Analele Universității din Oradea. Seria științe economice
TOM XXXIV, 2nd Issue, December 2025

ROMANIA'S LABOUR MARKET EXPOSURE TO AI

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Abstract: *New technologies are significant drivers of contemporary social transformations. These changes often lead to predictions about the future of jobs, primarily based on historical analogies and ideological suppositions. In addition to theoretical perspectives, the impact of artificial intelligence (AI) on the labour market is rigorously analyzed empirically, through task and skill assessments aimed at forecasting the future of work. We wish to extend these empirical methods to the Romanian labour market, using a model based on composing activities exposure evaluation within each occupation. Present research does not measure the impact of AI on labour market or predict the future of jobs or of employment. It measures the potential impact of AI to labour market by measuring its exposure, meaning the degree to which occupations or specific tasks within those occupations are likely to be affected by the present capabilities of artificial intelligence technologies. The results show that due to large employment numbers within occupations with low AI exposure scores, the average weighted AI exposure score for Romanian market, 6.75, is below the mean value of 6.81 and below the EU level of 6.79. By analyzing the evolution of high exposure occupation groups, presuming that automation and AI solutions are being applied, we can conclude that there is no correlation between AI exposure and employment trends on Romanian labour market. The study emphasizes the asymmetric impact of AI on different economies, depending on the structure of their labour market. The analysis does not indicate the existence of a substitution or complementation effect.*

Keywords: artificial-intelligence; automation; labour-market; employment; exposure.

JEL Classification: J21; O33

1. Introduction

The history of work has evolved along with that of humanity. From agricultural societies, through more organized forms within city states, to Fordism and today's digital Taylorism (Staab, 2017), work has been continuously transformed by technological advancements. Early industrial revolution deskilling was succeeded by a twentieth-century demand for skilled labour due to technological evolution. Now, artificial intelligence (AI) poses a new threat of deskilling. AI, with its promise of being the new general-purpose technology, predicts a broad impact across the economy, leading to significant productivity gains and societal changes. AI, while promising for increased productivity, also raises concerns about the future of jobs. There is concern not only about job displacement but also about the transformation of jobs. AI may drive automation in various labour-intensive sectors of the economy, potentially challenging the role of labour as a key production factor (Leontief, 1982). The potential impact of AI on labour market is being analyzed by scholars, who are confronted with the dynamic evolution of technology. The new capabilities of AI that enter deeply into the cognitive domain, agents, and co-inventions needed for applicability are constantly rewriting previous estimations. Existing research on the topic introduces new methods for measuring occupation's exposure to AI, defines and calculates AI exposure indicators. By analyzing occupations as a sum of different tasks, it became possible to quantify the susceptibility of various occupations to computerization. The advantage of occupation level analysis is that it can be combined with occupational data at sector or national level, making possible more applied research. A country's innovation system plays a crucial role in mediating AI's impact of AI on employment and economic growth, highlighting the context-dependent nature of AI's impact and challenging the notion of AI as universally beneficial or harmful (Guarascio and Reljic, 2025). Studies focus on occupational structures, estimating the automation potential of tasks or skills that characterize a given job, and linking these classifications to official labour market statistics to understand global, regional, and income-based differentials. The primary value of these studies was to facilitate understanding the potential trajectories of change. This understanding aids in the creation of suitable policy responses and offers valuable insights to governments and social partners, enabling them to formulate policies that promote equitable and collaborative transitions towards the future of work. This study examines the AI exposure of occupations based on composing activities within each occupation, particularly applied to the Romanian labour market. The study emphasizes the asymmetric impact of AI on different economies, based on their automation level and labour market structure. After determining AI exposure at the national and occupational levels, we were able to verify the correlation between AI exposure and annual employment growth. This may suggest that AI, at least until now, is more likely to be uncorrelated with employment trends. While the implementation of our methodology is similar to that of Felten (2021) and of Gmirek et al. (2023), we rely on different occupational activities AI exposure determination method. Ultimately, it provides a detailed ranking of occupations by their estimated probability of being automated, and a correlation analysis between AI exposure and employment evolution data.

2. Literature review

The problematics of technological unemployment, due to technological change, is dated more than 300 years ago. In 1812, Lord Byron discussed the protests of Luddite against knitting frames in the House of Lords (Leontief, 1982). In 1930, Keynes (1930) predicted a fifteen-hour workweek, and Leontief, in 1982 expressed his fear on human labour future status, which would not be the principal factor of production (1982). The relationship between humans and machines is changing and is continuously being challenged by the evolution of AI. The way that technological change reshapes labour market is described by two main theories, Skill Biased Technical Change (SBTC) and Routine Biased Technological Change (RBTC). The first hypothesis, SBTC, assumes that new technologies will benefit high-skilled workers, whereas low-skilled workers will be substituted (Acemoglu and Autor, 2011). It consists of an upskilling of occupations, contrary to the deskilling observed during the Industrial Revolution, when artisanal workers were replaced by machines. The upskilling effect is present in SBTC along with skill-biased theory, assuming that high-skilled workers are keener to use advanced technologies (Tinbergen, 1974). RBTC focuses on tasks, on how technology affects specific tasks rather than skills (Autor et al., 2003). The tasks categorized as routine are assumed to be susceptible to automatization, while non-routine tasks are less susceptible. Shifting from skills to tasks opens the perspective of a more detailed analysis of how capital becomes capable of performing different tasks using technology. Automation could substitute for labour, but it could complement it, generating higher output and, consequently, higher labour demand (Autor, 2015). The susceptibility of jobs to automation has been analyzed and measured mainly through their composing tasks or required skills using task or skill models (Autor et al., 2003). Frey and Osborne (2017) used a similar task model to calculate the probability of computerization at the occupational level, emphasizing creativity and social intelligence, as skills assessed as non-susceptible to computerization. Prior work on quantifying exposure to AI introduces a "suitability for the machine learning" (SML) metric and analyses its distribution across occupations and tasks (Brynjolfsson et al., 2018). Different automation exposure scores are present in literature as Mean Automation Score (Gmyrek et al., 2023), AI Occupational Exposure, AI Industry Exposure and AI Geographic Exposure indicator (Felten et al., 2021). These metrics link common AI applications to workplace abilities, enabling the assessment of potential impacts on various sectors. Similar indicators are Generative Artificial Intelligence (GenAI) and Language Modelling (LM) Occupational Exposure Scores (Nurski and Ruer, 2024), GPT Exposure Rating (Eloundou et al., 2023), without having one accepted as standard. These indicators do not predict and remain neutral on whether AI substitutes or complements labour but are perceived as disruptive signs, even if studies reveal growth in employment figures for AI-exposed occupations (Guarascio and Reljic, 2025). One weakness of these indicators is their focus on relatively near-term opportunities, which may need to be updated as AI as technology evolves.

3. Methodology

The present research aims to measure the Romanian labour market's exposure to AI. It does not attempt to indicate what will happen in the future with certain jobs, nor whether AI will complement or substitute for labour, but rather how exposed the occupation is to AI. This methodology involves calculating the AI's ability to replace human work. The starting point was the Occupational Information Network (O*NET), a database developed for the U.S. Department of Labour, which consists of detailed descriptions of work. O*NET provides 41 different work activities for each occupation and is associated with a scale of importance (0-5) and relevance (0-7). To determine the ability of AI to perform these activities instead of humans, having a repetitive task, we built an agent based on AI reasoning models GPT-4o and DeepSeek-R1 to evaluate on a scale from 1 to 10 the ability (A) of AI to replace human work and to reason each value generated. GPT-4o, developed by OpenAI, excels in handling complex reasoning tasks and is easily integrated due to its APIs. Similarly, DeepSeek-R1, developed by a Chinese AI startup owned by High-Flyer hedge fund, offers comparable flexibility, is more cost-effective, and performs well in reasoning tasks. This method has been previously described by Eloundou (2023). The tool used was n8n, a free and open node-based workflow automation tool connected to an AI agent via API calls. The logical structure of the agent is illustrated in Figure 1.

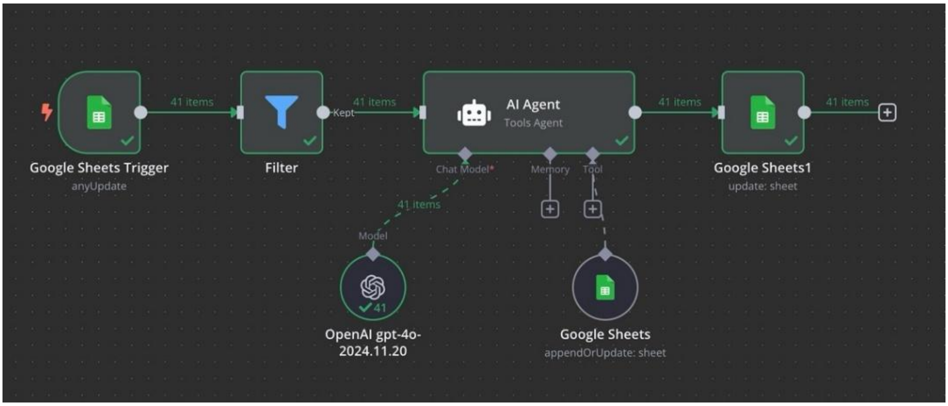


Figure 1: AI Agent structure
Source**:** Adapted from n8n.io

The reasoning capabilities of these models are measured by the Massive Multitask Language Understanding (MMLU) benchmark. According to MMLU's developers, the human experts achieve 0.898 accuracy (Hendrycks *et al.*, 2021), while GPT-4o has a score of 0.843 and DeepSeek R1 reasoning model achieved 0.872 ('MMLU - Holistic Evaluation of Language Models (HELM)', 2025). The scoring and associated reasoning examples are presented in Table 1.

Table 1: Activities' AI Ability Score and Reasoning

Element Name	**AI Ability Reasoning DeepSeek R1**	**AI Ability Reasoning GPT-4o**
Analyzing Data or Information	**Overall Value: 9**: AI excels at analyzing large datasets, identifying patterns, and performing statistical operations with speed and accuracy beyond human capability. It automates repetitive tasks, handles complex algorithms, and generates insights efficiently. However, it may lack nuanced contextual interpretation or creativity in ambiguous scenarios, requiring human oversight for strategic decision-making. For most data-driven tasks, AI is a near-perfect substitute.	9 - AI has a strong capability to analyses large datasets, identify patterns, and extract insights far more quickly and accurately than many humans. However, it may still require human oversight to contextualize findings, validate interpretations, or handle nuanced real-world complexities.

Element Name	AI Ability Reasoning DeepSeek R1	AI Ability Reasoning GPT-4o
Making Decisions and Solving Problems	**Overall Value: 7**: AI excels in structured, data-driven decision-making and problem-solving tasks (e.g., logistics optimization, pattern recognition) due to its ability to process vast datasets and identify trends quickly. However, it struggles with abstract reasoning, ethical nuance, creativity, and novel scenarios lacking historical data. While it can augment human judgment in many domains, it remains limited in contexts requiring emotional intelligence, moral reasoning, or adaptability to entirely new challenges.	8 - AI demonstrates strong analytical capabilities, logical reasoning, and data-driven decision-making, making it effective at solving structured problems and assisting in decision-making. However, it lacks human intuition, emotional intelligence, and creativity in ambiguous or highly nuanced situations, which limits it as a complete substitute for humans.
Thinking Creatively	**Overall Value: 7**: AI demonstrates significant ability to generate novel ideas, solve problems unconventionally, and mimic creative processes by leveraging vast datasets and pattern recognition. Tools like generative models produce art, stories, and solutions that often appear innovative. However, AI lacks intrinsic motivation, emotional depth, and consciousness, limiting its capacity for true originality or creativity rooted in lived experience. It excels as a collaborative tool but cannot fully replace human creativity's intuitive, context-aware, and meaning-driven aspects.	6 - While AI demonstrates a strong ability to generate innovative ideas, its creative thinking is largely based on patterns, data, and existing knowledge. It lacks true originality, emotional depth, and the intuitive spontaneity that humans bring to creative thought.

Source: O*NET data processed by OpenAI GPT-4o and DeepSeek-R1

To assess whether the differences in the scores between GPT-4o and DeepSeek-R1 were statistically significant, we performed a paired t-test. The t-statistic was approximately 3.51, and the p-value was approximately 0.00114. This indicates a statistically significant difference between the two AI ability scores at conventional levels (< 0.05), assuming that the assumptions of the paired t-test are met. The correlation coefficient between DeepSeek-R1 and GPT-4o was 0.7436, indicating a strong positive correlation between the ability scores of the two AI models. This means that when DeepSeek-R1 scores higher on a particular element, GPT-4o also tends to score higher and vice versa. This strong positive correlation suggests that both AI models generally agree on which elements they perform better or worse, although there are still some differences in their specific scoring patterns. The resulting AI ability level, as the mean of the two scores, was used to calculate our key variable using the occupational AI exposure indicator (Felten *et al.*, 2021):

$$AIE_k = \frac{\sum_{j=1}^{41} A_j \text{x} L_{jk} \text{ x } I_{jk}}{\sum_{j=1}^{41} L_{jk} \text{ x } I_{jk}} \quad (1)$$

The ability A of the AI to perform different activities (*j*) is weighted by the importance (I_{jk}) and prevalence (L_{jk}) within each occupation (k). The resulting AIE exposure indicators for the 349 occupations were analyzed using descriptive statistics. Conversion to the European Skills, Competences, Qualifications, and Occupations (ESCO) classification system developed by the European Commission was performed using the O*NET-SOC 2019 Crosswalks database. To extrapolate the results on the Romanian labour market, we used employment data up to 2023 by the International Standard Classification of Occupations 2008 (ISCO-08) 2-digit codification published by Eurostat. A regression analysis was conducted to assess the correlation between AI exposure scores and changes in employment.

4. Results and discussions

4.1. Activity level analysis

The analyzed 41 activities defined by O*NET generate AI Ability scores within a minimum of 3 for Performing General Physical Activities and a maximum of 9 for Analyzing Data or Information and Getting Information activities, with an overall mean value of 6,695. The lowest and highest ten activities are listed in Table 2.

Table 2: AI Ability Score by activity

Activity Name	**AI Ability Score**
Performing General Physical Activities	3
Establishing and Maintaining Interpersonal Relationships	3,5
Assisting and Caring for Others	3,5
Repairing and Maintaining Mechanical Equipment	4
Repairing and Maintaining Electronic Equipment	4,5
Resolving Conflicts and Negotiating with Others	4,5
Handling and Moving Objects	5
Staffing Organizational Units	5
Developing and Building Teams	5,5

Activity Name	**AI Ability Score**
Coaching and Developing Others	5,5
Evaluating Information to Determine Compliance with Standards	8
Updating and Using Relevant Knowledge	8
Controlling Machines and Processes	8
Performing Administrative Activities	8
Estimating the Quantifiable Characteristics of Products, Events, or Information	8,5
Processing Information	8,5
Working with Computers	8,5
Documenting/Recording Information	8,5
Getting Information	9
Analyzing Data or Information	9

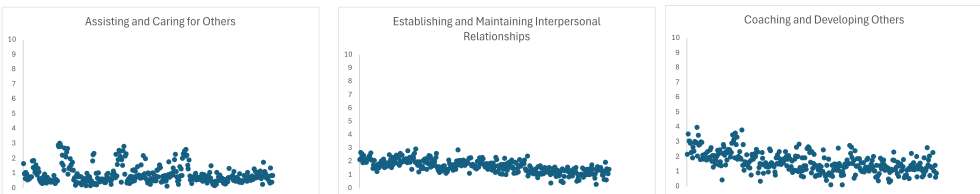
Source: O*NET data processed by OpenAI GPT-4o and DeepSeek-R1

4.2. Occupation level analysis

AI Ability Scores were applied to each activity within each occupation. By adding the importance and prevalence predefined by O*NET, we calculated the AI exposure (AIE) indicator:

$$AIE_j = \frac{A_j * L_j * I_j}{L_{max} * I_{max}} \qquad (2)$$

The distribution of occupations as a function of AI exposure is illustrated in Figure 2 (activities with the lowest and highest AI ability index).



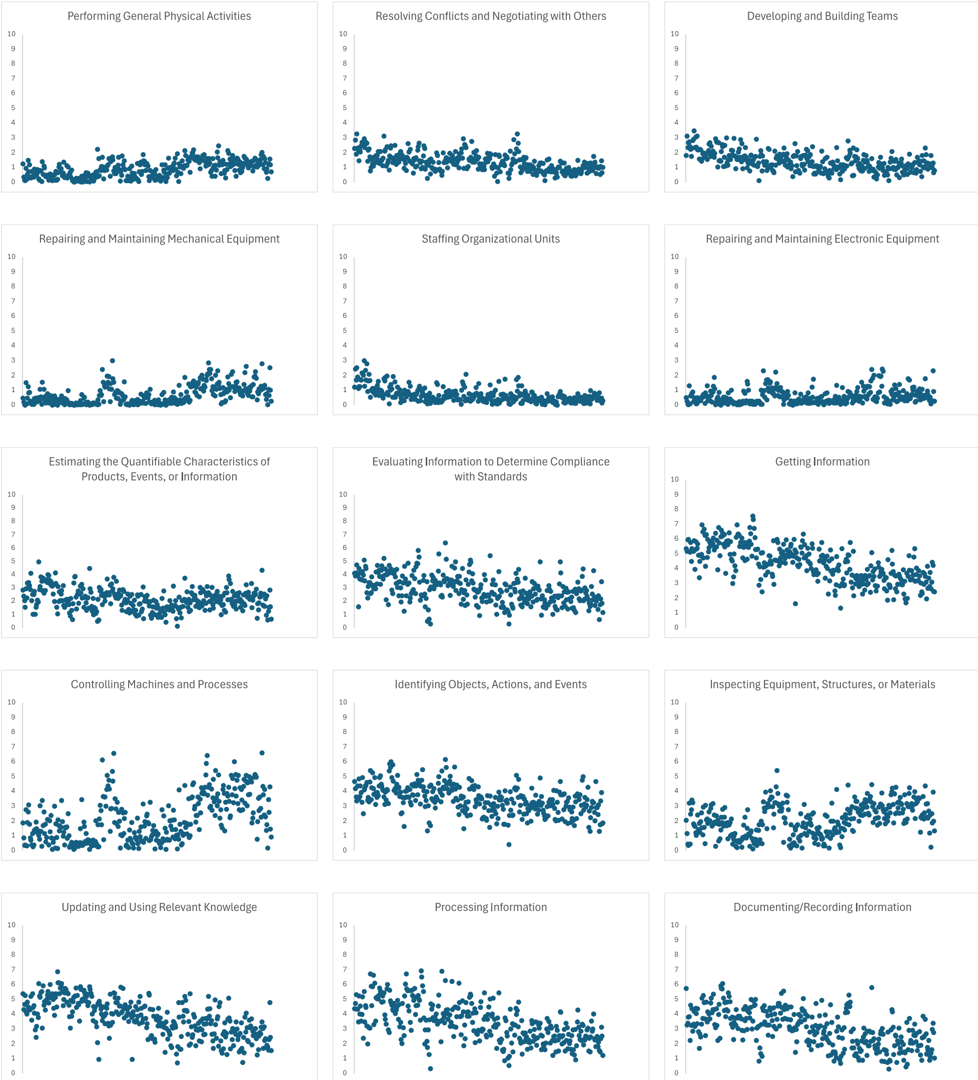


Figure 2: Occupation distribution by AI exposure
Source: Data from O*NET processed by the author.

The level of AI exposure within the occupations ranged from a minimum of 5,91 to a maximum of 7,43, with a mean of 6,81 and standard deviation of 0,2. In the box-and-whiskers plot presented in Figure 3, minimum and maximum values are outliers, while 50% of the values are between 6,67-6,96.

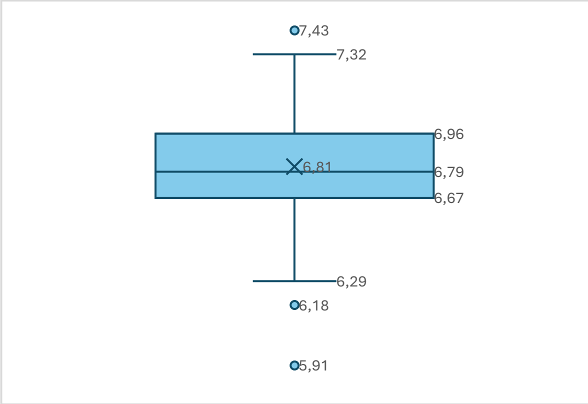


Figure 3: Occupation distribution by AI exposure
Source: Data from O*NET processed by the author.

We distinguished between high, medium, and low AI exposure by thresholding at values of 3.0 and 7.0. According to our estimates, there are no occupations without exposure to AI. 78,51% of the occupations have medium exposure, below 7, and the rest 21,49% were ranked as highly exposed to AI. It is important to mention that these figures do not clarify the meaning of exposure, whether it complement or substitute.

4.3. Romanian labour market level analysis

By weighting the obtained AI exposure scores with Romanian occupational data, we were able to determine the potential impact of AI on the labour market. As illustrated in Figure 4, most jobs have an AI exposure positioned below the mean value of 6,81. The overall weighted score is 6,75 < 6,81, which suggests a lower exposure of the Romanian labour market than the average.

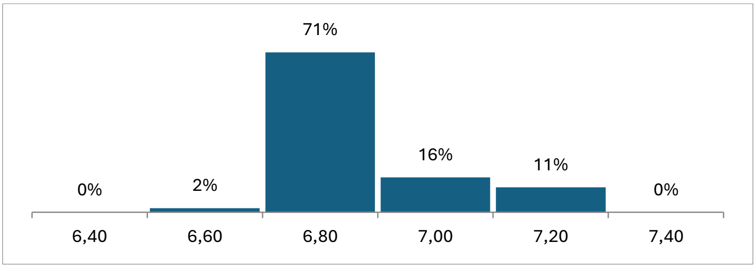


Figure 4: AI exposure across Romanian job categories
Source: Data from Eurostat and O*NET, processed by the author. https://ec.europa.eu/eurostat/databrowser/view/lfsa_egai2d__custom_15660881/default/table?lang=en. Accession date:17.03.2025

Jobs with high AI exposure accounted for 27% of active employment. This number is lower than that in EU countries, where high-exposure active jobs constitute 41%, as shown in Figure 5. The average AI exposure score for the EU countries was 6,79.

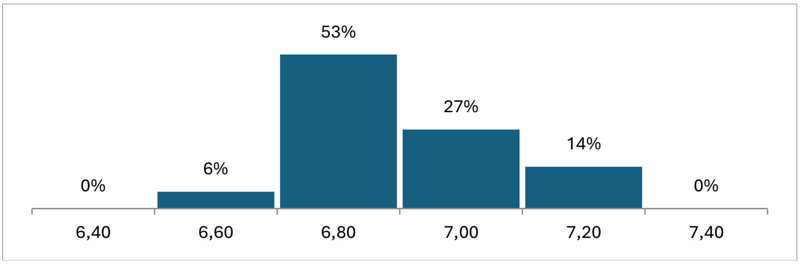


Figure 5: AI exposure across EU job categories
Source: Data from Eurostat and O*NET, processed by the author. https://ec.europa.eu/eurostat/databrowser/view/lfsa_egai2d__custom_15660881/default/table?lang=en. Accession date:17.03.2025

At the EU level, AI exposure demonstrates a more polarized distribution, with a higher proportion of jobs exhibiting lower levels of AI exposure at 6%, compared to 2% based on Romanian data. AI exposure index for each ISCO-08 2-digit classification combined with employed persons data are presented in Table 3:

Table 3: AI exposure index

Position	**AIE**	**Employed Persons RO 2023, % of Total**	**Employed Persons EU 2023, % of Total**
Market-oriented skilled forestry, fishery and hunting workers	6,50	0,1%	2,6%
Cleaners and helpers	6,59	1,8%	3,2%
Building and related trades workers, excluding electricians	6,60	6,0%	3,9%
Labourers in mining, construction, manufacturing and transport	6,61	4,7%	2,7%
Personal service workers	6,61	3,5%	1,6%
Sales workers	6,61	9,6%	6,9%
Refuse workers and other elementary workers	6,62	1,7%	1,0%
Personal care workers	6,62	1,6%	3,3%
Electrical and electronic trades workers	6,64	2,0%	1,6%
Food preparation assistants	6,66	0,2%	0,7%
Protective services workers	6,67	2,7%	1,6%
Metal, machinery and related trades workers	6,67	5,8%	3,7%
Stationary plant and machine operators	6,69	3,7%	2,5%
Agricultural, forestry and fishery labourers	6,69	2,1%	0,8%

Position	**AIE**	**Employed Persons RO 2023, % of Total**	**Employed Persons EU 2023, % of Total**
Drivers and mobile plant operators	6,70	8,4%	4,2%
Market-oriented skilled agricultural workers	6,70	7,9%	2,6%
Legal, social, cultural and related associate professionals	6,74	0,5%	3,0%
Hospitality, retail and other services managers	6,74	0,4%	1,2%
Food processing, wood working, garment and other craft and related trades workers	6,75	3,9%	2,0%
Assemblers	6,76	1,9%	0,9%
Teaching professionals	6,78	3,5%	5,5%
Health associate professionals	6,80	1,4%	3,2%
Handicraft and printing workers	6,80	0,3%	0,5%
Chief executives, senior officials and legislators	6,84	1,0%	0,8%
Production and specialised services managers	6,84	0,8%	1,7%
Health professionals	6,85	2,9%	3,0%
Customer services clerks	6,87	0,8%	1,8%
Science and engineering associate professionals	6,89	1,3%	3,7%
Legal, social and cultural professionals	6,89	2,0%	1,8%
Other clerical support workers	6,92	0,5%	0,8%
Administrative and commercial managers	6,92	0,5%	1,4%
Business and administration associate professionals	6,97	3,2%	4,7%
Information and communications technicians	6,98	0,6%	2,5%
General and keyboard clerks	6,99	1,8%	4,3%
Science and engineering professionals	7,04	3,5%	3,5%
Numerical and material recording clerks	7,05	1,7%	3,1%
Business and administration professionals	7,07	4,7%	6,7%
Information and communications technology professionals	7,15	1,3%	1,1%

Source: Data from Eurostat and O*NET, processed by the author. https://ec.europa.eu/eurostat/databrowser/view/lfsa_egai2d__custom_15660881/default/table?lang=en. Accession date: 17.03.2025

Our analysis of employment trends in the five most exposed groups shows that General and Keyboard clerks, as well as Science and Engineering Professionals, faced a larger decline than the average total employment over the past five years. Employment increased for Numerical and Material Recording Clerks and Business and Administration Professionals, while Information and Communications Technology Professionals showed no change, as shown in Figure 6.

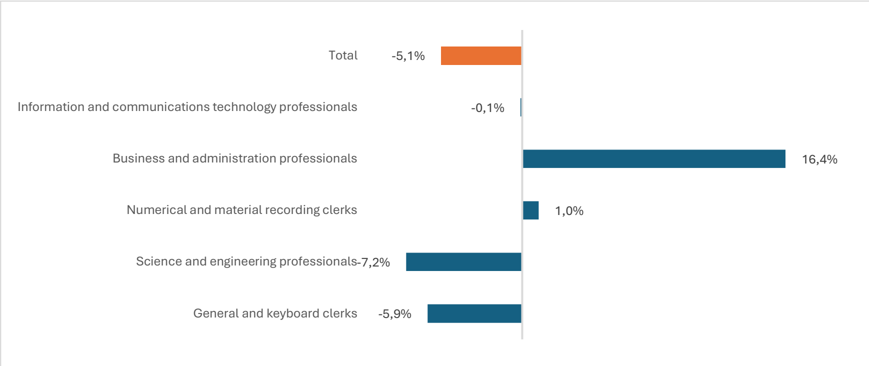


Figure 6: AI exposed groups employment evolution
Source: Data from Eurostat and O*NET, processed by the author. https://ec.europa.eu/eurostat/databrowser/view/lfsa_egai2d__custom_15660881/default/table?lang=en. Accession date:17.03.2025

Performing the correlation analysis between AIE (Artificial Intelligence Exposure) and Employment Evolution using regression, we conclude that the correlation coefficient is approximately 0.037, which indicates a weak positive correlation.

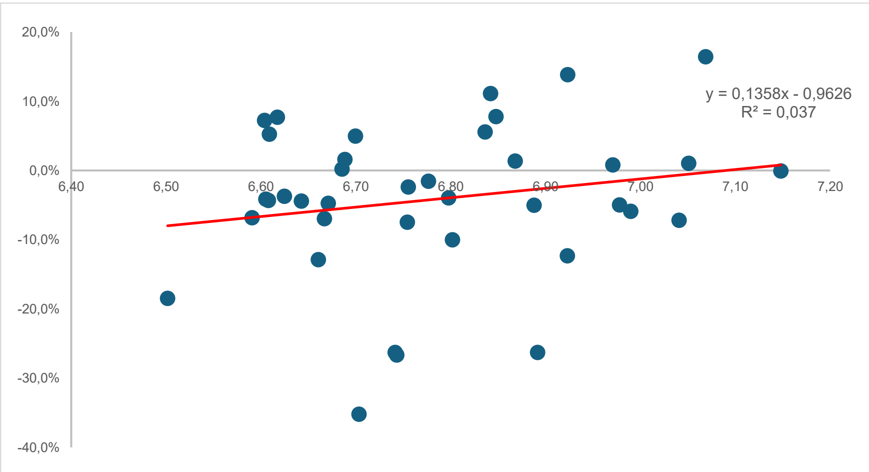


Figure 7: Correlation between AI exposure and employment evolution

Source: Data from Eurostat and O*NET, processed by the author. https://ec.europa.eu/eurostat/databrowser/view/lfsa_egai2d__custom_15660881/default/table?lang=en. Accession date:17.03.2025

The scatter plot in Figure 7. visualizes the relationship between these two variables, suggesting that as AIE increases, there is also a slight tendency for employment to increase. However, because the p-value is greater than 0.05 (approximately 0.23), we cannot reject the null hypothesis that there is no correlation between these variables. This indicates that the observed correlation could be due to random chance rather than a true relationship in the underlying population.

4.4. Discussions

The methodology used is widely recognized and is based on O*Net's detailed database, which includes tasks and activities for each occupation. AI reasoning requires a data validation process because reasoning can be susceptible to bias. However, one limitation of these indicators is that they are influenced by the evolution of AI and may be inconsistent over time. The measured occupational exposure to AI was based on the current nature of occupations and did not account for potential changes in task composition. Additionally, the methodology does not determine whether AI substitutes or complements human labour. Predictions about the causal relationship between AI exposure scores and changes in the labour market rely on simplifications and the exclusion of other important factors, such as economic, organizational, legal, cultural, and societal aspects. Therefore, these calculated AI exposure scores focus on the potential for automation as of the present day. On the positive side, such studies contribute to the discussion on possible changes in the labour markets resulting from AI implementation and analyses the potential directions of change to facilitate appropriate policy responses.

5. Conclusions

In this study, we aimed to identify the potential impact of AI on the Romanian labour market. By calculating an AI exposure index at the occupational level, we extrapolated the results and applied them at the country level, taking into consideration the composition of the Romanian labour market. The first conclusion is that due to large employment numbers within occupations with low AI exposure scores, the average weighted AI exposure score for the Romanian market (6.75) is below the mean value of 6.81 and below the EU level of 6.79. While there were no occupations without exposure to AI, 73% of Romanian jobs fell within the range of middle exposure, and only 27% had high exposure to AI. Exposure itself does not lead to substitution or complementation of jobs; it only indicates the possibility of such outcomes. By analyzing the evolution of high exposure occupation groups, presuming that within these categories automation and AI solutions are being applied, we can conclude that a reduction in employment within General and Keyboard Clerks and Science and Engineering Professionals groups could be interpreted as a substitution effect. Meanwhile, in groups such as Recording Clerks, ITC Professionals, and Business and Administration Professionals, automation solutions complemented their activities, increasing productivity and demand for those positions. Another conclusion is that AI and related automation will have an asymmetrical effect, as stated by Guarascio and Rejlic (2025), based on a country's labour market composition, innovation capabilities, and level of implementation. The analysis does not indicate the existence of a correlation between AI exposure and employment evolution in the Romanian labour market.

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