Mapping regional AI: application of neural network for classifying European regions based on AI technologies using enterprise-related data

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This study demonstrates the mosaic nature of European regions in terms of the usage and adoption of artificial intelligence (AI) technology. A dataset of EU27 NUTS 2 regions is compiled and analysed using multi-layer perceptron neural networks to produce original research results that contribute to the evolving discourse on regional AI. The findings indicate that considerable regional differences exist in AI-technology usage across European regions. Mapping results enhance understanding of the sharp performance disparities between and within countries. The study presents a clear centripetal development with the capital regions, metropolitan areas and Northern European regions generally outperforming the rest. It reveals a largely continuous corridor along the 'Aarhus–Bologna Axis' and the 'German Pentagon' area characterised by substantial capacity to use and adopt AI technology.

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Introduction

In recent years, discussions revolved around the need for more active participation of regions in the development and use of artificial intelligence (AI) at the European level (EC 2018, EPRS 2019, Kogler et al. 2022, EWCR 2023, Santos et al. 2025), mainly because the rapid breakthroughs in digital technologies, such as AI, not only generate growth (Kalai et al. 2024) but also territorial divide (Capello–Lenzi 2022, Lenzi 2025). Therefore, it is highly important to know more about the roles that AI-based technologies can play in enhancing the regional performance of European regions. Furthermore, it is crucial to have a better understanding of the main drivers and key determinants that promote regional artificial intelligence (RAI).

In the global landscape, it is already evidenced that substantial efforts have been made by industrial organisations and enterprises to use AI systems and technologies that can generate new business opportunities (Xu et al. 2021) and enhance management practices (Shukla–Agnihotri 2024). In sectoral breakdown, it is demonstrated that AI is playing a pivotal role in the transformation of service sector enterprises owing to its accelerating use (Singh et al. 2021, Belk et al. 2023, Noble–Mende 2023, Mariani–Borghi 2024). Church (2024) pointed out that several enterprises have already introduced AI-based software development tools and techniques that can be applied to different areas of interest in a company environment, including speech and image recognition, text mining and large data analytics (deep learning and machine learning). They concluded that regional economies have to adjust with changes caused by AI.

AI-related technologies appear to represent an evolving topic for regional science (Lazzeretti et al. 2023, Delcea et al. 2024) and economic geography (Lu et al. 2024). In the European context, the transformative role of AI has been shown to carry an important territorial dimension. Buarque et al. (2020) examined AI knowledge production and how AI patents were distributed across the EU28 regions between 1988 and 2013. Although the regions where AI is most embedded into the innovation landscape are the ones with the highest number of AI patents[1], to the best of my knowledge, no evidence regarding the determinants of AI knowledge creation have been reported. Cicerone et al. (2023) analysed the spatial patterns of AI knowledge stock over the period of 2014–2017 for the EU28 regions and concluded that the distribution of AI appears concentrated in a few 'hot spots'[2], mainly owing to the recent digital transformation and green-tech specialisation. However, a deeper understanding of the reasons behind the emergence of regional hubs of AI remains unknown. An interesting outcome of these investigations is that although regions with large cities top the lists, those with a relatively lower population count appear. It can be concluded that these smaller regions stand out owing to their large shares of expertise in AI-related technology sectors within their local knowledge spaces. Among the limited studies on the geographical mapping of AI-based technologies, Xiao–Boschma (2023) investigated how a regional knowledge base of ICTs influences the emergence of AI-based technologies in European regions from 1994 to 2017 and found that 'hot spots' of 'AI inventing' are concentrated in a few regions within

[1] According to Buarque et al. (2000), top 10 AI-producing regions are as follows: Ile de France (FR), Oberbayern (DE), Mittelfranken (DE), Noord-Brabant (BE), Stuttgart (DE), Karlsruhe (DE), Darmstadt (DE), East England (UK), Köln (DE) and Lombardia (IT).

[2] According to Cicerone et al. (2023), AI knowledge stock 'hot spots' can be found in the regions of the British Isles, the Benelux, Denmark, South of Sweden, Central and South of Finland, South of France, Rhône-Alpes (FR) and Pays de la Loire (FR), West of Germany, Central and Nord of Italy, as well as in capital regions (e.g. Budapest, Lisbon, Madrid, Paris, Tallinn, Vienna, Warsaw).

Western European countries[3]. Using patent data from European companies involved in AI innovation over the period of 1995–2016, Igna–Venturini (2023) concluded that company characteristics influence success in AI innovation, with patent productivity rising alongside the scale of innovation and research effort and is lower for companies with narrow technological competences. It was reported that AI-inventing companies benefitted from inter-firm knowledge spill-overs. Findings suggest that there was a small group of top innovators at the frontier of AI; however, evidence on the spatial distribution of these companies has not yet been sufficiently proven.

As empirical evidence on the regional endowment of AI and its reasons remains relatively unexplored and existing studies on RAI lack knowledge from firm-level evidence to date, the present study aims to respond to these calls. This lack of research highlights a promising gap for future studies, which the present study seeks to address at least partially by examining the usage and adoption of AI technology across European regions and exploring possible reasons for the existing regional differences. To this end, a dataset of EU27 NUTS 2[4] regions was compiled and analysed using multi-layer perceptron (MLP) neural networks – a sub-form of deep learning that has been used in resolving several regional science problems (Church 2024, Delcea et al. 2024) to identify patterns in data and then predict outputs for a new set of similar data (Kogler et al. 2022) – to produce original research results and contribute to the evolving discourse on RAI.

The remainder of this study is organised as follows. The next section concentrates on the theoretical and empirical underpinnings of RAI, preparing the ground for the presentation of the technical aspects of the estimation and classification procedures. The following section describes the database, applied method and results of the experiments, including test statistics, on which the empirical analysis is based. The succeeding section reveals the regional differences in the usage of AI technology across EU27 NUTS 2 regions based on the results of artificial neural network classification. The study concludes by highlighting the main findings, limitations, potential research directions and policy implications.

[3] According to Xiao–Boschma (2023), the top five regions account for almost 40% of all AI patent applications are North Brabant (NL), Oberbayern (DE), Stuttgart (DE), Inner London (UK) and Ile de France (FR) over the period 2012–2017.

[4] NUTS is Nomenclature of Territorial Units for Statistics (French: *Nomenclature des Unités Territoriales Statistiques*). It is a geocode standard for referencing the subdivisions of countries for statistical purposes.

Theoretical and empirical underpinnings: regional artificial intelligence and its key determinants

The literature on regional artificial intelligence (RAI) is scarce. What is clear from existing studies is that RAI is based on the latest achievements of new-generation information technologies (e.g. AI, big data, large language models and virtual reality) that promote the transformation and upgradation of industrial organisations and economic growth models (Hu et al. 2024). To confirm this, based on the examples from Chinese research studies, Lin et al. (2024) empirically demonstrated that the AI industry increases the overall level of the regional economy and concluded that AI-based technologies are an important driving force for high-quality regional economic growth and competitiveness. This study demonstrates that significant regional differences exist in the role of the AI industry in promoting high-quality regional economic growth. Moreover, there is a clear imbalance in the spatial distribution of the AI industry's development level among the western, centre and eastern regions of China, suggesting that differentiated AI-technology support increases regional differences.

Lu et al. (2024) pointed out that a better understanding of RAI helps determine the regions that are more or less exposed to AI, as RAI explains why and to what extent different regions engage with AI. Analysis of American companies revealed that the positive association between AI and business performance is only a partial reality. Findings suggest that settling down in a region with low- or high-level AI exposure would decline the business performance of any firm owing to the low net income or high cost, respectively. This resonates with the comment by Clifton et al. (2020) that many enterprises pursue incremental adoption, particularly in places with relatively low labour costs.

It is argued that RAI exhibits a high degree of synergy and complementarity with regional innovation ecosystems and their resilience (Hu et al. 2024) as well as the openness of the regional economy (Lu et al. 2024): if existing regional networks and ecosystems are not open enough, local enterprises with low-level AI knowledge may have limited access to new-generation information technologies. Recent studies have demonstrated that AI creation correlates with regional technological knowledge production (Buarque et al. 2020); however, patent applications capture only a part of the private and public investment activities in AI (Igna–Venturini 2023). Chun et al. (2024) pointed out that scientific research is a crucial foundation for technological progress in AI, which means that technological breakthroughs in AI often originate from foundational scientific research. Moreover, Czvetkó et al. (2021) suggested that regional development potential plays a pivotal role in the technological readiness of regions by pointing out that the equipment and flexibility of regional enterprises provide a suitable environment for adopting and utilising emerging technologies. Lee et al. (2024) indicated that AI requires highly developed resource endowment, particularly digital infrastructure. Furthermore, Zhao et al. (2025)

empirically demonstrated that the AI level on economic resilience markedly varies based on resource endowment.

Based on these findings, there is a good chance for further theoretical specifications, which combine two seemingly related aspects, namely, AI-technology usage at the regional level and possible key determinants that may affect the level of AI-technology adoption. This enables one to come up with an operationalisation attempt that may unlock the association of the following constituents more specifically across the European regions:

– *RAI*, which can be captured by AI-technology usage and adoption (as target variable);
– *regional innovation ecosystem*, which can be captured by regional innovation performance indicators (as predictor variables) (cf. EC 2023);
– *regional development potential and resource endowment*, which can be captured by territorial capital endowment (as predictor variable) (cf. Tóth 2023).

Concurrently, theoretical specification may seek to take account of sectoral characteristics, such as AI-technology usage, according to the sectors and branches of the regional economy. As in most European regions, the share of service sector activities has been large and AI is playing a pivotal role in the transformation of service sector enterprises (Singh et al. 2021, Belk et al. 2023, Noble–Mende 2023, Mariani–Borghi 2024); thus, it makes sense to conduct empirical studies with respect to the service sector.

The estimation procedure

I aimed to obtain the maximum spatial coverage at NUTS 2 level. Accordingly, the sample size (number of regions) and selection of variables were justified by the fact that my main interest was to cover most of the European territory. The construction of the database for 213 NUTS 2 regions[5] belonging to 27 EU member states was based on three data sources. Of particular help was the openly available database of the Regional Innovation Scoreboard, built by the European Commission, which enriches the dataset with regional data (EC 2023). A small amount of regional data was obtained from Eurostat; recent findings on territorial capital at the European level were used (cf. Tóth 2023). The dataset, which is presented in the Appendix Table A1, is based on 13 variables, which is an original and straightforward collection of regional data in line with the aforementioned theoretical specifications.

The choice of the classification technique was based on the need to overcome the weaknesses perceived in the earlier studies that lack or fail to measure the association between AI-technology usage and its reasons at the regional level. Accordingly, the

[5] Due to lack of available data, regions of Belgium (BE), Cyprus (CY), Estonia (EE), Latvia (LV), Luxembourg (LU), Malta (MT), as well as Åland (FI), Canarias (ES), Ciudad Autónoma de Ceuta (ES), Ciudad Autónoma de Melilla (ES), overseas French departments (FR), Valle d'Aosta/Vallée d'Aoste (IT), Liguria (IT), Região Autónoma dos Açores (PT) and Região Autónoma da Madeira (PT) are excluded from this analysis.

applied technique attempts to measure and evaluate this association. The approach followed to estimate the share of enterprises that used or adopted at least one AI-based technology[6] (as the dependent variable) is mostly imposed by data availability problems. However, the relevant independent variables required to estimate the dependent variable were available for all regions in my sample. Accordingly, I selected to estimate the missing values of the dependent variable in one cross-section, on 2013 NUTS 2 regions, in 1 year (2024)[7] and on this basis, I classified European regions.

To this end, neural networks were utilised to develop an analytical model and quantify the association between RAI and its determinants. Such networks were essentially mathematical models that consisted of a large number of interconnected items (units) and were capable of learning. The basis of learning was that the relative strength of connections evolved and changed during the learning process. When a large number of functional units were correctly connected, their combined operation and architecture, could solve highly complex tasks and provide a useful tool for practical applications, such as classification (decision) and prediction (estimation).

Neural networks have many advantages. On the one hand, they often seem to be more effective than regression methods, particularly when the independent variables are correlated and have a non-linear relationship with the dependent variable. On the other hand, they are robust, which means that missing data and data with low reliability do not disrupt the operation. In addition, variables (predictors and targets) could essentially be of any measurement level.[8]

The four basic steps for building learning algorithms with neural networks are as follows:

- *Training:* seen data (or training data) randomly taken from the active dataset, called training set, was utilised to train the model to reduce the error metrics, such as sum of squares error and relative error, between the model output and the actual output;
- *Testing:* data not yet seen in the training phase (or testing data) randomly taken from the active dataset, called testing set, was designed to monitor the results

[6] Enterprises that have used or adopted any AI-based technologies for the following purposes are involved in this analysis: text mining (performing analysis of written language), speech recognition (converting spoken language to readable format), natural language generation (generating spoken or written language), image recognition (identifying objects or persons based on images), deep learning (machine learning for data analysis), AI-based software robotic processes automation (automating different workflows and assisting decision making), and physical movement of machines via autonomous decisions (e.g. robots, drones, self-driving vehicles).

[7] Although the independent variables cover different periods than the dependent variable due to data availability constraints, this is not a serious problem. On the one hand, independent variables do not change much over time. Accordingly, using slightly different timeframes is acceptable in this research. On the other hand, there is no strong temporal relationship between the predictors and the dependent variable, meaning that independent variables affect AI adoption and usage over time. Furthermore, the present analysis contains average data over several years; therefore, the temporal mismatch might be less of an issue.

[8] A detailed description of this technique including the mathematical background is available in the scholarly literature (e.g. Clark 2012 [1989], Gurney 1998). The software implementation can also be found in related literature and handbooks (e.g. Borgulya 1998, Ketskeméty et al. 2011).

obtained from the model against reality during the learning process to minimise error metrics, such as the sum of squares error and relative error;

- *Holdout:* if the model has already recognised the association between input data (e.g. predictors or independent variables) and output data (e.g. targets or dependent variables) with the smallest possible error, one could evaluate the model's performance using additional independent data, called validation data (or validation set);
- *Running the model with new data:* knowing the error metrics and validation results, the model could be applied to new data for which the actual output data (e.g. dependent variables) were unknown so that the classification or prediction could be completed for the total sample.

The learning algorithm used in this analysis, referred to as MLP neural networks, has evolved from the classical procedure presented above with the addition of hidden layers that enhanced the efficiency of neural networks, and, thus, the learning performance. MLP-based neural networks are modelling tools specifically optimised for solving prediction and classification problems, and they are addressed in this study. There are various reasons for calling MLP-based neural networks into service as follows:

- MLPs performed well with a small amount of data without regularisation if the dataset is noise-free. Furthermore, a simple MLP architecture with few layers could reduce the model's capacity to overfit on a small dataset;
- MLPs tolerated multicollinearity as they are typically more flexible than traditional (linear) models and other types of deep learning-based models. They can learn internal representations that can 'merge' or 'reorganise' correlated predictors in such a way that the multicollinearity issue does not have the same negative impact as in other models;
- MLPs were flexible enough to capture complex relationships, and although they may not explicitly model spatial autocorrelation, they could still provide good results. If the sample size was small, implementing spatial regularisation might not yield sufficiently better results to justify the additional efforts.

As a rule of thumb, the partitioning ratio between the training, testing and holdout samples were ~7:2:1 (70%, 20% and 10%); however, in specific cases and based on careful considerations, other partitioning schemes can be applied. Accordingly, I looked at the possibilities of 6:3:1 and 6:2:2 partitioning in this analysis.

I used IBM SPSS (Statistical Package for Social Sciences, 30th version) to conduct the analysis. As it made sense to initially include only those cases for which the values of the dependent and independent variables were available, we selected the modelling sample of 55 NUTS 2 regions. I conducted a series of experiments: SPSS was run for 90 times. The design of the experiments was as follows: 30 tests were conducted with the 7:2:1 partitioning, another 30 tests with the 6:3:1 partitioning and finally, 30 more tests with the 6:2:2 partitioning.[9]

[9] A detailed report of test results is available at https://github.com/tothbalazsistvan/Regional_Statistics

I deeply analysed the combination of three principles that enabled the precise selection of possible solutions following the modelling procedure:

– *The number of valid cases must essentially reach the total size of the sample.* Herein, the number of valid cases reached the total size of the sample if at least 54 valid cases were included in the model-building process;
– *The test must essentially meet the predetermined partitioning ratio.* Herein, the test met the partitioning ratio if the actual partitioning would not have deviated by more than three percentage points from the originally determined partitioning ratios;
– *Relative errors must be essentially the same in the training, testing and holdout samples*, which indicates that there has been no overtraining; accordingly, one can hope that the model would continue to perform well with new data. Herein, relative errors were the same if they do not deviate by more than 0.20 in the training, testing and holdout samples.

Three of the 90 possible choices met the aforementioned criteria (hereinafter Solutions A, B and C). Table 1 summarises the test statistics that is broken down into three blocks: case processing summary, model summary and independent variable importance.[10] As Solution A was based on 54 valid cases (instead of 55), values of the dependent variable were estimated for 199 regions.[11] As for Solutions B and C, all regions were valid cases; thus, an estimation was made for 203 regions.[12]

The experiments yielded information on how sensitive the models are, particularly regarding independent variable importance. I found that the results were by far the most strongly determined by the independent variable of territorial capital endowment. In addition, significant independent variables were the share of research and development (R&D) expenditures in the business sector as well as of enterprises that have introduced at least one business process innovation. As for Solution A, another substantial factor was the share of high-growth enterprises and the value of PCT patent applications. As for Solution B, the amount of total innovation expenditure and the share of high-growth enterprises were pivotal. For Solution C, the share of individuals who have above the basic overall digital skills was important. The models react much less to changes in the share of innovative enterprises collaborating with others, the share of employment in knowledge-intensive activities and the total turnover of new or considerably improved products per total turnover of enterprises.

These findings suggest that regional resource endowment – material (tangible) and non-material (intangible) – played a key role in how AI was adopted and used. Below is a breakdown of possible reasons why territorial capital endowment and regional

[10] After calculating the raw importance scores for each independent variable, normalization was done by dividing each predictor's raw importance by the sum of all raw importance scores. This ensures that the importance scores are scaled to a range of 0 to 1, with the sum of all normalized importance scores being 1.

[11] Without Darmstadt, Köln, Oberbayern (DE), Eastern and Midland (IE), Ile de France (FR), Lombardia (IT), as well as Drenthe, Flevoland, Friesland, Gelderland, Groningen, Limburg, Overijssel and Zeeland (NL).

[12] Without Köln (DE), Ile de France (FR), as well as Drenthe, Flevoland, Friesland, Gelderland, Groningen, Limburg, Overijssel and Zeeland (NL).

innovation performances are crucial for AI adoption. In terms of material resource endowment (cf. Tóth 2023), broadband internet services and gross fixed capital formation could be essential for using AI technologies. Regions with high-speed internet and better access to funding can invest more in AI implementation. Besides, regions with a strong industrial base or technology sector were more likely to use AI for operation optimisation. In terms of non-material resource endowment (cf. Tóth 2023), regions with a skilled labour force (e.g. scientists, engineers and workers in high-technology sectors) were more likely to explore and integrate AI. A strong tertiary education system may increase AI literacy and innovation. Supportive laws and policies around data privacy as well as digital governance can facilitate AI usage. Moreover, societies that were more open to digital transformation could adopt AI faster. Accordingly, AI adoption is about the entire regional ecosystem rather than just financial capital and machinery: people (skilled labour force), education, policies, infrastructure and societal attitudes can be regarded as the key constituents of AI adoption and usage. Thus, differences in these factors among regions could potentially explain disparities in how quickly or effectively AI was adopted and used.

To further demonstrate the validity of the model, three charts are provided in the annex. Dot plots of the observed values on the horizontal axis (x-axis) and estimated values from the model on the vertical axis (y-axis) indicate that dots are relatively close to the 45° line; in other words, the values of the dependent variable are dispersed around the 45° line (see in Appendix Figures A1, A2, A3). Accordingly, this enables one to conclude that the proposed solutions could be used to estimate the missing values of the dependent variable for the total sample.

Table 1

MLP test statistics: case processing summary, model summary and independent variable importance according to the three possible solutions

Solutions		Solution A	Solution B	Solution C
Case processing summary and partitioning				
Modelling sample (55 regions)	valid	54	55	55
	excluded	1	0	0
Total sample (213 regions)	valid	199	203	203
	excluded[a)]	14	10	10
Predetermined partitioning ratio (training / testing / holdout, %)		70 / 20 / 10	70 / 20 / 10	60 / 30 / 10
Proposed partitioning	training	38 (70.4%)	39 (70.9%)	33 (60.0%)
	testing	10 (18.5%)	10 (18.2%)	18 (32.7%)
	holdout	6 (11.1%)	6 (10.9%)	4 (7.3%)
Model summary[b)]				
Training	SSE	1.222	1.709	4.731
	RE	0.066	0.090	0.296
Testing	SSE	0.413	0.428	2.642
	RE	0.167	0.155	0.243
Holdout	RE	0.259	0.157	0.254

(Table continues on the next page.)

(Continued.)

Independent variables	Independent variable importance					
	normalised importance	sort by importance	normalised importance	sort by importance	normalised importance	sort by importance
Territorial capital endowment (score)	0.373	1	0.358	1	0.352	1
Individuals who have above the basic overall digital skills (as % of individuals aged 16–74 years)	0.039	8	0.034	9	0.082	4
R&D expenditures in the business sector (as % of regional GDP)	0.112	2	0.103	4	0.085	3
Total innovation expenditure by enterprises (in PPS) per person employed	0.077	6	0.107	3	0.040	9
Enterprises introducing at least one business process innovation (as % of enterprises)	0.080	5	0.110	2	0.089	2
Innovative enterprises collaborating with others (as % of enterprises)	0.013	11	0.015	11	0.070	7
PCT patent applications per billion regional GDP (in PPS)	0.086	4	0.054	7	0.079	5
Trademark applications per billion regional GDP (in PPS)	0.060	7	0.046	8	0.063	8
Employment in knowledge-intensive activities (as % of total employment)	0.028	9	0.023	10	0.031	11
Employment in innovative enterprises (as % of total employment)	0.027	10	0.066	6	0.071	6
Total turnover of new or significantly improved products per total turnover of enterprises	0.008	12	0.008	12	0.005	12
High-growth enterprises (as % of active enterprises)	0.098	3	0.077	5	0.035	10

a) No estimated value.

b) Architecture: number of hidden layers: 1. Activation function: hyperbolic tangent. Number of output layers: 1. Activation function: identity. Type of training: Batch training.

Note: SSE: sum of squares error; RE: relative error; R&D: research and development; GDP: gross domestic product; PPS: purchasing power standard.

Source: own elaboration based on SPSS output tables.

Results of the classification procedure: empirical findings on RAI at the European level

This section extensively discusses the presentation of the individual solutions and the study of regional differences.

The initial important result, confirming previous findings on the subject (Buarque et al. 2020, Cicerone et al. 2023, Xiao–Boschma 2023), is that regional performances in terms of AI-technology usage are not homogenous across Europe. Figures 1, 2 and 3 show that AI-technology adoption is unevenly distributed across European regions. Overall, regions of the Nordic countries (DK, FI and SE), West Netherlands (NL), Baden-Württemberg (DE), Midi-Pyrénées (FR) and Northeast Italy (IT) normally have leading positions, whereas those belonging to Central (HU and PT) and Southeast Europe (BG, EL and RO) as well as South Italy (IT) perform much worse than the average and lag. Furthermore, there is an evident tendency towards concentrated AI-technology adoption in the capital regions of many EU member states (e.g. Athens, Berlin, Ljubljana, Prague, Vienna, Warsaw and Zagreb). In addition, intra-country disparities between the capitals and the countryside can be particularly high, as observed in case of Greece and Poland.

Further findings from this study indicate that AI-technology adoption concentrates a few regions; however, besides the single 'hot spots' pointed out by Cicerone et al. (2023) as well as Xiao–Boschma (2023), larger contiguous areas and corridors can be characterised with considerable capacity in AI technology.

Solution A in Figure 1 demonstrates that within peripheral areas, most of the agglomerated areas in Portugal and Spain (e.g. Lisbon, Community of Madrid, Catalonia, Valencian Community and Basque Community) outperform rural areas. A substantial capacity in AI technology can be detected in potential metropolitan areas along the coast of the Mediterranean Sea (Sun Belt), such as in Provence-Alpes-Côte d'Azur (FR), Rhône-Alpes (FR) and Piedmont (IT). Besides, there is a largely continuous corridor, the 'Aalborg–Bologna Axis', towards concentrated development in Central Europe, including agglomerations and regions with leading performance, such as Aarhus (DK), Odense (DK), Hamburg (DE), Braunschweig (DE), Baden-Württemberg (DE), Tirol (AT), Vorarlberg (AT), Veneto (IT) and Emilia-Romagna (IT). The main driving force behind the development of these regions is the high level of R&D expenditures alongside high-growth enterprises and relatively high territorial capital endowment.

Furthermore, except for some examples, the eastern and south-eastern regions of the EU record lower performance, which is probably because AI-based software development tools and techniques have not been introduced in the company environment at the required level. This finding is consistent with that by Cicerone et al. (2023), who reported similar conclusions as follows: some countries demonstrate a clear pattern in which the capital regions emerge as 'national champions'; however, intra-country disparities might grow owing to the weak catching-up that can be expected by lagging regions mainly owing to the absence of high-tech industries and lack of modernisation strategy support.

Solution B in Figure 2 demonstrates a more concentrated clustering of AI-technology adoption. On the one hand, the largely continuous corridor on the 'Aalborg–Bologna Axis' is more apparent. Among the winners, one can find German regions in addition to the previously mentioned ones, such as Darmstadt (including Frankfurt), Detmold, Düsseldorf, Lunenburg, Swabia and Upper Bavaria (including Munich). The key determinant of the development of this area is the concentration of business process innovation paired with the high level of total innovation expenditures and relatively high territorial capital endowment. On the other hand, compared with Solution A, the regions of France and Spain have moderate and below-average capacity in AI technology. Accordingly, the presence of a potential metropolitan area is not a sufficient condition, as evidenced by the average values of the Sun Belt regions.

Only a few regions in the countryside demonstrate a performance higher than the average, which indicates a larger territorial coverage in Austria, the Czech Republic as well as Northwest and Southeast Germany. The same uniform pattern with sizeable differences in terms of AI-technology adoption characterises the eastern and south-eastern regions of the EU, as demonstrated by Solution A.

Solution C in Figure 3 demonstrates an even more concentrated clustering of AI-technology adoption in Central Europe. Substantial capacity in AI technology can be evidenced in a core area, delimited by Düsseldorf, Braunschweig, Dresden, Munich and Freiburg, which can be labelled as the 'German Pentagon'. The main driving force behind the development of this area is the concentration of business process innovation alongside the high level of R&D expenditures and relatively high territorial capital endowment. The capital regions of the eastern part of the EU are generally worse off with respect to their results in Solutions A and B; however, their negative difference is not sizeable.

Figure 1

Share of service sector enterprises that use AI-based technologies in the EU27 NUTS 2 regions, according to Solution A

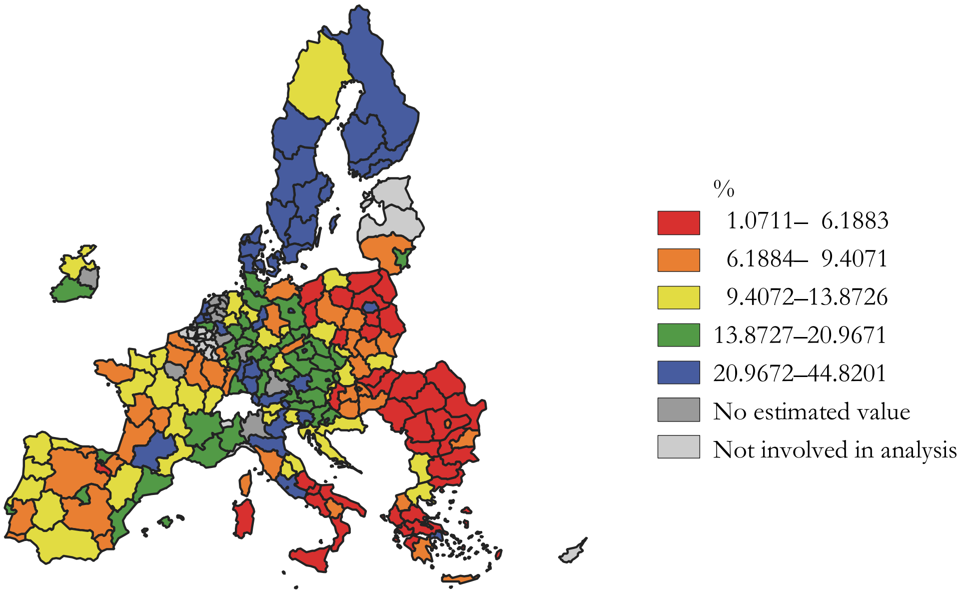


Figure 2

Share of service sector enterprises that use AI-based technologies in the EU27 NUTS 2 regions, according to Solution B

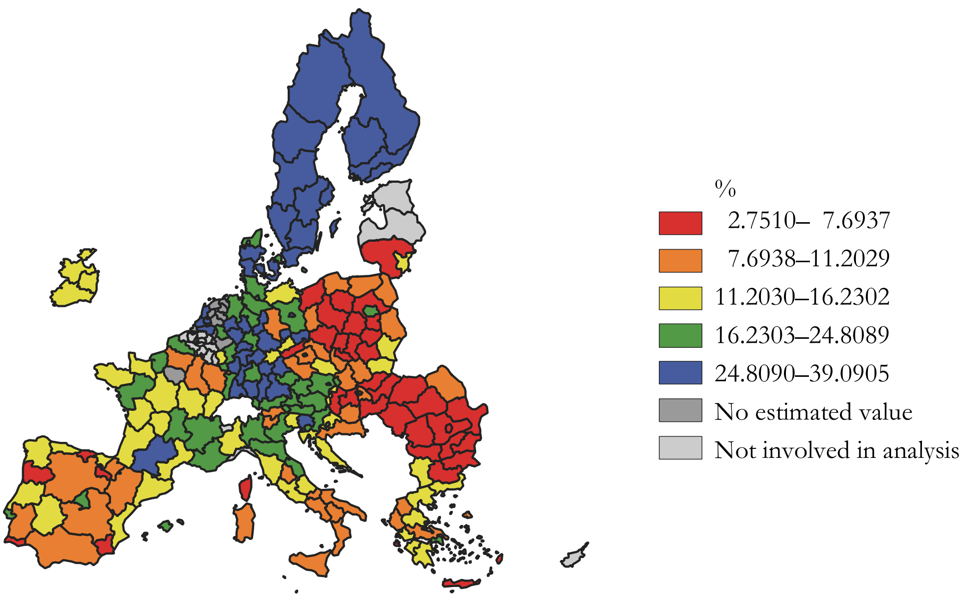
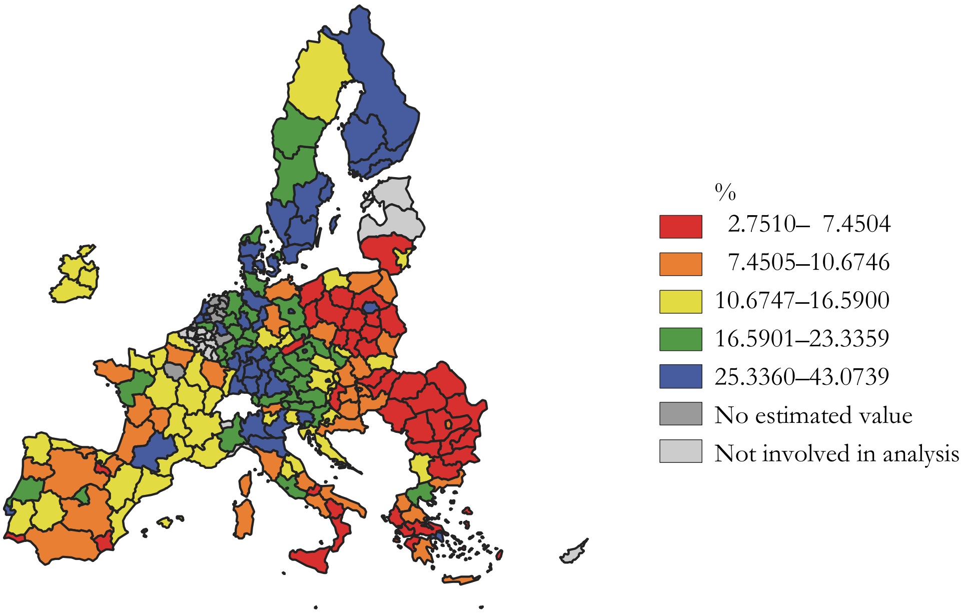


Figure 3

Share of service sector enterprises that use AI-based technologies in the EU27 NUTS 2 regions, according to Solution C



Conclusions

In line with the objectives outlined in the introduction, this study sought to decrease the knowledge gap on the regional endowment of AI and its reasons by analysing AI-technology usage and adoption across European regions and pointing out their mosaic-like patterns. Where previous studies have predominantly concentrated on AI development, typically measured through AI patents or R&D investments, this study emphasised AI adoption and usage by including a set of possible explanatory variables. This study should be considered an initial exploration to overcome the weaknesses perceived in the earlier studies that lack or fail to measure the association between AI-technology usage and its reasons at the regional level. To achieve this aim, a dataset of EU27 NUTS 2 regions was compiled and analysed using MLP neural networks to produce original research results that may contribute to the evolving discourse on RAI.

The findings suggest that extreme regional differences exist in AI-technology usage and adoption across the European regions. Mapping results provided a deeper insight into the sharp differences in inter- and intra-county performances; however, the three individually presented solutions do not yield extremely different results for Europe as a whole. Overall, the study demonstrates a clear centripetal development with the capital regions, metropolitan areas and Northern European regions generally outperforming the rest and demonstrates a largely continuous corridor along the 'Aarhus–Bologna Axis' and the 'German Pentagon' area characterised by considerable capacity in AI technology.

With regards to the drawbacks of this study, the limitation of available data has made it necessary to narrow the scope of inquiry and warrants future studies to confirm findings as well as shed more light on RAI across the European region. Given the nature of data, the primary purpose of the present study was to leverage the ability of the model to learn intricate patterns that simpler models may not have been able to capture. While I recognise the challenges that the lack of overfitting may cause, I believe that the insights gained from this analysis remain valuable. The lack of overfitting prevention techniques was justified by the assumption that the dataset is well-suited for MLP-based learning. However, I acknowledge that a small sample size may pose a limitation for training deep learning models. In addition, as the primary focus of the present analysis was on predictive accuracy, the ability of the model to capture complex associations outweighed the need for explicit spatial handling. This was consistent with my approach, where the ability of the model to generalise to unseen data is of greater importance than capturing spatial dependencies. However, I acknowledge that spatial autocorrelation could potentially influence the model. Accordingly, future investigations on this subject should be addressed based on handling spatial autocorrelation.

After overcoming problems in data availability constraints, another possible extension of the current research could be conducting empirical investigations at lower territorial units. For example, cities or functional urban areas could be good case study fields for further primary research studies. Further investigations at lower administrative units would more precisely reflect the existing dichotomies, and results derived from such investigations can be applied to practice and help policy-makers design a credible AI policy to empower the countryside as well as rural and peripheral areas, including sub-regions and settlements.

Looking ahead, I anticipate that future researchers could more comprehensively investigate how AI-technology usage and adoption impact regional competitiveness and regional resilience. Turning the EU into a global leader in AI development can only be achieved if its regions hold a strong and active position. Enhancing AI adoption in lagging regions is crucial for promoting cohesion, narrowing the gap with developed regions and creating new markets. To promote this, communication and collaboration among different governance levels as well as clear guidance and dedicated funds for AI-technology development are key factors for positioning the regions of the EU.

Appendix

Table A1

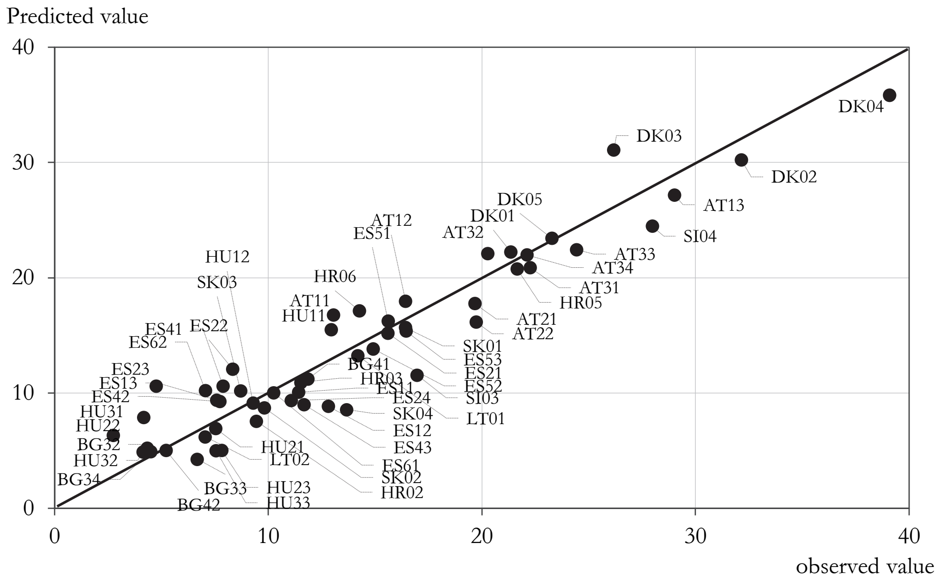
List of variables

Name of variable	Period covered	Definition of variable
	Dependent variable	
Enterprises using at least one of the AI-based technologies in the service sector (as % of enterprises)	2024	The variable measures the share of enterprises in the service sector with 10 employees or more that employ at least of one of the AI-based technologies (Eurostat).
	Independent variables	
Territorial capital endowment (score)	2010–2019	The variable reflects the classification (clusters) of the NUTS 2 regions based on material and non-material resource endowments (Tóth 2023).
Individuals who have above the basic overall digital skills (as % of individuals aged 16 to 74 years)	2017–2021	The variable measures the number of individuals with above basic overall digital skills divided by the number of individuals aged 16 to 74 years (EC 2023).
R&D expenditures in the business sector (as % of regional GDP)	2013–2020	The rate is obtained by dividing all R&D expenditures in the business sector (BERD) by the regional gross domestic product (EC 2023).
Total innovation expenditure by enterprises (in PPS) per person employed	2014–2020	The variable measures the monetary input directly related to innovation activities. The rate is obtained by dividing the sum of the total innovation expenditure of enterprises by the total employment in enterprises (EC 2023).
Enterprises introducing at least one business process innovation (as % of enterprises)	2014–2020	The variable measures the number of enterprises that introduced at least one business process innovation divided by the total number of enterprises (EC 2023).
Innovative enterprises collaborating with others (as % of enterprises)	2014–2020	The rate is obtained by dividing the number of enterprises with innovation co-operation activities by the total number of enterprises (EC 2023).
PCT patent applications per billion regional GDP (in PPS)	2014–2021	The variable measures the number of patents applied for at the European Patent Office divided by the regional gross domestic product (EC 2023).
Trademark applications per billion regional GDP (in PPS)	2015–2022	The rate is obtained by dividing the number of trademarks applied for at the European Union Intellectual Property Office by the regional gross domestic product (EC 2023).
Employment in knowledge-intensive activities (as % of total employment)	2014–2021	The variable measures the number of employed persons in the medium-high and high-tech sectors divided by the total workforce (EC 2023).
Employment in innovative enterprises (as % of total employment)	2018–2020	The rate is obtained by dividing the total employed persons in innovative enterprises with 10 or more employees by total employment in enterprises with 10 or more employees (EC 2023).
Total turnover of new or significantly improved products per total turnover of enterprises	2014–2020	The rate is obtained by dividing the sum of total turnover of new or significantly improved products by the total turnover of enterprises (EC 2023).
High-growth enterprises (as % of active enterprises)	2021–2022	The variable measures the number of high-growth enterprises divided by the number of active enterprises with at least 10 employees (Eurostat).

Notes: Coverage of service sector by NACE Rev. 2 activity: wholesale and retail trade; repair of motor vehicles and motorcycles, transport and storage, accommodation; food and beverage service activities, information and communication, real estate activities, professional, scientific and technical activities, administrative and support service activities, repair of computers and communication equipment. The statistical unit is the enterprise. The statistical population consists of enterprises with 10 or more employees.

Figure A1

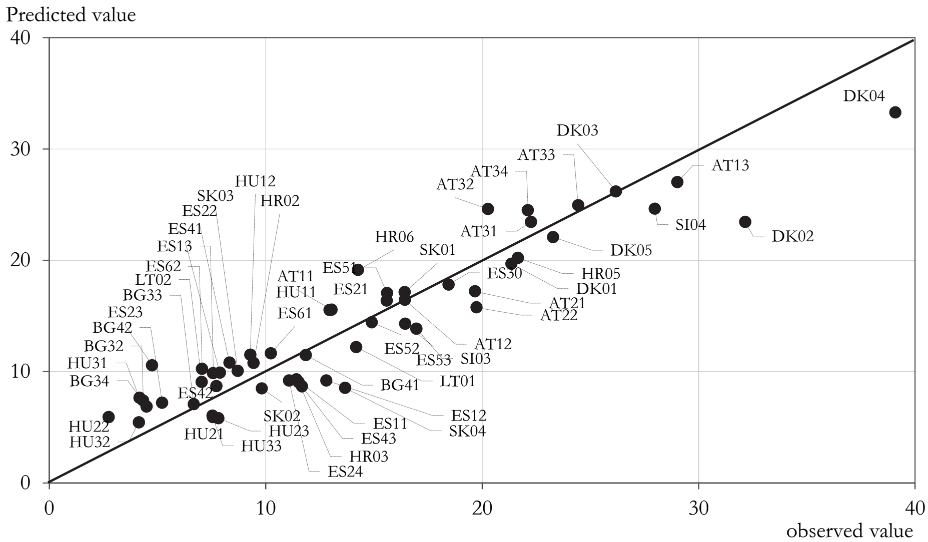
Dot plot of the observed and estimated values according to Solution A



Note: 55 valid cases (all NUTS 2 regions) are involved in the analysis. Without Comunidad de Madrid (ES30).

Figure A2

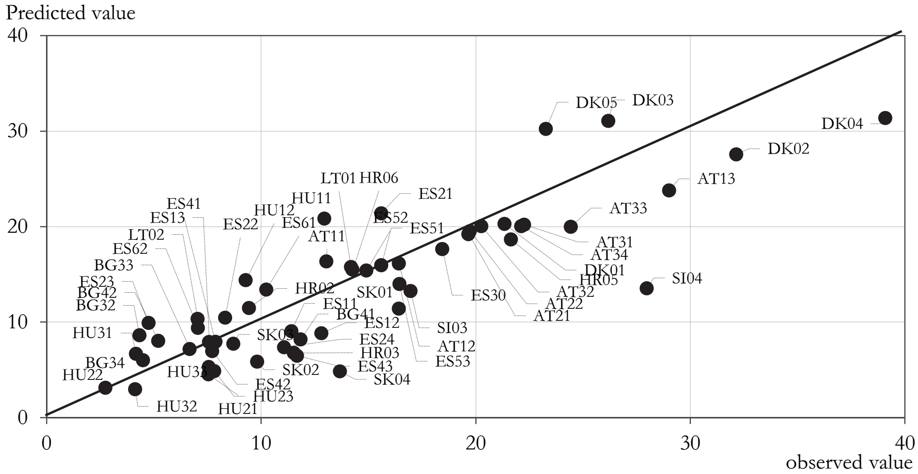
Dot plot of the observed and estimated values according to Solution B



Note: 55 valid cases (all NUTS 2 regions) are involved in the analysis.

Figure A3

Dot plot of the observed and estimated values according to Solution C



Note: 55 valid cases (all NUTS 2 regions) are involved in the analysis.

REFERENCES

BELK, R. W.–BELANCHE, D.–FLAVIÁN, C. (2023): Key concepts in artificial intelligence and technologies 4.0 in services *Service Business* 17 (1): 1–9. https://doi.org/10.1007/s11628-023-00528-w

BORGULYA, I. (1998): *Neurális hálózatok és fuzzy rendszerek* Dialóg Campus, Budapest–Pécs.

BUARQUE, B. S.–DAVIES, R. B.–HYNES, R. M.–KOGLER, D. F. (2020): OK Computer: the creation and integration of AI in Europe *Cambridge Journal of Regions, Economy and Society* 13 (1): 175–192. https://doi.org/10.1093/cjres/rsz023

CAPELLO, R.–LENZI, C. (2022): *The regional economics of technological transformations: Industry 4.0 and Servitisation in European regions* Routledge, Abingdon, New York.

CHUN, Y.–HUR, J.–HWANG, J. (2024): AI technology specialization and national competitiveness *PLoS ONE* 19 (4): 0301091. https://doi.org/10.1371/journal.pone.0301091

CHURCH, R. L. (2024): AI & regional Science: past, present and future *Eastern Journal of European Studies* 15 (2): 14–29. https://doi.org/10.47743/ejes-2024-0202

CICERONE, G.–FAGGIAN, A.–MONTRESOR, S.–RENTOCCHINI, F. (2023): Regional artificial intelligence and the geography of environmental technologies: does local AI knowledge help regional green-tech specialization? *Regional Studies* 57 (2): 330–343. https://doi.org/10.1080/00343404.2022.2092610

CLARK, J. W. (2012 [1989]): Introduction to neural networks. In: PROTO, A. N. (ed.): *Nonlinear phenomena in complex systems* pp. 1–102., Elsevier, North-Holland, Amsterdam, Oxford, New York, Tokyo. https://doi.org/10.1016/B978-0-444-88035-2.50005-5

CLIFTON, J.–GLASMEIER, A.–GRAY, M. (2020): When machines think for us: the consequences for work and place *Cambridge Journal of Regions, Economy and Society* 13 (1): 3–23. https://doi.org/10.1093/cjres/rsaa004

CZVETKÓ, T.–HONTI, G.–ABONYI. J. (2021): Regional development potentials of Industry 4.0: open data indicators of the Industry 4.0+ model *PLoS ONE* 16 (4): 0250247. https://doi.org/10.1371/journal.pone.0250247

DELCEA, C.–NICA, I.–IONESCU, Ș.–CIBU, B.–ȚIBREA, H. (2024): Mapping the frontier: a bibliometric analysis of artificial intelligence applications in local and regional studies *Algorithms* 17 (9): 418. https://doi.org/10.3390/a17090418

GURNEY, K. (1998): *An introduction to neural networks* Routledge, New York, London.

HU, R.–BAO, Z.–LIN, Z.–LV, K. (2024): The innovative construction of provinces, regional artificial intelligence development, and the resilience of regional innovation ecosystems: quasi-natural experiments based on spatial difference-in-differences models and double machine learning *Sustainability* 16 (18): 8251. https://doi.org/10.3390/su16188251

IGNA, J.–VENTURINI, F. (2023): The determinants of AI innovation across European firms *Research Policy* 52 (2): 104661. https://doi.org/10.1016/j.respol.2022.104661

KALAI, M.–BECHA, H.–HELALI, K. (2024): Effect of artificial intelligence on economic growth in European countries: a symmetric and asymmetric cointegration based on linear and non-linear ARDL approach *Journal of Economic Structures* 13: 22. https://doi.org/10.1186/s40008-024-00345-y

KETSKEMÉTY, L.–IZSÓ, L.–KÖNYVES TÓTH, E. (2011): *Bevezetés az IBM SPSS Statistics programrendszerbe* Artéria Stúdió Kft., Budapest.

KOGLER, D. F.–WHITTLE, A.–BUARQUE, B. (2022): The science space of artificial intelligence knowledge production: global and regional patterns, 1990–2016. In: KURZ, D. H.–SCHÜTZ, M.–STROHMAIER, R.–ZILIAN, S. S. (eds.): *The Routledge handbook of smart technologies: an economic and social perspective* pp. 241–268., Routledge, Abingdon, New York. https://doi.org/10.4324/9780429351921

LAZZERETTI, L.–INNOCENTI, N.–NANNELLI, M.–OLIVA, S. (2023): The emergence of artificial intelligence in the regional sciences: a literature review *European Planning Studies* 31 (7): 1304–1324. https://doi.org/10.1080/09654313.2022.2101880

LEE, C-C.–XUAN, C.–WANG, F. (2024): Natural resources and green economic growth: the role of artificial intelligence *Resources Policy* 98: 105322. https://doi.org/10.1016/j.resourpol.2024.105322

LENZI, C. (2025): The urban geography of artificial intelligence in Europe. In: BROITMAN, D.–KOPCZEWSKA, K.–CZAMASKI, D. (eds.): *Handbook on big data, artificial intelligence and cities* pp. 224–242., Edward Elgar, Northampton. https://doi.org/10.4337/9781803928050.00019

LIN, S.–WANG, M.–JING, C.–ZHANG, S.–CHEN, J.–LIU, R. (2024): The influence of AI on the economic growth of different regions in China *Scientific Reports* 14: 9169. https://doi.org/10.1038/s41598-024-59968-7

LU, R.–ZHENG, F.–MA, S-N.–YANG, R. (2023): Unpacking the inverted U-shape between regional AI and business performance *International Journal of the Economics of Business* 31 (1): 49–70. https://doi.org/10.1080/13571516.2023.2271755

MARIANI, M. M.–BORGHI, M. (2024): Artificial intelligence in service industries: customers' assessment of service production and resilient service operations *International Journal of Production Research* 62 (15): 5400–5416. https://doi.org/10.1080/00207543.2022.2160027

NOBLE, S. M.–MENDE, M. (2023): The future of artificial intelligence and robotics in the retail and service sector: sketching the field of consumer-robot-experiences *Journal of the Academy of Marketing Sciences* 51 (4): 747–756. https://doi.org/10.1007/s11747-023-00948-0
SANTOS, A. M.–MOLICA, F.–CARLOS, T-S. (2025): EU-funded investment in artificial intelligence and regional specialization *Regional Science Policy & Practice* 17 (7): 100190. https://doi.org/10.1016/j.rspp.2025.100190
SHUKLA, A.–AGNIHOTRI, A. (2024): AI-driven smart management processes: transforming decision-making and shaping the future *Library Progress International* 44 (3): 5471–5493.
SINGH, N.–BANDYOPADHYAY, T. K.–SAHOO, N.–TIWARI, K. (2021): Intellectual property issues in artificial intelligence: specific reference to the service sector *International Journal of Technological Learning, Innovation and Development* 13 (1): 82–100. https://doi.org/10.1504/IJTLID.2021.114920
TÓTH, B. I. (2023): Territorial capital in the European Union: measuring the territorial endowments of the EU-28 NUTS-2 regions over the 2010s *Regional Statistics* 13 (1): 3–35. https://doi.org/10.15196/RS130101
XIAO, J.–BOSCHMA, R. (2023): The emergence of artificial intelligence in European regions: the role of a local ICT base *The Annals of Regional Science* 71 (3): 747–773. https://doi.org/10.1007/s00168-022-01181-3
XU, D.–GUO, Y.–HUANG, M. (2021): Can artificial intelligence improve firms' competitiveness during the Covid-19 pandemic: international evidence *Emerging Markets Finance and Trade* 57 (10): 2812–2825. https://doi.org/10.1080/1540496X.2021.1899911
ZHAO, X.–ZHAI, G.–LEE, H.–APERGIS, N.–MA, X. (2025): Harnessing artificial intelligence for urban economic resilience *Applied Economics*. https://doi.org/10.1080/00036846.2025.2501352

INTERNET SOURCES

EUROPEAN COMMISSION [EC] (2018): *Artificial intelligence – A European perspective.* https://doi.org/10.2760/11251 (downloaded: January 2025)
EUROPEAN COMMISSION [EC] (2023): *Regional innovation scoreboard 2023.* https://data.europa.eu/doi/10.2777/70412 (downloaded: January 2025)
EUROPEAN PARLIAMENTARY RESEARCH SERVICE [EPRS] (2019): *Economic impacts of AI.* https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/637967/EPRS_BRI(2019)637967_EN.pdf (downloaded: February 2025)
EUROPEAN WEEK OF CITIES AND REGIONS [EWCR] (2023): *Regional artificial intelligence. The role of regions in AI development.* https://regions-and-cities.europa.eu/programme/2023/programme/2249 (downloaded: December 2024)

DATABASE/WEBSITE

EUROSTAT: *Artificial intelligence by NACE Rev. 2 activity and NUTS 2 regions Regional statistics by NUTS classification (reg) / Regional digital economy and society (reg_isoc) / Regional statistics on ICT usage in enterprises (reg_isoc_e).* https://ec.europa.eu/eurostat/web/main/data/database (downloaded: January 2025)