The Intersection of AI and ESG: Exploring Overlapping Skills in the Romanian Labour Market

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Abstract: *The twin transition between digital transformation and sustainability is reshaping industries and skill requirements in the modern labour market. This study explores the intersection of AI and ESG skills in the Romanian labour market, an area of critical importance as organisations start to integrate advanced technologies with sustainable practices. By analysing 791 online job postings from early 2025, the research employs TF-IDF (Term Frequency-Inverse Document Frequency) and cosine similarity to quantify skill overlap and illustrate the distribution of shared competencies. By applying a topic modelling analysis, a natural language processing (NLP) technique, we identify ESG-related data-driven initiatives, notably a key topic that encompasses digital and data-related terms in practical ESG applications and climate change challenges. Although this topic represents a small proportion of the total tokens, it highlights the emergence of a digital data-driven ESG domain, reinforcing the relevance of the twin transition in enhancing AI applications within ESG frameworks. Despite the potential of AI in driving sustainable development, advanced AI applications remain scarce in these roles, with ESG professionals primarily utilising tools like Python and SQL for data processing and reporting. Furthermore, the study found no evidence of ethical governance skills in AI job postings. Future research should expand datasets and observation periods while incorporating international comparisons to assess Romania's position in this evolving field. The study highlights the need for targeted interdisciplinary training programs to enhance the intersection between AI and ESG competencies, ensuring the Romanian labour market can adapt to global advancements.*

Keywords: Jobs, Skills, AI, ESG, Labour Market.

Introduction

The drivers of current structural changes in the labour market are multidimensional. Climate change and the transition to a low-carbon economy, alongside digital transformation, are defining challenges of the current economic landscape (Cedefop, 2023). The adoption of green technologies and environmental policies has the potential to create new jobs, while fundamentally reshaping skill demand across industries (ILO, 2024). Similarly, artificial intelligence (AI) can enhance productivity, but may also lead to job displacement or structural shifts in skill demand (OECD, 2023b).

Identifying the skills required for the green transition is more complex than for digital skills. Beyond technical expertise, attributes such as empathy are crucial in designing fair and sustainable business models. Communication skills are essential in fostering eco-conscious behaviour among consumers and citizens, promoting actions such as waste reduction and product repair.

DOI: 10.2478/picbe-2025-0121

Alongside driving sustainability, technological innovation is transforming jobs and skill requirements. Automation, robotisation, and digitalisation are reshaping job roles and skill needs across all sectors and qualification levels, even in traditionally low-skilled occupations.

The twin transition -technological and green transformation- as described by the European Centre for the Development of Vocational Training (Cedefop, 2023), is amplifying the demand for digital and data analysis skills. These competencies must be integrated into green education and training programmes to ensure workforce readiness.

The Romanian labour market, similar to the broader European workforce, is undergoing rapid transformation due to the dual forces of AI-driven automation and ESG-driven regulatory and corporate shifts. The strong links between the digital and green transitions highlight the need for greater alignment between formal education, labour market policies, and their implementation (Cedefop, 2023). Understanding the intersection of AI-related and ESG-related occupations is essential for policymakers, businesses, and educators aiming to foster a resilient workforce.

The motivation for this research stems from the need to anticipate the combined impact of these transformations on labour market skill demand. Examining the simultaneous effects of the transition to a zero-emission economy and the expansion of automation will generate valuable insights for government institutions and higher education policymakers. Identifying emerging skills is crucial to inform education and training policies, ensuring that workers can reskill and adapt effectively.

By leveraging data from online job postings, this research aims to analyse the relationship between AI and ESG skill demands. Using Natural Language Processing (NLP) techniques such as skill similarity analysis and topic modelling, the study explores patterns in job descriptions, highlights emerging trends, and examines how organisations incorporate AI and ESG principles into hiring practices. The findings contribute to a deeper understanding of how AI and ESG shape occupational structures, providing insights for workforce development strategies and curriculum design.

Globally, existing research highlights a growing integration of AI into ESG applications (e.g., machine learning for climate forecasting, energy optimisation, and sustainable finance), as well as the incorporation of ESG principles into AI governance and ethics frameworks. However, in Romania, this integration has yet to reach its full potential, with AI-driven ESG applications and ESG-related AI requirements still underrepresented in hiring practices.

This research is particularly relevant within the European Union's policy agenda, which prioritizes digital transformation and sustainability as key pillars of economic development and labour market skill evolution (European Commission, 2024). By assessing how AI and ESG-related competencies are framed within job descriptions, this study provides a foundation for understanding how these transitions are evolving in the Romanian labour market. The results will help inform education, training, and employment policies, supporting sustainable workforce development in the context of technological progress and environmental imperatives.

Literature Review

Artificial Intelligence (AI) technologies are increasingly recognized as pivotal enablers of sustainable development, with applications that encompass environmental monitoring, ethical decision-making in business, and the automation of governance processes. At the same time, Environmental, Social, and Governance (ESG) considerations are becoming central to corporate strategies, regulatory frameworks, and workforce planning, prompting a need to explore the skills necessary to facilitate these transformations.

To meet the objectives outlined in the Paris Agreement, which aims to limit global temperature rise to below 2 °C, various global ecological transition initiatives are currently in progress. Investments in the green transition, the widespread adoption of ESG standards, and strategies for adapting to climate change are expected to significantly boost job creation, particularly in the energy and infrastructure sectors (WEF, 2023).

The International Energy Agency (IEA, 2021) projects that by 2030, the transition to a zero-carbon economy could generate over 14 million jobs in the energy sector, while simultaneously displacing approximately 5 million jobs in fossil fuel industries. Additionally, Ram et al. (2022) predict a substantial increase in renewable energy jobs, estimating growth from 57 million in 2020 to around 134 million by 2050. However, this transition is characterized by asymmetry, leading to uneven impacts across different sectors and regions.

Furthermore, the study by Saussay et al. (2022) explores skill gaps and wage gaps in the context of the transition to climate neutrality, using data from job postings. This study highlights the emerging skills needed for the green transition and highlights the need to address wage inequalities in this process.

From a digitalization perspective, the research by Alekseeva et al. (2021) suggests that the demand for artificial intelligence skills will continue to grow, significantly influencing the structure of the labour market. Taking into account the effect of AI, the occupations most at risk of automation represent about 27% of employment. Furthermore, three out of five workers, especially those in the field of AI, are concerned about the stability of their positions in the next 10 years (OECD, 2023a). Tyson and Zysman (2022) further argue that artificial intelligence will have a negative impact on process automation, potentially implying inequalities for the population with medium or low qualifications.

However, effective regulation could mitigate the adverse effects of artificial intelligence. Yazdanian et al. (2022) emphasize the importance of anticipating skills demand to help educational institutions prepare for future labour market needs. This research uses artificial intelligence algorithms to predict skills demand, providing early warnings for members of the academic community.

Conversely, the integration of ESG principles into AI development is essential for ensuring that AI technologies are deployed responsibly and ethically. Lee et al. (2024) propose a framework for evaluating and disclosing the ESG-related impacts of AI, emphasizing the need for organizations to assess both the positive and negative implications of their AI systems. This framework encourages transparency and accountability in AI deployment, aligning technological advancements with sustainability goals.

Moreover, ethical AI governance is a critical consideration in the ESG context. Cihon et al. (2021) highlight the significant role corporations play in AI research, development, and deployment, with far-reaching societal consequences. Their study explores opportunities for corporations to govern AI responsibly in the public interest, involving multiple stakeholders such as workers, investors, corporate partners, competitors, and governments.

The demand for interdisciplinary knowledge is further supported by Lin and Zhu (2024), who argue that a supply chain perspective on AI and ESG can enhance corporate ESG ratings. This perspective highlights the importance of understanding the interplay between technological advancements and sustainability practices, necessitating a workforce that is well-versed in both fields.

The interplay between AI and ESG is reshaping corporate practices and investment strategies, highlighting the need for a skilled workforce that can navigate this complex landscape.

As AI technologies enhance ESG performance and ESG principles guide AI development, the demand for interdisciplinary skills will continue to grow. Educational institutions and organizations must adapt their curricula and training programs to equip professionals with the necessary knowledge and skills to thrive in this evolving environment.

Methodology

The data for this study were collected by web scraping job postings from Glassdoor using Selenium in Python. The data collection period spanned from December 2024 to January 2025.

The web scraping process involved searching Glassdoor with specific criteria to identify relevant job listings. The search was performed by querying the platform with two key attributes: job titles associated with Artificial Intelligence, Machine Learning, Climate, Environmental, and ESG (Environmental, Social, and Governance) and specifying Romania as the location. This search resulted in 912 job postings, which were then scraped for detailed information.

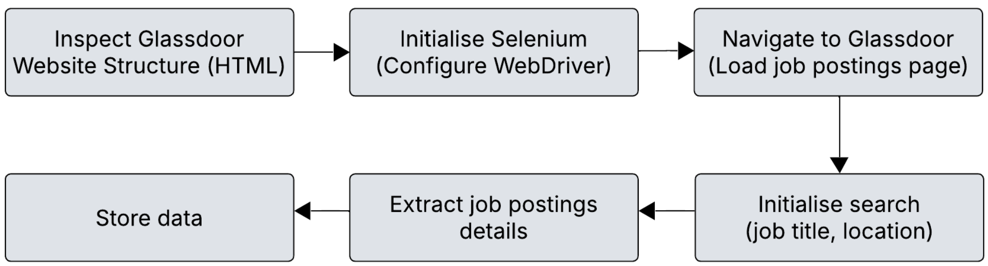

Figure 1. Data collection workflow

Source: Authors' own research.

The dataset includes the following attributes for each job posting, described in Table 1.

Table 1. Scraped Attributes

Attribute	Description
Company	The name of the company posting the job.
Job Title	The position being advertised
Location	The location of the job, specifically in Romania
Posting Age	The time elapsed since the job posting was published.
Sector	The sector within which the company operates

Source: Authors' own research.

The dataset collected from Glassdoor contains noisy text, including HTML tags, stop-words (e.g., prepositions and articles), special characters, and numbers. Since this noise is not useful for analysis, a pre-processing step is applied to clean the text and prepare it for modelling. Stop-word removal is performed using a standard English stop-word list. Additionally, converting text to lowercase and applying lemmatization help normalize words and improve the accuracy of word frequency calculations (Gottipati et al., 2021).

To ensure consistency and usability of the dataset, a series of pre-processing steps were applied to the collected job postings:

1. Translation: Some job postings were in Romanian. These were translated into English using GoogleTranslator from the deep_translator library in Python. This ensured that all job descriptions and titles were in a uniform language for analysis.
2. Removal of Duplicates: Duplicate job postings were identified and removed, reducing the dataset from 912 to 791 unique postings. Given that only 36 out of 912 postings were in Romanian, the accuracy of the translations was manually assessed, and no discrepancies or misinterpretations of industry-specific terminology were identified. However, due to the nature of technical job descriptions, the risk of misinterpreting specialised terms could be assessed in the future by incorporating of domain-specific glossaries (Naveen & Trojovský, 2024).
3. Text Pre-processing: Several cleaning operations were applied to job descriptions, as outlined below:
   - Lowercasing: Standardized text by converting all characters to lowercase.
   - Expanding contractions: Common contractions were expanded to their full forms to enhance consistency across job descriptions (e.g., “we're” was transformed into “we are”)
   - Stop-word removal: Eliminated common English stopwords using NLTK's predefined list (Bird et al., 2009). Industry-specific keywords were not removed, as they were not included in the predefined stopword list. The terms related to AI and ESG were preserved to ensure that important domain-specific information was retained for further analysis.
   - Non-alphabetical character removal: Removed numbers, punctuation, and special characters.
   - Lemmatization: Converted words to their base form (e.g., “running” to “run”), reducing variation across job descriptions.
   - N-gram Tokenization: Split text into unigrams, bigrams and trigrams, to be further used in the topic modelling process.
4. Job Title Normalization: Job titles were standardized to group similar roles under a common name (e.g., “Machine Learning Engineer” and “ML Engineer” were unified).
5. Skill Extraction: Job descriptions were analysed to extract required skills using the Lightcast API, which maps relevant competencies to job postings from a comprehensive taxonomy of more than 32,000 skills (Lightcast, n.d). Following this process, 3065 unique skills were identified from the job descriptions. However, as this study's focus is the analysis of mainly technical skills, a list of usual soft competencies was excluded from the analysis:

{"Creativity", "Curiosity", "Interpersonal Communication", "German Language", "Detail Oriented", "Teamwork", "Communication", "English Language", "Problem Solving", "Innovation", "Leadership", "Romanian Language", "Continuous Improvement Process", "Organizational Skills"}

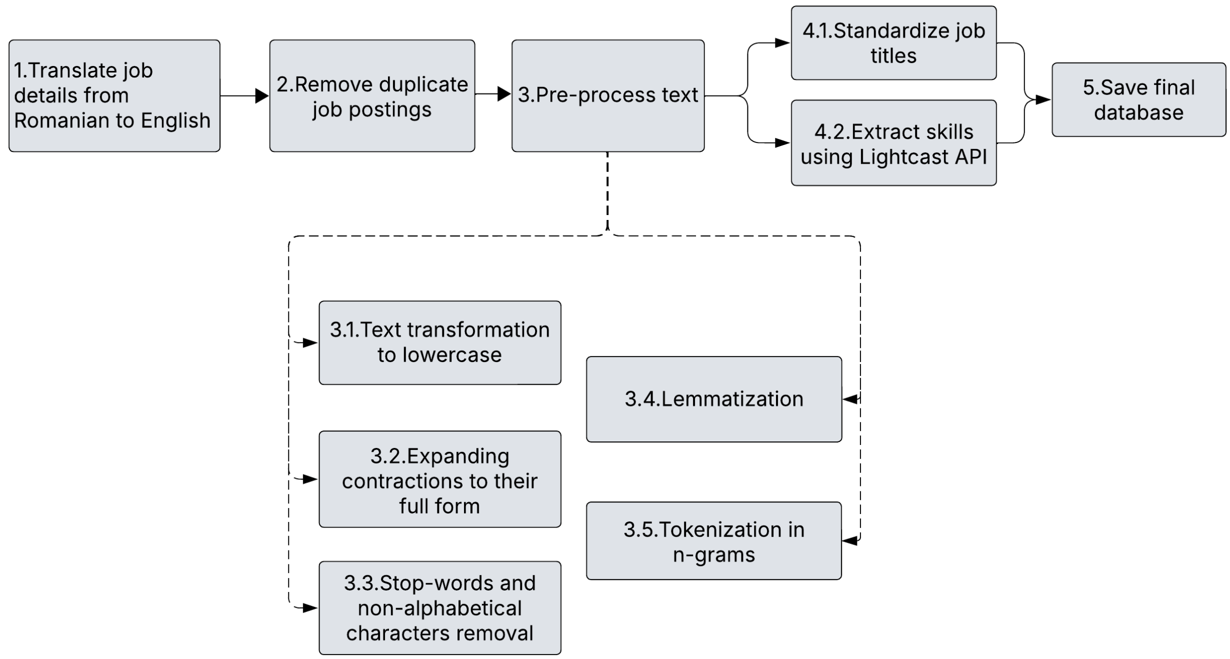

Figure 2. Data preparation workflow

Source: Authors' own research.

Following the initial data preparation process, the extracted skill sets were transformed into a vector space, where each element represents a unique skill.

To analyse the relationship between AI and ESG skills, a word-document matrix $X(n \times m)$, was constructed, where n represents the number of unique skills, and m represents the two skill categories (AI and ESG). Each entry $x_{s,d}$ in the matrix corresponds to the occurrence of skill s within the respective document d. To assess the importance of each skill within its category, the Term Frequency-Inverse Document Frequency (TF-IDF) technique was applied.

The TF-IDF algorithm assesses the significance of words within a textual corpus by considering their occurrence within a document while adjusting for their overall frequency across the corpus. This approach ensures that commonly used words have lower importance, whereas less frequent but contextually relevant terms are given more weight (Chiny et al., 2021). This is done by multiplying two metrics: how many times a word appears in a document (term frequency), and the inverse document frequency of the word across a set of documents.

Term Frequency (TF) quantifies how often a word appears in a corpus and is calculated using the following relationship:

$$tf_i = \frac{n_i}{\sum_k n_k} \tag{1}$$

where n_i represents the number of word appearances and $\sum_k n_k$ is the total number of words in the corpus.

Inverse Document Frequency (IDF) evaluates a term's significance across the whole corpus by computing the logarithm of the inverse proportion of documents that include the term (Chiny et al., 2021). IDF is computed using the formula:

$$idf_i = \log \frac{|D|}{\left|\{d_j : t_i \in d_j\}\right|} \tag{2}$$

where $|D|$ is the total number of documents in the corpus and $\left|\{d_j : t_i \in d_j\}\right|$ is the number of documents where the term is present.

However, *TF-IDF* has some inherent limitations. It can be sensitive to document length, meaning longer documents may disproportionately influence the results. Additionally, TF-IDF is unable to check the co-occurrence of words (Qaiser & Ali, 2018) and struggles to handle synonyms effectively, as different forms of a word may be treated as distinct terms (Ramos, 2003). These challenges can impact the accuracy of capturing the true relevance of terms. The synonym issue, however, can be overcome by employing specific text normalization techniques such as stemming or lemmatization (Qaiser & Ali, 2018). Additionally, the use of n-grams mitigates some of TF-IDF's limitations by incorporating word combinations, which helps to retain contextual information and maintain the order of word occurrences (Allam et al., 2025; Setiawan et al., 2024).

Furthermore, *cosine similarity* was applied to measure the degree of overlap between AI and ESG-related skills. This statistical technique, widely used in natural language processing, quantifies the similarity between texts of varying lengths by computing the cosine of the angle between two vectors, A and B (Sidorov et al., 2014). It is computed using the formula:

$$cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} \tag{3}$$

where A represents the vector of ESG-related skills, and B corresponds to the vector of AI-related skills.

Lastly, to identify underlying topics within job descriptions that could shape the future of the Romanian labour market and indicate emerging trends, *Latent Dirichlet Allocation (LDA)* was employed on uni-, bi-, and tri-grams. LDA is a generative probabilistic model designed for collections of discrete data, such as text corpora (Blei et al., 2003). It relies on the Dirichlet distribution, assuming that occupations are associated with a limited number of topics and that each topic is characterized by a small set of words. By analysing all the words in a document, LDA determines the topics present, thus generating a topic distribution (Alibasic et al., 2022).

The Dirichlet uses two parameters, α (the parameter of the Dirichlet prior on the per-document topic distributions) and β (the parameter of the Dirichlet prior on the per-topic word distribution). To obtain distinct topics, these parameters should be set to low values. However, due to overlapping skills, some words may appear in multiple topics, which aligns with the objective of this study. In the LDA model, the only observed variable is the set of words, while the unobserved (latent) variables are the topics, which are inferred from the observed words. The joint distribution of a topic mixture θ, a set of topics z, and a set of words w is given by:

$$p(\theta, z, w | \alpha, \beta) = p(\theta | \alpha) \prod_{n=1}^{N} p(z_n | \theta)\, p(w_n | z_n, \beta) \tag{4}$$

where $p(z_n | \theta)$ represents the θ_i and parameters α and β (Alibasic et al., 2022).

The number of topics was determined using two techniques: an approximation based on the matrix formed by the collection of documents and the Coherence Score. The second technique was applied using the results of the first.

The initial approximation was used to estimate the number of topics required, considering the corpus dimensions. This was calculated using the following formula:

$$k = \frac{m \times n}{t} \tag{5}$$

where t represents the number of non-zero entries in D, m is number of documents, n is the vocabulary size, and is the document-term matrix formed from the collection of documents (Can et al., 1990)

Regarding the Coherence score, for a topic to be more intuitive, its coherence score should be higher. Coherence is given by the formula:

$$C\left(t;V^{(t)}\right)=\sum_{m=2}^{M}\sum_{l=1}^{m-2}\log\frac{D\left(v_m^{(t)},v_l^{(t)}\right)+1}{D\left(v_l^{(t)}\right)} \tag{6}$$

where $D(v)$ is the document frequency of word type v and $D(v,w)$ represents the co-document frequency of word types v and w. Additionally, $V(t) = (v_1(t), v_2(t), \dots, v_M(t))$ is the list of most probable M words in topic t (Mimno et al., 2011).

Results and discussions

AI job postings were identified using the keywords "artificial intelligence" and "machine learning", while ESG-related roles were mapped based on terms such as "ESG", "climate" and "environmental". Notably, some job postings appeared in both categories, suggesting a potential overlap between AI and ESG competencies.

The AI category is dominated by highly technical roles, such as software engineer and data scientist. These roles reflect the core competencies required in AI fields, such as software development, data analysis, and machine learning engineering. The homogeneity of these job titles underscores the strong technical foundation required for artificial intelligence-related careers.

In contrast, the ESG category features a mix of traditional ESG roles and technical positions. Beyond the expected role of ESG consultant**,** the presence of titles like technical lead and data analyst suggests a growing demand for technical expertise in sustainability-focused roles. This diversity highlights the interdisciplinary nature of ESG careers, which increasingly require both sustainability knowledge and data-driven skills. It also points to a rising interest in ESG-driven digital transformation, particularly in industries where compliance, risk assessment, and environmental data analysis are critical.

Among the roles that appeared in both categories, AI-related positions were more prevalent and diverse, indicating a stronger integration of AI competencies within ESG-related job postings.

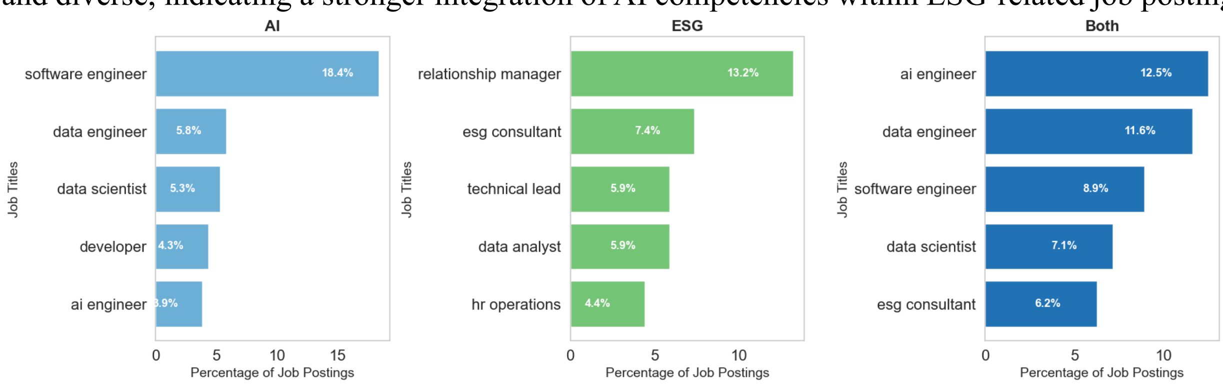

Figure 3. Top 5 job titles by category

Source: Authors' own research.

Information Technology, Manufacturing, Energy, Mining & Utilities are each accounting for over 10% of total job postings in the database. An interesting insight emerges when examining the distribution of AI and ESG-related jobs across these sectors.

While AI jobs are in high demand across all industries, an unexpected trend appears at the ICT sector level. Specifically, this sector is actively seeking ESG specialists, suggesting early signs of skill transferability between technology and sustainability-focused roles. This may indicate a growing intersection between digital innovation and environmental expertise within the labour market. This trend could be driven by increasing regulatory pressures on technology firms to integrate sustainability considerations into their operations, as well as the broader corporate shift towards embedding ESG principles in business strategies (TCFD, 2023). Moreover, the prominence of AI roles in the Energy & Utilities sector suggests that automation, predictive analytics, and optimization are playing a crucial role in energy management and sustainability efforts (Safari et al., 2024). On the other hand, the substantial presence of ESG roles in IT Support Services indicates a rising demand for professionals who can ensure sustainability compliance, address data privacy concerns, and implement green IT initiatives.

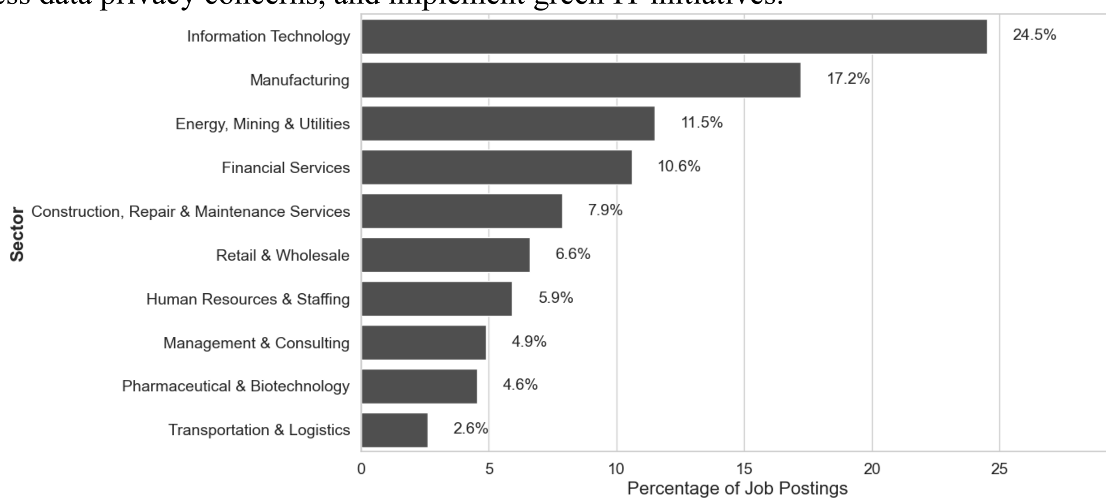

Figure 4. Top 10 sectors: % share in job postings

Source: Authors' own research.

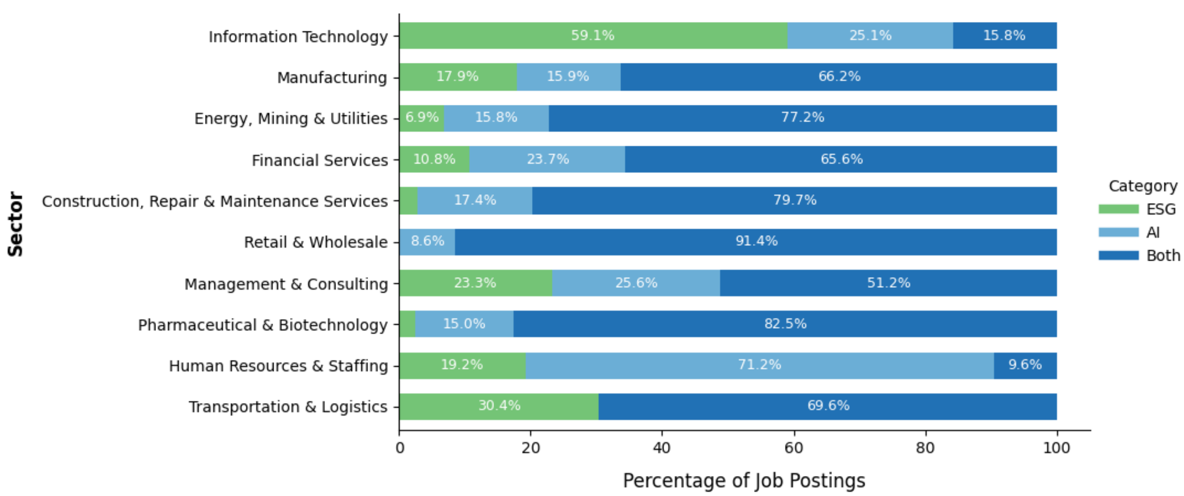

Figure 5. Top 10 sectors by category (ESG vs. AI)

Source: Authors' own research.

While the exploratory analysis provides an overview of the AI and ESG job landscape, the following section details skill relationships and their similarities.

The word clouds generated for each category illustrate distinct patterns in skill distribution. AI job postings are predominantly characterized by highly technical skills**,** including artificial intelligence, software development, Python and cloud computing. This reflects the strong emphasis on programming, data science, and computational techniques in AI-related roles.

Figure 6. Skills for AI jobs

Source: Authors' own research.

In contrast, ESG job postings exhibit a more diverse skill set, combining corporate governance, finance, consulting, and regulatory compliance with certain technical skills, such as Microsoft Office, SQL, and SAP. The presence of these technologies suggests that data-driven decision-making is becoming increasingly relevant in ESG roles, although its application still limits to reporting, compliance, and business intelligence rather than advanced AI-driven modelling, as further detailed by the topic modelling analysis**.**

Additionally, the presence of financial and governance-related skills in ESG job postings suggests that companies are prioritizing regulatory compliance, risk assessment, and strategic sustainability planning over advanced data-driven ESG analytics. However, as ESG-related regulations become more complex, it is likely that the demand for AI-driven analytics in ESG will rise, requiring a convergence of AI and sustainability expertise.

Figure 7. Skills for ESG jobs

Source: Authors' own research.

The Venn diagram of AI and ESG skill overlap further confirms this distinction. The presence of 949 shared skills between AI and ESG demonstrates a substantial intersection in the competencies required across these domains. However, the high number of ESG-exclusive skills (1,399) compared to AI-exclusive skills (704) indicates that ESG jobs maintain a broader, governance-oriented focus, while AI jobs require highly specialized technical expertise in machine learning and software engineering. This finding highlights a significant divergence in the way AI-related tools are utilized within ESG contexts, where their function is largely limited to automation and data processing, rather than predictive analytics or AI-driven sustainability initiatives.

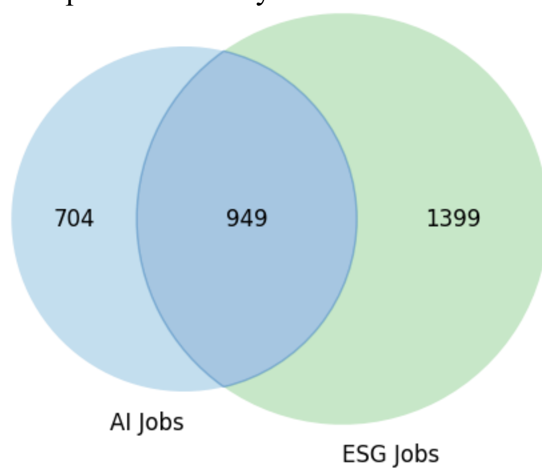

Figure 8. AI and ESG skills overlap

Source: Authors' own research.

The cosine similarity score of 0.8988 quantitatively supports this observation, indicating a high degree of similarity between AI and ESG skill sets, but mostly due to general skill requirements. However, despite this statistical resemblance, the practical implementation of these skills differs substantially. While AI professionals leverage these tools for predictive modelling, automation, and artificial intelligence development, ESG professionals primarily employ them for financial modelling, and sustainability reporting. The absence of machine learning, artificial intelligence, and data science techniques in ESG job postings suggests that AI-driven sustainability analytics, climate risk modelling, and ESG-focused predictive algorithms remain underdeveloped in the Romanian labour market.

A closer examination of the most frequently common occurring skills in AI and ESG roles highlights these distinctions (Figure 9 and Figure 10). AI-related postings emphasize machine learning, artificial intelligence, Python, and SQL, reinforcing the highly technical nature of these roles. However, no significant presence of ethical or environmental considerations appears in AI job postings, suggesting that the AI sector might be lacking ESG principles and is primarily focused on technical considerations. While ESG roles are also enabled by programming languages and automation, their share of occurrence in job postings is still low. It appears that skills like Python, SQL, and automation are more commonly used for data analysis than for machine learning and data science techniques needed in climate modelling (e.g., forecasting physical and transitional risks).

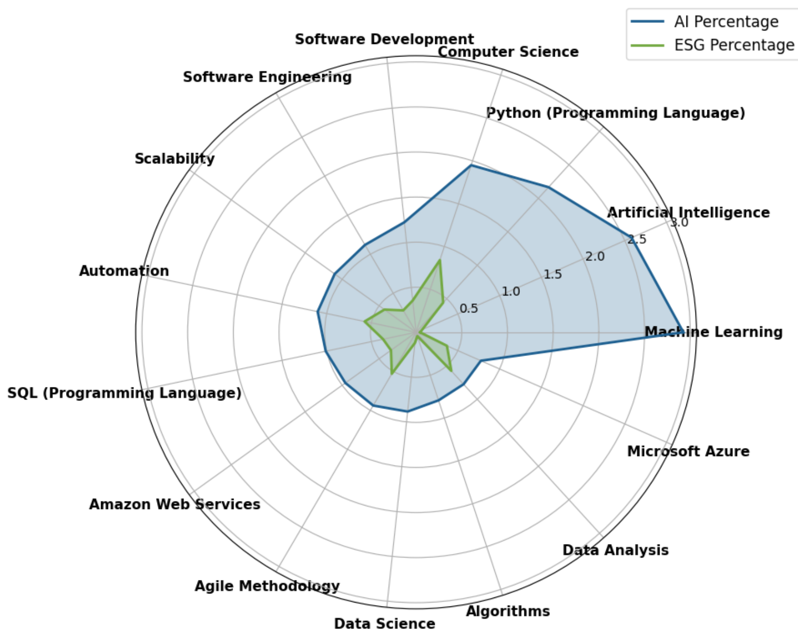

Figure 9. Top 15 AI skills overlapping with ESG

Source: Authors' own research.

In contrast, ESG job postings feature consulting, finance, and tools such as Microsoft Excel, SAP, indicating a focus on data management and compliance rather than AI-driven analysis. While computer science appears in both fields, its application in ESG remains limited to business intelligence and reporting rather than advanced AI-driven decision-making, as further detailed in the topic modelling analysis. While less underscored than the ESG sector, the AI techniques are confirmed to be enabling other domains, such as research and finance.

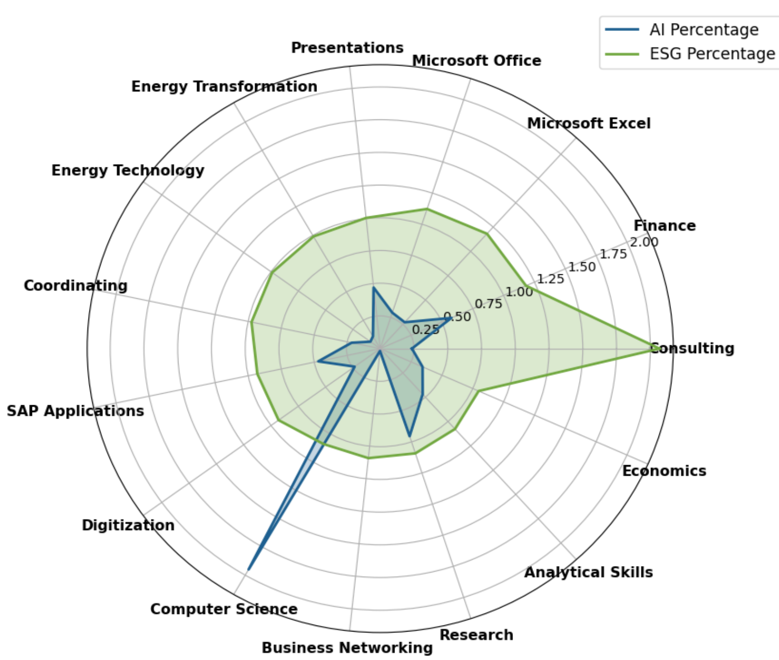

Figure 10. Top 15 ESG skills overlapping with AI

Source: Authors' own research

These findings underscore a potential opportunity for the Romanian labour market to further integrate AI techniques into ESG domains, particularly in areas such as climate risk modelling, ESG predictive analytics, and AI-enabled sustainability solutions.

To better understand the separate and overlapping skills of AI and ESG domains, a topic modelling analysis was conducted on the job description text using the Latent Dirichlet Allocation (LDA) model.

The number of topics inherent in the available job description was first computed based on the number of the collection of documents and the vocabulary size, as detailed in the methodology. The resulting number of topics was 15, calculated using the formula:

$$k = \frac{m \times n}{t} = \frac{791 \times 2165}{113132} \tag{7}$$

where m = 791 is the number of documents (job descriptions), n = 2165 is the number of unique words in the job descriptions, and t = 113132 is the total number of words across all documents.

Based on this approximation, the Coherence score was then computed for 15 topics, where the highest coherence score was identified for 12 topics, at a level of 0.52, as outlined in Figure 11 below.

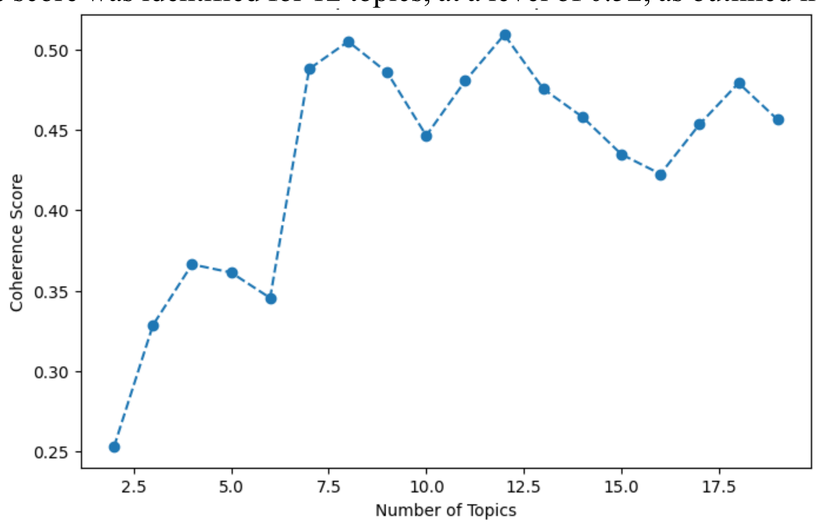

Figure 11. Optimal number of topics – LDA

Source: Authors' own research.

Using the pyLDAvis library, the visualizations presented below illustrate the distribution of topics within the data. The size of each circle indicates the frequency of the corresponding topic, with larger circles representing more frequently required skills and the most discussed topics in job postings. Additionally, the visualizations provide significant insights into the estimated term frequency within a selected topic (indicated in red) compared to the overall frequency of that term across all topics (shown in blue).

As expected, two of the most frequent topics are ESG-related (Topic 1), with 16.6% of tokens and AI-related (Topic 3), with 12.3% of tokens.

This finding aligns with the overall trend towards an increased emphasis on sustainability and governance within the job market. The analysis reveals that ESG job requirements primarily focus on reporting and compliance with standard sustainability and governance methodologies. This involves employing relevant team-oriented research and subsequent analyses, with some of the most relevant terms for Topic 1 being "report", "risk", "compliance", "legal", "regulatory", "standard", "sustainability".

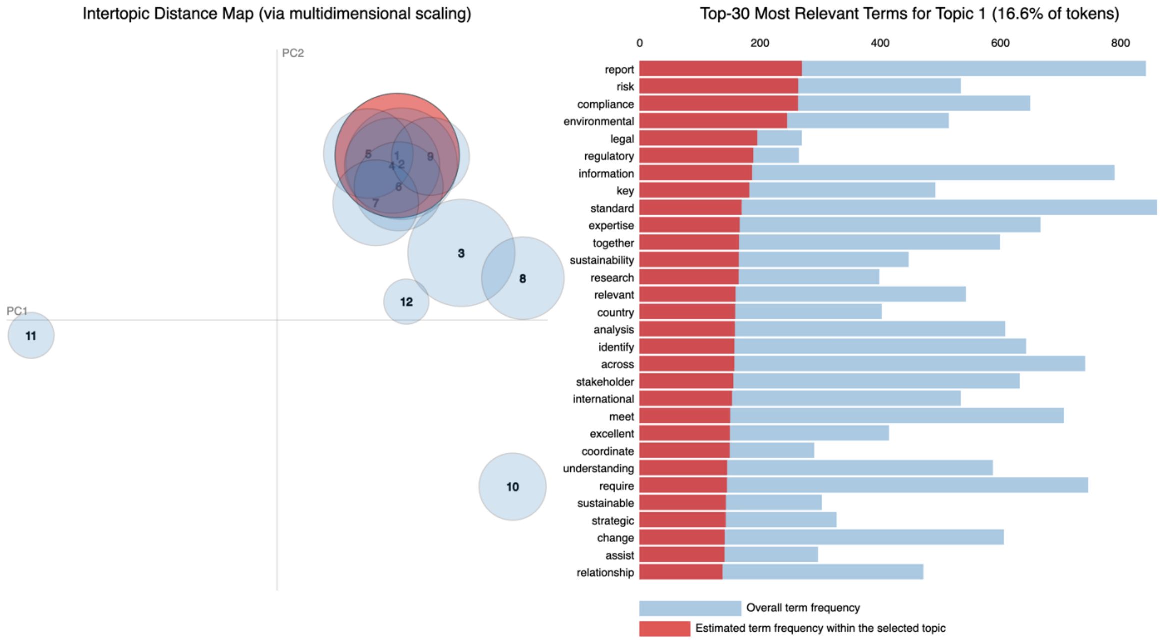

Figure 12. Topic 1 description: ESG related

Source: Authors' own research.

As highlighted by Topic 3, the AI job requirements are primarily technical-oriented, emphasising the need for specific skills and expertise in this rapidly evolving field. Key terms associated with these roles include "data", "python", "model", "pipeline", and "machine learning". These keywords highlight the strong emphasis on technical competencies that are essential for developing and implementing AI solutions effectively. Candidates are often expected to have a robust understanding of data manipulation and analysis, as well as proficiency in programming languages like Python, which is widely used for building machine learning models.

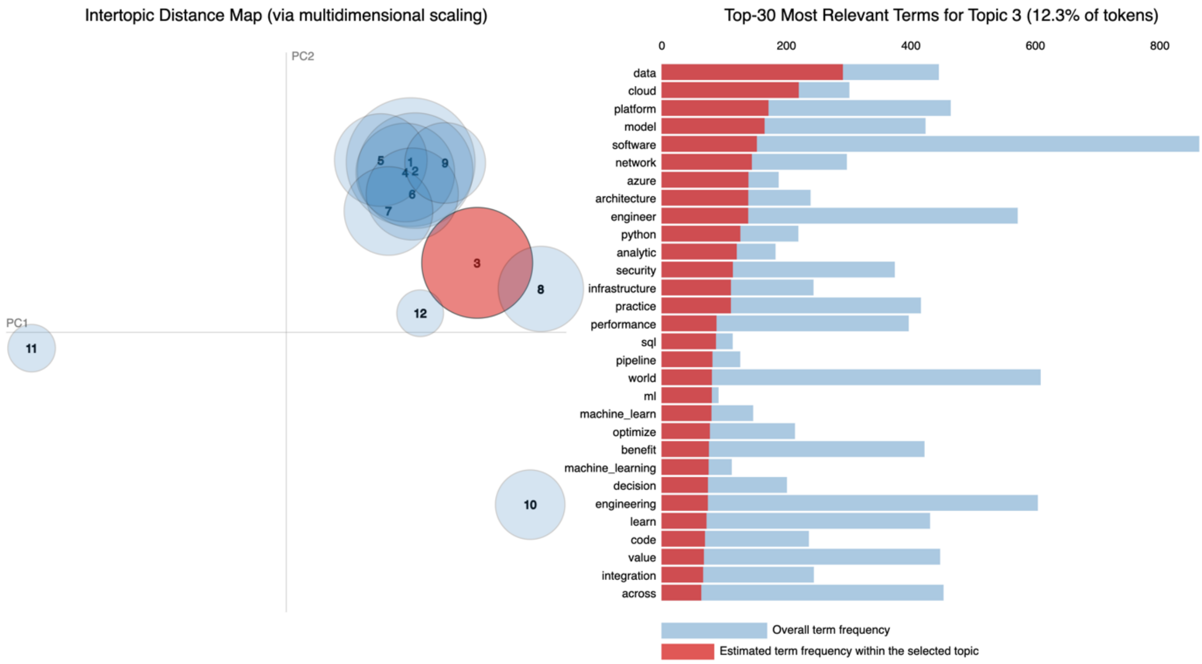

Figure 13. Topic 3 description: AI related

Source: Authors' own research.

Interestingly, the second topic, which comprises 13.4% of the total tokens, features multiple crosswords between ESG and technical AI-specific terms. This topic illustrates the growing convergence of environmental, social, and governance (ESG) considerations with technical skills required in the AI field. The co-occurrence of ESG-related keywords such as "sustainability" and "environmental," alongside technical terms like "engineering" and "software," showcases the increasing demand for professionals who possess both sets of competencies.

This intersection is particularly relevant as organisations seek to integrate sustainable practices within their technological frameworks, highlighting the importance of interdisciplinary knowledge. The presence of these keywords not only indicates a shift in job requirements but also reflects the broader trend of incorporating sustainability into technology-driven roles. Moreover, the fact that this topic ranks as the second-largest in terms of token share underscores its significance in the current labour market, suggesting that employers are actively seeking candidates who can bridge the gap between ESG principles and technical expertise.

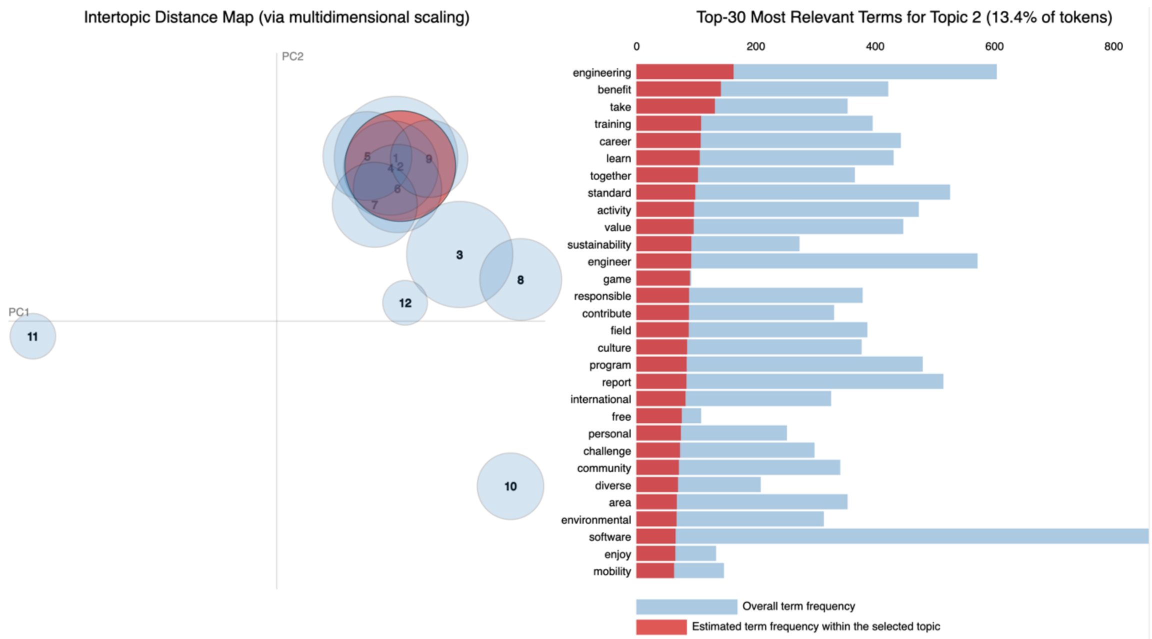

Figure 14. Topic 2 description: AI & ESG related

Source: Authors' own research.

Additionally, a topic was identified that contains digital and data-related terms relevant to practical ESG applications and climate change challenges. Although it represents a smaller share of the total tokens (2.2%), this topic emerges as a significant digital data-driven ESG domain, reinforcing the concept of the twin transition between digital transformation and sustainability.

The key terms associated with this topic can be categorized into two groups: data-related ("digital", "trust_data", "digital_inclusion", and "database") and ESG-related terms ("esg_practice_commit", "digital_foundation", and "commitment_wether_fight_climate").

Overall, this topic illustrates the critical intersection of digital innovation and sustainability, showcasing how data-driven approaches can facilitate the transition to more sustainable practices and contribute to the global fight against climate change.

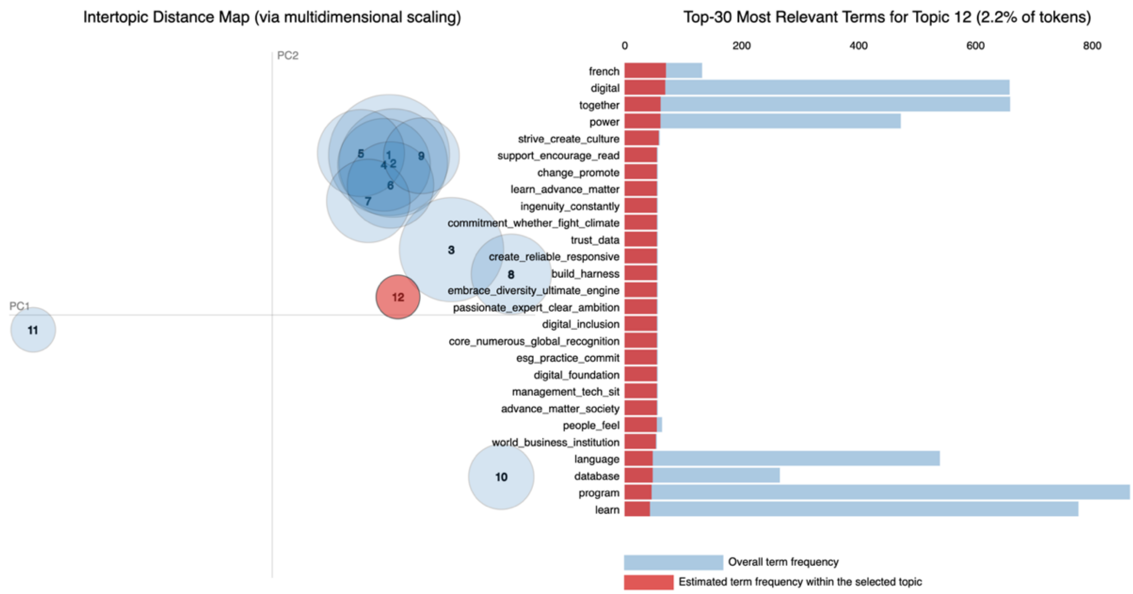

Figure 15. Topic 12 description: data-driven ESG related

Source: Authors' own research.

However, the findings indicate that ESG implications in AI domains remain largely unexplored in Romania, with limited requirements for ethical governance in AI and big data applications. This gap raises concerns about the responsible use of AI technologies, as the absence of clear ethical frameworks could perpetuate biases and inequalities. Addressing these ethical considerations is essential for promoting a more responsible integration of AI within the Romanian landscape.

Conclusion

The findings suggest a growing intersection between AI and ESG roles, though practical implementations remain distinct. While AI job postings are predominantly technical, requiring expertise in machine learning, software engineering, and programming, ESG roles encompass a broader skill set that integrates corporate governance, compliance, and financial analysis with a growing demand for data-related competencies. This indicates an increasing recognition of data science and automation within ESG-related positions, but with a more limited application compared to AI-centric roles.

Despite the observed overlap in skill requirements, AI applications in ESG remain underdeveloped in the Romanian labour market. The findings indicate that while AI technologies such as Python, SQL, and automation tools are present in ESG roles, their usage is primarily focused on data management and reporting rather than predictive modelling or AI-driven sustainability solutions. The absence of machine learning and artificial intelligence techniques in ESG postings highlights a missed opportunity to leverage AI for climate risk modelling, environmental impact assessments, and ESG-driven predictive analytics. This gap suggests that businesses in Romania have yet to fully integrate AI capabilities into their sustainability strategies.

At the sector level, the demand of ESG specialists in traditionally technology-driven sectors, such as ICT, suggests early signs of skill transferability and an increasing demand for interdisciplinary expertise. The identification of shared competencies between AI and ESG roles reinforces the potential for cross-domain collaboration, where technological advancements could be used to enhance sustainability initiatives. However, the lack of ethical AI governance requirements in AI job postings signals an area for improvement, particularly in ensuring responsible AI development aligned with ESG principles.

The evolving nature of job market demands highlights the necessity for interdisciplinary expertise bridging AI and ESG domains. As AI continues to shape the future of work, integrating sustainability-oriented skills into AI-related roles - and vice versa - could foster a more comprehensive approach to innovation and responsible technology deployment. Educational and professional training initiatives should consider equipping AI professionals with ESG competencies and ESG specialists with more technical skills in order to support the intersection of these fields.

This study provides an empirical analysis of the skills required for roles in AI and ESG domains, in the Romanian labour market. However, several limitations must be acknowledged when interpreting the findings. One of the primary constraints of this research is the limited availability of job postings, which may not fully capture the complete landscape of AI and ESG-related skill sets. While the focus was on the skills needed for these domains, it is important to note that many roles also require interdisciplinary skills that go beyond the core areas of AI and ESG.

Another limitation arises from the short time frame of data collection, which presents only a snapshot of the Romanian labour market at a specific moment in time. Given the rapid evolution of AI applications and the increasing regulatory focus on ESG, the integration of these fields is expected to change over time. A longitudinal approach, tracking job postings over multiple periods, would provide a more accurate representation of whether AI in ESG roles is increasing and how the demand for ESG expertise in AI-related jobs is evolving. Without an extended period of observation, it remains difficult to determine whether the current trends identified in this study are reflective of long-term labour market shifts or temporary fluctuations.

Furthermore, this study focuses exclusively on the Romanian labour market. While it offers valuable insights for national workforce, it limits the ability to contextualise these findings within broader international trends. Given the global nature of AI adoption and ESG regulation, a comparative analysis with other labour markets would provide a deeper understanding of how Romania aligns with international practices.

Considering these limitations, future research should focus on expanding the dataset to include a larger sample of job postings from multiple sources, such as LinkedIn, Glassdoor, and Romanian career pages. This would enhance the robustness of the analysis and improve the generalizability of the results. Additionally, an extended data collection period would allow for the examination of long-term trends, capturing how the relationship between AI and ESG skills evolves over time. This would be particularly useful in assessing whether AI adoption in ESG remains limited or whether increasing regulatory and technological developments lead to a greater convergence of these fields.

Given the increasing demand of interdisciplinary skills in the labour market, future research should expand its focus to explore the specific skills related to digital transformation, regulatory compliance, and leadership. Including these aspects would provide a more holistic understanding of the evolving skill demands in AI-ESG roles, especially as organizations continue to face complex regulatory challenges and technological changes. A job posting analysis incorporating these interdisciplinary skills could further highlight the convergence of AI and ESG with other sectors.

Another direction for future research could involve analysing global trends to compare Romania's position in AI-ESG integration with other countries. By assessing labour market patterns in regions where AI-driven sustainability initiatives are more established, potential future developments in Romania could be anticipated.

Overall, while this study contributes to the understanding of AI and ESG skill overlap in the Romanian labour market, addressing these limitations through extensive datasets, longer observation periods, a more detailed analysis of interdisciplinary skills, and global comparative analyses, would offer deeper insights into the evolving demand for AI and ESG competencies. Given the growing importance of AI in addressing sustainability challenges, future research on the intersection of these fields will be essential for informing workforce development strategies and policy decisions.

References

Allam, H., Makubvure, L., Gyamfi, B., Graham, K. N., & Akinwolere, K. (2025). Text Classification: How Machine Learning Is Revolutionizing Text Categorization. Information, 16(2), 130. https://doi.org/10.3390/info16020130

Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. Labour economics, 71, 102002. https://doi.org/10.1016/j.labeco.2021.102002

Alibasic, A., Upadhyay, H., Simsekler, M. C. E., Kurfess, T., Woon, W. L., & Omar, M. A. (2022). Evaluation of the trends in jobs and skill-sets using data analytics: A case study. Journal of Big Data, 9(1), 32. https://doi.org/10.1186/s40537-022-00576-5

Bird, S., Loper, E., & Klein, E. (2009), Natural Language Processing with Python. O'Reilly Media Inc.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. Journal of machine Learning research, 3(Jan), 993-1022.

Can, F., & Ozkarahan, E. A. (1990). Concepts and effectiveness of the cover-coefficient-based clustering methodology for text databases. *ACM Transactions on Database Systems (TODS)*, *15*(4), 483-517.

Centre for the Development of Vocational Training (Cedefop). (2023). Skills in transition: the way to 2035 Luxembourg: Publications Office. http://data.europa.eu/doi/10.2801/438491

Cihon, P., Schuett, J., & Baum, S. D. (2021). Corporate governance of artificial intelligence in the public interest. Information, 12(7), 275. https://doi.org/10.3390/info12070275

Chiny, M., Chihab, M., Bencharef, O., & Chihab, Y. (2022). Netflix recommendation system based on TF-IDF and cosine similarity algorithms. no. Bml, 15-20. https://doi.org/10.5220/0010727500003101

European Commission. (2024). "Labour and skills shortages in the EU: an action plan," Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. Available: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:52024DC0131

Gottipati, S., Shim, K. J., & Sahoo, S. (2021). Glassdoor job description analytics–Analyzing data science professional roles and skills. In 2021 IEEE Global Engineering Education Conference (EDUCON) (pp. 1329-1336). IEEE. https://doi.org/10.1109/EDUCON46332.2021.9453931

International Energy Agency (IEA). (2021). The importance of focusing on jobs and fairness in clean energy transitions, IEA, Paris.https://www.iea.org/commentaries/the-importance-of-focusing-on-jobs-and-fairness-in-clean-energy-transitions

International Labour Organization (ILO). (2024). World Employment and Social Outlook: Trends 2024. Geneva: International Labour Office. https://doi.org/10.54394/HQAE1085

Qaiser, S., & Ali, R. (2018). Text mining: use of TF-IDF to examine the relevance of words to documents. International journal of computer applications, 181(1), 25-29.
Lee, S. U., Perera, H., Liu, Y., Xia, B., Lu, Q., Zhu, L. (2024). Integrating ESG and AI: A Comprehensive Responsible AI Assessment Framework. arXiv preprint arXiv:2408.00965.
Lightcast. (n.d.). Lightcast Skills API. Lightcast API. https://docs.lightcast.dev/apis/skills#post-find-related-skills
Lin, B., & Zhu, Y. (2025). Does AI elevate corporate ESG performance? A supply chain perspective. Business Strategy and the Environment. https://doi.org/10.1002/bse.3999
Mimno, D., Wallach, H., Talley, E., Leenders, M., & McCallum, A. (2011). Optimizing semantic coherence in topic models. In Proceedings of the 2011 conference on empirical methods in natural language processing (pp. 262-272).
OECD. (2023), OECD Employment Outlook 2023: Artificial Intelligence and the Labour Market, OECD Publishing, Paris. https://doi.org/10.1787/08785bba-en
OECD. (2023). OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition, OECD Publishing, Paris. https://doi.org/10.1787/27452f29-en
Naveen, P., & Trojovský, P. (2024). Overview and challenges of machine translation for contextually appropriate translations. Iscience, 27(10). https://doi.org/10.1016/j.isci.2024.110878
Ram, M., Osorio-Aravena, J. C., Aghahosseini, A., Bogdanov, D., & Breyer, C. (2022). Job creation during a climate compliant global energy transition across the power, heat, transport, and desalination sectors by 2050. Energy, 238, 121690. https://doi.org/10.1016/j.energy.2021.121690
Ramos, J. (2003). Using TF-IDF to Determine Word Relevance in Document Queries. In Proceedings of the first instructional conference on machine learning (Vol. 242, No. 1, pp. 29-48).
Safari, A., Daneshvar, M., & Anvari-Moghaddam, A. (2024). Energy Intelligence: A Systematic Review of Artificial Intelligence for Energy Management. Applied Sciences, 14(23), 11112. https://doi.org/10.3390/app142311112
Saussay, A., Sato, M., Vona, F., & O'Kane, L. (2022). Who's fit for the low-carbon transition? Emerging skills and wage gaps in job ad data.
Setiawan, Y., Maulidevi, N. U., & Surendro, K. (2024). The Optimization of n-Gram Feature Extraction Based on Term Occurrence for Cyberbullying Classification. Data Science Journal, 23(1). https://doi.org/10.5334/dsj-2024-031
Sidorov, G., Gelbukh, A., Gómez-Adorno, H., & Pinto, D. (2014). Soft similarity and soft cosine measure: Similarity of features in vector space model. Computación y Sistemas, 18(3), 491-504. https://doi.org/10.13053/CyS-18-3-2043
Task Force on Climate-related Financial Disclosures (TCFD). (2023). 2023 Status Report. Available: https://www.fsb.org/uploads/P121023-2.pdf
Tyson, L. D., & Zysman, J. (2022). Automation, AI & work. Daedalus, 151(2), 256-271. https://doi.org/10.1162/DAED_a_01914
World Economic Forum (WEF). (2023). The Future of Jobs Report 2023, https://www.weforum.org/publications/the-future-of-jobs-report-2023/
Yazdanian, R., Davis, R. L., Guo, X., Lim, F., Dillenbourg, P., & Kan, M. Y. (2022). On the radar: Predicting near-future surges in skills' hiring demand to provide early warning to educators. Computers and Education: Artificial Intelligence, 3, 100043. https://doi.org/10.1016/j.caeai.2021.100043