Geospatial Analysis of High-Tech Employment in Europe: Accelerated AI Development and Increased AI Act Risks

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Please cite this paper as:
Ciurea, I.C., 2024. Geospatial Analysis of High-Tech Employment in Europe: Accelerated AI Development and Increased AI Act Risks. In: R. Pamfilie, V. Dinu, C. Vasiliu, D. Pleșea, L. Tăchiciu eds. 2024. *10th BASIQ International Conference on New Trends in Sustainable Business and Consumption.* Almeria, Spain, 6-8 June 2024. Bucharest: Editura ASE, pp. 213-220
DOI: 10.24818/BASIQ/2024/10/041

Abstract

The EU AI Act serves as a first-of-its-kind regulation meant to forward the European Union's journey towards responsible and ethical AI. Posing new implications for its member states, the purpose of this paper is to identify the specific geographical regions within the EU27 nations that are to be substantially affected by the AI Act. The research is designed to map the distribution of employees working in high-tech roles and analyze the distribution and density of the workforce engaged in high-tech roles across the chosen sectors within the EU27 area. Further on we analyze the countries most prone to being affected by the AI Act provisions, proportional to the employed population engaged in high-tech roles per the affected sectors. Through geospatial analysis we find distinct clusters, with the Scandinavian region leading in tech, potentially facing the most impact from the AI Act. Western Europe consistently scores high across tech sectors, while a unique cluster including Ireland, the Netherlands, Belgium, Slovenia, Croatia and Estonia leads in finance and health. Southern Europe emphasizes high-tech education, with Eastern Europe focused on high-tech accommodation. Malta, as a small specialized economy, may experience disproportionate AI Act effects. The contribution of this paper to existing research lies in the comprehensive mapping of high-tech European workforce across sectors and countries in Europe, categorized by the "high-risk" level as per the AI Act. The research helps highlight key areas of concern and opportunities for industry and policy-makers to address potential risks. Possible practical implications include tailoring policy responses to be cluster-specific in order to balance AI development and mitigate any risks and negative impacts.

Keywords

Artificial Intelligence, Artificial Intelligence Act, AI governance, high-tech employment, geospatial analysis, risk management, European Union.

DOI: 10.24818/BASIQ/2024/10/041

Introduction

The artificial intelligence (AI) field has seen tremendous advancement in the early 2020s, causing significant upheaval in multiple sectors and spawning innovative business models, while at the same time raising an array of concerns, such as data privacy or bias and discrimination, to name a few. Due to the fast pace of technology advancements, policymakers are tasked with the responsibility of navigating these complexities in order to guarantee that rules are not only applicable, but also representative of the many facets of artificial intelligence. The policies governing artificial intelligence aim to transform ideas into action plans that provide concrete information on essential issues such as funding and investments, governance strategies, areas of development, and risk mitigation (Foffano et al., 2023). Risk regulation has so far been at the forefront of AI governance (Kaminski, 2023). Risk-based regulation places emphasis on outcomes rather than particular rules and procedures as the primary objective of regulation (OECD, 2021). Examples of such a tool are represented in the United States by the newly Artificial Intelligence Risk Management Framework (AI RMF) developed by the National Institute of Standards and Technology (NIST) of the US Department of Commerce, the US Algorithmic Accountability Act of 2022 (Mökander et al., 2022) and, in the European Union, by the EU AI Act, the latter serving as the first major attempt at governing artificial intelligence in a significant jurisdiction (Schuett, 2023).

The proposed research objective of the paper is the identification of geographical areas within the EU27 countries most likely to be (regulatorily) affected by the AI Act by examining the concentration of "high-tech" occupations within each member's economy, as sectorized by the EU CEDEFOP (2020) Skills Forecast and European Union Labour Force Survey (EU LFS) datasets (Eurostat, 2024). The identification of the geographical groups will be made through the KMeans clusterization algorithm as implemented in the GeoDa spatial data science tool.

1. Review of the scientific literature

The AI Act is one of the initiatives meant to forward the EU's vision of establishing itself as the leading region for advancing and implementing state-of-the-art ethical, and secure AI (European Commission, 2018). In line with this vision, the EU Member States are encouraged to develop and adopt their own national AI strategies (Van Noordt, Medaglia and Tangi, 2023), with the AI Act serving as a governance tool.

According to the European Commission (2024), "the AI Act aims to provide AI developers and deployers with clear requirements and obligations regarding specific uses of AI". It does this by classifying the AI models into four levels (risk categories), namely minimal, limited, high, and unacceptable risks (Kalodanis, Rizomiliotis and Anagnostopoulos, 2023; Wagner, Borg and Runeson, 2024), based on the intended area of usage, data utilized to generate the models, and their potential dangers of abuse (Stuurman and Lachaud, 2022). Unacceptable risks are AI systems concerning cognitive, behavioral, manipulation, social scoring, biometric, identification and classification practices. The high-risk category involves those AI models collecting personal data such as health, location, behavior, among other elements of a person's life. In fact, most of the material focuses on the AI models falling under this category, putting emphasis on the relationship between developers and deployers (users) and their obligations. Under limited risks fall the general-purpose AI (GPAI) models, such as generative AI, where the users must be informed that the content, they are interacting with is AI-generated. The last category, minimal risk, refers to models used for image creation, video editing, video games or spam filters.

While the general purpose of the regulation is to alleviate administrative and monetary difficulties for businesses (European Commission, 2024), its impact on the labor market and the overall economy could vary depending on the specifics of the sectors and countries it is applied in, given the large effect artificial intelligence has on the economy (Furman & Seamans, 2018). Literature shows that the higher the levels of AI, the greater its impact on technological innovation and vice-versa (Gonzales, 2023; Liu et al., 2020). Therefore, AI innovation and model development is likely to happen in labor markets with high levels of technological intensity. In the following sections we focus on identifying the distribution and density of high-tech workers across various sectors in the selected EU27 countries in order to map the regions where AI innovation is most likely to be implemented and, therefore, affected by the EU AI Act.

2. Research methodology

The constructed dataset contains features for each EU27 member regarding the absolute number of employed persons in that sector, the percentage value of "high-tech" workers in each sector, as well as the absolute number of "high-tech" employees. The "high-tech" category is defined as a number of occupations listed in the International Standard Classification of Occupations (ISCO), such as researchers and engineering or IC&T professionals, or namely codes 21, 31, 25 and 35 of ISCO. According to CEDEFOP (2020), the EU-wide rate of employment in "high-tech occupations" was 8.4%. Going forward, the paper assumes that a higher rate of technological intensity in employment for a sector/country will generally lead to a higher probability of AI models being researched, developed and eventually implemented in that area.

For the purpose of our analysis we will be focusing only on the percentage features, which are implicitly scaled (0 to 1) and are thus more easily comparable between countries than absolute numbers, particularly with regard to small countries such as Malta, Luxembourg and Cyprus which may skew our analysis results.

The analysis is made through the KMeans clusterization algorithm, running with a maximum of 10000 iterations and 1500 random center starts (selected with the KMeans++ method). The number of clusters is selected using an Elbow plot, as shown in figures 1 and 2.

As an incipient step, in the exploration of the dataset, we may label the categories of employment most affected by the "High-risk" categories in the AI Act. Looking towards use-cases provided in the AI Act

(European Commission, 2024), we find that the sectors at high-risk will be as follows: non-banned biometrics, critical infrastructure, education, employment, essential services, law enforcement, migration/asylum/border control, and administration of justice and democratic processes. Intersecting these with our features, we will have to also look at the EU Critical Infrastructure Resilience initiative, which expands upon the sectors deemed as critical infrastructure, namely Energy, Transport, Banking, Financial market infrastructure, Health, Drinking water, Wastewater, Digital Infrastructure, Public Administration, Space, Production, processing and distribution of Food.

Intersecting these areas with our variables, we find that the only ones not clearly falling under this umbrella are “Arts & recreation and other services” and “Wholesale & Retail Trade”. These sectors may indeed fall into high-risk depending on the use-case, but depending on the use-case and digitalization level, risky models may be implemented and thus we may not freely exclude these sectors from our analysis – as a result, we will run our clusterization using all available data across our 17 features/sectors. Following the initial clusterization, we will elect to explore a small subset of variables of interest, namely Education and Healthcare.

In order to clusterize the countries we need to choose a suitable number of clusters:

Figure no. 1. Elbow plot between / total cluster sum of squares

Source: author’s own elaboration

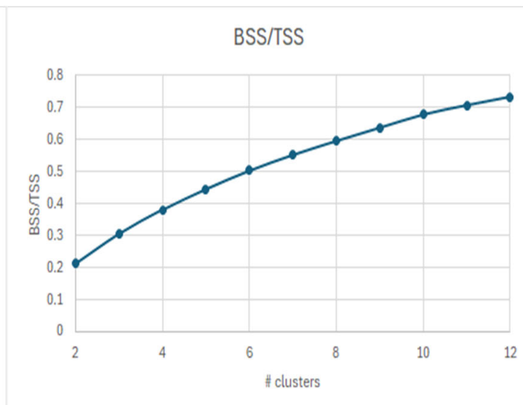

Figure no. 2. Elbow plot within cluster sum of squares

Source: author’s own elaboration

As we may observe in (Figure no.1) and (Figure no. 2), there is no significant increase in the “quality” of our clusters at any particular step, therefore taking into consideration the low number of observations to be clustered (27 countries) we will elect to have at most 6 clusters for the overall country grouping. The basic concept applicable to clusterization algorithms is that the within-cluster distances should be minimized, while the between-cluster distances should be maximized, within reason, in order to have well-defined clusters that do not overlap or group new observations wrongly. In our case however new observations would entail new EU members and we do not have many observations as is, therefore as aforementioned, we choose at most 6. This number allows for a balance between having a manageable number of clusters and ensuring that each cluster is distinct enough to be meaningful without unnecessarily fragmenting the country grouping. This is particularly important given the limited dataset size and the need to avoid overfitting, which could result from too many clusters. Given the context of EU countries, it is also worth noting that while new members may be added, the frequency and number of new entrants are relatively low. Hence, maintaining a lower number of clusters is pragmatic and sufficient for the current set of countries. This approach also provides a framework that is less likely to require significant restructuring in the event of future EU expansion.

3. Results and discussion

Geographically, we obtain the following map charts for 2, 3, 4, 5, and 6 clusters.

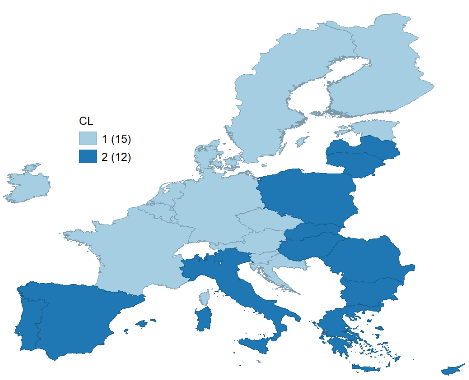

Figure no. 3. EU Digital Economy - 2 clusters
Source:author's own elaboration based on composite dataset

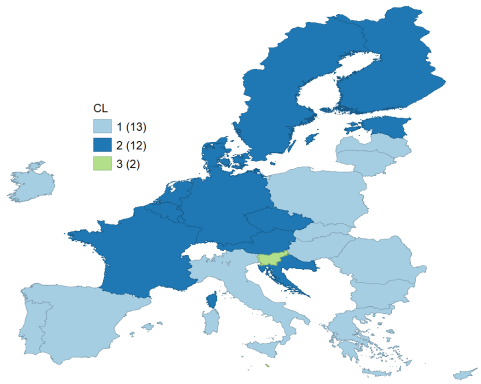

Figure no. 4. EU Digital Economy - 3 clusters
Source:author's own elaboration based on composite dataset

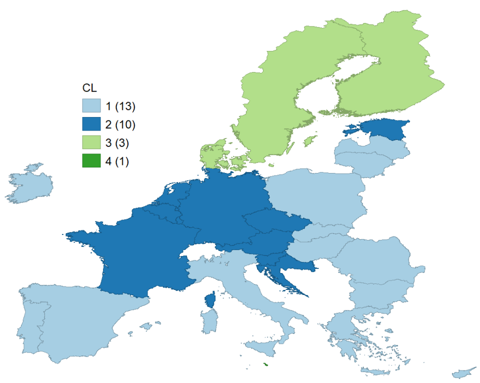

Figure no. 5. EU Digital Economy - 4 clusters
Source:author's own elaboration based on composite dataset

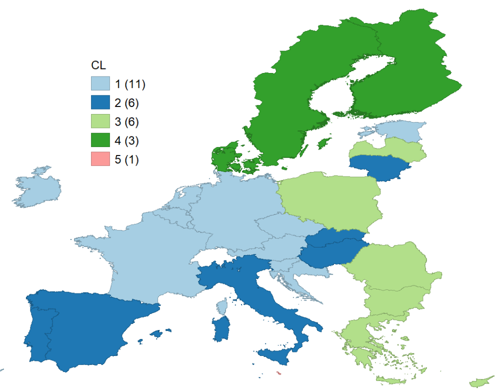

Figure no. 6. EU Digital Economy - 5 clusters
Source:author's own elaboration based on composite dataset

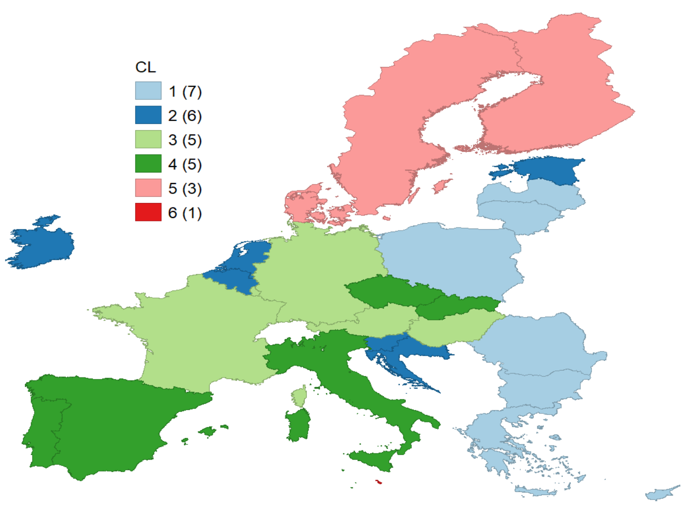

Figure no. 7. EU Digital Economy - 6 clusters
Source:author's own elaboration based on composite dataset

We observe that at n = 2 (Figure no. 3) and n = 3 (Figure no. 4) clusters, the map coagulates along 2 main poles, north/western and south/eastern Europe. At n=3 the algorithm interestingly separates two countries, Malta and Slovenia, into cluster #3. A quick look at the cluster properties shows that the two have a very low WSS, a very well-defined cluster:

```
|  |Within cluster S.S.|
|--|-------------------|
|C1|144.961            |
|C2|147.128            |
|C3|15.3021            |
```

Figure no. 8. Within cluster sum of squares for n=3
Source:author's own elaboration based on composite dataset

Table no. 1. Cluster properties by sector for n=3

Sector	C1	C2	C3
Accommodation & food	0.022	0.011	0.004
Administrative services	0.032	0.063	0.099
Agriculture, forestry & fishing	0.057	0.112	0.080
Arts & recreation and other services	0.042	0.069	0.081
Construction	0.106	0.184	0.143
Education	0.036	0.046	0.027
Energy supply services	0.408	0.392	0.585
Finance & insurance	0.111	0.169	0.118
Health & social care	0.020	0.024	0.087
ICT services	0.537	0.567	0.475
Manufacturing	0.142	0.241	0.176
Mining & quarrying	0.176	0.250	0.501
Professional services	0.154	0.233	0.078
Public sector & defence	0.087	0.116	0.113
Transport & storage	0.069	0.114	0.113
Water and waste treatment	0.155	0.271	0.299

Source: author's own elaboration from composite dataset

Looking at the cluster properties, it is important to analyze both the overall cluster centers as well as taking them sector-by-sector. In our clusterization (Table no. 1) we may observe that the C2 - North/West cluster has clearly higher levels of technological concentration than cluster C1 - South/East. However, in a few sectors the difference is negligible, such as in Energy supply services, ICT Services and to an extent Health & Social care. Cluster 3 has some interesting properties however, such as the most high-tech healthcare, energy supply, arts, water/waste management, administrative services and mining sectors, but also the lowest percentages in Education, ICT services, professional services and the accommodation/food sector. Cluster 1 - South/East excels only in the latter sector, accommodation/food. In accordance with our goal, for the three clusters defined, we observe that the generally higher-risk countries for AI model implementation and therefore regulation will be in Cluster 2, as these have a clear technological advantage over Cluster 1. Cluster 3 may be impacted to an extent, but due to the very small population size, namely Malta at approximately 530 thousand (World Bank, 2022) and Slovenia at approximately 2.1 million (World Bank, 2022), the impact may be expected to be lower, as a smaller specialized workforce will mean fewer companies and projects directly involved with AI model research and development. The same principle may apply to the small countries captured in Clusters 1 & 2, such as Luxembourg and Cyprus.

Table no. 2. Cluster properties by sector for n=4

Sector	C1	C2	C3	C4
Accommodation & food	0.022	0.011	0.010	0.007
Administrative services	0.032	0.054	0.081	0.162
Agriculture, forestry & fishing	0.057	0.090	0.187	0.051
Arts & recreation and other services	0.042	0.068	0.067	0.108
Construction	0.106	0.178	0.203	0.102
Education	0.036	0.042	0.045	0.046
Energy supply services	0.408	0.374	0.501	0.628
Finance & insurance	0.111	0.164	0.181	0.077
Health & social care	0.020	0.032	0.014	0.101
ICT services	0.537	0.543	0.622	0.451
Manufacturing	0.142	0.205	0.345	0.164
Mining & quarrying	0.176	0.251	0.301	0.582
Professional services	0.154	0.204	0.287	0.054
Public sector & defence	0.087	0.100	0.164	0.125
Transport & storage	0.069	0.111	0.136	0.073
Water and waste treatment	0.155	0.266	0.293	0.310
Wholesale & retail trade	0.035	0.072	0.116	0.051

Source: author's own elaboration from composite dataset

Increasing the cluster number to 4 in (Table no. 2) does not significantly change the landscape of the EU members, the main difference now being that the "anomaly" cluster has moved to separate Sweden, Finland and Denmark from the rest, with Malta being now a 1-observation cluster. The Scandinavian cluster now appears to be the most "high-tech" between the four, thus now being the higher-risk category of countries most capable of developing AI models across the EU. As Cluster 4 only includes Malta, its properties are identical to the country's.

The clusterizations for n = 5 and n = 6 both exclude Malta into its own separate cluster, therefore we will not be including it in the following two tables, instead referencing the above (Table no. 2) C4 column when needed.

Additionally, we will include the minimap next to the table for an easier visual analysis when examining the tables. In (Table no. 3) we notice that the countries composing the high-tech cluster initially are now in C1, while the initial South/East cluster has been split into two separate South (C2) and East (C3) clusters with small exceptions (Lithuania in "South", Latvia in "East").

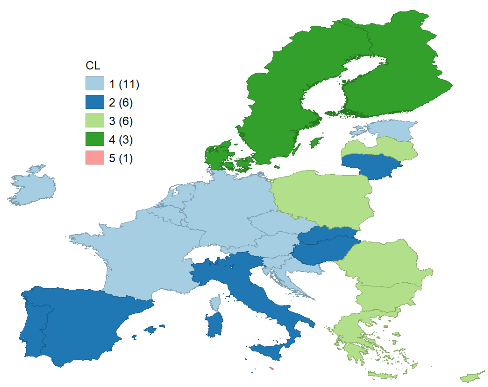

Figure no. 6. EU Digital Economy - 5 clusters (repeated from page 4)

Table no. 3. Cluster properties by sector for n=5, excluding C5 (Malta)

Sector	C1	C2	C3	C4
Accommodation & food	0.011	0.010	0.036	0.010
Administrative services	0.061	0.022	0.026	0.081
Agriculture, forestry & fishing	0.083	0.079	0.043	0.187
Arts & recreation and other services	0.067	0.042	0.037	0.067
Construction	0.165	0.129	0.096	0.203
Education	0.041	0.058	0.017	0.045
Energy supply services	0.378	0.444	0.371	0.501
Finance & insurance	0.166	0.114	0.097	0.181
Health & social care	0.031	0.025	0.014	0.014
ICT services	0.539	0.618	0.463	0.622
Manufacturing	0.202	0.159	0.120	0.345
Mining & quarrying	0.246	0.167	0.180	0.301
Professional services	0.201	0.166	0.140	0.287
Public sector & defence	0.106	0.083	0.077	0.164
Transport & storage	0.109	0.054	0.081	0.136
Water and waste treatment	0.262	0.185	0.116	0.293
Wholesale & retail trade	0.069	0.040	0.029	0.116

Source: author's own elaboration from composite dataset

The Scandinavian cluster (C4) remains the most high-tech cluster with the highest levels of technological concentrations across most sectors. The "West" cluster (C1) takes the lead in Arts & recreation and Health & Social care, while the "South" cluster (C2) has the most high-tech Education, and the "East" cluster (C3) the most high-tech Accommodation & food. At the opposite end, C3 has the lowest levels of technological concentrations across most sectors, with particularly low scores in Education, Public sector & defense, Water and waste treatment, Wholesale & retail trade, and Health & social care (interestingly enough, tying here with C4). Out of all clusters, C1 and C4 have clear technological advantages over the others, thus having a higher possibility of implementing high-risk AI models and being affected by the EU AI Act.

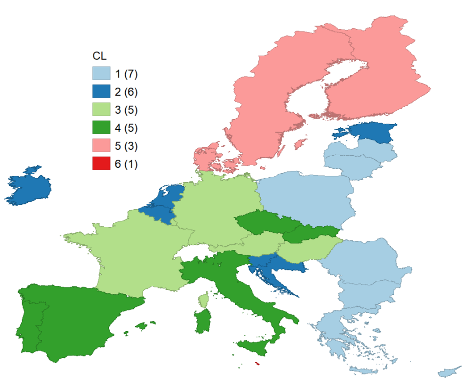

Figure no. 7. EU Digital Economy - 6 clusters (repeated from page 4)

Table no. 4. Cluster properties by sector for n=6, excluding C6 (Malta)

Sector	C1	C2	C3	C4	C5
Accommodation & food	0.034	0.011	0.014	0.004	0.010
Administrative services	0.024	0.075	0.051	0.018	0.081
Agriculture, forestry & fishing	0.040	0.077	0.071	0.110	0.187
Arts & recreation and other services	0.037	0.061	0.079	0.040	0.067
Construction	0.096	0.144	0.183	0.141	0.203
Education	0.024	0.030	0.050	0.059	0.045
Energy supply services	0.374	0.398	0.368	0.440	0.501
Finance & insurance	0.104	0.206	0.097	0.128	0.181
Health & social care	0.018	0.035	0.025	0.023	0.014
ICT services	0.476	0.551	0.492	0.664	0.622
Manufacturing	0.119	0.192	0.207	0.176	0.345
Mining & quarrying	0.167	0.317	0.171	0.174	0.301
Professional services	0.131	0.201	0.192	0.193	0.287
Public sector & defence	0.079	0.118	0.086	0.088	0.164
Transport & storage	0.077	0.116	0.085	0.070	0.136
Water and waste treatment	0.123	0.264	0.261	0.186	0.293
Wholesale & retail trade	0.032	0.046	0.098	0.037	0.116

Source: author's own elaboration based on composite dataset

The main differences that we observe in the clusterization for n=6 in (Table no. 4) is the separation of the "West" cluster (previously C1 for n=5 clusterization) into now C2 (encompassing Belgium, The Netherlands, Ireland, Slovenia, Croatia and Estonia) and C3 (France, Germany, Austria, Hungary and Luxembourg). The Scandinavian (C5) and East (C1) clusters remain the same, while the South (C4) cluster loses Hungary. Cluster 5 remains consistent in having the highest levels of technological concentrations across most sectors, while Cluster 1 remains consistent in having the lowest levels. We notice now that the newly formed Cluster 2 has the most high-tech Finance & insurance, Health & social care, and Mining & quarrying among all clusters. Interestingly, Cluster 3 has the most high-tech capabilities in Arts & recreation and the lowest in Energy supply services and Finance & insurance. Cluster 4 dominates in Education and ICT services, while achieving lowest performances in Accommodation & food, Administrative services, and Transport & storage.

Introducing a higher number of clusters enables us to identify more specific patterns and interactions between sectors and regions that were not apparent in the broader clusterization. By fine-tuning the clusters, we can better match regions with their economic and technological profiles, identifying the regions most likely to be affected by the EU AI Act with greater precision. Our geospatial analysis reveals that there is significant diversity in the concentration of high-tech occupations across EU27, resulting in distinct clusters. Out of all clusters, the Scandinavian one consistently shows the highest levels of technological concentrations across most sectors, showcasing its technological leadership. Due to their technological capabilities, Scandinavian countries may be more significantly impacted by the AI Act. Following are Western Europe cluster countries (mostly represented by Germany, France, Luxembourg, Ireland, the Netherlands, Austria) which, while not having the highest levels across sectors, do score consistently high, with differences often negligible compared to their Scandinavian counterparts. While most of the clusterization algorithms grouped the aforementioned countries together, hence generalizing them as "Western Europe" we should still consider the last clusterization for n=6 (Table no. 4), which grouped Ireland, the Netherlands, Belgium, Slovenia, Croatia and Estonia together, noting them as leaders in the Finance, Health and Mining sectors, hence the sectors where these countries are prone to be most impacted by the AI Act. Countries with high scores across high-tech sectors should pay close attention to the product development of AI technology, hence focus on the obligations of the developers showcased in the AI Act.

The "Southern" Europe cluster, most often showcased by Italy, Spain, Portugal and, interestingly, Slovakia, has a strong emphasis on high-tech education and, when joined by the Czech Republic, also on high-tech ICT services as shown in (Table no. 4). The East cluster (formed mostly by Romania, Poland, Bulgaria, Greece, Lithuania and Latvia) is highlighted consistently for high-tech accommodation, but shows the lowest levels of technological concentration in most of the other sectors. Such countries should concentrate on the obligations of the deployers shown in the AI Act, as the focus in those regions will be on the usage, rather than the development of AI models. The small state of Malta forms its own cluster, due to its size and focused economic sectors. The AI Act may have a disproportionally larger impact on smaller economies due to their specialization in certain sectors. As a result of the different sector-specific impacts, policymakers will need to consider the unique economic profiles of these clusters to minimize any negative impacts and support a balanced development of AI technologies across the EU.

Conclusions

By mapping the concentrations of "high-tech" occupations we can anticipate the different challenges regions and sectors might face due to the regulatory changes the AI Act introduces. We identify specific regional and sectoral strengths and vulnerabilities, aligning with the objectives of the EU AI Act for shaping effective, equitable AI policies that support innovation while protecting the interests of all stakeholders in the diverse economic landscape of the European Union.

One of the limitations of the study is that it does not take into consideration the absolute values of the "high-tech" occupations, therefore overlooking the scale at which some economies operate in these sectors. As such, a small economy could show a high concentration of high-tech occupations relative to its size, but the actual number of jobs or overall economic output might be minimal compared to larger economies with a lower relative concentration. In this sense, economies with a substantial absolute number of "high-tech" jobs might face more considerable challenges in compliance costs and restructuring, simply due to the volume of affected workers and companies.

Future research could aim to include absolute values to provide a more comprehensive understanding of the potential impact. Some areas for further study include developing a framework to assess the risk levels of different sectors in compliance with the AI Act, as well as generating a heatmap of Europe indicating the geographic distribution of the sectors according to their risk levels, illustrating how risk levels vary by sector and location. Other research ramifications could lie in investigating GDPR compliance among AI-utilizing industries, identifying which countries and industries have faced the most fines, which would help in deepening the understanding of the regulatory environment and its impact on AI deployment.

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