Innovations and development of artificial intelligence in Europe: some empirical evidences

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Abstract

Purpose – The objective of this paper is to analyze the relationship between innovation and the development of artificial intelligence (AI) and digital technologies in Europe. The use of digital technologies among European companies is studied through a composite index, while the relationship between innovation and AI is studied through a log-linear regression model. The results of the model have made possible to develop interesting indications for economic and industrial policy.

Design/methodology/approach – The use of digital technologies among European companies is studied through a composite index of AI and information technology (ICT) (using the Fair and Sustainable Welfare methodology) with the aim of measuring territorial gaps and to know which European countries are more or less inclined to its use, while the relationship between innovation and AI is studied through a log-linear regression model.

Findings – In the paper, two different methodologies were used to analyze the relationship between innovation and the development of digital technologies in Europe. The synthetic indicator made possible to develop a taxonomy between the different countries, the log-linear model made possible to identify and explain the determinants of innovation.

Originality/value – The description of the biunivocal relationship between innovation and AI is a topical and relevant issue that is treated in the paper in an original way using a synthetic indicator and a log-linear model.

Keywords Innovation, Artificial intelligence, Policies

Paper type Research paper

1. Introduction

A country's innovation is an important factor influencing the artificial intelligence (AI) endowment of firms. Indeed, companies operating in countries with a high level of innovation tend to be more advanced in their adoption and use of AI. There are several reasons why this is the case. First, more innovative countries tend to have a more advanced technological culture and infrastructure, which means that firms have access to more resources and technological knowledge. This allows them to invest more in AI research and development and use it more effectively. More innovative countries tend to have a more favorable

JEL Classification — O25, O31, O32

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environment for entrepreneurship and for the development of innovative start-ups, which are often at the forefront of AI adoption and use (Makridakis, 2017). This, in turn, can stimulate a virtuous cycle of innovation and AI development, in which more advanced firms attract highly skilled talent and investment, prompting other firms to follow suit. Ultimately, the level of innovation in a country can have a significant impact on the AI endowment of firms. However, there are also other factors, such as the availability of quality data and access to skilled talent, that can affect the ability of firms to use AI effectively. The level of AI in companies can influence innovation in a country (Agrawal *et al.*, 2019). Companies that invest in AI research and development and use AI effectively can become market leaders in their sector and stimulate innovation in other sectors. Furthermore, the adoption of AI by businesses can lead to greater efficiency and productivity, reducing costs and improving the quality of products offered (Perifanis and Kitsios, 2023).This in turn can stimulate economic growth and innovation in other sectors. Therefore, innovation and AI development are interdependent factors, where innovation can lead to AI development and vice versa. The presence of a favorable technology ecosystem and business environment can foster the development of both, helping to create a virtuous circle of innovation and economic growth. To better understand the relationship between innovation and AI development, it is important to consider some key factors that influence both. This means that businesses must have access to adequate funding, infrastructure and support services, as well as a culture of innovation and collaboration (Ziakis *et al.*, 2022). Finally, the availability of high-quality data is a key factor for AI development. Companies need data to train their machine learning algorithms and improve their data processing capabilities. Therefore, countries that invest in creating an open and accessible data environment can stimulate the development of AI (Gao and Janssen, 2020).

To achieve the goal of making the link between AI and innovation more virtuous, the 'Digital Europe' program was launched. It is certainly a central element of the Commission's overall response to the challenge of digital transformation and is included in the proposal on the Multiannual Financial Framework (MFF) for the period 2021–2027. Its objective is to provide a spending instrument adapted to the operational requirements of capacity building in the areas identified by the European Council and to exploit synergies between them. The program aims, *inter alia*, to develop and strengthen core competences in AI, such as data resources and archives of AI algorithms, and to make them accessible to all businesses and public administrations; to ensure that the essential capabilities needed to secure the EU digital economy, society and democracy are available and accessible to the EU public sector and businesses; and to improve the competitiveness of the EU cybersecurity industry; expand the optimal use of digital capabilities, in particular high-performance computing, AI and cybersecurity, in all sectors of the economy, areas of public interest and society, including the implementation of interoperable solutions in areas of public interest, and facilitate access to technology and know-how for all businesses.

To better understand the phenomenon, this study aims to analyze the use of digital technology among European firms through a composite index of AI and information technology (ICT) (using the Fair and Sustainable Welfare Methodology) to measure territorial gaps and to know which European countries are more or less inclined to its use, and to study the relationship between innovation and AI through a log-linear regression model.

To this end, this contribution is developed with the following structure:

(1) Survey of literature (paragraph 2),

(2) Description of the methodology for constructing the composite indicator and log-linear regression; in particular, the robustness of the methods and results will be discussed (paragraph 3),

(3) Description of the results obtained with the two methods (section 4),

(4) Discussion of the results (paragraph 5),

(5) Conclusions (paragraph 6).

2. Background

The relationship between innovation and the development of AI is one of the most relevant research topics in recent years, because the tumultuous development of AI is rapidly changing the concept of innovation and also the taxonomy of key factors that characterize the process of innovation growth. The virtuous relationship between innovative technologies and competitive advantage was extensively described many years ago by Porter (1985). Artificial intelligence and its applications are among the most innovative emerging technologies today. According to a recent study conducted by the World Economic Forum, a strong correlation emerged between companies' AI endowment and their ability to innovate. Companies that use AI improve their efficiency, reduce costs and improve the quality of their products. This can spur innovation in other sectors and contribute to overall economic growth. Moreover, as a recent McKinsey Global Institute report points out, the economic potential of AI is enormous and can help generate significant productivity and value-added gains in various sectors. However, the report also stresses the importance of effective regulation to ensure responsible use of AI and mitigate the risks associated with its adoption. In addition, to fully exploit the benefits of AI, it is important to create a corporate culture conducive to innovation and experimentation. The academic literature on this topic is quite extensive, and only the main papers that refer to these issues are reported in this paper. Among the most interesting survey papers are Mariani *et al.* (2023), Mariani *et al.* (2022), which propose a systematic overview of innovation research strands revolving around AI. The results provide an up-to-date overview of the existing literature, embedded in an interpretive model that allows us to distinguish all the main modes and consequences of the introduction of AI in the context of innovation. The first and fundamental aspect to be investigated is that of the relationship between the introduction from AI, innovation and organizational change. In Haefner *et al.* (2021) there is an interesting analysis of how Artificial Intelligence (AI) reshapes companies and how innovation management is organized. Consistent with rapid technological development and the replacement of human organization, AI may actually force management to rethink the entire innovation process of a company. Verganti *et al.* (2020) propose a framework for understanding AI design and innovation. Specifically, the authors note that as creative problem solving is significantly conducted by algorithms, human design increasingly becomes a sensemaking activity, i.e. understanding the problems that should or could be addressed. This shift in focus requires new theories and brings design closer to leadership, which is inherently a sensemaking activity. Allam (2016) analyzes how AI transforms businesses and organizes innovation activities. AI could force companies to restructure the entire innovation process in response to rapid technological progress and human resource reorganization. Society in general sees AI as a representation of unlimited possibilities. Lee *et al.* (2019) provide a brief overview of AI, current issues faced in AI development, and explain how it transforms business models. The case study of two companies that have innovated their business models using AI shows its potential impact. The paper illustrates how executives can create an innovative AI-based culture by reformulating the process of AI-based business model innovation. Companies that successfully leverage AI can create disruptive innovation through their new business models and processes, enabling them to potentially transform the global competitive landscape. Wang *et al.* (2022) show that the increasing evolution of business and the latest Artificial

Intelligence (AI) means that different business practices are enhanced by the ability to create new means of collaboration. The experimental result suggests that digital transformation is generally considered essential and enhances business innovation strategies.

It is also important to examine the relationship between the introduction of AI, innovation and the emergence of new businesses. May *et al.* (2020) analyze the role of AI for digital innovation and how it affects the process of business creation, we conduct an in-depth case study of a heavily funded imaging AI company. The case study reveals four tensions caused by AI that a digital enterprise must address and four ways to counter them: (1) managing excessive expectations of AI, (2) designing work routines for AI, (3) dealing with users' opposing perceptions of AI, and (4) integrating domain expertise with AI.

The introduction of AI then also impacts the area of corporate social responsibility. Buhmann and Christian (2021) apply a deliberative approach to propose a framework for responsible innovation in AI. This framework foregrounds discursive principles that help offset these challenges of opacity. To support better public governance, we consider the roles and mutual dependencies of organizations developing and applying AI, as well as civil society actors and investigative media in exploring pathways for responsible AI innovation. Cockburn *et al.* (2018) aim to hypothesize that deep learning represents a general method of invention and outline some preliminary implications of this hypothesis for management, institutions, and policy. Also important is the aspect of new job profiles required by the market. Kakatkar *et al.* (2020) show that AI is a very fast emerging technology that is being applied in many areas. A wide range of innovative solutions are being developed and some have already reached the market. However, the specific business models for AI are less clear and still developing. Companies face multiple challenges, from regulation to human resources and data collection. Managing AI-based innovations will be particularly difficult for small businesses, where problems are often more pronounced than in larger industries. Explicit challenges for managing AI-based innovations include the necessary focus on managing expectations and ensuring historical metadata expertise, which is essential for many AI-based solutions. Policies to support AI-based innovation should therefore focus on the human aspects. This includes increasing the availability of AI experts, but it also concerns the development of new job profiles, such as AI training experts. AI innovators also need clear regulation of AI and investment in research on key challenges, such as explainable AI.

A final point to explore in the literature is the relationship between strategic forecasting and research. Mühlroth and Grottke (2020) apply strategic foresight in technology and innovation management to detect discontinuous changes early, assess their expected consequences, and develop a future course of action to achieve superior business performance; they derive theoretical and practical implications for enterprise technology and innovation management and suggest future research opportunities to further advance this field. Soni *et al.* (2020) analyze the overall impact of AI-from research and innovation to deployment-and address the most influential academic achievements and innovations in the field of AI; their impact on business activities and thus on the global marketplace. The paper also helps investigate the factors responsible for AI advancement and provide a better understanding of how AI can transform business operations and thus the global economy. Brem *et al.* (2021) describe Artificial Intelligence (AI) as an emerging technological field with immense potential for transformation. Here, they discuss the different ways in which AI is transforming innovation, introducing a conceptual framework in which AI plays the following two roles: creator and facilitator of innovation.

The literature survey has shown that there is evidence demonstrating a strong correlation between firms' AI endowment and their ability to innovate, and that AI represents a great opportunity for firms to innovate and remain competitive, but it is important to adopt a strategy of responsible use of AI and investment in research and development to fully exploit its innovative potential. The analyses that follow will attempt to empirically verify these considerations by econometrically identifying the links between innovation and the use of AI.

3. Materials and methods

3.1 Synthetic index

The approach used involves the construction of macro areas (pillars) by aggregating elementary indicators (Table 1). Both pillars and elementary indicators have been considered non-replaceable. To construct synthetic index, we adopted the following indicators all with positive polarity:

The matrix relating to data on European enterprises was divided into four progressive steps:

(1) Selection of a set of basic indicators based on an ad hoc evaluation model hinging upon the existence of quality requirements.

(2) Further selection aimed at balancing the set of indicators within the theoretical framework of the structure. Outcome indicators are impact indicators as the ultimate result of an action as a result of a stakeholder activity or process.

(3) Calculation of synthetic indices (pillars), by making use of the methodology proved more appropriate to obtain usable analytical information.

(4) Processing of a final synthetic index as a rapid empirical reference concerning the degree of digital technology of European enterprises.

Missing values were attributed via the *hot-deck* imputation and, where not possible, with Europe's average value.

The choice of the synthesis method is based on the assumption of a formative measurement model, in which it is believed that the elementary indicators are not replaceable, which is to say, cannot compensate each other.

Macro areas	Indicators
Artificial Intelligence	Percentage of enterprises analyzing big data internally using machine learning (VAR1)
	Percentage of enterprises analyzing big data internally using natural language processing, natural language generation or speech recognition (VAR2)
	Percentage of enterprises using service robots (VAR3)
	Percentage of enterprises with a chat service where a chatbot or a virtual agent replies to customers (VAR4)
	Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5)
	Percentage of enterprises that use two AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6)
	Percentage of enterprises that use three AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR7)
ICT	Percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8)
	Percentage of enterprises' total turnover from e-commerce sales (VAR9)
	Percentage of enterprises provided training to their personnel to develop their ICT skills (VAR10)
	Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills (VAR11)
	Percentage of enterprises that employ ICT specialists (VAR12)

Source(s): Eurostat, 2021 - our selection

Table 1. Macro areas and Indicators

The exploratory analysis of input data was performed by calculating the mean, average standard deviation and frequency, as well as correlation matrix and principal component analysis. Since this is a non-compensatory approach, the simple aggregation of elementary indicators was carried out using the correct arithmetic average with a penalty proportional to the "horizontal" variability.

Normalization of primary indicators took place by conversion into relative indexes compared to the variation range (*min-max*).

Attribution of weights to each elementary indicator has followed a subjective approach, opting for the same weight for each of them. Since, in some cases, the elementary indicators showed different polarity, it was necessary to reverse the sign of negative polarities by linear transformation.

For the synthetic indicator calculation, we used the Adjusted Mazziotta-Pareto Index (AMPI), which is used for the min-max standardization of elementary indicators and aggregate with the mathematical average penalized by the "horizontal" variability of the indicators themselves. In practice, the compensatory effect of the arithmetic mean (average effect) is corrected by adding a factor to the average (penalty coefficient) which depends on the variability of the normalized values of each unit (called horizontal variability) or by the variability of the indicators compared to the values of reference used for the normalization.

The synthetic index of the i-th unit, which usually varies between 70 and 130, is obtained by applying, with negative penalty, the correct version of the penalty method for variation coefficient (AMPI +/−), where:

$$\mathrm{AMPIi}- = \mathrm{Mri} - \mathrm{Sricvi} \tag{1}$$

where *Mri* e *Sri* are, respectively, the arithmetic mean and the standard deviation of the normalized values of the indicators of the i unit, and cvi = *Sri* / *Mri* is the coefficient of variation of the normalized values of the indicators of the i unit.

The correction factor is a direct function of the variation coefficient of the normalized values of the indicators for each unit and, having the same arithmetic mean, it is possible to penalize units that have an increased imbalance between the indicators, pushing down the index value (the lower the index value, the lower the level of digital technology).

This method satisfies all requirements for the statistical synthesis:

(1) Spatial and temporal comparison

(2) Irreplaceability of elementary indicators

(3) Simplicity and transparency of computation

(4) Immediate use and interpretation of the obtained results

(5) Strength of the obtained results

An influence analysis was also performed to assess the robustness of the method and to verify if and with which intensity the composite index rankings change following elimination from the starting set of a primary indicator. This process has also permitted us to analyze the most significant indicators.

The analysis was conducted using the *COMIC* (Composite Indices Creator) software, developed by ISTAT. The software allows calculating synthetic indices and building rankings, as well as easily comparing different synthesis methods to select the most suitable among them, and write an effective report based upon results.

3.2 Method: log-linear analysis

Log-linear regression belongs to the class of generalized linear models (GLM).

General Linear Models (GLM) are a flexible and powerful tool for modeling complex relationships between data and have a wide range of applications in fields such as psychology, economics, medicine and ecology. GLM extends the traditional linear regression model by allowing for non-normal error distributions and non-constant variances. They can handle a variety of response types, including continuous, binary, count and categorical data, and can incorporate multiple sources of variation, such as random effects and repeated measures. The most common log-linear regression is the Poisson regression. It is also possible to use two other distributions: the Gamma and the exponential. The response function defines how the response (dependent) variable is related to the model's independent variables. It is a mathematical function that describes the relationship between the mean of the response variable and the model's independent variables. The GLM model uses the response function to estimate the model parameters and to predict the values of the response variable based on the values of the independent variables. The choice of the appropriate response function depends on the properties of the response variable and the specifications of the research problem. Unlike linear regression, there is no exact analytical solution. It is therefore necessary to use an iterative algorithm.

We assume that the response variable is written as the logarithm of a function of the explanatory variables. In general, we can write the equation of the model in the following form:

$$\mathrm{Log(Y)} = \mathrm{a_1B_1} + \mathrm{a_2b_2} + .. + \mathrm{a_nB_n} + \varepsilon$$

In exponential form can be written:

$$\mathrm{Y} = \mathrm{e_1^{a1B}} + \mathrm{e^{a2B2}} + .. + \mathrm{e^{anBn}} + \varepsilon'$$

These models allow us to estimate the net contributions of each variable and the probabilities of participation associated with different profiles constructed from different associations of variables. The effect of individual variables on the final ordering of the response function is investigated to derive indications of the relevance and significance of the variables and identify those with a greater explanatory power on the volunteer's life satisfaction.

As far as the goodness of fit is concerned, if χ^2, which is the equivalent of the Fisher's F-test of the linear model, is less than 0.001 for the LR (likelihood ratio), then the model is highly significant, and the variables contain a large amount of information.

4. Results

4.1 Result synthetic index

Tables 2–4 reveal a good variability. Tables 5–7 show significant correlations between AI e ICT macro areas (r = 0.683) and, in particularly, there are significant direct correlations between percentage of enterprises analyzing big data internally using machine learning (VAR1) and percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) (r = 0.907), between percentage of enterprises analyzing big data internally using machine learning (VAR1) and Percentage of enterprises that use two AI

	AI	ICT
Mean	100.969	101.903
σ	9.172	11.49
Frequency	29	29

Source(s): Eurostat, 2021 - Our elaborations

Table 2. Mean, σ and frequency macro areas

systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6) (r = 0.708), between Percentage of enterprises with a chat service where a chatbot or a virtual agent replies to customers (VAR4) and Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) (r = 0.714) and Percentage of enterprises that use one AI system (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR5) and Percentage of enterprises that use two AI systems (of E_CHTB, E_BDAML, E_BDANL, E_RBTS) (VAR6) (r = 0.779), between Percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8) and Percentage of enterprises' total turnover from e-commerce sales (VAR9) (r = 0.651), between Percentage of enterprises provided training to their personnel to develop their ICT skills (VAR10) and Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills (VAR11)) (r = 0.616).

The influence analysis describes the indicators that most influence the composition of rosters of European countries. In analyzing Tables 8–10, we can see that the most significant macro area is ICT (mean = 2.862, σ = 3.280) and the most important indicators concerns

Table 3.
Mean, σ and frequency AI macro area

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7
Mean	3.31	1.207	2.034	2.207	5.931	0.897	0.103
σ	3.892	0.94	1.052	1.424	3.909	0.724	0.31
Frequency	29	29	29	29	29	29	29

Source(s): Eurostat, 2021 - Our elaborations

Table 4.
Mean, σ and frequency ICT macro area

	VAR8	VAR9	VAR10	VAR11	VAR12
Mean	20.103	17.966	21.31	8.966	20.897
σ	7.734	8.437	7.802	3.438	5.115
Frequency	29	29	29	29	29

Source(s): Eurostat, 2021 - Our elaborations

Table 5.
Correlation matrix of the macro areas

Macro areas	AI	ICT
AI	1.000	
ICT	0.683	1000

Source(s): Eurostat, 2021 - Our elaborations

Table 6.
Correlation matrix of the AI's indicators

Indicators	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6	VAR7
VAR1	1.000						
VAR2	0.216	1.000					
VAR3	0.215	0.173	1.000				
VAR4	0.497	0.180	0.495	1.000			
VAR5	0.907	0.305	0.504	0.714	1.000		
VAR6	0.708	0.452	0.614	0.610	0.779	1.000	
VAR7	0.475	0.169	0.098	0.273	0.418	0.208	1.000

Source(s): Eurostat, 2021 - Our elaborations percentage of enterprises with e-commerce sales of at least 1% turnover (VAR8) (mean = 1.793, σ = 1.864), percentage of enterprises with a chat service where a chat-bot or a virtual agent replies to customers (VAR4) (mean = 1.621, σ = 1.622) and percentage of enterprises that employ ICT specialists (VAR12) (mean = 1.517, σ = 1.567).

Indicators	VAR8	VAR9	VAR10	VAR11	VAR12
VAR8	1.000				
VAR9	0.651	1.000			
VAR10	0.552	0.531	1.000		
VAR11	0.415	0.353	0.616	1.000	
VAR12	0.313	0.503	0.570	0.611	1.000

Source(s): Eurostat, 2021 - Our elaborations

Table 7. Correlation matrix of the ICT's indicators

Macro areas	Mean	σ
IA	2.621	2.833
ICT	2.862	3.280
Mean	2.741	3.057
σ	0.121	0.223

Source(s): Eurostat, 2021 - Our elaborations

Table 8. Influence Analysis: mean and s of the shifts of the rankings by basic indicator removed of macro areas

Indicators	Mean	σ
VAR1	0.621	0.762
VAR2	1.276	1.236
VAR3	1.034	1.066
VAR4	1.621	1.622
VAR5	0.414	0.683
VAR6	0.345	0.603
VAR7	0.690	1.289
Mean	0.857	1.037
σ	0.436	0.346

Source(s): Eurostat, 2021 - Our elaborations

Table 9. Influence Analysis: mean and s of the shifts of the rankings by basic indicator removed of AI's indicators

Indicators	Mean	σ
VAR8	1.793	1.864
VAR9	1.448	1.567
VAR10	1.379	1.518
VAR11	1.379	1.324
VAR12	1.517	1.567
Mean	1.503	1.567
σ	0.154	0.173

Source(s): Eurostat, 2021 - Our elaborations

Table 10. Influence analysis: mean and s of the shifts of the rankings by basic indicator removed of ICT's indicators

The values of the composite index of Artificial Intelligence (AI), information technologies (ICT) and digital technology are described in Table 11, Table 12 and Figure 1,

In particular, as regards digital technology, the "best" performances are grouped in north-eastern Europe, in particular in Denmark, Finland, Belgium, Sweden and Lithuania, but the most digital European nation is Ireland (total index 135.6, AI index 124.2, ICT index 123.9) followed by Malta (index 126.0) and Denmark (index 125.7). Italy ranks 24th (out of 29) in the ranking of digital technology (index 111.18), in particular 10th in the ranking of AI (index 103.3) and 26th (index 85.9) for the use of ICT, a clear sign that AI is widespread in the few companies that use ICT.

The synthetic index can be useful to get an idea of the use of digital technologies at a territorial level, but above all it can constitute a support for the decisions of European policy makers who must encourage companies to develop them, as part of one of the 6 priorities of the European Commission 2019–2024, namely «A Europe ready for the digital age».

In this *scenario*, a type of "compensatory" or "add-on" regional development policy ends up accentuating the differences between regions, which are due to the different regional response to policies stimuli. Instead of fostering convergence, traditional policies create underdevelopment traps.

Peripheral regions are the ones most exposed to loss of competitiveness since the rules governing the economic system promote the aggregation of factors and "classic" regional

Nations	Value	Rank
Ireland	124,24	1
Malta	120,90	2
Finland	114,36	3
Lithuania	113,50	4
Denmark	110,86	5
Belgium	106,11	6
Portugal	104,24	7
Sweden	103,85	8
Slovakia	103,52	9
Italy	103,35	10
Spain	102,87	11
Germany	101,87	12
Czechia	101,55	13
Norway	100,00	14
Austria	99,78	15
Luxembourg	99,56	16
Croatia	99,50	17
France	99,50	18
Netherlands	98,04	19
Estonia	97,65	20
Romania	95,16	21
Bulgaria	93,51	22
Poland	93,09	23
Slovenia	93,09	24
Bosnia and Herzegovina	92,03	25
Cyprus	91,77	26
Latvia	89,69	27
Hungary	89,68	28
Greece	84,86	29
EUROPE	100,00	

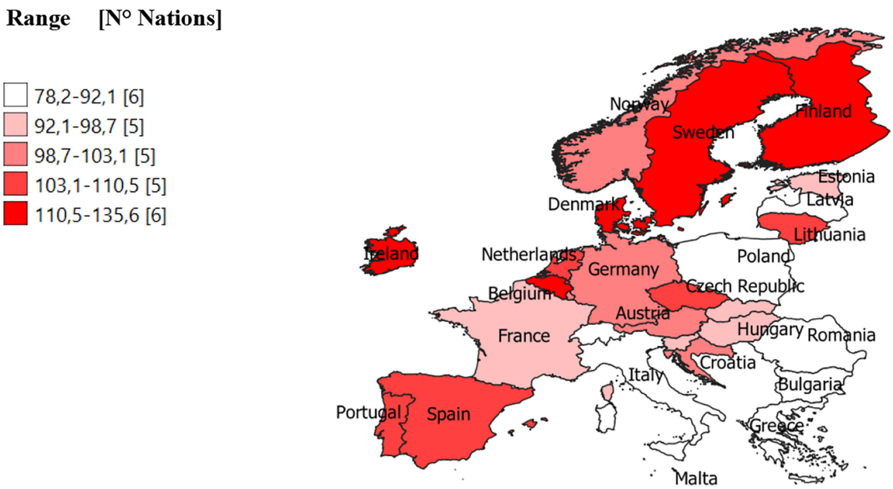
Source(s): Eurostat, 2021 - Our elaborations

Table 11.
Synthetic European index ranking of AI

Nations	Value	Rank
Belgium	126,28	1
Denmark	125,53	2
Ireland	123,96	3
Finland	115,77	4
Malta	114,45	5
Sweden	112,36	6
Czechia	108,05	7
Netherlands	107,08	8
Spain	104,10	9
Norway	103,62	10
Croatia	103,21	11
Hungary	102,44	12
Germany	102,31	13
Portugal	101,71	14
Austria	101,23	15
Cyprus	100,96	16
Luxembourg	99,65	17
Slovenia	99,04	18
France	97,17	19
Lithuania	97,16	20
Poland	96,19	21
Estonia	94,40	22
Slovakia	94,36	23
Bosnia and Herzegovina	91,44	24
Latvia	91,30	25
Italy	85,97	26
Greece	85,75	27
Romania	85,31	28
Bulgaria	84,38	29
EUROPE	100,00	

Source(s): Eurostat, 2021 - Our elaborations

Table 12. Synthetic European index ranking of ICT



Source(s): Figure by authors

Figure 1. Territorial distribution of the European synthetic index of digital technology

policy is unable to counter this trend, despite generous financial compensation. An effective regional policy should work on two levels: modify the response function of regional economy and also provide an investment able to generate diffuse positive externalities. Moreover, interventions should be minimal and aimed at creating stronger connections between economic agents and, in particular, combining production activities with services, to foster the servitization that probably influences "soft" factors inside the regional economy.

4.2 Results of loglinear regression

For the estimation of the Model, the synthetic innovation indicator European Innovation Scoreboard (EIS) (source Eurostat, 2021) will be used as the dependent variable (response) which provides a comparative analysis of innovation performance in EU countries, other European countries and regional neighboring countries. It helps countries assess the relative strengths and weaknesses of their national innovation systems and identify challenges to be addressed, while the variables described in Table 1 will be used as independent variables.

Table 13 gives several indicators of the quality of the model (or goodness of fit). These results are equivalent to the R^2 and to the analysis of variance table in linear regression and ANOVA. The most important value to look at is the probability of Chi-square test on the log ratio. This is equivalent to the Fisher's F test: we try to evaluate if the variables bring significant information by comparing the model as it is defined with a simpler model with only one constant. In this case, as the probability is lower than 0.0001, we can conclude that significant information is brought by the variables.

Table 14 highlights the circumstance that one can reject the assumption that the dependent variable (response) is a constant.

Statistic	Independent	Full
Observations	27	27
Sum of weights	27,000	27,000
DF	26	14
−2 Log(Likelihood)	265,633	225,108
R^2(McFadden)	0.000	0.153
R^2(Cox and Snell)	0.000	0.777
R^2(Nagelkerke)	0.000	0.777
AIC	269,633	253,108
SBC	272,225	271,250
Deviance	3,041	0.688
Pearson Chi-square	2,507	0.648
Iterations	0	14

Source(s): Eurostat, 2021 - Our elaborations

Table 13.
Regression of variable EIS

sStatistic	DF	Chi-square	Pr > Chi^2
−2 Log(Likelihood)	12	40,525	<0.0001
Score	12	66,945	<0.0001
Wald	12	99,263	<0.0001

Source(s): Eurostat, 2021 - Our elaborations

Table 14.
Test of the null hypothesis H0: Y=Constant (Variable EIS)

Table 15 shows the estimated value of the coefficients for the fitted model. To assess whether a variable provides significant information, a statistical test is displayed. In our case, we note that the 8 out of 12 variables and the intercept have a significance level above 95%.

The fact that 8 variables and the intercept are highly significant highlights a certain robustness of the results and allows us to make the following considerations. Let us then analyze the eight significant variables starting from the sign of the coefficient.

Var1 Percentage of enterprises analyzing big data internally using machine learning has a high level of significance and a positive coefficient. This means that this variable contributes significantly to explaining the values of the development indicator and that high values of this variable correspond to high values in the development indicator.

Var2 Percentage of enterprises analyzing big data internally using natural language processing, natural language generation or speech recognition also has a high level of significance, the sign of the coefficient is positive and therefore shows the same type of contribution to the explanation of the synthetic development indicator as the previous variable. In this case, it can be said that it reinforces the previous result because it gives an indication of the fact that not only the use of AI contributes to the growth of the development indicator, but also the greater technological advancement of companies using AI.

Also significant is the Var3 Percentage of enterprises using service robots which in this case links the development indicator to a higher density of companies using robots.

Var5 Percentage of enterprises that use one AI system although significant, does not contribute to the increase in the values of the development indicator, a sign that the use of AI systems, being positive for individual companies, has no advantages in aggregate terms for generating development.

Var 8 Percentage of enterprises with e-commerce sales of at least 1% turnover is significant but has a negative coefficient and does not contribute to increasing the values of the development indicator. This can be explained by the fact that the threshold of at least 1% turnover from e-commerce is too restrictive and in this class of companies we find many companies with a very low rate and very low innovation capacity.

Var 9 Percentage of enterprises' total turnover from e-commerce sales is, on the other hand, significant and has a positive coefficient, a sign that it contributes positively to development. In this case, these are highly innovative companies that contribute to a positive environment for development.

Source	Value	Standard error	Wald Chi-square	Pr > Chi^2	Wald lower bound (95%)	Wald upper bound (95%)
Intercept	4.146	0.179	536.656	<0.0001	3.795	4.497 ****
VAR1	0.156	0.055	7.915	0.005	0.047	0.265 ****
VAR2	0.180	0.066	7.545	0.006	0.052	0.309 ****
VAR3	0.231	0.090	6.598	0.010	0.055	0.407 ****
VAR4	0.032	0.056	0.314	0.575	−0.079	0.142
VAR5	−0.164	0.056	8.522	0.004	−0.273	−0.054 ****
VAR6	−0.096	0.155	0.384	0.536	−0.400	0.208
VAR7	−0.071	0.156	0.208	0.649	−0.377	0.235
VAR8	−0.028	0.008	11.716	0.001	−0.044	−0.012 ****
VAR9	0.015	0.006	5.452	0.020	0.002	0.027 ***
VAR10	0.027	0.009	9.434	0.002	0.010	0.044 ****
VAR11	0.030	0.016	3.656	0.05	−0.001	0.061 ***
VAR12	−0.015	0.013	1.412	0.235	−0.039	0.010

Note(s): ****>99%, ***>95%, **>90% * >80%
Source(s): Eurostat, 2021 - Our elaborations

Table 15. Model parameters for the components (Variable EIS)

Var 10 Percentage of enterprises provided training to their personnel to develop their ICT skills is, on the other hand, significant and has a positive coefficient, a sign that it contributes positively to development. In this case, these are highly innovative companies that contribute to a positive environment for development.

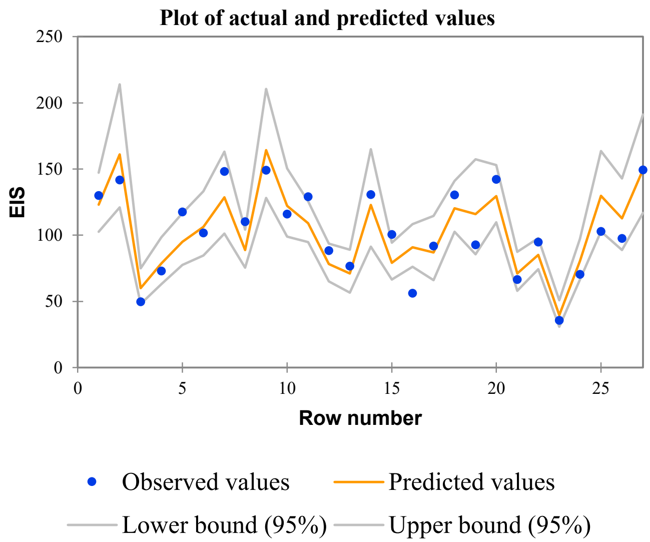
Same for Var11 Percentage of enterprises that recruited/tried to recruit personnel for jobs requiring ICT specialist skills where the higher density of companies that are attentive to the recruitment of ICT specialists is a factor that helps to raise the overall degree of innovation in the system.

The final form of the model equation is:

Equation of the model for the components (Variable EIS) is the next:

$$\begin{aligned}\text{Pred(EIS)} = \exp(&4,14622375444966 + 0,156046146184724 * \text{VAR1} \\ &+ 0,180208302806588 * \text{VAR2} + 0,230830981290547 * \text{VAR3} \\ &+ 3,16502935587467\text{E} - 02 * \text{VAR4} - 0,163615810079877 * \text{VAR5} \\ &- 9,60363061293875\text{E} - 02 * \text{VAR6} - 7,10923298992073\text{E} - 02 * \text{VAR7} \\ &- 2,78755781037564\text{E} - 02 * \text{VAR8} + 1,48118398932973\text{E} - 02 * \text{VAR9} \\ &+ 2,67788822721428\text{E} - 02 * \text{VAR10} + 3,01547375831776\text{E} - 02 * \text{VAR11} \\ &- 0,014861020511171 * \text{VAR12})\end{aligned}$$

Figure 2 highlights the distribution of the actual and predicted values of the EIS, which as can be seen, and expect for one outlier, always remain within the tolerance limits, sign that the results are robust.



Source(s): Figure by authors

Figure 2.
Actual vs predicted values

5. Discussion and policies

Analyzing the results of the synthetic indicator and the resulting country taxonomy, it can be seen that Peripheral regions are the ones most exposed to loss of competitiveness since the rules governing the economic system promote the aggregation of factors and "classic" regional policy is unable to counter this trend, despite generous financial compensation. An effective regional policy should work on two levels: modify the response function of regional economy and also provide an investment able to generate diffuse positive externalities. Policies should be minimized and focused on building networks between economic agents. Linking productive activities with services and fostering servitisation that influences 'soft' factors within the regional economy become priority interventions. In this *scenario*, a type of "compensatory" or "add-on" regional development policy ends up accentuating the differences between regions, which are due to the different regional response to policies stimuli. Instead of fostering convergence, traditional policies create underdevelopment traps. The analysis of the results of the regression model shows how development is the overall capacity of a territorial economic system, both on a regional and national basis, which is enhanced by investments that aim to make the business system innovative. It is a matter of creating innovative ecosystems in which businesses, the higher education system and institutions cooperate together to increase the overall level of innovation of the economic system. It is the strictly targeted investments that create the virtuous circuits that can grow not only individual companies, but the entire business system and the entire economic system. It is the demand for innovation that drives the supply of innovation, but for the system to grow it is necessary that this demand can be satisfied within the same territorial context. And to do this, all policies must be coordinated and aimed at creating innovation ecosystems. In this sense key policies to foster AI innovation and development in businesses is to invest in research and development and support financially the universities and companies conducting AI research to help them to develop new AI technologies and applications that can be used by businesses. In addition, governments can incentivize innovation through tax breaks and subsidies to companies that invest in research and development. In addition to research and development, it is crucial that companies invest in training their employees so that they are able to use new AI technologies. In addition, companies can create partnerships with universities and research centers to access talent and resources specialized in AI. Another important policy to foster the virtuous circle between innovation and AI development is to promote data sharing. Companies that share data can benefit from new discoveries and applications of AI, as the availability of more data enables the development of more accurate and useful machine learning models. It is important that governments and businesses work together to appropriately regulate the use of AI to minimize the associated risks and ensure that innovations are used ethically and responsibly. In this sense, it is important to develop common standards for data security and privacy protection, and rules for the use of AI in sensitive areas such as healthcare and public safety. The virtuous circle between innovation and AI development in businesses requires policies and strategies that foster research and development, employee training, data sharing and appropriate regulation. Only in this way can businesses maximize the benefits of AI and minimize the associated risks, for a future in which technological innovation serves economic and social progress. These policies should help create an ecosystem conducive to innovation and AI deployment in businesses, fostering the virtuous circle between innovation and AI development. However, it is important that these policies are not undifferentiated, but are adapted to the specific regional as well as national context and to the needs of firms with a territorial dimension. The innovation differentials between the different European countries which we measured with the synthetic indicator can therefore be explained by the different capacities to create innovation ecosystems, the level of investment in research and development, the quality of the higher education system to meet the innovative training demands of companies, and the ability of institutions to create incentives that can stimulate not simply companies, but primarily innovative companies.

6. Conclusions

In the paper, two different methodologies were used to analyze the relationship between innovation and the development of digital technologies in Europe. The synthetic indicator made it possible to develop a taxonomy between the different countries, the log-linear model made it possible to identify and explain the determinants of innovation. It is the demand for innovation that drives the supply of innovation, but for the system to grow it is necessary that this demand can be satisfied within the same territorial context. And to do this, all policies must be coordinated and aimed at creating innovation ecosystems. In this sense key policies to foster AI innovation and development in businesses is to invest in research and development and support financially the universities and companies conducting AI research to help them to develop new AI technologies and applications that can be used by businesses. In addition, governments can incentivize innovation through tax breaks and subsidies to companies that invest in research and development. The innovation differentials between the different European countries which we measured with the synthetic indicator can therefore be explained by the different capacities to create innovation ecosystems, the level of investment in research and development, the quality of the higher education system to meet the innovative training demands of companies, and the ability of institutions to create incentives that can stimulate not simply companies, but primarily innovative companies.

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