AGORA International Journal of Economical Sciences, http://univagora.ro/jour/index.php/aijes
ISSN 2067-3310, E-ISSN 2067-7669
Vol. 20, No. 1 (2026), pp. 111-122

ARTIFICIAL INTELLIGENCE AND LABOR DEMAND IN ROMANIA: EARLY EVIDENCE FROM ONLINE JOB POSTINGS

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Abstract: *The rapid diffusion of artificial intelligence (AI) technologies is expected to reshape labour demand, yet empirical evidence for emerging European economies remains limited. This paper examines short-run trends in AI-related labour demand in Romania using a high-frequency dataset of 1,874 online job postings from October 2025 to March 2026. Adopting Web Labour Market Information (LMI) approach, the study aims to elucidate the structural characteristics and professional archetypes of AI diffusion in Romanian economy. Results highlight increasing concentration of AI-related labour demand in service sector (35,8%) and a transition towards standardized production phase characterized by a robust technical middle class. Evidence reveals a shift toward skills-based hiring behaviour, where 54% of vacancies do not require a formal degree. Furthermore, the market exhibits signs of opportunistic upskilling, where employers are raising entry barriers. Hard skills were found to be the strongest predictor of the number of years of professional experience required for a position, whereas soft skills showed no statistically significant impact on the seniority level. The objective of the paper is to deliver a quantitative assessment of the impact of AI transformation on the Romanian labour market. By providing early empirical evidence from a high-frequency vacancy dataset, the paper contributes to the literature on AI, labour markets, and technological diffusion in emerging EU economies.*

Keywords: *Artificial Intelligence, Labour Market, Web Labour Market Intelligence, Occupational Analysis, Emerging European Economies*

1 Introduction

Technological progress arises not solely from capital accumulation, but also from the cultivation of a culture that values the accumulation of meaningful knowledge and upholds principles such as work ethic, discipline, and innovation (Mokyr, 2017). The labour market, the legitimisation of work and the pursuit of practical knowledge are essential mechanisms through which cultural values interact with economic factors to drive technological advancement. These dynamics illustrate how cultural values and institutional frameworks complement capital accumulation to foster sustained technological development. Social acceleration is driven by technological advancements, which quicken the pace of life. This faster rhythm, in turn, stimulates further technological innovation, creating a self-reinforcing cycle of acceleration (Rosa & Trejo-Mathys, 2013). From the perspective of the labour market, its dynamics are incompatible with the accelerated pace. While it is unable to react quickly to accelerated technological change, it can itself be an obstacle to accelerated development.

In the case of the Romanian labour market, we identified four structural barriers that undermine the large-scale diffusion of AI: demography, economics, education, and socio-political factors. Demography refers to the aging workforce and population decline, which limits the adoption of new technologies (OECD, 2025). Economic constraints include limited investment in digital infrastructure, hindering the development and integration of AI solutions. Educational gaps result from low level of digital literacy, low tertiary education participation and outdated curricula that do not adequately prepare workers for AI-related skills (European

Commission. Directorate General for Research and Innovation., 2024). Central and Eastern European labor markets often manifests an acute mismatch between emerging digital demands and existing workforce competencies (Aškerc Zadravec et al., 2025). Socio-political factors involve resistance to change and policy reluctancy to adress technology related reglementations, both of which can slow the implementation of innovative technologies (Tugwell, 1931). AI-exposed businesses may hire more non-AI workers if AI either boosts worker productivity through task complementarity or, by replacing some roles, increases overall productivity enough to create new demand for non-automated tasks (Acemoglu & Restrepo, 2019). In emerging economies like Romania, AI tend to be treated as an infrastructure for outsourcing rather then a driver of domestic innovation, treatening with the trap of middle-income (Eichengreen et al., 2013). The asymmetrical nature of AI implementation depends on a country's existing labour market composition and its level of capabilities (Guarascio & Reljic, 2025). Countries with highly skilled workforces may experience different patterns of AI adoption compared to those with predominantly low-skilled labour, which in turn affects both economic outcomes and social dynamics.

The ability of an economy to capitalize on AI technologies largely depends on the configuration of its human capital. In a pyramidal structure, the higher levels (research and development specialists, machine learning researchers, algorithm engineers, cloud and accelerated hardware experts) cannot perform their function without a broad base of workforce with complementary basic digital skills and general digital competencies (OECD, 2023). At the intermediate level, we identify two distinct groups, one of the applied engineering, which translates solutions into scalable products (data engineers, developers, system architects, data security and governance specialists), and the second group, consisting of domain translators and transformation managers: professionals with dual expertise, both technological and sector-specific (finance, health, industry), who redesign processes and ensure system compatibility with a specific domain. They are capable of operating AI systems and collaborate in multidisciplinary teams and generate endogenous technological advantage and determine the rate at which proprietary solutions can be exported (Brynjolfsson et al., 2021). Focusing on such roles reduces the gap between concept and industry-level adoption (Cohen & Levinthal, 1990). The emergence of AI-related vacancies indicates a paradigm shift where firms with high R&D intensity and digital literacy grow more rapidly than non-adopters, signaling the intrinsic value of specialized technical human capital as a catalyst for innovation-led growth (Acemoglu et al., 2022).

A significant portion of labour market demand is communicated through specialised online portals. The accelerated pace of AI deployment necessitates a shift from traditional, time-lagged labour market surveys to real-time web-based Labour Market Information (LMI) systems that utilise machine learning techniques (Boselli et al., 2018). These systems analyse data from online job portals to provide up-to-date insights into labour market demand. Online job advertisement main provocation derive from the fact that they are not using standard taxonomy and the classification needed for extracting useful knowledge from unstructured text (Boselli et al., 2018). Combining online AI postings with AI exposure index (Felten et al., 2021), resulted in a conclusion, that greater exposure to AI has no significant employment impact (Acemoglu et al., 2022). While the labour displacement remains a central concern for the future of work, contemporary recruitment data indicates no substantial divergence in hiring trends strictly based on role's level of AI exposure. Roles characterized as augmented have consistently outpaced broader market hiring growth since mid-2024 (LinkedIn, 2026). AI job postings have been used to define distinct job categories within AI domain. They have also helped to identify the specific hard and soft skills required across these categories (Nakash & Peretz, 2025). Adopting a multidimensional Web Labour Market Intelligence (LMI) approach allows for a granular analysis of AI related jobs, confirming that AI is a transformative technology that penetrates almost all sectors of the economy, with varying degrees of intensity (Demand for AI Skills in Jobs, 2021). In addition to automating tasks, the successful integration of AI in the workplace requires adaptive strategies that emphasize the ongoing development of human skills to ensure alignment with AI-supported workflows. (Babashahi et al., 2024). Employees should possess not only the capability to utilize AI tools, but also the expertise to incorporate them into business processes through effective teamwork. Communication, problem-solving, management skills form the foundation of the soft-skill package required for AI jobs (Lightcast, 2025). Skill-based hiring is often present for AI related jobs, lowering the reward for degrees and suggesting alternative skill-oriented education (Bone et al., 2025). This emergent skill-based paradigm invigorates Becker's human capital accumulation theory (Becker, 1964), shifting the focus from formal educational credentials back to the intrinsic value of specialized, technical human capital, a dynamic portfolio that must be continuously updated.

The AI labour market increasingly values soft skills and creativity. The co-occurrence of AI expertise and creativity has become more pronounced since the introduction of large language models (Wang et al., 2025). The opportunistic upskilling (Modestino et al., 2020) refers to employers taking advantage of periods of high competitivity to raise technical and experience requirements, even for entry-level positions. This practice often results in increased barriers for new entrants to the workforce, making it more difficult for recent graduates and those seeking career changes to secure entry-level roles. Following the framework of Web LMI (Boselli et al., 2018), this study moves beyond traditional surveys to provide a multidimensional view of the Romanian AI market. This approach allows for a granular representation of knowledge across sectors and territories.

The purpose of this study is to capture the current state of AI-driven changes, such as sector concentration or evolving skill requirements, on the Romanian labour market. Specifically, the research aims to examine whether global trends, including increased demand for digital and soft skills, are evident within Romania. To achieve this, we employ quantitative analysis, providing a comprehensive assessment of both the impact of AI transformation and the presence of international patterns in the local context.

2 Methodology

2.1 Data collection

The data collection was based on AI-related job postings for Romania sourced from LinkedIn. To comply with strict scrapping policy of the company, but to avoid manually gathering process, we used LLM-based data collection (RapidAPI). Conducted in March 2026, the research utilised a RapidAI subscription granting access to the active LinkedIn jobs that were posted during the last six months. To transform unstructured text into ordinal and categorical variables, we first identified relevant keywords based on industry trends and the specific requirements of AI-related roles. We used the keywords 'AI', 'Artificial Intelligence', 'Machine Learning', 'Data Engineer or Developer or Scientist or Analyst', 'Software' and 'Intelligence', together with the location filter 'Romania', to extract detailed job descriptions. This workflow ensures data gathering by automating both the identification and content extraction steps. Covering a six-month period (October 2025-March 2026), we gathered publicly available data from 6,551 AI vacancies.

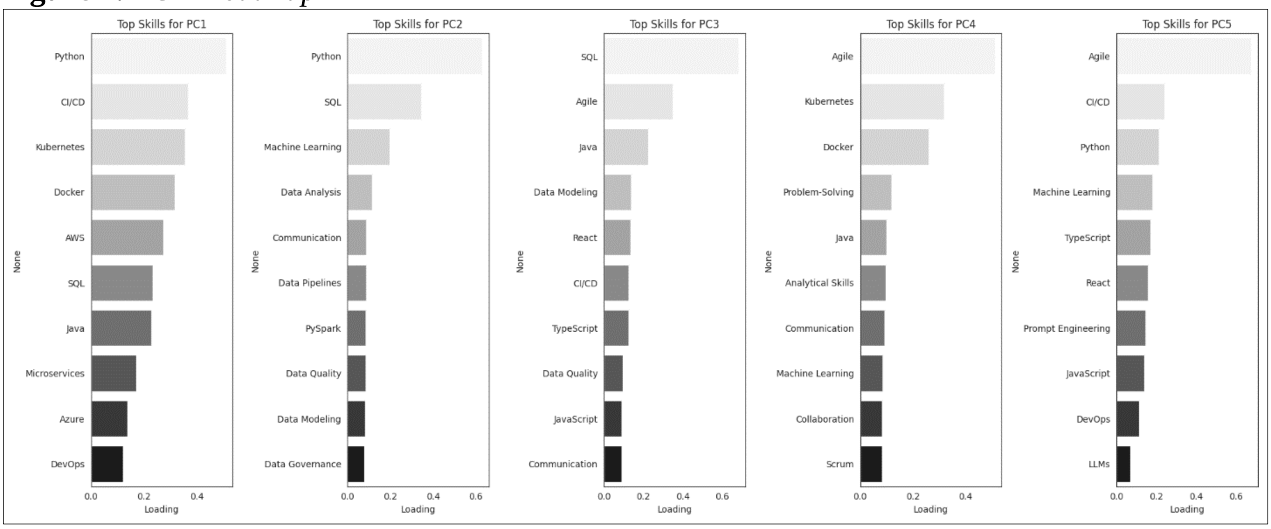
2.2 Data pre-processing

Queries were constructed using Phyton to mark jobs as AI relevant based on a predefined AI lexicon, resulting 1,958 relevant postings. To verify the results, we labelled each job with its corresponding term from the lexicon. Entity extraction queries (automated searches used to identify specific skill keywords within each job description) were employed to isolate relevant skills from lengthy text. Following this, normalisation was carried out by standardising variations in terminology, while the categorisation process involved grouping similar skills into predefined categories such as technical or interpersonal competencies. To ensure accuracy, sample extracted skill was checked against the lexicon manually, and any discrepancies were resolved. Python was used to mitigate the ambiguity of requirement language and to transform raw descriptions into structured dataset suitable for statistical analysis. A ruled-based Natural Language Processing (NLP) approach was utilized to convert qualitative descriptions into quantitative variables: to capture numerical years of experience, to map educational level by defining a four-tier hierarchy (Bachelor's, Master's, PhD and Not Specified) and scanning for academic terminology. To address the high variance in technical terminology (e.g. "LLM" vs "Large Language Models"), Semantic Dictionary strategies were implemented. A Semantic Dictionary is a tool that standardises different terms referring to similar concepts. This resulted in the consolidation of specific technologies into broader professional domains; for example, Docker, Kubernetes, and CI/CD were grouped under MLOps /Infrastructure. To address the high number of skills and job titles, Principal Component Analysis (PCA) was performed on a binary matrix of the top frequent 50 hard and 20 soft skills. This reduction generated five distinct skill clusters, representing professional archetypes. After the statistical extraction of clusters, a qualitative labelling process was performed. The core skill categories defined through the PCA are presented in Table 1 and its component skills in Figure 1.

Table 1. *Skills categories defined by PCA*

Category Name	Key Skills (High Positive Loadings)	Defining Logic
PC1. MLOps & Cloud Infrastructure	Python, CI/CD, Kubernetes, Docker, AWS	Focuses on the deployment and scaling of AI. These are roles that ensure models run reliably in production environments.
PC2. Data Science & ML Research	Machine Learning, PyTorch, TensorFlow, SQL	Focuses on modeling and insight. These roles require heavy statistical and mathematical foundations.
PC3. Enterprise Backend Engineering	Java, Microservices, Spring, SQL	Focuses on integration. This represents AI being built into large-scale, corporate software architectures.
PC4. AI Interface & Web Development	React, TypeScript, JavaScript, Node.js	Focuses on the user experience. These roles build the front-end tools and web-apps that allow users to interact with AI.
PC5. Agile Project Delivery	Agile, Scrum, Communication, Problem-Solving	Focuses on methodology. This category represents the "soft" layer of the market—how AI projects are managed and delivered in teams.

Figure 1. *PCA Heatmap*



2.3 Data analysis

Descriptive statistics were used to identify general patterns and tendencies and to check if variables are biased. On a second level, we focused on identifying and verifying the strength of relationships between our primary variables. We used Spearman correlation matrix analysis because, for variables such as Experience, Degree, Skills, or Seniority, it uses ranks rather than raw values. Spearman correlation is particularly suitable because these variables are often ordinal and may not follow a normal distribution, making rank-based analysis more appropriate than methods relying on raw values. Variables such as education and experience were converted into ordinal scales based on predefined levels (education was ranked as not mentioned = 0, bachelor's = 1, master's = 2, and PhD = 3). Experience was similarly categorised according to numerical years or specified ranges, from 1 to 4. The number of hard and soft skills was counted separately for each category, ensuring a clear distinction between technical and interpersonal competencies. To determine how much one or more independent variables contribute to a dependent variable we used linear regression analysis. The synthesized skills components were utilised as independent variables in the OLS regression model. Finally, inferential statistics (Kruskal-Wallis) was used to test if observed differences between groups are statistically significant.

3 Results

3.1 Descriptive Statistics

Within our database, we identified 1,958 valid AI job listings. After removing agency postings to avoid duplicates and ensure data integrity, we obtained 1,874 unique job listings. Sectors with less than 10 postings, representing 9.66%, were aggregated in Other Sectors categories. Distributions presented in Table 2 shows an IT dominance (services, consulting and software development), with more than 50% of total.

Table 2. *Job Postings Distribution by Sectors*

Sector	Job Count	Percentage (%)
IT Services and IT Consulting	575	30,68%
Software Development	490	26,15%
Other Sectors (< 10)	181	9,66%
Automotive & Manufacturing	174	9,28%
FinTech & Finance	172	9,18%
Technology, Information and Internet	93	4,96%
Professional Services	71	3,79%
Telecom & Media	69	3,68%
Engineering Services	25	1,33%
Internet Marketplace Platforms	14	0,75%
Computer and Network Security	10	0,53%

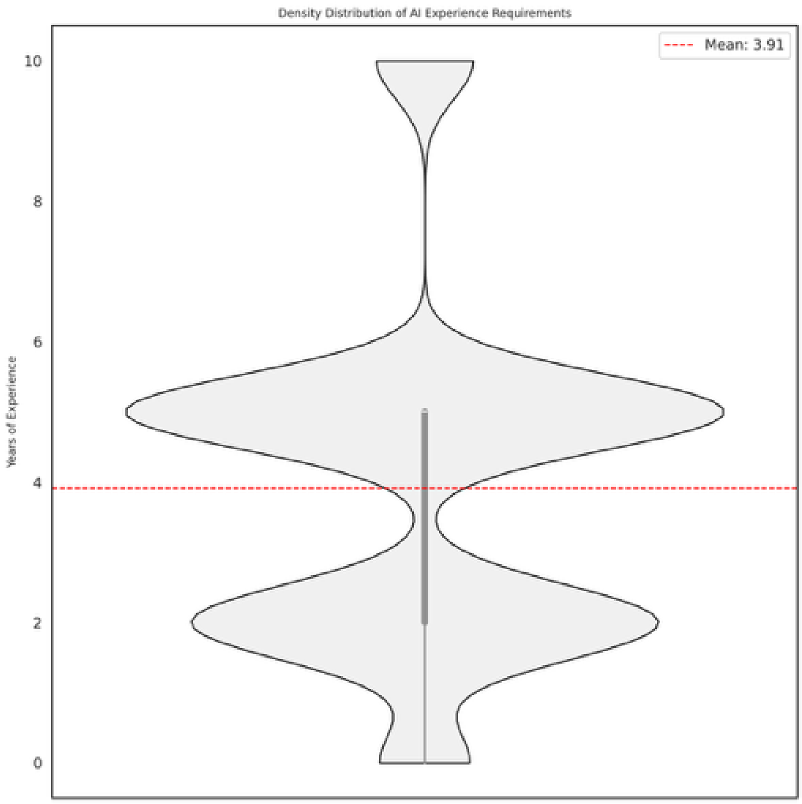
Service type AI jobs represent 35,8% of total, confirming that Romanian AI market is primarily an outsourcing and service market. Most AI engineers are hired to work for other clients rather than developing internal products in sectors like Automotive & manufacturing (9,28%) and FinTech & Finance (9,18%). The high share of Other Sectors (9,66%), gathering sectors with less than 10 postings, suggest that AI is widely spread across industries, rather than being a niche. Analysis of AI jobs by categories reveals a clear market leader of Data Engine (16.3%) that build the AI infrastructure. Presence of software engineers (SE) MLOps on second position (13,4%) suggest that market is focused on deployment in production, also. Data Scientist (6.2%) represent the specialised core that designs the logic needed for further product implementation. The presence of 176 Management & Tech Lead (9,4%) indicates that market is maturing into structured teams with dedicated leadership. Based on their prevalence, dominant technical skills are Phyton being present in 43,7% of all jobs, followed by SQL (24,3%), CI/CD (18,5%), Java (16,7%), Kubernetes (15,7%), Docker (13,1%), AWS (13,3%) and Machine Learning (11,4%). On soft skills, there are a set of competencies that appeared consistently across the job descriptions: Agile (18.4%), Communication (15.8%), Management/ Leadership (7.8%), Problem Solving (6.5%) and Collaboration (6.5%). Almost 16% of all job listings do not specify a seniority level, suggesting a high degree of flexibility from companies which are hiring based on a skills approach rather than traditional experience-based levels, as presented in Table 3. The most present seniority level is Mid-level (64,4%) followed by Associate (9,7%) and Entry Level (7,6%).

Table 3. *Job Postings Distribution by Seniority Levels*

Seniority Level	Average experience (years)	Job Count	Percentage (%)
Not Specified	3,88	297	15,8%
Internship	0,00	13	0,7%
Entry level	0,99	142	7,6%
Associate	3,54	182	9,7%
Mid level	4,34	1206	64,4%
Executive/Management	4,68	34	1,8%

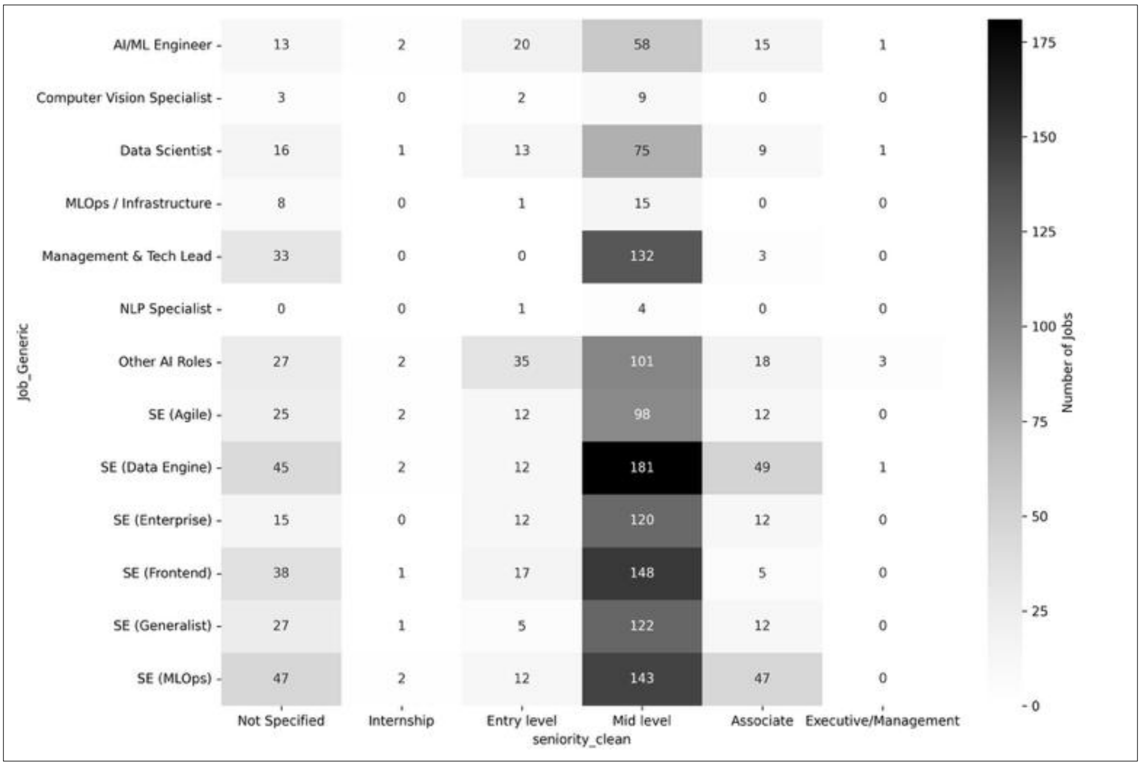
Mapping the average years of experience required for each level, we encounter more than 3 years difference between entry level and mid-level, while from mid to executive level the difference is less than half year. The average required experience is 3,91 years (Figure 2).

Figure 2. *Density Distribution of AI Experience Requirements*



When we mapped Seniority vs Job Category in Figure 3, we can identify which roles are more likely to be Seniority-heavy.

Figure 3. *Seniority vs Job Category Heatmap Analysis*



The industry is heavily middle-weighted, focused on people who can deliver immediately rather that those who need training. Numbers of Entry Level, especially for AI/ML Engineer, or Not Specified (SE MLOps, Data Engine, Management, Agile), suggests that companies are open to various levels of expertise as long as the core data skill is present. Internship row is almost completely white. Dominance of Mid-level and Associate in SE MLOps prove a high level of maturity of the market, companies looking for competent workforce to run already standardized engineering processes. The analysis of educational requirements in the dataset reveals that formal education is often secondary to demonstrate technical proficiency. Most job listings do not explicitly specify degree requirements (54%). When specified, bachelor's degree is most often requested (31%) over a master or PhD degree (14%). The regional distribution of AI job postings reveals a highly concentrated market. Bucharest and the three main university centres (Cluj-Napoca, Iasi, and Timisoara) account for 68% of jobs, with a substantial remote component (20%).

3.2 Correlation Analysis

For identifying the inter-relationships between our primary variables, we used a correlation matrix presented in Tabel 4.

Table 4. *Spearman Correlation Matrix of AI Job Requirements (ρ)*

	Seniority_Num	Exp_Num	Education_Num	Hard_Skills_Count	Soft_Skills_Count
Seniority_Num	1	*0,645*	0,090	0,346	-0,163
Exp_Num	*0,645*	1	0,131	*0,353*	-0,210
Education_Num	0,090	0,131	1	-0,082	0,061
Hard_Skills_Count	*0,346*	*0,353*	-0,082	1	*-0,821*
Soft_Skills_Count	-0,163	-0,210	0,061	*-0,821*	1

The strongest observed correlation in the analysis is between Soft Skills and Hard Skills, with a coefficient of -0.821. This value indicates a strong negative relationship, meaning that highly technical roles mention fewer soft skills. This is a clear differentiation between AI professionals and facilitators. On positive side, there is a strong correlation between Seniority and Experience (0,645), meaning that as seniority level increase, the required year of experience moves up. The analysis shows that education has a low correlation with all measured parameters, variables being relatively independent. Specifically, holding a higher degree does not predict seniority, and the skills required for roles are not closely tied to educational degrees. Both Seniority (0.346) and Experience (0.353) have a moderate positive correlation with the Hard Skills. As you move up on seniority, you are expected to know more tools and as candidates accumulate more professional experience, they are likely to possess a wider and more diverse technical skillset. It demonstrates a clear trend without being so strong as to suggest that experience is associated with technical capability.

3.3 Regression Analysis

Using OLS regression analysis, we identify the answer for how much each additional skill or degree add to the required years of experience. While the total database comprises 1874 job postings, the regression models were performed on a subset of 337 cases that provided explicit data for all variables analysed: Seniority Level, Education level, Soft Skills and Hard Skills, as independent variables, and Years of Experience as dependent variable. The model is highly explanatory (R^2 = 0.425) for the variance in required years of experience, highly significant (F = 9.83e^{-39}) and the Durbin-Watson (1.3) indicates no significant autocorrelation in residuals. Results are presented in Table 5.

Table 5. *OLS Regression Results*

Variable	Coefficient (Beta)	Std, Error	t-Statistic	p-Value	Conf, Interval Lower (0.025)	Conf, Interval Upper (0.975)
const	-0,6855	0,271	-2,53	0,012	-1,219	-0,153
Education_Num	0,1508	0,055	2,729	0,007	0,042	0,26
Hard_Skills_Count	0,0361	0,018	2,032	0,043	0,001	0,071
Soft_Skills_Count	-0,0074	0,034	-0,218	0,827	-0,074	0,059
Seniority_Num	0,8242	0,064	12,873	0	0,698	0,95

The negative value of Intercept suggests a certain entry barrier, a baseline experience requirement. The most powerful predictors are Seniority (0,82) and Education (0,15). Every increase in education adds 0,15 years to the expected experience level. Hard Skills accumulation remain significant (p = 0,043), but Soft Skills has no statistical impact on required experience.

3.4 Inferential Statistics

Given the non-normal distribution of skill counts, we employed the Kruskal-Wallis H-test to compare technical requirements across groups. The null hypothesis states that the median skills count is the same across all job categories. Rejecting it (p < 0.0001) means that there is a statistically significant difference in the median number of hard skills requested among the various AI job categories. The test resulted an H-statistic of 160,76, indicating that job categories are defined by distinct level of skills.

Table 6. *Kruskal-Wallis H-test Results*

Job_Generic	Mean Hard Skills Count	Median Hard Skills Count	Std Dev Hard Skills Count	N sample	Mean Rank
SE (MLOps)	15,1	16	1,586	251	1169,789
MLOps / Infrastructure	15,0	16	1,805	24	1156,917
SE (Enterprise)	15,0	16	1,639	159	1136,579
SE (Frontend)	14,7	16	1,866	210	1053,626
SE (Data Engine)	14,4	15	1,879	305	941,390
SE (Agile)	14,1	15	2,249	150	854,693
Data Scientist	14,1	15	2,034	116	853,845
Management & Tech Lead	14,1	15	1,971	176	852,097
AI/ML Engineer	14,0	15	2,400	110	845,882
Computer Vision Specialist	13,7	14	2,673	14	828,143
SE (Generalist)	14,0	14	2,022	167	809,446
Other AI Roles	13,2	14	2,600	187	672,497

All generic roles require between 13,2 and 15,1 mean hard skills. Engineering roles, such as MLOps, Infrastructure and Enterprise, related with AI integration and scale, demand a broader technical skill set (mean >15), highlighting the value placed on versatility in these roles. Data Scientist and AI/ML Engineer positions have an average number of required skills of 14.1 and 14.0, respectively. This relatively lower skill complexity suggests that these roles prioritize specialized expertise in a few key areas, rather than a broad range of skills. In other words, candidates are expected to possess deeper knowledge in core competencies, such as advanced statistical modeling or machine learning techniques, instead of being familiar with many unrelated tools. For example, a Data Scientist may be expected to demonstrate a high level of proficiency in data analysis and statistical methods, while an AI/ML Engineer might focus on mastering machine learning algorithms and frameworks. Relative to median required skills, all job categories exhibit a low standard deviation, suggesting that these has a high level of standardization.

4 Discussion

The empirical investigation into the Romanian AI labour market reveals a landscape characterized by a transition toward a skill-based hiring paradigm, where competence often outweighs formal credentials (Bone et al., 2025). This is typical of high-growth tech hubs where the speed of innovation outpaces formal university curricula. Bachelor's remains the most common academic requirement. The Spearman correlation analysis reveals a labour market characterized by technical pragmatism. While required years of experience predictably align with seniority levels, formal education shows a negligible relationship with career advancement, suggesting that the Romanian AI sector prioritizes accumulated professional expertise over academic credentials.

By synthesizing the results from 1,874 unique job postings, this study confirms that Romania serves primarily as an outsourcing and service-oriented hub, with 35.8% of roles explicitly categorized as service-type AI positions. This finding aligns with the theoretical framework of Guarascio and Reljic (2025), which affirm that AI implementation is asymmetrical and dependent on a country’s existing labour market composition and baseline capabilities. The analysis of hiring criteria provides a contemporary validation of Becker’s (1964) human capital accumulation theory, showing a shift where technical proficiency often supersedes formal educational credentials: 54% of job listings omit degree requirements. The middle-weighted nature of the market, where 64.4% of vacancies target mid-level professionals, indicates a preference for immediate delivery over long-term talent cultivation. This preference potentially exacerbates the opportunistic upskilling trend described by Modestino et al. (2020), where high competitiveness allows employers to raise experience barriers, further marginalizing recent graduates. Employers' average requirement of 3.91 years of experience is raising entry barriers, as shown by few internships (0.7%) and a large gap between entry- and mid-level jobs.

While sectorial analysis shows high service sector concentration, the distribution of job categories suggests a more nuanced, cross-sectorial implementation hub architecture, with deployment specialists (SE MLOps 13,4%) and structured teams with dedicated leadership (Management & Tech Lead 9,4%). The presence of Associate-level positions (9,7%) signifies that the Romanian AI sector is transitioning into a standardized production phase. The market is no longer seeking pioneers (Entry Level 7,6%) to define the field, but rather a robust technical middle class capable of independent execution in scaling and maintaining AI systems within established corporate frameworks. Romania's AI labour market continues to be remote friendly (20%) and concentrated in cities that host major universities (68%), underscoring the crucial role that academic centres play in attracting this sector.

The empirical results of this study concerning soft skills within the Romanian AI labour market provide a compelling counter-narrative to international trends, revealing a sector currently defined by a separation between technical and human skills. While global literature, such as that by Nakash and Peretz (2025), identifies communication (50.93%) as the most in-demand AI skill and emphasizes a strong connection between leadership and technical competencies, the Romanian market exhibits a sharp negative correlation (-0.821) between hard and soft skills. The regression analysis in this study further underscores this structural rigidity: while seniority and technical human capital are significant predictors of professional experience requirements ($p = 0.043$), soft skills have no statistical impact on the required years of experience ($p = 0.827$). This highlights a significant differentiation between technical professionals and organizational facilitators. This disconnect suggests that while Romanian firms are successfully adopting AI at a technical level, they may face the skill transformation challenges noted by Babashahi et al. (2024), where the integration of AI tools into business processes requires more effective teamwork and management skills. As demonstrated by Aškerc Zadravec et al. (2025), when organizations navigate technological disruptions, critical competency shortages rapidly emerge in strategic HRM and employee development. However, by ignoring soft skills at the recruitment level, the Romanian AI ecosystem risks exacerbating these exact shortages, constructing highly technical but structurally isolated teams that lack the relational framework required to manage the complex, ethical, and human-centric dimensions of AI transformation.

A primary strength of this study is the application of real-time, high-frequency Web Labour Market Information (LMI) systems, which offer a more granular view than traditional, lagged surveys. By utilizing LLM-based data collection and Principal Component Analysis (PCA), the research identifies five distinct professional archetypes that define the market's technical core. However, a notable weakness is the six-month temporal window (October 2025–March 2026), which may not capture long-term cyclical shifts or the full impact of technology. While these findings are highly representative of the Romanian AI sector, generalization to other emerging European economies should be approached with caution, because its specificity.

A critical direction for future research lies in performing a comprehensive gap analysis between academic curricula and the industry demanded skill sets identified in this study. The existing literature underscores a profound mismatch between the pace of evolution in formal education and the requirements of the labour market (Dwivedi et al., 2024), often resulting in a significant disconnect between academic training and industry priorities. To address the already identified structural barriers (demography, economics, education, and socio-political factors), policy interventions must modernize educational curricula to align with the requirements of the industry. Specifically, there is a need for specialized training in MLOps and Data Engineering, which currently demand the broadest technical skill sets. To address a possible skills gap and mitigate the structural barriers, it is imperative to enlarge formal education opportunities to systematically provide the specialized technical and hybrid competencies demanded by the industry, particularly as increasing attention is being paid to candidates' skills acquired outside formal education (Fuller et al., 2022). For the private sector, it is recommended to move away from mid-heavy hiring, to loose the entry barriers and invest in entry-level pipelines to ensure long-term workforce sustainability and counter the effects of an aging workforce. Further research is needed to determine if this implementation hub status evolves into domestic product innovation or remains a service-oriented niche. Within the Romanian context, which is already constrained by outdated curricula and low tertiary education participation, the risk of a skills gap is particularly acute, where academic programs may fail to provide the specialized technical capital required for the modern AI workforce.

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