learning, deep learning, robotics, visual image recognition, and data analysis.

The Lightcast report (2024) captured the same trends in the AI job market, adding an increased demand for data engineers, while the OECD (2023) highlighted the relevance of data analysts at the company level. According to the ARISA report (2023), machine learning and deep learning are mandatory prerequisites for data analysis literacy. Furthermore, in the questionnaire on the most important soft skills for the successful implementation of AI, more than 50% of the European companies participating in the survey established the relevance, in order, of problem-solving, critical thinking, effective communication, and innovative mindset.

The process of continuous workforce training can be reflected using the concepts of upskilling and reskilling, which have different meanings, although both involve acquiring new skills. Both types of programmes facilitate the adaptation of personnel to innovative transformations induced by the adoption of AI technologies and systems within companies. These can include, among other things, specialised programs for employees, online courses, machine learning courses, and data analysis courses (La Torre et al., 2021). Cramarenco et al. (2023) identified the implications of technological changes resulting from AI adoption on employees' skills and the professional development programmes implemented within companies, with arguments for an integrated approach to both types of skills (Li et al., 2023). Jaiswal et al. (2021) argued for the importance of professional skills such as data analysis, digital skills, and decision-making, which should be included in training programmes for both AI specialists and non-specialists. According to the ARISA report (2023), ICT specialists in Europe will become less efficient in the absence of progress regarding soft, and non-technical skills.

According to Acemoglu et al. (2022), very rapid progress in AI leads to narrowing the window of opportunity for implementing skills development programmes within companies, as hard skills will undergo significant transformations in the medium term. Hammer and Karmakar (2021) drew attention to the reduced adaptability potential of less developed countries to new workforce skill challenges due to factors such as national educational systems not keeping pace with the demand for AI specialists, brain drain, a

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high proportion of the labour force performing lower-skilled jobs, lack of investment, and organisational culture promoting professional training programmes within companies.

#### 1.2. The adoption of AI in CEE countries and the adequate skills

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In general, the CEE countries have a high capacity to create talents in the field of technological and digital transformations, but a lower capacity to retain them in their economies, due to the brain drain phenomenon towards economies where there is a high potential for professional development. Woszczyna and Mania (2023) analysed some of the national strategies for the adoption of AI developed by CEE countries, with main action directions including investments in human capital regarding new skills, reducing the intensity of specialist migration, digitising companies through the acquisition of suitable software and hardware infrastructure, research and development investments, applying research results in domestic companies, creating and sharing data and software through open licences for AI development.

Analysing the AI ecosystem in CEE countries, The Recursive Report (2023) concluded that not only does the migration of specialists characterise these countries, but also the migration of AI start-ups, with one-fifth of them preferring to relocate their headquarters to other countries to easily obtain funding from international investors and to expand their customer base. Dobriansky et al. (2020) explained that the educational systems in CEE countries underperform in providing those AI skills that will have high demand in the coming years. Furthermore, these countries are characterised by a polarisation between IT specialists and globally competitive STEM graduates, on the one hand, and a large portion of the population with low digital skills, on the other.

According to the European Commission's Digitalisation Report (2023), Croatia, the Czech Republic, Estonia, and Slovakia have a relatively higher percentage of people with basic skills compared to the European average (54% of the total population of working age), with the greatest disparities recorded in Romania (28%), Bulgaria (33%), and Poland (43%). Regarding the share of ICT employees in the workforce, Estonia, Bulgaria, and the Czech Republic have a relatively higher value compared to the European average of 4.6%, while Romania has only 2.8%, recording the lowest value among the CEE countries. However, Romania has a share of ICT graduates in the total number of graduates of 7%, compared to a European average of only 4.2%, being the second CEE country, after Estonia, where 1 in 10 graduates have such a specialisation.

The CBI Report (2023) concluded that the development of the ICT sector is an opportunity for the most dynamic economies of the CEE in terms of creating and developing of technology companies. Therefore, the attraction of multinational technology companies for software development in CEE countries and the emergence of AI hubs will contribute to reducing the migration of specialists and companies. On the one hand, these economies need to adapt the educational system and vocational training to new professional skills, but on the other hand, there is a high risk that some specialised human capital will migrate to other economies. Brodny and Tutak (2023) used the MCDM methodology for CEE countries, signalling their low innovation capacity, both due to low funding and the lack of a specialised labour force.

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In conclusion, the literature review reveals not only the specific transformations of the labour market as a result of the adoption of AI technology, but also the action directions regarding the improvement of workforce professional skills, from the perspective of skills typology and professional development programmes. Based on these, the most important evaluation criteria for human resource preparedness have been identified and presented in the second section, taking into account the specificity of the CEE countries and the second research question. The relevance of the criteria was established based on three specific MCDM methods, the foundations of which are detailed in the next section.

#### 2. Research methodology

This study is a novelty in the specialised literature as we aim to analyse the adequacy of employees' skills in CEE countries with the use of AI technologies by companies, based on a set of evaluation criteria and assessment variables.

The objectives of the research are to identify the most relevant literature, to select on their basis the criteria for assessing the readiness of employees for AI, to establish a pattern of technological transformation, and to rank CEE countries in terms of technological performance.

Given the multicriteria nature of the research target, we employed three specific Multiplecriteria decision-making (MCDM) techniques, one of which (Entropy) aimed to objectively determine the weights/importance of each variable used to assess the potential of human resource adaptation to AI, while the other two methods were used to rank the CEE countries based on the resulting composite indicators – Evaluation Based on Distance from Average Solution (EDAS) and Multi-Objective Optimisation Ratio Analysis (MOORA). Finally, we use the Spearman rank correlation coefficient to assess the degree of compatibility between the potential of human resources to adapt to AI and the use of AI technologies by companies, as well as the level of economic development of these countries. The Spearman rank correlation coefficient tests the agreement in the ranking of values between two variables, with values closer to 1 indicating a very strong correlation.

The Entropy method was developed by Shannon (1948) as the basis of information theory and aims to measure the information contained within a decision matrix for processes involving a large number of criteria, variables, and alternatives. This technique involves first constructing a decision matrix, based on the assumed objective, consisting of the relevant variables and 11 alternatives, i.e., the CEE countries included in the sample. The subsequent steps included normalising the evaluation variables of the objective, determining entropy and entropy variance for each variable, and determining the weight of entropy within each variable. The higher the weight of entropy associated with a variable, the more useful that variable is in influencing decision-making based on the established objective.

The EDAS multidimensional analysis method, proposed by Ghorabaee (2015), was used to evaluate the performance of CEE economies in adapting to AI based on the distance from an average reference variant. Torkayesh et al. (2023) argued for the wide applicability of this method, including in the economic and new technology domains, and its advantages over other multi-criteria analysis methods. The algorithm of the EDAS method involves using the decision matrix, weights according to the Entropy method, creating two

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evaluation measures, the positive distance from the average for variables beneficial to AI and the negative distance from the average for variables that hinder AI adaptation, and calculating the average of these two measures and the distance relative to it.

The MOORA analysis method was introduced by Brauers (2004) and offers more precise and objective results compared to other methods in complex decision-making scenarios with multiple criteria and alternatives (Alinezhad and Khalili, 2019). In this study, MOORA aims to classify the 11 CEE countries according to their performance in relation to each of the relevant variables, using normalisation to the average of the group. The algorithm of the method involves creating the initial decision matrix, the normalised matrix, and determining the final score for each country, with the most performant economy having the highest score.

According to the literature, the adoption of AI technologies by European companies is influenced by the level and complexity of the professional skills of the personnel, their ability to adapt to new technological challenges, including through professional training programmes, and the ability to attract talents produced by national educational systems. Therefore, we structured the analysis based on four criteria to evaluate the readiness of the labour force in the CEE countries in the context of the new AI-centred industrial revolution (Table no. 1).

Evaluation	Variables	Unit of
criteria	Variables	measurement
Talent –	V1. Students in STEM Education Fields	per thousand individuals aged 20-29
potential	V2. Students in the ICT Field	% of total students
offered by the	V3. Tertiary graduates in ICT	% of total graduates
system	V4. Graduates in the fields of science, mathematics, engineering, industry, and construction (proxy for STEM)	per thousand individuals aged 20-29
Talent –	V5. Percentage of ICT Employees	% of total employment
utilised at the	V6. R&D personnel and researchers	% of total employment
level	V7. Enterprise had hard-to-fill vacancies for jobs requiring ICT specialist skills	% of total companies
	V8. Individuals who have written code in a programming language (3 months)	% of working-age population
	V9. Individuals with above basic digital content creation skills	% of working-age population
I aval of hand	V10. Individuals with above basic information and data literacy skills	% of working-age population
and soft skills	V11. Individuals have checked the truthfulness of the information or content found on the internet (3 months) by using a AI technology (proxy for critical thinking skills)	% of working-age population
	V12. Individuals with above basic communication and collaboration skills	% of working-age population
	V13. Individuals with above basic problem-solving skills	% of working-age population

Table no. 1. Variables used in multiple-criteria decision-making methods

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Evaluation criteria	Variables	Unit of measurement
	V14. Enterprise provided training to their personnel to develop their ICT skills	% of total companies
Upskilling and reskilling programmes	V15. CVT courses and/or other forms of CVT	% of total companies
	V16. Enterprise aiming to improve Professional IT Skills through CVT	% of total companies
	V17. Enterprise aiming to improve problem-solving Skills through CVT	% of total companies

Source: Eurostat, 2024, considering the latest available data (2020-2023) for each variable

#### 3. Research results

The statistical analysis of the 17 variables suggests significant heterogeneity in the performance of the 11 countries in the group (Table no. 2). According to the coefficients of variation, the CEE countries are more similar in terms of variables V12, V10, and V4, while 9 of the 17 variables exhibit high variability of individual values relative to the means. The largest differences between countries are observed in the criterion related to professional development programmes, suggesting that current disparities in adaptation to AI technologies will persist due to the varying capacities to provide human resource training.

Variables	Minimum value	Maximum value	Standard Deviation	Coefficient of variation	Skewness	Kurtosis
V1	48.9 (SK)	113.1 (SI)	18.49	0.22	-0.25	-0.79
V2	4.9 (HR)	10.8 (EE)	1.65	0.25	1.25	0.88
V3	4.1 (PL)	10.1 (EE)	1.63	0.30	1.98	2.97
V4	13.2 (SK)	21.6 (SI)	2.78	0.16	-0.04	-1.37
V5	2.8 (RO)	6.6 (EE)	0.89	0.21	1.22	2.09
V6	0.46 (RO)	1.8 (SI)	0.38	0.33	0.14	-0.57
V7	2.4 (PL)	6.8 (SI)	1.41	0.32	0.01	-1.36
V8	1.4 (BG)	8 (EE)	1.86	0.39	-0.46	-0.35
V9	21.7 (RO)	53.1 (EE)	8.87	0.23	-0.50	-0.23
V10	54.1 (RO)	85.1 (HU)	10.00	0.14	-0.69	-0.60
V11	10 (RO)	29.8 (SK)	6.62	0.33	-0.03	-1.47
V12	71.7 (PL)	87.2 (HU)	5.24	0.07	0.12	-1.32
V13	21.9 (RO)	66.9 (EE)	13.24	0.27	-1.01	0.09
V14	8.8 (RO)	28.9 (SI)	6.04	0.34	0.13	-0.87
V15	17.5 (RO)	96.8 (LV)	23.19	0.40	0.08	-1.02
V16	2.8 (RO)	12.5 (SK)	3.05	0.40	0.11	-1.00
V17	4.1 (CZ)	16.2 (SI)	3.43	0.40	0.79	-0.16

Table no. 2. Statistical analysis of the variables

Source: own processing of data from Eurostat, 2024

The most skewed distributions of CEE-specific values, according to Skewness, are found for the potential generated by students, graduates, and ICT-specialised employees, with the top values concentrated on the left side of the mean. Furthermore, 10 of the 11 economies,

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excluding Poland, have values above the European average (4.2%) in terms of graduates with such a specialisation, indicating a significant reservoir of digital talent in these economies. The most distorted distribution of a variable, but with top values located on the right side of the mean, is in the case of variable V13. The high disparities between the group's countries are also reflected using Kurtosis, which highlights the low concentration of individual values around their means and a flatter distribution relative to the normal distribution for 16 out of the 17 variables analysed. The only exception is for graduates in ICT, where there is a high concentration that resembles a normal distribution.

Applying the Entropy method to estimate the importance of variables for the rapid adaptation of the workforce to AI technologies reveals a very high concentration of weights, with a cumulative relevance of 40% for the professional development criterion for AI (Figure no. 1). Therefore, it becomes essential for CEE countries to encourage the implementation of workforce training programmes within companies, focussing on both hard and soft skills development, as there is a shortage of specialised workforce for the AI field. Therefore, it is important not only to offer continuous vocational training (CVT) courses, but also to tailor their content to develop specialised ICT skills and problem solving skills.

The criterion related to the level of hard and soft skills possessed by individuals contributes to approximately 30% of the assumed objective. The skills that most improve employee adaptation to AI focus on hard skills, such as programming and critical thinking, which are associated with skills in data analysis and soft problem-solving skills. Skills above the average in the communication, collaboration, and information domains are less important, suggesting that they are not decisive relative to others in the actual technological transition.

The third criterion, with a cumulative impact of 17%, focusses on companies' participation in finding individuals with specialised ICT skills according to the new labour market requirements, as well as using researchers and individuals involved in research and development activities. Economies that allocate the most GDP to research and development (Slovenia - 2.11%, Czechia - 1.96%, and Estonia - 1.68%) are the most innovative in the region, slightly below the EU average, and have the highest proportion of employees engaged in such activities. Consequently, these countries will have the ability to achieve performances similar to the European average with respect to the development of AI technologies within companies.

Although often the adaptation capacity to AI of CEE countries is judged through the first criterion, the talents offered by the educational system, the obtained results confirm that professional talents are a necessary but not sufficient condition for rapid progress toward the adoption of new technologies, the relevance of the criterion being only 13% of the total. Therefore, young people need to pursue ICT or STEM specialisations in tertiary education, but it would be ideal for these graduates to become predominantly employed in domestic companies to accelerate the development of AI technologies and their implementation in economic sectors. On the contrary, CEE countries are characterised by the highest brain drain in the EU, with a direct relationship between the proportion of specialised graduates and the migration of talent. The results confirm this reality, with the educational field contributing 8.8% through specialised graduates and students, while the importance of ICT employees is much lower, at only 2.8%, demonstrating the weak capacity of CEE countries to retain and exploit such specialised skills within domestic companies.

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As revealed by the hierarchy of the relevance of the four criteria, we propose prioritising certain measures within any skills development strategy in CEE countries:

• Measure 1 - Developing existing skills of the workforce through professional development programmes that foresee above-average development of certain hard and soft skills suitable for interaction with AI.

• Measure 2 - Promoting professional retraining programmes within companies to compensate for the shortage of specialised personnel, in line with the growth of research-development-innovation capacity within companies.

• Measure 3 - Reconfiguring the educational system according to the new skills requirements of the labour market by increasing the proportion of graduates from fields correlated with AI and adapting the curriculum to the specificities of these technologies.

• Measure 4 - Providing opportunities to leverage the specialised skills of graduates within domestic companies.



Figure no. 1. Ranking of variables from the perspective of relevance, according to the Entropy method

To answer the third question of the research, we used the weights of the 17 variables determined earlier, applying the Entropy-EDAS method, whose possible values range from 0 to 1, depending on the distance to the best alternative (Table no. 3). The closer the evaluation index is to 1, the more performant an economy is, having a human resource capable of contributing to accelerating companies' adaptation to the AI domain, while values closer to 0 correspond to economies with very limited capacity to implement AI. When applying the Entropy-MOORA method, there are relatively smaller differences between countries due to the way the evaluation indicator is determined, that is, by comparing it with the average value compared to the optimal value, as in the case of EDAS.

According to the results obtained, the standard deviation, and the mean value, the CEE economies can be classified into four subgroups, among which there is high heterogeneity, proving the existence of significant differences in the potential for adaptation of human resources to the AI domain.

I. The performance of the subgroup is similar to the European average, but there are significant differences with respect to the adoption of AI technologies between Slovenia

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and Estonia. Although Estonia has a human resource more compatible with AI technologies, the implementation of these at the company level is inferior to other CEE countries, which may exacerbate the brain drain phenomenon.

II. The five economies of the subgroup must invest more in continuous training programmes for personnel and adapt the educational system more to the demands of the labour market to reach the level of the most performing subgroup.

III. The two economies of the subgroup show a relatively high scarcity in professional training of human resources to acquire specific AI skills, this criterion having the highest weight in the index and decisively influencing their classification.

IV. The only criterion in which the countries of this subgroup perform well is that of talents generated by the educational system, but which are not sufficiently valorised by internal companies.

Ranking of countries (Subgroups)	CEE countries	Evaluation Index according to Entropy- EDAS	Ranking of countries (Subgroups)	CEE countries	Evaluation Index according to Entropy- MOORA
1 (I)	Estonia	0.9775	1 (I)	Estonia	0.2645
2 (I)	Slovenia	0.9165	2 (I)	Slovenia	0.2592
3 (II)	Latvia	0.7022	3 (II)	Slovakia	0.2267
4 (II)	Slovakia	0.6743	4 (II)	Latvia	0.2073
5 (II)	the Czech Republic	0.6647	5 (II)	Croatia	0.2054
6 (II)	Croatia	0.5218	6 (II)	Czech Republic	0.2052
7 (II)	Hungary	0.5012	7 (II)	Hungary	0.2006
8 (III)	Lithuania	0.4575	8 (III)	Poland	0.1912
9 (III)	Poland	0.4437	9 (III)	Lithuania	0.1888
10 (IV)	Bulgaria	0.1751	10 (IV)	Bulgaria	0.1341
11 (IV)	România	0.0673	11 (IV)	Romania	0.1162
Standard deviation (Sd)		0.2637	Standard deviation (Sd)		0.0427
Mean		0.5547	Mean		0.1999
Mean + Sd		0.8185	Mean + Sd		0.2426
Mean – Sd		0.2909	Mean – Sd		0.1572

Table no. 3. Classification of CEE countries according to the two MCDM methods

Assessing the compatibility of the labour force with AI technologies is essential to estimate the potential to bridge digital gaps, but it must be complemented by the stage of technological development, the innovation capacity, and the level of economic development. If enterprises implement new technologies and the personnel lack the necessary skills, or if technological progress is too slow, then either the new technologies are not exploited, or the skills of human capital are not harnessed. Therefore, there must be a high degree of alignment between the technological stage and the potential for AI adaptation of the workforce, an aspect analysed using the Spearman rank correlation (Table no. 4).

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The two evaluation indices are strongly correlated with variables reflecting the use of AI technologies by companies in CEE countries, indicating a high level of consistency between technological progress and the skills of the workforce. The correlation is slightly weaker for the Composite Index of AI Technology Use and stronger for the use of a single AI technology. Furthermore, we identified a strong correlation with the innovation capacity of CEE countries, demonstrating the transformative nature of AI technologies and the importance of professional development through the acquisition of specific skills. Estonia and Slovenia are the most innovative CEE countries, with scores just below the EU average, while Romania has the lowest innovation capacity, being considerably distant even from Bulgaria, the second-to-last country in the EU ranking in this regard. However, there is no significant correlation between GDP per capita and evaluation indices. Therefore, countries such as Slovakia and Latvia, located in the high-performance subgroup, have a lower GDP per capita than Romania, which is less prepared for technological transformations. Therefore, countries are in different stages of economic development, but the technological transition is slow enough not to generate a strong impetus for economic growth in the high-performing countries in this group.

	Composite index of AI Technology utilisation * (2023)	Companies using at least one AI technology (2023)	High digital intensity companies using at least one AI technology (2023)	European Innovation Scoreboard (2023)	GDP per capita (EU27 = 100) (2022)
Entropy-	0.671**	0.738**	0.820**	0.682**	0.284
EDAS	(0.029)	(0.013)	(0.004)	(0.025)	(0.399)
Index					
Entropy-	0.680**	0.770**	0.861**	0.636**	0.188
MOORA	(0.026)	(0.008)	(0.001)	(0.040)	(0.583)
Index					

Table no. 4. Spearman	statistical	correlation
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*Notes:* \*) It is determined by adding the weights of companies that use one, two or at least three AI technologies multiplied by the number of technologies used.

\*\*) Values correspond to statistically significant correlation coefficients, with a 5% probability of nonacceptance. Values in parentheses correspond to the P-value.

#### Conclusions

The analysis conducted in this study confirms the importance of improving hard skills and professional development programmes, which cumulatively account for more than 50% of achieving the target of labour force adaptation to AI. However, the criterion related to the ICT and STEM talents generated by the educational system, for which CEE countries are globally recognised, has the lowest influence, demonstrating the need for both internal utilisation of their potential and curriculum revision to meet future labour market demands.

The results obtained are consistent with those found in the specialised literature focusing on companies and employees from countries of the European Union. For example, Mihai et al. (2023) identified significant digitalisation gaps at the European level, which explains the differences in the AI technology adoption process. Brodny and Tutak (2024) argued that the

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countries in subgroups III and IV, as previously explained, have companies that are less willing to pursue research and development, innovation, technological development and the adoption of new technologies, including AI. Additionally, Sati (2024) used MCDCM models and explained that most CEE countries are below the EU average in terms of AI technology adoption due to different digital innovation performances.

The ranking of CEE countries using Entropy-EDAS and Entropy-MOORA multi-criteria analysis methods reveals that Bulgaria and Romania, as a national average, have the least prepared human resources for AI adoption, despite their high potential to generate specialised talents. Meanwhile, Estonia and Slovenia have performed close to the European average due to their established digital infrastructure and the development of start-up ecosystems specialised in AI innovations, which enhance workers' skills. Rapid adaptation to AI depends not only on skill progression but also on the speed of AI implementation in companies, with Spearman correlation coefficient values indicating high compatibility between both processes. As the contribution of AI to GDP is still relatively low in CEE countries, the level of its development, approximated by GDP per capita, is currently only marginally influenced by technological progress.

Therefore, in the short term, CEE countries with significant technological gaps, such as Romania, may experience higher growth rates, but in the medium and long term, they will fall into a middle income trap, requiring a technological leap that AI can provide. In larger countries like Romania and Poland, regional disparities in development and digital literacy are significant, meaning that not only will these economies have capable programmers contributing to the development and management of AI technologies, but also more than 50% of individuals lack basic digital skills. These countries risk developing only technological enclaves in urban agglomerations and large university towns. Consequently, their progress in AI will only be judged based on these technological enclaves, while the national average will be significantly influenced by the digital underdevelopment of the poorer areas. If more technologically advanced areas can ensure funding for research and development activities, retain talent in the ICT and STEM fields, and attract innovative multinational companies, the brain drain and start-up exodus will diminish, accelerating the adoption of AI technologies.

Specifically, regarding Romania, we believe that a strategy to boost AI adoption is needed, involving the creation of research and technological development ecosystems (universities - research institutes - companies) to support the improvement of hard and soft AI-related skills; consortia to implement internships, internship programmes, undergraduate, master's, and professional doctoral programmes in AI; grants and vouchers for adult training and professional reconversion to stem the migration of talents in the ICT and STEM fields, as well as individual learning accounts in smart specialisation programmes, industrial clusters, and entrepreneurship.

A limitation of this study concerns the analysis of the 17 variables of the proposed model only based on the latest available value according to the Eurostat database, without performing a dynamic analysis over a longer period. For example, there are frequent methodological changes regarding the collection of data related to individuals' hard and soft skills, which leads to certain constraints in the analysis. Additionally, the results obtained are influenced by the chosen variables and the methodology used, given that the process of evaluating employees' skills adequacy is complex according to the specialised literature. Moreover, we believe that examining the readiness of the workforce for adopting AI

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technologies should be complemented by analysing the diffusion of these technologies at the level of companies in CEE countries in future research to improve the relevance of the proposed strategic directions.

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