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Defining and measuring AI Economic Capacity: Focusing on the EU-27 Countries

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Abstract

This paper defines and measures the economic capacity of Artificial Intelligence (AI) across the EU-27. Moving beyond fragmented approaches, it explains that the economic significance of Artificial Intelligence is a broader concept. Specifically, economic capacity should be understood as a multidimensional configuration of resources, innovation capabilities and diffusion conditions that enable national economies to develop, absorb and scale the value associated with AI and to capture this, the paper constructs an Artificial Intelligence Economic Capacity Index (AI-ECI). Adopting the framework of the three pillars: Inputs, Modeling and Deployment, the index shows a clear pattern of divergence within the EU. Finland, Sweden, the Netherlands, Luxembourg, Denmark and Ireland form the top group, while Bulgaria, Greece, Romania, Latvia and Croatia remain at the lower end of the distribution. Principal Component Analysis supports the multidimensional logic of the index: PC1 captures a broad dimension of AI capacity, while PC2 differentiates between distinct national AI profiles. Therefore, the paper shows how national political economies convert infrastructure, skills, research and diffusion at the firm level into potential economic value.

Keywords: Artificial Intelligence; AI Economic Capacity; European Union; Comparative Political Economy; Digital Economy

1. Introduction

The recent breakthroughs in Artificial Intelligence (AI) -especially the development of large language models and their rapid spreading with OpenAI's release of GPT-3 in June 2020 being a notable example- sparked a surge of interest in AI (Heaven, 2020) across societies. The European Union is directly affected by these developments. The projections from the European Parliament's Think Tank suggested that by 2035, labor productivity linked to AI could increase by 11-37%, potentially boosting the EU's economic power significantly (European Parliament, 2025). The notable size of this indicative assessment regarding AI's impact on labor productivity reflects the magnitude of changes that AI brings to the EU economy and, consequently, its countries' governance and societies.

Nevertheless, the above transition, according to the first indications, does not seem to happen in a uniform way for each country, with the economic impact of AI differing significantly by country, region and sector, as we observe differentiated growth and welfare strategies over time from each country (Hall & Soskice, 2001; Hassel & Palier, 2021). This paper therefore attempts to define the economic capacity of AI and to study whether cross-national differences in AI uptake and deployment patterns are observable in the data. So, while the European Union has made significant strides in regulating Artificial Intelligence through landmark legislation such as the EU AI Act (European Commission, 2024) and has committed substantial resources through initiatives like the AI Continent Action Plan announced in April 2025 (European Commission, 2025a), questions persist regarding which EU countries are genuinely succeeding in integrating AI into their socio-economic frameworks and what the appropriate metrics for measuring this "success" should be. This paper aims to address this gap by proposing a comprehensive framework for defining and measuring AI capacity across European nations, contributing both to academic understanding and to practical policy guidance for member states and EU institutions.

The European approach to Artificial Intelligence has been characterized by an emphasis on *"excellence and trust [...] strengthening competitiveness and technological sovereignty",* through boosting research, industrial capacity and ensuring safety with fundamental rights (European Commission, 2025b). However, beyond manifestation the practical application of this *"excellence and trust"* remains unevenly distributed across member states, with data from Eurostat (2025b) revealing that while 20.0% of EU enterprises with ten or more employees had

adopted at least one AI technology by 2025 -an increase from 8% in 2023 and 13.5% in 2024- someone could identify concerning variation across countries and regions. Denmark leads with 42.0% adoption, more than double the EU average, while Romania records only 5.2%, reflecting a divergence in AI readiness that has profound implications for economic competitiveness and productivity.

Table 1.1. Use of Artificial Intelligence by enterprises (EU-27 and selected European Countries, % of enterprises, 2025).

TIME	2021		2023		2024		2025	
GEO (Labels)								
European Union - 27 countries (from 2020)	7,65		8,06		13,48		19,95	
Belgium	10,32		13,81		24,71		34,54	
Bulgaria	3,29		3,62		6,47		8,55	
Czechia	4,46		5,90		11,26		17,60	
Denmark	23,89		15,17		27,58		42,03	
Germany	10,56		11,55		19,75		25,97	
Estonia	2,77		5,19		13,89		23,40	
Ireland	7,88		8,01		14,90		19,64	
Greece	2,61		3,98		9,81		8,93	
Spain	7,67		9,18		11,31		20,27	
France	6,67		5,88	b	9,91		18,16	
Croatia	8,74		7,89		11,76		15,19	
Italy	6,17		5,05		8,20		16,40	
Cyprus	2,59		4,67		7,90		9,27	

Latvia	3,72		4,53		8,83		12,21	
Lithuania	4,45		4,86		8,76		21,30	
Luxembourg	13,00		14,45		23,73		33,61	
Hungary	2,98		3,68		7,41		10,37	
Malta	10,16		13,17		17,30		21,56	
Netherlands	13,10		14,10		23,06		33,21	b
Austria	8,83		10,79		20,27		29,95	
Poland	2,86		3,67		5,90		8,36	
Portugal	7,20		7,86		8,63		11,54	
Romania	1,38		1,51		3,07		5,21	
Slovenia	11,73		11,37		20,89		21,61	
Slovakia	5,19		7,04		10,78		18,00	
Finland	15,79		15,10		24,37		37,82	
Sweden	9,92		10,37	b	25,09		35,04	
Norway	10,82		9,17		20,77		28,89	
Bosnia and Herzegovina	2,07		5,34		6,36		10,78	
Montenegro	3,34		5,61		7,91		10,05	
North Macedonia	:	C	:		:		:	
Albania	3,67		:		:		:	
Serbia	0,90		1,82		6,95		10,12	
Türkiye	2,69		5,51		4,42		7,41	

Source: Eurostat (2025b)

Yet do the data above, on their own, really explain what “capacity” in the AI economy looks like? They certainly offer a useful indication of what is happening at the national level. But is it enough? Adoption is clearly part of the story and perhaps even one of the most visible “end-stage” indicators of economic capacity but it rests on a wider set of enabling conditions such as access to computing power, data availability and quality, a skilled workforce, a supportive innovation ecosystem, funding, competition, strategic autonomy, sovereignty, and more. Therefore, understanding divergences like those in Table 1.1. and developing holistic measurements of capacity in the AI economy is essential not only for academic purposes but also for informing policy-making at both the national and supranational European levels. As highlighted in the recent reports by Draghi (2024) and Letta (2024) on European competitiveness, the EU risks becoming economically irrelevant if it does not swiftly overcome its structural weaknesses and to enhance its competitive advantage compared to nations like China and the US. Nurturing a strong digital and AI ecosystem could be the key. According to Google AI alone could add €1.2-1.4 trillion to the EU's GDP over ten years, representing an 8% increase in gross domestic product—a figure that would dramatically transform European economic prospects if realized (Thelle et al., 2024).

Hence, realizing Europe’s AI economic potential requires more than investment and policy statements. It requires a clear understanding of what AI economic capacity looks like and how to measure progress toward it and this is the first research question that this paper aspires to address: which EU countries possess stronger AI economic capacity, and how can this capacity be defined and compared? This question deliberately shifts the focus from the popular dipole of “success” or “failure” to capacity recognizing that "success" in Artificial Intelligence is not a simple or unidimensional concept and it cannot be reduced to adoption rates alone, nor can it be measured solely by investment levels or patent counts. Rather, in order to achieve genuine success in the AI economy requires building comprehensive capabilities across multiple domains while maintaining democratic legitimacy and social inclusion.

2. Conceptual Framework; AI economic capacity and the political economy of technological change

Before defining AI economic capacity, it is important to delineate what we mean by “Artificial Intelligence”, given its rapid evolution and expanding range of applications. Establishing an agreed-upon notion of AI is inherently complex because the technology evolves rapidly and its applications are expanding across domains, which makes it difficult to delimit AI as a distinct

object of analysis within the wider economy (Maslej et al., 2025). The same challenge has been evident in recent years when defining the digital economy, which extends beyond the boundaries of the foundational IT/ICT sector into traditional business operations and organizational structures, making the distinction between digital and non-digital economic activities difficult for typesetting (OECD, 2013; European Parliament, 2015).

The difficulty, in other words, is not only conceptual but also empirical, because if AI is treated too broadly, it becomes harder to delimit a distinct object of measurement that is separable from the wider digital transformation of the economy and subsequently from the economy itself (Hassel & Palier, 2021). For that reason, this in this study, Artificial Intelligence (AI) is treated as a general-purpose digital technology (Frey, 2019; Turovets et al., 2020), which means it's not a single tool, but a system of software and/or hardware that can, with some degree of autonomy, perceive information, learn from data, and make decisions or recommendations automatically - often by training on large datasets and generalizing from observed examples in ways that can approximate elements of human behavior (Acemoglu, 2024; Autor, 2015; Maslej et al., 2025).

Moreover, in order to understand the structural capacity of EU Member States to produce, absorb and diffuse economic value related to Artificial Intelligence, this article adopts an approach to the economic capacity of Artificial Intelligence that sees it as the nationally embedded set of productive resources, innovation capabilities, absorptive capacities and diffusion variables that shape the ability of an economy to develop, adopt, scale and extract economic value from Artificial Intelligence over time. The concept is based on the literature on productive capabilities, which understands economic growth as dependent on the productive resources, entrepreneurial capabilities and productive linkages that allow countries to produce and develop (UN Trade and Development, ed.), as well as on the concept of national innovative capacity, which is defined as the ability of a country to produce and commercialize new technologies in the long term (Furman et al., 2002). It is also based on the idea of absorptive capacity, which translates to the ability to identify, assimilate and apply external knowledge for productive use (Cohen & Levinthal, 1990). In this sense, the economic capacity of AI should be distinguished from the realized economic performance.

While economic performance refers to macroeconomic variables, such as productivity gains, wage increases, GDP per capita growth, or total factor productivity, the notion of economic capacity of AI refers to the structural conditions under which economic performance associated with AI can be made possible. As Autor (2015) and Acemoglu (2024) underline, the macroeconomic impacts of automation and AI depend on many aspects such as job-level

transformation, complementarity with work and organizational adaptation, showing that the important factor is the extent to which technological change is embedded in productive systems. Therefore, the distinction between capacity and performance is crucial and the indicator constructed in this paper should be understood under the light of a measurement that attempts to document the capacity of EU Member States to produce, absorb and diffuse economic value related to Artificial Intelligence, rather than a direct measure of the realized economic performance driven by Artificial Intelligence.

Therefore, if technological progress depends on the direction of development across tasks (Acemoglu, 2024), then "AI economic capacity" must be conceptualized across the entire chain that transforms knowledge and infrastructure into productivity-related use. At the same time, comparative political economy suggests that institutional backgrounds and different development regimes shape each stage of this chain and what countries can invest in, innovate in, and scale up (Hall & Soskice, 2001; Hassel & Palier, 2021). For this reason, in order to effectively measure economic capacity in terms of the AI economy, it is necessary to identify appropriate variables. Beyond traditional metrics such as growth rate, economic competitiveness and productivity (Acemoglu, 2024), it is essential to take into account factors that, in some cases, precede the aforementioned dimensions. Drawing inspiration from the French Ministry of Finance report (Chardon-Boucaud et al., 2024), which attempts to define success across the entire AI value chain, this research will focus on the following three key aspects:

1. **Inputs:** The inputs for AI development, including, according to Chardon-Boucaud et al. (2024), *"computing capacity, data, and skilled labor"*.
2. **Modeling:** Refers to the development of AI applications (Sarker, 2022).
3. **Deployment:** The implementation stage, during which these solutions are integrated and used by end users to improve their experience, enhance productivity, and, therefore, promote economic growth.

These three pillars will be used to create a coherent and composite variable, the AI Economic Capacity Index. This index is constructed using publicly available datasets (e.g., Eurostat, OECD AI Policy Observatory) and serves as a variable that will in the future allow for a more thorough examination of its association with various independent variables, including institutional frameworks and socio-political acceptance factors. At the same time, this index will help us to understand and evaluate in a more comprehensive basis the national differences and assess the overall progress of EU countries in the field of AI through the lens of economic impact.

Before constructing such an index, another important step is reviewing the relevant literature in order to document the main methods and tools used to measure "success" in the AI economy and, more broadly, in the digital economy. Beyond traditional macroeconomic indicators, such as GDP, employment, and labour productivity, due to their limitations (Ahmad & Schreyer, 2016) the economic measurement in the digital/AI economy typically follows several routes. First, valuation methods apply classical approaches such as the usage approach, aiming to estimate the magnitude of digital applications through individual, household and enterprise metrics (Avezov, 2025). Second, at the micro level, firm-level productivity measurement evaluates AI outcomes by tracking pre- and post-implementation key performance indicators, such as labor productivity gains, overall equipment effectiveness in manufacturing, and customer lifetime value or digital/AI adoption, organizational readiness (e.g., skills, leadership, culture), and the existence of a coherent transformation strategy (Kargas et al., 2023; Avezov, 2025).

Additionally, digitalization and technological advancement generate measurable labor market consequences, representing a critical dimension of economic impact (Novikova et al., 2022). Another approach is the innovation-based one, which measures AI and digital economic outcomes using a framework that combines development and adoption indicators with traditional metrics (publications, patents, R&D investment, human capital) and in some cases linking them with more recent datasets and methodologies such as big-data and semantic analysis (Turovets et al., 2020). Furthermore, many scholars and practitioners include composite digital indices, such as the Digital Economy and Society Index (European Commission, 2022), which aggregate multiple indicators across five core dimensions: connectivity, human capital, internet use, integration of digital technology, and digital public services (Katz et al., 2014; Grinberga-Zalite & Hernik, 2019). This approach is adopted in this paper building on a supply-and-demand framework, in order to distinguish AI development (e.g., publications, patents, R&D investment, and human capital) and AI adoption (e.g., organizational implementation rates and the scope of deployment).

Indices provide the opportunity to make cross-country comparison more feasible by turning "digitalization" into a common variable, so someone can understand in a more holistic way who is ahead, who is catching up, and how these differences relate to economic outcomes. Many frameworks group countries into stages, framing them as starters, adopters, and frontrunners, and in most cases countries who rank in the higher stages tend to go hand-in-hand with higher income levels (e.g., GDP per capita). Similarly, indices track how quickly ICT access, use, and capabilities expand, on the assumption that faster digital progress is closely tied to broader economic development. Many of the measurements listed in Table 3.1 reflect this logic and this is

also the expanded rationale for adapting an index-based approach in this research and constructing an AI Economic Capacity Index that captures where countries stand along the various AI value chain stages, enabling cross-country comparison within the EU and beyond.

Table 2.1. Indices of the digital economy used in cross-country comparisons

Index name	Full name of index	Originator	First publication	Number of covered countries	Number of partial indicators
ISI	Information Society Index	IDC	1997	53	< 20
ERI	E-Readiness Index	EIU	2000	70	< 100
KEI	Knowledge Economy Index	WEF	2005	140	< 20
EGDI	E-Government Development Index	UNPAP	2002	182	< 10
IDI	ICT Development Index	ITU	2002	154	< 20
DAI	Digital Access Index	ITU	2003	178	< 10
TAI	Technology Achievement Index	UNDP	2001	72	< 10
NRI	Networked Readiness Index	WEF	2002	148	< 80

DOI	Digital Opportunity Index	ITU	2005	181	< 20
ICT-OI	ICT Opportunity Index	ITU	2005	183	< 20
ICT-DI	ICT Diffusion Index	UNCTAD	2006	180	< 10
IS	Infostates	ORBICOM	2003	183	< 20
DESI	Digital Economy and Society Index	EU	2014	28	< 40

Source: Adapted from Moroz (2017) based on Kononova (2015, p. 939)

The first approach, which is technical, mainly emphasizes on performance measurement: benchmarks, leaderboards, and task-specific evaluation, explaining basically, "how good is the AI at a specific task?". Such an approach mainly explains us about model quality, not economic performance or capacity -because a model can score high on benchmarks and still fail to spread widely, boost productivity, or create broad economic value. A second, more economically grounded way to apply the usage-based approach is to shift the focus from model scores to the question of who is using a digital or AI application, how much they use it, and where they use it (at the individual, household, or firm level) like is depicted in Table 3.2. with different measurements of digital usage metrics (Milošević et al., 2018; Hanna, 2020; Avezov, 2025). This helps estimate the application's economic footprint when prices and standard statistics don't capture it accurately. A related idea is AI exposure, with researchers estimating how much AI could affect the tasks inside jobs (for example, what share of a job's tasks could be automated or improved), and then scaling that up from tasks to jobs, to industries and get a sense of how big the impact could be for the whole economy (Acemoglu, 2024). Specifically, building on Eloundou et al. (2023) and Svanberg et al. (2024), Acemoglu (2024) estimates the fraction of tasks exposed to AI and the cost savings associated with these tasks.

Table 2.2. Internet connectivity, cloud use, and e-commerce indicators included in the CIDI

VarID	Variable	CIDI Weight
E5	Computer Internet Connections used by the Employees in Enterprises	9.32%
P4	Use of Cloud Services by Individuals	8.84%
E6	Mobile Internet Connections used by the Employees in Enterprises	8.64%
P1	Level of Internet Access in Households	8.43%
P3	Mobile Internet Access by Individuals	8.16%
P2	Internet Use by Individuals	8.08%
P5	Internet Purchases by Individuals	8.06%
E1	E-commerce Purchases of Enterprises	7.82%
E7	Enterprises that have a Website	7.79%
E3	Internet Advertising of Enterprises	7.38%
E2	E-commerce Sales of Enterprises	6.98%
E8	Enterprises that Employ ICT Specialists	5.50%
E4	Value of E-Commerce Sales of Enterprises	4.99%

Source: Milošević, N., Dobrota, M., & Rakočević, S. B. (2018, p.870)

Second, at the micro/firm level, productivity measurement evaluates AI outcomes mainly by tracking pre- and post-implementation key performance indicators comparing productivity

before vs. after implementation (or with vs. without AI) and attributing changes to the AI-supported interventions, using business and operational KPIs such as revenues (Pandey et al., 2021). The KPIs layer can include labor productivity improvements, Overall Equipment Effectiveness (OEE) in manufacturing, faster Time-To-Market (TTM), and higher Customer Lifetime Value (CLV) or customer retention in retail and services (Avezov, 2025), where most importantly the measurement usually treats "adoption" as a value which is realized only when AI is integrated into core workflows at scale (Pandey et al., 2021). Subsequently, AI economic performance is usually judged by whether business productivity improves after deployment in areas like the ones mentioned above and translates into a coherent digital transformation strategy and, by extension, a viable digital business model (Kargas et al., 2023). This underscores that outcomes are multi-dimensional and "economic success" may require counting complementary changes (workflow redesign, skill mix, downstream process changes).

A third approach focuses on, adoption and transformation of the labor market as a method to evaluate progress in the digital or AI economy (Novikova et al., 2022). Digitalization and integration of AI translates into observable labor-market transitions beyond vague productivity gains, with routine tasks transforming and employment trends changing -i.e., job polarization, displacement and replacement (Autor, 2015). This can be implemented by documenting the share of AI-related job postings (regionally or sectorally), AI-related skills in advertisements or quantitative research, the percentage of workers employed in AI-affected or AI-exposed services, task-based indicators and wage growth or stagnation across different skill levels (Ernst et al., 2019; Georgieff & Hyee, 2021; Makridis & Mishra, 2022). Those measurements are essential for understanding the many-sided impacts of AI on the economy and society, providing a guideline for evaluating successful integration of new technologies, by monitoring if benefits are distributed equitably, if the workforce is prepared for the challenges and opportunities of technological transformation, and the state of the labor market under the prism of digital innovation influence (Ernst et al., 2019; Wu & Yang, 2022; Filippucci et al., 2024).

Additionally, a fourth approach, which is very common in cross-country comparisons, concerns innovation capacity through indicators such as AI-related publications and citations, AI patents, R&D expenditure , private funding/venture capital regarding new technologies and the dynamism of the start-up ecosystem (Furman et al., 2002; Hollanders & Celikel-Esser, 2007; Ma et al., 2025). This approach evaluates a country's ability to generate, support, and sustain innovation, providing a holistic view of a nation's digital ecosystem with measurable data that can be compared across countries and can provide a reliable indication on the status quo and the

prospects of technological growth in this region (Miškufová et al., 2025; Xue & Jin, 2025). The rationale for this stems from the fact that innovation is a key driver of economic growth, with countries with strong innovation capabilities being better positioned to develop new technologies, attract investment, and create high-value jobs.

As outlined earlier, the main advantage of an index approach is comparability across countries and over time. The trade-off, however, is addressing homogeneity or overlapping variables in data and conceptual scope (Farrugia, 2007). In order to manage this obstacle, indicator frameworks distinguish between core indicators, those with broad coverage and relatively stable methods (e.g. number of patents or AI publications, investment levels and labour force statistics), and complementary indicators that are more detailed but less standardized (Burford et al., 2016). In line with this approach, the AI Economic Capacity Index is organized around three pillars that correspond to key stages of the AI development lifecycle (Inputs, Modeling, and Deployment). Each pillar represents a thematic area from the fundamental enabling conditions for AI economic capacity, through the creation of AI technologies, to their diffusion and impact on the economy.

The Inputs pillar captures the necessary conditions for the development of AI, including - among others- the fundamental resources, infrastructure and human capital that enable establishing a strong AI ecosystem (Wang et al., 2025). This encompasses the digital infrastructure, such as high-speed internet networks, cloud computing facilities and supercomputing capacity and the data environment (availability of large, high-quality datasets and maturity in data governance) in which AI is shaped and trained (Chen, Chen, et al., 2021; Mohammed et al., 2022). It also covers human capital and skills (Chen, 2025), like the supply of AI talent and professionals with STEM education, as well as the prevalence of digital infrastructure to support the workforce (Bughin et al., 2017; Fatima et al., 2020; Radu, 2021; Horowitz et al., 2018; Appiah, 2025). In addition, financial and research inputs are reflected here, including R&D spending, public and private investment in AI and supportive policy or institutional frameworks (Jacobides et al., 2021). Strong performance in the Input pillar indicates that a country or region has created the necessary infrastructure and preconditions under which the development, training and validation of Artificial Intelligence software can thrive.

The Modeling axis reflects the ability to innovate and create technology in AI, measuring the development of AI capabilities and essentially how well inputs are converted into tangible AI design. The key variables of this pillar focus on research output and innovation in Artificial Intelligence, such as the volume of scientific publications and patents related to Artificial Intelligence, which showcase knowledge production and innovative activity in this field (Fujii &

Managi, 2018; Gong et al., 2025). This pillar also includes metrics for application development, for example the investments notable models attracted, and contributions to AI open source software, which demonstrate how ideas are translated into practical tools, financially impactful innovations and systems that find real-world application (Langenkamp & Yue, 2022). Overall, through this dimension an attempt is made to measure how effectively a country creates new AI models, algorithms, and applications, which represent the innovative output of its AI ecosystem.

Last but not least, deployment is connected to the diffusion and adoption of AI technologies across the broader economy and society, assessing the extent to which AI solutions are becoming part of the economic fabric in ways that increase productivity or bring other tangible benefits to enterprises, labour force and market (Chen, Li, et al., 2021; Filippucci et al., 2024). Indicators in this pillar assess AI adoption rates, considering the share of businesses or public sector organizations that use AI in their operations or the prevalence of AI-based products and services in the market (Antoniuk & Kolyada, 2024; Socol et al., 2024; Laitsou et al., 2025). Another way that is utilized in order to capture the diffusion of technology is through complementary metrics such as the use of cloud computing and advanced digital tools in businesses, the general level of digital skills of the population ensuring that organizations can effectively implement AI, and the presence of AI in economic outputs such as the share of exports that are digitally deliverable or high-tech (Gonçalves et al., 2023; Katz & Jung, 2024; Tudor et al., 2025). Hence, the Deployment pillar looks at measures of productivity and impact, linking AI adoption to improvements in efficiency or economic value added, considering that strong growth capacity shows that AI is not just being deployed in theory, but is actually integrated into business processes, public services and everyday life -thereby contributing to wider economic and social benefits.

3. Construction Methodology: Artificial Intelligence Economic Capacity Index (AI-ECI)

The Artificial Intelligence Economic Capacity Index (AI-ECI) is a composite indicator designed to capture and categorize variables that help assess a country's ability to develop, deploy and derive economic value from Artificial Intelligence, with a particular focus on the EU-27[1]. The specific set countries were selected for two reasons: (a) because the aim is to be able to identify differences across Member States in the development and integration of AI and to provide a

[1] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden.

framework for future study of the determinants that influence its development and (b) for practical reasons of data availability that allow for in-depth study. In addition, 2025 data is utilized, using 2024 data where 2025 values were not yet available.

The choice to develop an index draws inspiration from the Knowledge Economy Index (Diessner et al., 2025) based on the structure of the World Bank's Knowledge Economy Index framework (Chen & Dahlman, 2006; Ojanperä et al., 2019) and the French Ministry of Finance on the value chain of Artificial Intelligence approach (Chardon-Boucaud et al., 2024). Following this logic, the Artificial Intelligence Economic Capacity Index (AI-ECI) aggregates capacity across multiple dimensions (or "pillars") that are critical for AI-driven economic growth. The AI-ECI pillars reflect the enabling environment for AI to develop and its effective -or not- implementation and diffusion in the economy, showing how factors such as education, innovation, ICT infrastructure and the broader framework of economic incentives, public policies and development decisively influence a country's economic capacity in the race for Artificial Intelligence.

Hence, each pillar of the Artificial Intelligence Economic Capacity Index (AI-ECI) consists of a set of variables that capture a country's capacity to convert AI into economic value, and all indicators are then normalized to allow for comparability and segmentation of the countries under consideration (see Figure 3.1). The overall index is calculated as the simple average of the three pillar scores: inputs, modelling and deployment. This transparent aggregation strategy follows the logic of composite indicator construction, where multidimensional phenomena are summarised through normalisation, weighting and aggregation choices (OECD & Joint Research Centre-European Commission, 2008). Figure 3.1. provides a schematic overview of this framework, showing how the individual indicators are grouped into pillars and then combined into the composite index.

Figure 3.1. Structure of the AI-ECI Pillars and Indicators

Pillar	Variable	Source
Inputs	Supercomputers	(TOP500.org, 2025)
	Internet Speed (More than 100 Mbps)	(Eurostat, 2025a)
	Cloud infrastructure (Number of Data Centers)	(Cloudscene, n.d.)

	Data availability and quality	(Page et al., 2024)
	Education (STEM doctoral graduates)	(European Commission, Directorate-General for Research and Innovation, 2025)
	R&D investment (GERD by sector of performance)	(Eurostat, 2026)
	AI Private Investment (VC investments in AI)	(OECD.AI Policy Observatory, n.d.)
Modeling	AI publications	(World Bank, n.d.)
	Scientific publications among the top-10% most cited	(European Commission, Directorate-General for Research and Innovation, 2025)
	AI patents/ PCT patent applications per billion GDP	(European Commission, Directorate-General for Research and Innovation, 2025)
	ICT specialists (%of total employment)	(European Commission, Directorate-General for Research and Innovation, 2025)
	Frontier capability: Notable Models Funding	(OECD.AI Policy Observatory, n.d.)
	Open-source activity	(Wachs et al., 2022)
	AI GitHub Projects (Python)	(OECD.AI Policy Observatory, n.d.)
Deployment	Firm adoption rate of AI	(Eurostat, 2025c)
	AI Job Postings (% of Total)	(OECD.AI Policy Observatory, n.d.)
	*Exports of medium/high technology products as a share of total exports	(European Commission, Directorate-General for Research and Innovation, 2025)
	Relative AI Skill Penetration	(OECD.AI Policy Observatory, n.d.)
	Workforce readiness/Individuals who have above basic overall digital skills	(European Commission, Directorate-General for Research and Innovation, 2025)
	Exports in digitally-deliverable services (Millions/2023)	(UNCTAD, n.d.)

	Cloud Computing in Enterprises (Enterprises with 10 or more persons employed that reported using cloud computing services)	(European Commission, Directorate-General for Research and Innovation, 2025)

3.1. Variable Selection

Before it is possible to develop AI applications and spread its use among employees and the general population, it is necessary to have the fundamental resources, infrastructure, financial and cognitive conditions necessary for its development (Pramanik et al., 2024; Hewage, 2024). Thus, the first pillar examined whether economies have the necessary human, capital and digital infrastructure for the continuous development of Artificial Intelligence models and the diffusion of their use in society. Therefore, the economic capacity in the field of AI depends to a large extent on the magnitude of the aforementioned variables.

First and foremost, digital infrastructure is the cornerstone of this pillar, encompassing the hardware and network capabilities that enable AI development and subconsequently diffusion. For this reason, the index places particular emphasis on core infrastructure indicators such as a country's high-performance computing capacity, captured through "supercomputer power" as recorded twice a year with verified LINPACK results, broadband connectivity -such as the share of households with ultra-fast internet >100 Mbps- and cloud computing infrastructure through the number of data centers and cloud availability (Maslej et al., 2025). For a state, adequate digital infrastructure is a critical prerequisite for the subsequent development of new AI models and applications, with countries with a strong presence in these indicators providing the computational backbone that enables AI innovation at scale (Zhao & Aaron, 2025).

Nevertheless, infrastructure alone is not enough for successful AI development and therefore strong economic capacity. The availability of quality data is a critical and often overlooked variable and the driving force behind AI model training, with the EU Data Quality Index providing a broad picture of data availability, quality and good data governance. Those elements are essential for developing models that are reliable in the long term (Androutsopoulou et al., 2025). A strong and accessible data ecosystem enables businesses and researchers to train better models (Janssen et al., 2020; Mohammed et al. 2022). Within the EU, differences in data ecosystem scores correspond to how well Member States have implemented open data policies and data governance frameworks that protect users and cultivate trust alongside credibility (European Commission, Directorate-General for Research and Innovation, 2025).

Moreover, the human and financial resources directed towards AI are critical variables to identify the potential of AI in an economy. That is why the paper includes as a method of recording AI-related talent the number of PhD graduates in STEM (science, technology, engineering, and mathematics) fields (Draca et al., 2024) per 1000 inhabitants (European Commission, Directorate-General for Research and Innovation, 2025). Specialized human capital is a necessary condition that allows us to understand the existence of a sufficient workforce to respond to AI and contribute to its development, but also to measure its potential footprint in the labor market (Johnson et al., 2021). Of course, in the economic resources aspect, R&D and investment indicators include total R&D expenditure (GERD as % of GDP) and private investment in AI, which translates to venture capital funding for AI startups. Through those variables, it is possible to examine both the size of the investment market, which operates in a cyclical manner, and the strategic investment of each economy in innovative activities that in turn favor the development of AI technologies.

Another key pillar that reflects an economy's capacity in the AI sector is knowledge creation and innovation (Liu et al., 2020; Gonzáles, 2023; Huy et al., 2024). This is the stage at which infrastructure and resources are transformed into AI applications and products. To explore this area, the research focuses on the production of AI research publications (number of scientific publications related to AI) and the quality of research such as the share of a country's scientific publications that are ranked in the top 10% of the world's most popular -an indicator of research impact (Maslej et al., 2025).

Hence, the ability to create innovative solutions in the field of AI is captured by patent filings on Artificial Intelligence such as PCT patent applications in Artificial Intelligence per billion GDP (European Commission, Directorate-General for Research and Innovation, 2025). It is also possible to quantify the impact of AI research through open source activity – for example, the number of AI-related projects on GitHub (specifically measuring public repositories using Python for AI, as aggregated from GitHub data) and a general open source contribution index by country (OECD.AI Policy Observatory, n.d.).

At the same time, the economic impact of this technology is recorded with indicators such as "Leading AI model development" recording the investments on notable large-scale AI models produced by each country (Vijayakumar, 2021; Maslej et al., 2025). and the "openness of leading edge development" which means whether the large AI models from the specific country are open source or closed (Wachs et al., 2022). However, data for these leading edge indicators were scarce or only available for a few countries, so they were treated with caution and excluded if the coverage

was insufficient. Finally, the impact on the labor market is also examined through ICT specialists (% of total employment), as a proxy for understanding the size of the impact of digital applications and therefore of AI applications on the labor market (Başol & Yalçın, 2021; Pantelimon et al., 2024; Davidescu et al., 2025).

Finally, the most obvious area at first glance regarding the dynamics of an economy in AI is adoption and impact. In this context, it is studied how widespread Artificial Intelligence and advanced digital technologies are in the economy and society, with a key indicator being the adoption rate of Artificial Intelligence among businesses (Villanueva, 2024) and specifically the percentage of businesses, usually with 10+ employees, that use at least one Artificial Intelligence technology (Eurostat, 2025c). Eurostat's (2025c) survey on the use of technology in businesses provides this data by focusing on businesses that use Artificial Intelligence for tasks such as machine learning, natural language processing, computer vision and many more applications.

Furthermore, the digital skills readiness of the workforce is crucial, as measured by the penetration of AI skills in the workforce and captured in the relative concentration of AI skills in professional networks, which indicates how common AI expertise is in each country's workforce. Through OECD.AI Policy Observatory (n.d.) and processed data from LinkedIn, this measurement is possible , but not entirely accurate. Nevertheless, it's crucial to understand the prevalence of AI skills in a job market. Also crucial is the digital skills readiness of the workforce, as measured by the percentage of individuals with above basic overall digital skills (European Commission, Directorate-General for Research and Innovation, 2025), offering a comprehensive overview of both preparedness for AI but also the digitization of an economy.

In addition, AI-related productivity gains are examined from studies that measure the prevalence of cloud computing in businesses as the percentage of businesses using cloud services (European Commission, Directorate-General for Research and Innovation, 2025). Two trade-related indicators are also included. Most specifically, this research investigates economic impact in deployment through the share of high-tech products in national exports, reflecting a country's specialization in producing advanced technology, and the value of exports of digitally delivered services (IT services, software, etc.), which indicates a country's role in digital services -and subsequently AI- trade. These indicators serve as proxies for a country's integration into the digital economy and indirectly its ability to produce and export AI-related products or services.

3.2. Data Collection and Normalization

The Index includes all 27 EU Member States, using data from 2025, except in cases where data for an indicator was not yet available. In these cases, the latest available year (most oftenly 2024) was used as a substitute, in order to maximise data coverage while maintaining the focus on the most recent available information. The idea behind this practice is to mitigate the lack of data on the digital and AI economy. The indicators were collected from reports and datasets of international organisations (e.g. Eurostat, OECD, World Bank and sources cited in the Stanford HAI - AI Index Report) and published academic literature, serving the ultimate goal of drawing on credible datasets and references of established institutions, in order to ensure that the index is built upon reliable data (Figure 3.1.).

A major methodological obstacle that arises in the attempt to create an Index is the fact that because the indices come from multiple sources they measure in different units and scales that are not consistent with each other (Hudrliková, 2013). This has the consequence that including percentages, normalized indices and absolute numbers, makes it imperative that they be normalized to a common scale before aggregation. To do this, min-max normalization, a widely used method in the construction of composite indices (Zhang et al., 2024), was chosen to rescale each index to a unitless range from 0 to 1 (higher = better). For a given index x, the raw value of each country was transformed using the formula:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$

Choosing the min-max approach helps all indicators to be visually comparable, the resulting scores to be readable (0 = lowest observed capacity; 1 = highest), and the normalized indicators to be aggregated into pillar and overall index scores without one variable dominating solely because of the unit of measurement (e.g., million euros versus percentage). The min-max index can be sensitive to outliers, where countries with extreme capacity can compress the variance between the rest of the countries, but this is not a major obstacle at the level of presentation of the index, which is addressed below in Factor analysis via PCA by using z-scores.

Additionally, where raw values were provided as absolute or monetary values, they were converted to intensity measures as the purpose was to capture relative capacity. More specifically, GDP-based denominators (World Bank, 2025a) were used for economic intensity and innovation intensity indices and population (labor force) denominator (World Bank, 2025b) was used for skills and labor market indices. As a result supercomputers, compute capacity, number of data

centres, AI publications, notable AI models produced, open-source activity and AI GitHub projects were divided by the 2025 labour force and expressed as values per million. Simultaneously, monetary and export-based indicators, such as AI private investment and exports in digitally deliverable services were divided by 2024 GDP in current US dollars. This process helps ensure that the AI-ECI measures the relative integration of AI capabilities into national economies, rather than simply reproducing differences in country economy size.

4. Results

4.1 Min-max AI Economic Capacity Index Rankings

The Index shows significant variation across countries in the EU-27, with scores ranging from 0.63 for Finland to 0.13 for Bulgaria, indicating a critical gap between countries. The average overall score in the EU-27 is around 0.36, while the results bring to the surface a minority of Member States which have a significant gap from the vast majority, performing strongly across all three stages of the AI value chain.

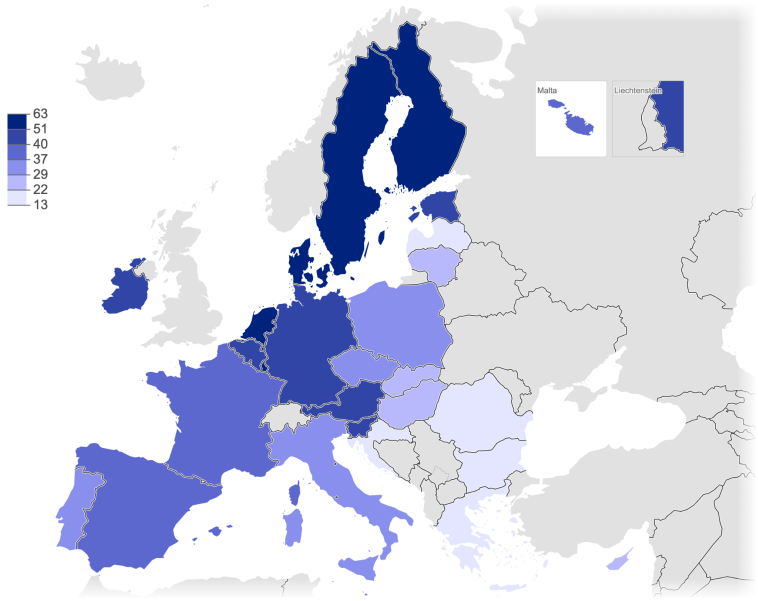
Table 4.1. AI Economic Capacity Index Rankings and Pillar Scores for EU-27 Countries (2025)

Rank	Country	Total Average	Input Average	Modeling Average	Deployment Average
1	Finland	0.63	0.66	0.55	0.67
2	Sweden	0.61	0.56	0.65	0.61
3	Netherlands	0.55	0.48	0.57	0.59
4	Luxembourg	0.54	0.63	0.52	0.46
5	Denmark	0.52	0.50	0.45	0.61
6	Ireland	0.49	0.42	0.39	0.68
7	Malta	0.45	0.18	0.48	0.71
8	Germany	0.44	0.49	0.30	0.52
9	Slovenia	0.42	0.50	0.32	0.45
10	Estonia	0.41	0.43	0.39	0.42
11	Austria	0.40	0.42	0.31	0.47
12	Belgium	0.40	0.41	0.32	0.46
13	Spain	0.38	0.38	0.29	0.46

14	France	0.36	0.47	0.24	0.38
15	Italy	0.36	0.39	0.19	0.49
16	Portugal	0.35	0.36	0.35	0.35
17	Czech Republic	0.30	0.34	0.16	0.39
18	Poland	0.30	0.29	0.25	0.35
19	Slovakia	0.29	0.33	0.15	0.40
20	Hungary	0.28	0.25	0.13	0.46
21	Cyprus	0.27	0.28	0.24	0.27
22	Lithuania	0.25	0.30	0.17	0.30
23	Croatia	0.20	0.19	0.15	0.26
24	Latvia	0.20	0.23	0.14	0.23
25	Romania	0.19	0.19	0.10	0.30
26	Greece	0.16	0.13	0.18	0.18
27	Bulgaria	0.12	0.20	0.11	0.07

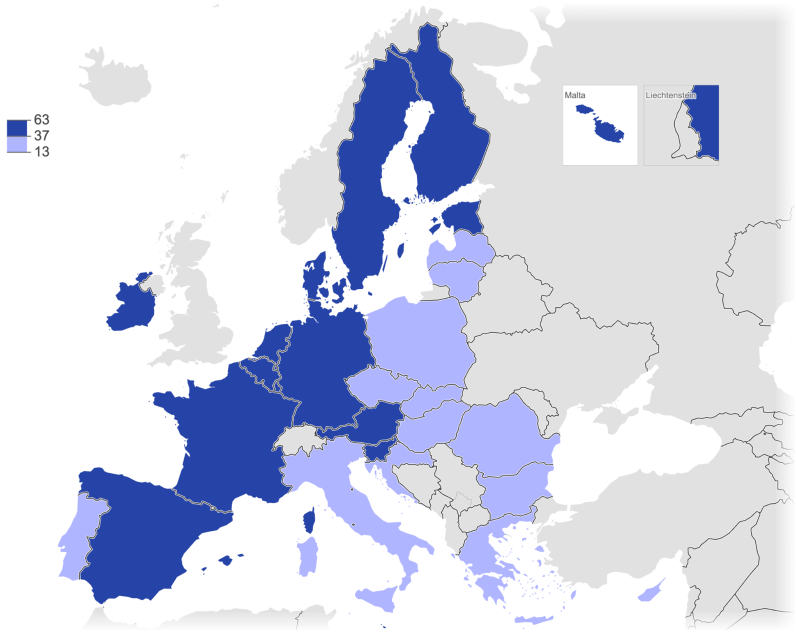
The top group is mainly composed of countries from Northern and Western Europe, with a focus on the Nordic countries. More specifically, Finland ranks first with an overall score of 0.63, followed by Sweden (0.60), the Netherlands (0.55), Luxembourg (0.54) and Denmark (0.52), with these countries performing well not only because they have relatively high levels of AI adoption, but also because they combine adoption with broader enabling conditions such as strong digital infrastructure, research capacity, human capital, open source activity, ICT employment and cloud-based business transformation. This confirms one of the main conceptual assumptions of the index, that the economic capacity of AI is not simply a matter of company-level adoption, but a broader configuration of resources, capabilities and diffusion mechanisms.

Figure 4.2. Geographic Distribution of AI Economic Capacity Scores Across the European Union (2025)



A second group includes countries with moderate-high but more uneven economic capacity, such as Ireland, Germany, Malta, Slovenia, Estonia, Austria and Belgium. Ireland, for example, scores particularly strongly on diffusion (0.68) but less strongly on inputs (0.42) and modelling (0.39), suggesting a model based on strong digital service integration and enterprise-level diffusion rather than domestic AI production capacity. Germany, in contrast, has stronger input capacity (0.49) and deployment (0.52) but a weaker modelling score (0.30).

Figure 4.3. Binary Classification of AI Economic Capacity Across the European Union (2025)



The bottom half of the ranking is dominated by countries in Southern and Eastern Europe. Bulgaria ranks last with an overall score of 0.13, followed by Greece (0.16), Romania (0.19), Latvia (0.20) and Croatia (0.20). These countries tend to lag behind in more than one pillar, suggesting that their position is not only a result of weaker AI adoption, but also weaker entry conditions and lower modeling capacity. Greece, for example, lags behind in all three pillars scoring 0.13 in inputs, 0.18 in modeling, and 0.18 in deployment. This suggests a broad structural difference compared to the rest of the EU, rather than a single missing variable.

The top countries in the index are not only digitally advanced, but they are also countries with stronger knowledge economy foundations, more developed innovation systems, higher levels of human capital and more advanced digital business environments (Diessner et al., 2025). In contrast, the performance of several Southern and Eastern European countries in the Index suggests that the AI gap in Europe is structural and not limited to the adoption of AI. Bulgaria, Greece, Romania, Latvia and Croatia tend to lag behind in more than one pillar, which means that the index captures a broader development divide within the EU's knowledge economy. Nevertheless, it's evident that the EU faces a significant risk of splitting into two distinct tiers (Bughin et al., 2016) when it comes to AI economic capacity where countries like Greece -a Southern European and Balkan country recovering from a severe economic crisis (Albani et al.,

2019)- seem to become AI "laggards" confirming previous observations that documented a decline for Southeastern countries (e.g. Greece and Italy) in efficiency and in equity (Petropoulos et al., 2019).

4.2 Robustness and Sensitivity Analysis

To examine the strength of the AI-ECI, the index was recalculated using three different methods: (a) excluding small states, (b) winsorizing raw indicators at the 5th and 95th percentiles, and (c) using equal-indicator weighting instead of equal-pillar weighting. The results show that the index remains stable, with the equal-indicator method almost matching the equal-pillar one, with a Spearman rank correlation of $\rho = 0.996$. This suggests that the main findings are not affected by whether we aggregate at the pillar or indicator level. However, excluding small states results in lower but still meaningful correlations, resulting in a value of $\rho = 0.992$ when Luxembourg and Malta are excluded and $\rho = 0.996$ when Luxembourg, Malta, Cyprus, and Ireland are excluded. This means small states do not impact the distinction between stronger Northern and Western European economies and weaker Southern and Eastern European economies in terms of AI economic capacity. The winsorised specification is slightly more sensitive, but still strongly correlated with the baseline ranking, with a Spearman correlation of o $\rho = 0.985$.

4.3 Factor Analysis through Principal Component Analysis (PCA)

In order to understand how the indicators structure cross-country variation in AI economic capacity, the indicators were initially standardized to z-scores and, to reduce sensitivity to omissions, we retained indicators with ≥70% country coverage and non-zero variance, resulting in 22 indicators for N = 27 EU countries. Afterwards, an exploratory Principal Component Analysis (PCA) was conducted, aiming to understand how the indicator space is structured, with the first components providing evidence that a substantial share of the variance between countries is organised around a common underlying dimension. PC1 explains ~34% of the total variance, while PC2 explains ~13%. Therefore, the first two components together account for approximately 47% of the total variance, while if PC3 and PC4 are added, the cumulative explained variance further increases to about two-thirds (~65%).

Table 4.4. Eigenvalues and explained variance (EU-27 PCA on z-scores)

Principal Component	Eigenvalue	Explained Variance Ratio	Cumulative Explained Variance
PC1	7.61	0.34	0.34
PC2	2.81	0.13	0.47
PC3	2.14	0.10	0.56
PC4	2.00	0.09	0.65
PC5	1.34	0.06	0.71
PC6	1.22	0.05	0.77
PC7	1.04	0.05	0.81
PC8	0.88	0.04	0.85
PC9	0.67	0.03	0.88
PC10	0.61	0.03	0.91

The first component (PC1) weights indicators that cover all the three pillars that are investigated through this index, rather than focusing exclusively on inputs. The strongest loadings are associated with enterprise-level AI adoption, open source activity, ICT specialists, highly cited scientific publications, STEM PhD graduates, digital workforce readiness, R&D investment, and supercomputing capacity. In other words, PC1 depicts broad AI capacity and diffusion, with countries scoring high when they simultaneously demonstrate strong research quality, digital labor market capacity, enterprise-level adoption, foundational investment, and infrastructure. This highlights the importance of dividing the study of the economic capacity of Artificial Intelligence into three levels, while showing that "success" is not only reflected in adoption and diffusion, but also significantly depends on the conditions that allow the development of Artificial Intelligence capabilities, their transformation into innovation and their integration into the wider economy.

Table 4.5. Top absolute loadings on PC1 (EU-27).

Variable	Category	PC1 loading
Firm adoption rate	Deployment	0.33
Open-source activity	Modeling	0.33
ICT specialists	Modeling	0.32
Scientific publications	Modeling	0.31
PhD STEM graduates	Inputs	0.28
Workforce readiness	Deployment	0.27
R&D investment	Inputs	0.25
Supercomputers	Inputs	0.25

Cloud Computing in Enterprises	Deployment	0.24
AI publications	Modeling	0.23
Compute Capacity (Rmax)	Inputs	0.22
Number of Data Centers	Inputs	0.21
AI Private Investment	Inputs	0.19
Frontier capability	Modeling	0.17
Exports in digital services	Deployment	0.16
Internet Speed	Inputs	0.08
Exports of technology products	Deployment	0.06
Data availability and quality	Inputs	0.05
AI Skill Penetration	Deployment	0.04
AI GitHub Projects)	Modeling	0.04
AI patents	Modeling	0.02
AI Job Postings.	Deployment	0.00

The second component (PC2) differentiates countries according to different forms of AI economic positioning, loading positively on indicators such as exports in digitally deliverable services, data-centre infrastructure, AI publications, and supercomputers, while negative loadings appear for R&D investment, cloud computing in enterprises, private AI investment, relative AI skill penetration, and workforce digital readiness. PC2 should therefore not be interpreted as a second capacity ranking, but as a specialisation axis. It distinguishes countries with internationally embedded digital-service and infrastructure-heavy profiles from countries where AI capacity is more strongly associated with internal diffusion, investment, skills, and workforce readiness. This metric therefore unravels two different AI economic pathways, having on the one hand, countries such as Luxembourg and Ireland that appear closer to a digital-services and data-infrastructure -with Luxembourg standing out. On the other hand, countries such as Finland, Sweden, Denmark, Germany and Estonia combine strong PC1 scores with negative PC2 scores, suggesting an AI capacity based on R&D, skills, workforce readiness, enterprise adoption, and private-sector diffusion.

Table 4.6. Top absolute loadings on PC2 (EU-27).

Variable	Category	PC2 loading
Exports of digital services	Deployment	0.47
Number of Data Centers	Inputs	0.41
AI publications	Modeling	0.33
Supercomputers	Inputs	0.27

PhD STEM graduates	Inputs	0.10
Scientific publications	Modeling	0.03
ICT specialists	Modeling	0.00
Firm adoption rate of AI	Deployment	-0.04
Data availability and quality	Inputs	-0.05
Internet Speed	Inputs	-0.06
Compute Capacity (Rmax)	Inputs	-0.09
Open-source activity	Modeling	-0.10
AI GitHub Projects	Modeling	-0.11
Frontier capability	Modeling	-0.13
AI Job Postings	Deployment	-0.15
AI patents	Modeling	-0.17
Exports of technology products	Deployment	-0.19
Workforce readiness	Deployment	-0.21
AI Skill Penetration	Deployment	-0.23
AI Private Investment	Inputs	-0.23
Cloud Computing in Enterprises	Deployment	-0.24
R&D investment	Inputs	-0.25

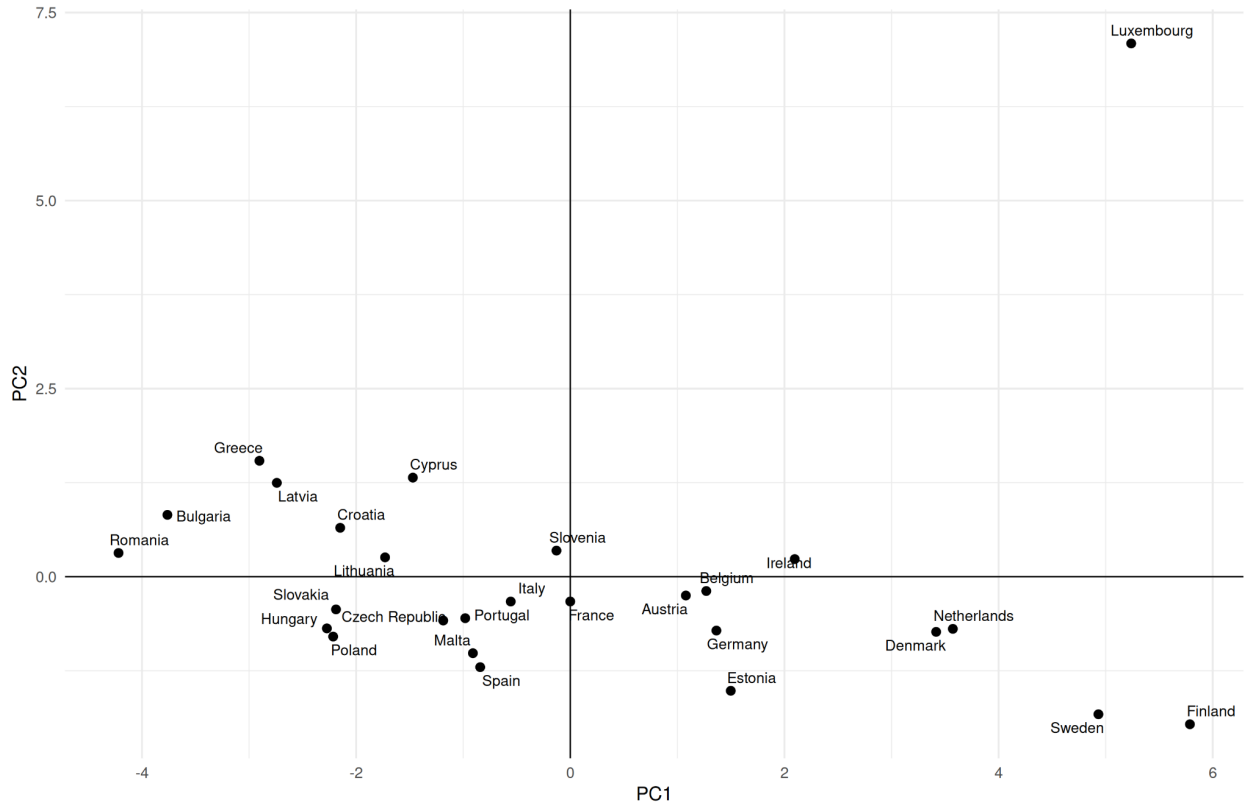
4.4 Comparative Analysis

The PCA table 4.7. depicts the position of EU-27 countries in the first two main components of the AI-ECI indicator set. The horizontal axis, PC1, captures the main dimension of cross-country variation and can be interpreted as a broad axis of economic AI capacity and the vertical axis, PC2, differentiates the types of economic deployment of AI -and should not be interpreted as a second ranking of capacity. Countries leaning towards the right, such as Finland, Sweden, Luxembourg, the Netherlands and Denmark, combine stronger AI-related infrastructure, research capacity, digital skills, business adoption and innovative activity, while those on the left, including Romania, Bulgaria, Greece, Latvia and Hungary, show weaker overall AI economic capacity across the indicator space.

Moreover, countries higher on PC2 are more associated with digital services, data infrastructure and publication-oriented profiles, while countries lower on PC2 are more associated with R&D, workforce readiness, private investment, business adoption and skills-based diffusion. Luxembourg appears as a clear exception, reflecting its particular profile in digital services and infrastructure. In contrast, Finland, Sweden, Denmark, the Netherlands,

Germany and Estonia combine high PC1 scores with negative PC2 scores, suggesting a more embedded skills-based AI capability, business use and broader economic diffusion.

Graph 4.7. PC1 vs PC2: General Capacity and AI Profile Differentiation



5. Discussion

The results of the AI Economic Capacity Index illustrate a clear pattern of divergence within the EU-27, with the economic capacity of AI being unevenly distributed across Member States. At the same time, it shows that economic capacity is not a one-size-fits-all measure of AI diffusion in businesses, but encapsulates a set of critical variables such as business adoption, private investment, patents or research output. Thus, the ranking shows that a small group of countries perform strongly at different stages of the AI value chain, while others remain weak across multiple pillars. Finland, Sweden, the Netherlands, Luxembourg, Denmark and Ireland form the top group, while Bulgaria, Greece, Romania, Latvia and Croatia occupy the lower end of the index,

suggesting that the economic returns of AI are cumulative and countries that already have stronger digital infrastructure, research systems, human capital, ICT labour markets and business digitalisation are better placed to convert AI-related capabilities into economic value (Mhlanga, 2021).

Automation and digital technologies not only substitute for work, but also complement certain skills and tasks (Autor, 2015) and therefore, countries with stronger complementary capabilities are more likely to benefit from. So, the macroeconomic impact of AI depends on the jobs affected, the cost savings created and how productivity gains are integrated into the wider economy (Acemoglu, 2024). This is reflected in PC1 supporting the conceptual argument that the economic capacity of Artificial Intelligence should be measured as a multidimensional phenomenon. Of course, when a multidimensional strategy for the economic development of AI is not feasible, PC2 highlights countries with a profile that focuses more on digital services and data infrastructure.

This finding is consistent with the broader literature on technological change and economic growth. In the tradition of Solow (1956), technological progress is seen as central to long-term growth, but largely as an external driver of productivity, while later theories of endogenous growth, notably Romer's (1990) work on technological innovation, situate knowledge production within the process of innovation and investment. The results of this research come closer to this second interpretation, as AI does not appear to simply "arrive" in national economies as a deus ex machina that automatically generates economic performance. Instead, its economic impact depends on whether countries have the complementary conditions that allow for the development, adaptation, financing, scaling and diffusion of new technologies. This is also consistent with the literature on national innovative capacity, which emphasizes that innovation depends on the interaction between research systems, human capital, investment, firms and institutions and not just on individual inputs (Furman et al., 2002; Zhao, 2019; Acemoglu, 2024).

The strong economic capacity of Nordic and Western European countries should therefore be understood as a result of ecosystem-level advantages which are also evident in previous studies regarding digitalization performance (Brattberg et al., 2020). Finland, Sweden, the Netherlands, Luxembourg, Denmark and Ireland do not lead because they perform well on just one dimension of the index, but because of a combination of strong input conditions, modelling capacity and deployment. This reinforces the central argument of the research that the economic capacity of AI is not only a question of whether companies adopt AI, but also of whether the wider economy has the capacity to support the development, innovation and diffusion of AI at three levels of the

supply chain -moving beyond techno-centric and neoclassical approaches that emphasize only on modeling and diffusion.

Despite the fact that the Varieties of Capitalism literature would suggest that coordinated market economies (CME) should perform relatively well in AI where technology depends on patient investment, skilled labor, applied research, business coordination, and institutional complementarity (Hall & Soskice, 2001; Schneider & Soskice, 2009; Thelen, 2014), this research observes that Germany and France do not perform as strongly as one might expect, especially in modeling. Of course, in contrast, Finland, Sweden, Denmark, and the Netherlands perform strongly because they combine several elements that are relevant for AI: digital infrastructure, human capital, research capacity, business adoption, ICT employment, and workforce readiness. In this sense, it is confirmed that the economic capacity of AI does not appear out of nowhere, but is based on long-term institutional capabilities (Friel, 2024).

The case of Germany is particularly interesting because it has many of the characteristics that the VoC literature would normally associate with technological competitiveness such as strong vocational training, applied industrial capacity, coordinated wage negotiations, and dense firm-level coordination (Bathelt & Gertler, 2005). France also has strong state capacity, public research institutions, and a tradition of industrial policy (Schmidt, 2002; Mazzucato, 2013). However, in the AI-ECI index, both appear further behind than expected and this is where Hall and Thelen's critique that institutions are not simply reproduced, but they are constantly reshaped through political coalitions, strategic employers, and state action (Hall & Thelen, 2009) becomes relevant. In the context of AI, the key question is therefore not whether a country is a CME or an LME (Liberal Market Economies), but whether its inherited institutions can be transformed to new technological ends. So, Germany may still have strong industrial coordination, but if this coordination remains tied to mature manufacturing sectors, it may not automatically create pioneering AI modeling capacity, while France may have a strong state, but state capacity does not automatically solve the problem of scaling up firms, attracting private capital, or translating research into globally competitive AI products.

Institutions shape incentives, investment, innovation, coordination and the distribution of economic opportunities (Acemoglu et al., 2005; Acemoglu & Robinson, 2013), but their effect depends on whether they are able to support the specific technological capabilities required in a given period. This additional level from Baccaro and Pontusson (2016) shifts the focus to demand-side drivers of growth such as consumption, exports, and so on. Hassel and Palier (2021) take this further by arguing that welfare states are not external to growth regimes, but part of how national

economies create demand, skills, and adaptive capacity. Therefore, AI capacity is not just a supply-side issue, but depends on numerous variables such as whether growth is linked to exports, domestic consumption, foreign direct investment, finance, services, or public investment.

From this perspective, the strong Nordic performance becomes more understandable, considering the fact that Finland and Sweden combine export capacity with social investment, education, labour market adaptability and relatively inclusive welfare institutions (Dølvik & Steen, 2018; Hiilamo, 2021; Rolandsson, 2020). Their AI capacity seems broad because the institutional foundations of the knowledge economy are not limited to businesses. They include public education, active labour market policy, digital skills, research ecosystems and social trust. The result is a form of AI capacity that is more akin to embedded technological adaptation than pure market disruption combining innovation and social protection as key elements to technological change (Alsos & Dølvik, 2021; Eichhorst et al., 2022).

On the other hand, Ireland, a LME (Liberal Market Economies), represents a different model, where its relatively strong position is consistent with a growth regime financed by foreign direct investment. Ireland is deeply embedded in multinational digital value chains, which gives it a strong position in high-tech services and digitally delivered products (Barry, 2019; Porto et al., 2021). But this does not necessarily mean that Ireland has the same type of domestic AI capacity as Finland or Sweden, as its high position reflects its role as a country that agglomerates multinational activity rather than as a stand-alone national AI producer. Ireland can therefore be interpreted as a global value chain AI economy which is strongly positioned, but also exposed to decisions made by multinationals and external fiscal, regulatory and geopolitical shifts.

Regarding Malta and Luxembourg their high scores should not be interpreted in the same way as Finland or Sweden, as small states can score strongly when the indicators are normalized by population, labor force, or GDP, especially when they host concentrated data center activity, financial services, digital services, or internationally oriented companies (Briguglio,2016; Brodny & Tutak, 2022). Ornston's work on small states is useful here because it shows that small countries can make significant high-tech leaps, but through different institutional pathways. Finland and Denmark relied more on creative corporate adaptation, while Ireland relied more on competitive corporate character and attracting foreign direct investment (Ornston, 2012). The AI-ECI results suggest something similar with small states being highly visible in AI-related indicators, but the significance of this visibility being connected to niche specialisation and externally anchored multinational oriented activity.

So the AI challenge for the EU is about whether existing institutions can be transformed to support new functions. For example, can public research institutions be more directly linked to the AI economy? Can welfare states support worker mobility? Can industrial policy be redirected towards data, computing and AI development? The Draghi report directly addresses this problem, as Europe's weakness is not simply a lack of ideas or talent, but an inability to convert innovation into commercialization and scale (Draghi, 2024). The index therefore captures not only technological capacity, but also the extent to which different European political economies are responding to a new phase of capitalism. The AI-ECI may therefore not be able to prove that Artificial Intelligence has increased productivity, wages or GDP growth, but it does partially confirm comparative political economy: countries do not enter the AI economy as a tabula rasa, but their ability to develop the AI economy is shaped by welfare states, innovation institutions, development regimes, business structures and state strategies.

6. Conclusion

This paper aims to define and measure the economic capacity of Artificial Intelligence across the EU-27 and does so by constructing an index and conducting PCA (Principal Component Analysis) to highlight the main variables that determine success in the field of AI. The study shows that the economic capacity of Artificial Intelligence is multidimensional and cannot be limited to a single indicator, such as business adoption, patents, private investment or research output. Instead, the economic capacity of Artificial Intelligence depends on the interaction between the conditions that allow the development of Artificial Intelligence, the capacity to produce innovation related to Artificial Intelligence and the capacity to disseminate Artificial Intelligence technologies throughout the wider economy.

To capture this multidimensional structure, the paper developed the Artificial Intelligence Economic Capacity Index (AI-ECI), which is organized around three pillars: inputs, modeling, and deployment. The results show significant differences across EU member states. A small group of countries in Northern and Western Europe perform strongly across the entire index, while several countries in Southern and Eastern Europe lag behind across multiple pillars. This confirms that the European AI economy is characterized by clear geographical and cross-national divergence.

At the same time, the PCA results support the main claim of the paper, as PC1 captures a broad axis of AI capability and diffusion, with positive loadings on all indicators from all three pillars. Countries that score high on PC1 tend to combine infrastructure, research quality, ICT skills,

investment, open source activity, business adoption and workforce readiness. This suggests that the economic capacity of AI is best understood as a cumulative configuration of capabilities rather than a single indicator of technology adoption. On the other hand, PC2 adds further subtlety by distinguishing different forms of economic positioning of AI. It shows that countries can be strong in different ways, with some more closely linked to digital services, data infrastructure and internationally connected AI profiles, while others are more closely linked to R&D, skills, business adoption, workforce readiness and diffusion in the private sector. This confirms that there is no single European strategy for the economic capacity of AI, but rather a set of national strategies that fit within the historical context of each economy.

The contribution of the paper is therefore twofold, as it provides a framework for understanding the economic capacity of AI as a value chain process moving from inputs to modelling and development, while empirically, it offers a first comparative measurement of the economic capacity of AI across the EU-27. Thus, the AI-ECI makes it possible to identify countries that are leading, countries that are lagging and countries that follow different economic AI profiles, providing the basis for future research. As this first step defines and measures the outcome, the next stage is to explain it. By using the AI-ECI as a dependent variable, future research can examine the institutional, political and socio-economic factors that determine the capacity of AI, including development models, labour market institutions, welfare state structures, innovation systems, regulatory preferences and public investment capacity. This would allow the study of AI in Europe to move beyond general claims towards more precise and coordinated policy.

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