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Advancing the measurement of investments in artificial intelligence

François Fonteneau, Jeff Mollins, Sara Marchi, Lucia Russo, Angélina Gentaz, Melhem Daoud, Antoine-Alexandre André

Note to Delegations:

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Corrigendum

Page 9:

The Netherlands has been listed as one of the leading investing countries to accurately reflect data in figure 4.2.

Page 9 and page 43:

The investment in AI R&D for the United States has been rounded to 90 billion euros to more accurately reflect the estimated figure.

Throughout the paper:

“Data equipment” has been corrected to “Data and equipment” to reflect the proper denomination for the investment category.

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Abstract

This working paper presents a methodology for estimating public and private artificial intelligence (AI) investments in European Union (EU) Member States, focusing on assets and capabilities. It categorises investments into four groups: Skills, Research and development (R&D), Data and equipment, and Other intellectual property products (IPPs). Using publicly available national accounts and sector-specific sources, AI investments are estimated by applying AI intensity coefficients derived from patent data, academic programmes, and workforce statistics. The estimates highlight how AI investments are distributed across EU countries. The methodology also disaggregates investments in areas such as Information and Communication Technologies specialist remuneration, Corporate training, Software and databases, and Telecommunications equipment. This work supports efforts to measure the evolving AI investment landscape in the EU.

Résumé

Ce document présente une méthodologie d'estimation des investissements publics et privés en intelligence artificielle (IA) dans les États membres de l'Union européenne (UE). Il se concentre sur les actifs et les capacités. Il catégorise les investissements en quatre groupes : compétences, recherche et développement, données et équipements, et autres produits de propriété intellectuelle. À partir des comptes nationaux accessibles au public et de sources sectorielles spécifiques, les investissements en IA sont estimés en appliquant des coefficients d'intensité de l'IA dérivés des données sur les brevets, des programmes universitaires et des statistiques sur la main-d'œuvre. Les estimations montrent la répartition des investissements en IA entre les pays de l'UE, en mettant en évidence les priorités nationales. La méthodologie détaille également les investissements dans des domaines tels que la rémunération des spécialistes des technologies de l'information et de la communication, la formation en entreprise, les logiciels et bases de données, et les équipements de télécommunications. Ce travail soutient les efforts visant à mesurer l'évolution des investissements en IA dans l'UE.

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Executive summary

Despite growing global interest in quantifying investments in artificial intelligence (AI), the lack of standardised frameworks and inconsistent data make reliable and comparable estimates scarce. This report proposes a robust and transparent measurement framework to address this challenge and estimate AI investments across EU countries and selected third countries[1].

The framework defines AI as a general-purpose technology with transformative potential across sectors, requiring substantial investments not only in core technology, but also in complementary assets such as skills, data, hardware, and organisational capital. It classifies investments into four main groups: Skills, Research and development (R&D), Data and equipment, and Other intellectual property products (IPP).

The methodology follows a two-step approach. First, it gathers economy-wide aggregates from official data sources, including Eurostat and the EUKLEMS & INTANProd databases (Bontadini et al., 2023[1]). Second, it applies AI intensity coefficients derived from patent data, educational statistics, and AI-specific Academic programmes. The coefficients serve as multipliers to estimate the AI-specific portion of total investments.

Several **key findings** emerge from this research:

- The estimated total AI investment in the EU27 for 2023 ranges between 220 and 294 billion euros, with a baseline estimate of 257 billion euros.
- Private sector investments account for approximately 73% of the total, emphasising the significant role of private funding in AI development.
- The largest investment categories are Skills (40.97%) and Data and equipment (37.11%), followed by R&D (12.99%) and Other IPP (8.93%).
- Germany, France, and the Netherlands stand out as the leading investors, driven predominantly by Skills and Data and equipment.
- The report also compares EU27 AI investments in R&D, Data and equipment with those of the United States, Canada, the United Kingdom, and Japan.
- The United States leads, investing approximately 90 billion euros in AI R&D alone in 2023.

This framework provides estimates of AI investments using a transparent and comprehensive methodology. There are, however, inherent limitations related to data availability and calculating proxies for AI intensity. The findings underscore the need for continuous methodological advancements to track AI investments accurately, supporting evidence-based policymaking.

1 Introduction

Measurement approaches and challenges

Despite rising global interest in measuring AI investment, reliable and comparable estimates remain scarce. While policymakers, businesses, academia, and the media see AI as transformative, the landscape of AI investment is clouded by fragmented data, inconsistent methodologies, and a lack of standardised measurement frameworks. News headlines, political announcements, and corporate press releases frequently highlight ambitious AI funding commitments, yet these figures often lack transparency, comparability, or verification.

The noise around AI investment data arises from the diverse nature of reported figures. Some numbers reflect actual expenditures, while others represent soft commitments, budget allocations, or multi-year political plans. Furthermore, AI investment data often conflate different scopes, sometimes only including research and development (R&D), while at other times encompassing broader uses such as military AI. This variation makes it challenging to distinguish between real financial flows and forecasts.

While statistically sound methodologies are being developed under the System of National Account (SNA) framework (see below) and the Frascati Manual (for R&D), these inclusive and universally accepted frameworks will take time to be finalised, endorsed and implemented. This situation underscores the need for a rigorous approach that can provide robust, cross-country estimates of both public and private AI investment, offering a clearer foundation for policy and economic analysis.

Selected studies and measures

Quantifying public investment in AI is challenging because there is no standardised and comparable data across countries. Nonetheless, a few studies provide insights into public investments, in particular.

AI Watch, an initiative of the European Commission's Joint Research Centre (JRC), published reports estimating AI investments within the EU, following a macroeconomic modelling approach based on national accounts data (JRC, 2022[2]). A 2022 report by AI Watch estimated that in 2020, the EU invested between €12.7 and €16 billion in AI, marking a growth of 20-28% from the previous year (JRC, 2022[2]).

The Brookings Institute analysed the United States of America’s federal AI spending using a bottom-up method to aggregate projects, revealing a $4.6 billion rise in AI R&D spending from August 2022 - August 2023 (Brookings, 2024[3]). Eticas followed a similar micro-level approach (Eticas, 2023[4]) to estimate the EU's allocation of €10 billion to AI projects between 2014 and 2020. Using data scraped from various EU funding sources, the study identifies sectoral trends and offers recommendations at different levels. The OECD also looked at the potential of micro-level analysis of AI R&D, using decentralised data from national sources (Yamashita et al., 2021[5]). However, these studies use very different definitions, methodologies and data sources and therefore cannot be easily compared.

Information regarding the People’s Republic of China (hereafter “China”) is even scarcer. The Center for Security and Emerging Technology (CSET) estimated China’s investment in AI R&D (CSET, 2019[6]) in a 2023 blog post. The study uses a two-step approach: first, it analyses macro-level R&D data from the

Ministry of Finance; second, it applies AI intensity coefficients derived from research funding programmes to estimate AI-specific expenditures. The report distinguishes between civilian and military investments, offering critical insights into the interplay between public and private sectors, particularly through government guidance funds. These findings show how state-led initiatives shape AI innovation ecosystems in China.

Quantifying private sector AI investments is equally challenging. Yet, several organisations and firms provide estimates, though methodologies and coverage vary. Preqin, a leading provider of financial data, offers insights into venture capital and private equity investments in AI-focused startups and companies. Similarly, Stanford University's Human-Centered Artificial Intelligence (HAI) Institute publishes the AI Index Report, which tracks global private investment trends in AI, including funding, sectoral allocation, and geographical distribution. Despite data standardisation challenges, these sources help understand the landscape of private AI investment.

Public and private investments in AI

Public investment theory suggests that government intervention is necessary to address market failures, particularly when private investment is insufficient due to high risk or long-term benefits. This applies to technologies like AI, which often require significant upfront costs and may generate uncertain returns. By investing in R&D, infrastructure, and education, governments can boost innovation, create new industries, and improve overall economic productivity.

Public investment in AI is expected to yield numerous and significant benefits across multiple dimensions, accelerating technological progress, economic development, and societal well-being. By reducing the financial barriers associated with high-risk, high-reward AI research, public investment can encourage people to develop and adopt AI-driven solutions. It may also support startups, and smaller enterprises, preventing market concentration and ensuring a more competitive AI ecosystem.

In public services, AI-powered solutions can revolutionise sectors such as healthcare, education, and urban infrastructure. AI-driven diagnostics, personalised medicine, and predictive analytics can improve healthcare. Intelligent tutoring systems and adaptive learning platforms can improve educational outcomes. Smart city projects use AI for traffic management, energy optimisation, and emergency response, making urban environments more resilient.

In national security, sustained public investment in AI R&D is an important tool for advancing cybersecurity, defence, and strategic intelligence. AI-driven threat detection, autonomous defence systems, and secure communication technologies can bolster national resilience against emerging cyber and geopolitical risks (National Security Commission on Artificial Intelligence, 2021[7]).

Private investment plays an equally vital role in the development and deployment of AI technologies, fostering innovation and commercialisation across industries. As public investment often emphasises foundational research and long-term societal benefits, private sector investment is mainly driven by the prospects of creating a competitive edge, cost efficiencies, and increased revenue.

Venture capital, corporate R&D, and private equity are major sources of AI financing, fuelling breakthroughs in automation, predictive analytics, and generative models (Agrawal, Gans and Goldfarb, 2018[8]). However, AI investment in the private sector is highly diverse, ranging from large-scale funding by tech giants to early-stage funding for AI startups, leading to varying levels of risk appetite and strategic focus.

While firms in technology-intensive industries, such as finance, healthcare, and manufacturing, are at the forefront of AI adoption, smaller enterprises often face barriers to investment due to high capital requirements, limited expertise, and uncertain returns (Cockburn, Henderson and Stern, 2018[9]).

Additionally, the competitive nature of AI innovation has led to concentrated investments in a few dominant firms, raising concerns about market power and industry consolidation. Despite these issues, private sector investment remains the primary driver of AI commercialisation, enabling the rapid scaling of new applications, the integration of AI into existing business models, and the acceleration of digital transformation across economies.

How to better measure AI investments using official statistics

A broad range of measurement challenges

Several factors make it challenging to find good data on public investment in AI:

- Diverse definitions of AI: AI is a rapidly evolving field with no universally accepted definition, beyond the OECD definition of an AI system included in the OECD Recommendation on AI [OECD/LEGAL/0049]. Different countries and organisations within countries may classify AI-related activities differently, making it difficult to compare investment data calculated on this ground.
- Blurred lines between AI and other technologies: AI is often integrated with other technologies, such as robotics. This makes it challenging to isolate AI-specific investments from broader technological investments or IT infrastructure.
- Diverse public funding sources: Public investment in AI can come from various sources, including government agencies, research institutions, and public-private partnerships. Tracking all these sources can be complex and time-consuming. JRC (2023[10]) has produced a useful inventory of the diverse public funding sources for the EU.
- Private investment data: Private companies often do not disclose detailed information about their AI investments, especially when considered proprietary or strategic. This makes it difficult to accurately assess the scale of private investment in AI. When available, investment data for companies that have other, non-AI activities can be difficult to interpret.
- Data confidentiality: Detailed data on AI investments in sensitive or strategic sectors such as defence or security is even more scarce.
- Rapid technological advancements: The rapid AI development quickly outpaces data collection and analysis efforts, making it challenging to keep up with the latest trends and innovations.
- The absence of robust statistical frameworks specifically designed to capture AI investments exacerbates the challenge. Traditional economic classifications often fail to adequately distinguish between AI-specific investments and broader technological expenditures. This makes it difficult to isolate and quantify the impact of AI investments on economic growth and innovation.
- Moreover, the decentralised nature of both public and private AI investment presents significant challenges for any attempts of direct surveying. Public funding can be dispersed across various government agencies, research institutions, and public-private partnerships, making it difficult to aggregate and track. Private investment in AI is even more fragmented, with investments coming from a wide range of sources, including venture capital firms, corporations, and individual investors. Surveying and tracking these diverse sources of investment is a complex and time-consuming task.

A key challenge in measuring AI is determining its valuation method. From a National Account perspective, AI investment differs from AI expenditures, as the market value of AI assets is not necessarily equivalent to their production costs. In national accounting, the valuation of own-account production of intellectual property products (IPPs) - which includes R&D, software, and data in the 2025 System of National Accounts (2025 SNA) - typically follows the sum-of-costs approach, incorporating relevant expenditures along with a mark-up to approximate market value. However, there is ongoing debate within both the statistical community and academia regarding the appropriate magnitude and methodology of this mark-up and whether investment and stock estimates of IPPs in national accounts accurately reflect their true market value. Addressing this issue remains one of the most pressing challenges for the evolution of national accounting frameworks, particularly as the impact of AI and data on the economy continue to expand.

AI in the System of National Accounts

The UN Statistical Commission adopted the 2025 SNA at its 56th Session in March 2025. For the first time, it includes AI as an IPP.

However, the current study looks at years where the previous version of the SNA (2008 SNA) was in place. In 2008 AI was not yet a priority for national accounts research and innovation. Progress on this front will be instrumental for harmonised and quality data on investment in AI. The inclusion of AI was initiated by a multistakeholder task team on digitalisation who proposed the following guidance (Inter-secretariat Working Group on National Accounts, 2025[11]):

- First, the definition of Intellectual Property Products should be updated to the result of research, development, investigation, or innovation leading to knowledge or the creation of artificial intelligence systems that the developers can market or use to their own benefit in production, because the use of the knowledge or system is restricted by means of legal or other protection.
- Second, the updated SNA should include the following definition of AI. AI is a “computer program operating a system capable of recognition, reasoning, communication, and prediction emulating human recognition, reasoning, and communication”.
- Third, AI should be explicitly mentioned in the asset classification in a new class called “Computer Software, including Artificial Intelligence Systems”, derived from the current “Computer Software and Databases” class by separating Databases (which will be merged with Data in a separate class). In this new class, AI systems would appear with an “of which” class.
- Fourth, the value of the cost of producing training datasets should be excluded from the value of own-account AI and included instead in the value of Data assets.
- Fifth, the value of the cost of recurring data services required by an AI should be excluded from the value of AI and recorded as intermediate consumption.
- Sixth, the next Central Product Classification (CPC) update should include specific groups, classes, and/or subclasses for AI systems and that this guidance note serves as the SNA drafting recommendations.
- Seventh, the International Standard Industrial Classification of All Economic Activities (ISIC) update should consider the need to clarify the classification of AI systems, and that this guidance note serves as the SNA drafting recommendations.

The SNA approach is likely to generate conservative estimates for AI investment, not because AI would be classified under the “software and databases” IPP, but because of the “sum of costs” approach followed to value it, which might not fully capture the market value of AI creation. The first national estimates for AI investments in line with 2025 SNA are expected no later than in 2029-2030. Earlier and tentative estimates are likely to be shared before by the most advanced national statistical systems, which will be immensely useful for this study’s measurement objective.

This study’s methodology recognises AI as a general-purpose technology and examines its adoption across value chains and economic sectors, including the necessary downstream investments following its development. In the SNA, this uptake can be captured in various ways, such as through the intermediate consumption of AI-related services.

AI in official surveys

Recognising the transformative potential of AI, many National Statistics Offices (NSOs) have begun tracking and reporting on AI adoption and usage through nationally representative surveys. These surveys provide valuable indicators of AI-related activity at the national level, but they do not yet explicitly capture AI investment or gross fixed capital formation.

The changes proposed in the 2025 SNA could support efforts to improve comparability of AI investment data across countries. By providing clearer definitions and classifications, particularly through proposed guidance such as the satellite accounts on AI, the revised framework may help lay a foundation for more aligned approaches, even if methodological harmonisation will still largely depend on implementation choices at the national level.

2 Measurement framework

Measurement objective, definitions and assumptions

Aware of the caveats and methodological challenges outlined in Chapter 1, this paper aims to develop a robust, comparable metric for AI investment across countries. The proposed methodology has clear limitations but relies on transparent hypotheses. The resulting estimates from this methodology should be understood for what they are: broad estimates intended to illustrate both the strengths and the limitations of the approach.

In the absence of more precise alternatives, this metric aims to provide policymakers, researchers, and international organisations with a clear, standardised framework for assessing AI investment, facilitating data-driven policy discussions and fostering deeper international collaboration. By offering a consistent and transparent measure, this paper aims to enable meaningful comparisons of AI investment on a global scale.

The metric will be designed to capture both public and private sector contributions to AI regardless of data availability disparities. Drawing on macroeconomic estimates derived from national accounts, the model will bridge the data gaps often encountered in cross-country comparisons and provide a comprehensive view of AI investment flows.

This approach will enable the aggregation of diverse investment activities, ranging from R&D expenditures to infrastructure development, skills, and other intangibles into a single, comparable framework. By establishing this metric, the paper seeks to provide an order of magnitude that enhances transparency, reduces uncertainty, and enables more informed decision-making regarding AI policy, funding priorities, and international co-operation in AI research and development.

The paper uses the OECD definition of an AI system, where "An AI system is a machine-based system that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments. Different AI systems vary in their levels of autonomy and adaptiveness after deployment" (OECD, 2024[12]).

"Investment" is defined in its broadest sense, where it refers to the allocation of resources into physical and intangible assets with the expectation of future benefits.[2] It encompasses a wide range of targets, including skill development, R&D, data, software, hardware, and ICT infrastructure. Other intellectual property products such as institutional capital, brand and design, are also considered.

The definition of investment employed in this paper differs from gross fixed capital formation as measured by national accounts in several ways. Firstly, human capital acquisition by individuals is explicitly treated as final consumption in the national accounts. Our relatively broader definition of investment is not limited to fixed assets used in production processes and can therefore include the allocation of economic agents' resources toward intangible assets. Secondly, other intangible and intellectual property products, such as own-account software, are often measured by taking a percentage of ICT specialist remuneration that represents time spent on software capital formation. However, this percentage is derived from integrated and mature technology infrastructure. The relative immaturity of AI assets and their rapid pace of development imply that both human capital formation and the entirety of its use may be considered investments under our framework.

The framework in this study builds on the work proposed by (Nepelski and Sobolewski, 2020[13]). The model is based on the same three assumptions:

- AI as a General-Purpose Technology (GPT): AI's transformative potential lies in its ability to modernise the entire economy, rather than just strengthening the AI-producing sector. Its impact extends across industries by enhancing productivity and innovation. This assumption is reflected in the categories of investment and in the operational definition of AI considered, particularly in defining AI intensity coefficients, including AI patents.
- The need for complementary investments: Successfully leveraging AI requires more than just investing in software (proposed approach in SNA) and core technology development. Widespread adoption depends on substantial investments in complementary assets such as human skills, data, hardware and ICT, and Organisational capital to ensure AI's integration across sectors.
- The coexistence of public and private Investment: Both sectors play crucial and complementary roles in AI's development and diffusion. A balanced investment strategy is essential for AI adoption at scale.

Given these principles, the framework takes a broad approach to AI investments. It includes expenditures on labour, skills, physical capital, and intellectual property products by public and private entities, aimed at developing and deploying AI to enhance business processes, improve existing products, and create new services.

A measurement framework applicable to a general-purpose technology

The literature on investment in GPTs highlights their potential to generate significant spillover effects and positive externalities. AI, widely recognised as a GPT, has the ability to revolutionise multiple industries and sectors, resulting in notable productivity gains and economic growth (Brynjolfsson and McAfee, 2014[14]). However, due to their inherent uncertainty and high upfront costs, private sector investment in GPTs might be inadequate (Arrow, 1972[15]). Public investment can play an essential role in mitigating market failures and encouraging research and development in these fields. This can be achieved through various mechanisms, such as direct funding for research organisations, tax incentives, and public-private partnerships. By backing basic research, promoting technological innovation, and building the necessary infrastructure, governments can help realise the full potential of GPTs and make sure their benefits are broadly shared across society (Malerba, 2004[16]; Jones and Williams, 2000[17]).

Like other GPTs, AI requires comprehensive investment and support to drive innovation and enhance competitiveness at both firm and national levels (Nepelski and Sobolewski, 2020[13]). This involves funding the entire innovation value chain, from early-stage research and technology development to market commercialisation, while ensuring both AI-producing and AI-using sectors benefit. Beyond direct investments in AI technology, resources must also be allocated to complementary assets such as skills, software, data, and organisational capital. The successful integration of AI into businesses depends on a combination of technical, managerial, and financial expertise.

From an economic perspective, GPTs enhance productivity by improving the efficiency of labour and capital, ultimately contributing to GDP growth. AI adoption drives this process by augmenting production inputs, increasing output, and fostering long-term economic expansion. The investment framework presented in this study, therefore, categorises expenditures based on their role in both AI creation and application across industries, ensuring that businesses can effectively integrate AI into their operations and maximise its economic impact.

The framework identifies expenditure categories that are pertinent to the development and deployment of AI technology by producers throughout various sectors of the economy, in terms of enhanced capital and labour inputs. As such, the framework considers investments in both tangible and intellectual property products, as well as labour costs. Additionally, since effective AI implementation means reorganising companies around new technology, along with new organisational practices and staff training, the framework also includes expenditures on Organisational capital.

The methodology differentiates between public and private sector investments, recognising their distinct roles in advancing AI. Public investments mainly support foundational research and public service applications, while private investments concentrate on development, adoption, and commercialisation. This distinction offers a clearer understanding of resource allocation and emphasises the complementary functions of the two sectors.

Investment categories and sub-categories

In line with our definition of “investment”, the study identifies areas where resources are directed to foster AI development, uptake and impact. These areas are grouped into four categories and ten subcategories, in-line with the framework proposed by (Nepelski and Sobolewski, 2020[13]).

Skills

Investments in AI-related skills predominantly focus on developing technical competencies, such as programming, machine learning, and data analysis, which are essential for creating and implementing AI technologies. These technical skills enhance the accessibility of AI for enterprises, influencing both the creation of human capital for technological development and the application of AI in organisational processes.

However, the deployment of AI technologies in real-world business environments also requires specialised managerial competencies. These include the ability to recognise opportunities for AI adoption and to effectively integrate these technologies across diverse economic sectors. By broadening investments to include both technical and managerial skillsets, public spending on AI education and training contributes to both innovation and the scalable application of AI solutions. Therefore, this category includes:

- Compensation of Academic teachers,
- Compensation of AI ICT specialists,
- AI-related corporate training.

Research and Development (R&D)

According to the System of National Accounts (2008 SNA), R&D consists of the value of expenditures on creative work undertaken systematically to increase the stock of knowledge, including knowledge of man, culture and society. The use of this stock of knowledge to develop new applications for AI R&D expenditures plays a pivotal role in driving innovation.

Data, software and equipment

The availability and accessibility of high-quality data, coupled with relevant software and ICT infrastructure, are crucial determinants of AI development, uptake and impact. Public investments in this domain enhance AI’s technological backbone. The data sources used for this target come from SNA, with some well-known limitations, particularly in terms of the data sub-category. However, in 2008, the SNA data were not properly valued; more guidance is being made available in the 2025 SNA.

Consequently, this category contains AI-related investments in:

- *Computer hardware:* It refers to the physical components of a computer system that enable processing, storage, and connectivity. It includes computers and peripheral equipment (e.g., servers, desktops, laptops), data storage devices (e.g., SSDs, HDDs), and networking and processing hardware (e.g., GPUs, CPUs).
- *Computer software and databases*: In 2008 SNA, computer software consists of computer programs, program descriptions and supporting materials for both systems and applications software. Databases consist of files of data organised in such a way as to permit resource-effective access and use of the data. (2008 SNA).
- *Telecommunications equipment*: It comprises network infrastructure (e.g., routers, switches, fiber optics), broadcasting and communication devices (e.g., antennas, satellites, modems), mobile and fixed communication systems.

Other intellectual property products

Investments in intellectual property products aim to build organisational readiness, fostering environments where AI solutions can be adopted seamlessly and scaled effectively. This form of capital ensures that firms can align their structures and practices with the transformative potential of AI.

Under this category:

- *Organisational capital* refers to the stock of knowledge within a firm about how the organisation functions. The range of tasks identified by existing studies as crucial for generating and accumulating organisational knowledge includes: developing objectives and strategies; organising, planning, and prioritising work; building teams, matching employees to tasks, and providing training; supervising and coordinating activities; and communicating across and within groups to offer guidance and motivation.
- *Brand equity* refers to the value a Brand holds in the minds of consumers based on perceptions, recognition, and loyalty. It contributes to a company's competitive advantage by influencing consumer preferences, pricing power, and overall market positioning. Strong Brand equity is built through factors such as Brand awareness, perceived quality, customer loyalty, and positive associations.
- *Product Design* is the strategic process of creating and developing products that balance functionality, aesthetics, user experience, and market viability. It encompasses everything from conceptualisation and prototyping to final production, ensuring that products meet user needs while aligning with business goals. In a broader sense, Product Design integrates human-centred design principles, technological innovation, and sustainability to craft solutions that are both practical and desirable.

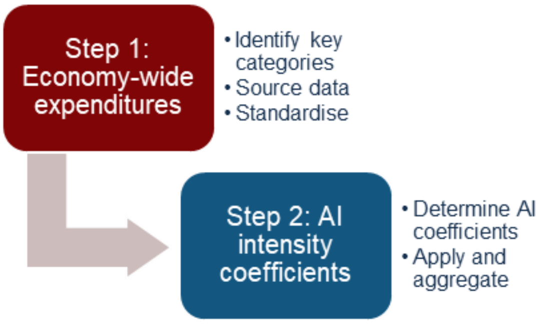
The specific data sources used for each of these categories and sub-categories, as well as the overall methodology, are detailed in the following section.

3 Data sources and methodology

This methodology builds on Nepelski and Sobolewski (2020[13]) using a two-step approach. In the initial step, data on economy-wide aggregates related to the specified investment categories from Chapter 2 are gathered, mainly from official sources (including national accounts). In the second step, these expenditures are weighted using AI intensity coefficients to determine the share related to AI development and adoption.

This section presents the overall methodology and the data sources utilised for the investment targets and AI intensity coefficients.

Figure 3.1. Top-down approach for measuring AI investment



Data sources

Economy-wide aggregates

The methodology draws extensively on Eurostat data, which provide comprehensive and comparable statistics on economic activities, including expenditures categorised by public and private sectors. National Accounts data are key for analysing investment flows, as they distinguish between public-sector activities and private-sector activities. Most Eurostat datasets thus use aggregation levels of the NACE Rev.2 classification to define industry breakdowns. The NACE Rev.2 classification (*Nomenclature générale des Activités économiques dans les Communautés Européennes,* General nomenclature of economic activities in the European Communities) is a widely used statistical classification for economic activities.

The methodology further leverages Eurostat's ICT statistics, which encompass the status of digital infrastructure and technological adoption across the EU. These statistics are crucial for understanding spending on AI-enabling technologies, such as computing hardware, software, and telecommunications equipment.

Eurostat’s educational statistics are instrumental in gauging investments in AI-related competencies. They include Compensation for academic teachers and provide data on the aggregate populations of teachers and academic staff.

The EUKLEMS & INTANProd data supplement Eurostat's by offering detailed data on investments in intangible assets across a broad spectrum of countries and industries. While these data are based on estimates, the database contains information for EU27 countries, the UK, and the US.

Table 3.1.Overview of datasets by investment item

Category	Investment Item	Dataset
Skills	ICT specialist compensation	Eurostat – National Accounts (nama_10_a64_e, lc_lci_lev, isoc_sks_itspe)
	Academic teacher compensation	Eurostat – National Accounts (educ_uoe_fini01)
	Corporate training	EUKLEMS & INTANProd (LUISS)
R&D	Research & Development	Eurostat – National Accounts (nama_10_a64_p5)
Data and equipment	Computer hardware	
	Computer software and databases	
	Telecommunications equipment	
Other intellectual property products	Organisational capital	EUKLEMS & INTANProd (LUISS)
	Brand	
	Design	

Note: Based on Nepelski and Sobolewski (2020[13])

AI shares of investments

To estimate the AI-related share for each investment category, a set of specific intensity coefficients were developed. These coefficients are constructed as shares and serve as multipliers for the aggregate expenditure data. These coefficients proxy the AI-specific portion of each investment category. Each investment item is matched with exactly one coefficient that best captures its AI intensity. However, in the case of R&D, an average of two coefficients was used. The coefficients are derived from various data sources, including patent data from the OECD, Academic programme information from StudyPortals and UNESCO World Higher Education Database (WHED) Portal.

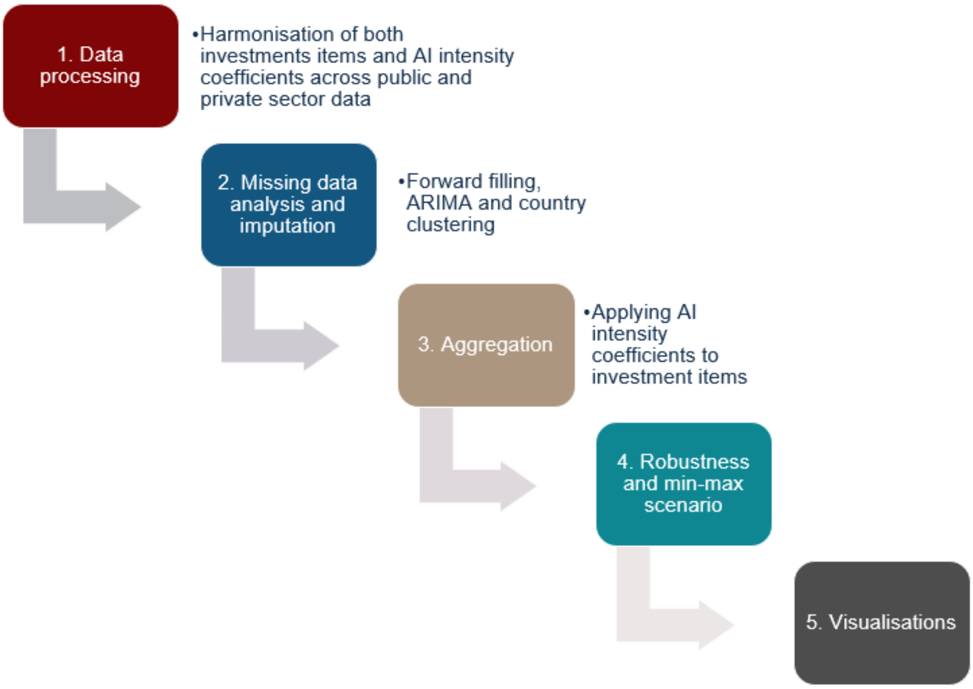
Table 3.2. Overview of datasets used for the AI intensity coefficients

Category	Investment Item	AI intensity coefficient applied	Dataset
Skills	ICT specialist compensation	% AI ICT specialists in country's total number of ICT specialists	JRC and Eurostat
	Academic teacher compensation	% of AI university programmes in country's total programmes	StudyPortals and World Higher Education Database (WHED) Portal
	Corporate training	% of AI patents in country's number of patents	OECD based on OpenAlex and PATSTAT
Other intellectual property products	Organisational capital		
	Brand		
	Design		
R&D	Research & Development	% of AI patents in country's total number of patents AND % of AI publications in country's total number of publications	
Data and equipment	Computer hardware	% of AI patents in country's total number of ICT patents	
	Computer software and databases		
	Telecommunications equipment		

Data pipeline

The data processing pipeline consists of five sequential stages. The process begins with data harmonisation to align investment items across public and private sectors. The second stage addresses data quality through comprehensive missing data analysis and imputation, to achieve complete coverage for all EU countries. This necessitated the implementation of multiple imputation techniques, including ARIMA modelling and country clustering methodologies, selected based on the specific characteristics of the datasets at hand. Subsequently, the aggregation phase involves the application of AI intensity coefficients to the corresponding investment items. The fourth stage implements robustness checks and develops min-max scenarios to ensure analytical reliability. The final step in the pipeline is the visualisation stage, where the processed data is transformed into interpretable graphical representations.

Figure 3.2. Data pipeline



Compiling data on investment items

The public sector is defined as NACE Rev.2 categories O (Public administration and defence; compulsory social security), P (Education), and Q (Human health and social work activities). The private sector is then derived as the remainder of economic activities.

To estimate ICT specialist compensation across public and private sectors, a multi-step approach combining several Eurostat datasets was developed:

1. Average Annual Hours Worked: Using nama_10_a64_e dataset, average annual hours worked per worker by sector was calculated. Public sector hours worked are the sum of hours in categories O, P, and Q, while the private sector was derived as total hours minus public sector hours.
2. Average Hourly Labor Costs: Using lc_lci_lev dataset, the study determines average hourly labor costs. After having selected for ‘Labour cost for LCI (compensation of employees plus taxes minus

subsidies)', for the public sector, it uses categories P and Q, while the private sector is represented by the business economy [B-N]. Notably, category O couldn't be included in this step due to dataset limitations. This creates a partial mismatch in sector definitions between steps 1 and 2, which is acknowledged as a methodological limitation.

3. Annual Labor Cost per Worker: This is calculated by multiplying the average hourly labour costs by average annual hours worked per worker for each sector.
4. Total ICT Specialist Compensation: The final calculation is made by multiplying the annual labour cost per worker by the number of ICT specialists (from the isoc_sks_itspe dataset).

The methodology assumes that **ICT specialist compensation** patterns follow overall sector-specific labour costs. However, there are important dataset mapping limitations to consider. Different NACE categorisations across datasets create imperfect sector mappings, particularly as the private sector definition varies between steps (total minus O,P,Q in step 1 versus business economy [B-N] in step 2). However, it is assumed that the method of combining different NACE breakdowns across datasets (between nama_10_a64_e and lc_lci_lev) provides valid comparisons despite their different categorisation structure. Additionally, it is assumed that the exclusion of categories A (agriculture) and T-U (activities of households and extraterritorial organisations) has minimal impact on results. Alternative datasets were considered (earn_ses_hourly and lfsa_esegn2), but these were ultimately deemed unsuitable due to their inadequate NACE category coverage and redundancy with the selected approach.

Data for **Other intellectual property products** and **Corporate training** investments were sourced from the EUKLEMS & INTANProd database, maintained by the Luiss Lab of Economics and Energy Transition. This database, developed as part of the WIPO-Luiss Business School Partnership "Intangible Assets in the Global Economy: Better Data for Better Policy," represents a significant advancement in measuring intangible investments. The database's analytical module was used to extract investment figures for Organisational capital (I_OrgCap), Brand equity (I_Brand), Design (I_Design), and corporate training (I_Train). These figures are expressed as gross fixed capital formation (GFCF) in current prices and national currencies. It should be noted that these variables represent investments in intangible assets that extend beyond those traditionally captured in National Accounts. This extension follows the methodological framework established by INTAN-Invest. To ensure consistency in our analysis, all values were converted to euros using European Central Bank exchange rate time series data.

For **Data and equipment** and **R&D**, this study relies on Eurostat's National Accounts data, specifically the nama_10_a64_p5' dataset (Capital formation by industry (NACE Rev.2) and detailed asset type). Three assets were selected for analysis: Computer software and databases, Telecommunications equipment, and R&D. As in previous steps, NACE categories O through Q are classified as public investments, while all the remaining categories are treated as private. **Data and equipment** and **R&D** investments also relies on the 'nama_10_nfa_fl' dataset (Cross-classification of gross fixed capital formation by industry and by asset (flows)). This dataset provides detailed information on CFCF across different industries and asset types. The data is reported in current prices in million euros and offers a breakdown of capital formation across EU Member States, though with some data gaps for some countries addressed in a subsequent step.

To calculate the **Academic teacher compensation**, this study uses Eurostat's dataset "educ_uoe_fini01," which compiles data on educational institutions' expenditures by educational level, programme orientation, institution type, and expenditure category. Data are then filtered to identify "expenditure for compensation of teachers (with active teaching responsibilities)" in tertiary education, encompassing ISCED categories 5-8, and included all relevant institution types. The data are expressed in million euros. It is important to note that this expenditure encompasses all institutions providing educational services, thus precluding the possibility of distinguishing between public and private sectors. Consequently, all expenditures were allocated to the public sector.

Missingness analysis and imputation

Imputing missing data was necessary to build a comprehensive dataset on AI investments across EU countries. The following details the imputation strategies across investment categories.

For datasets where only 2023 values were missing and where historical data was limited, a simpler forward-filling imputation method was adopted. For **Other intellectual property products**, where data was available from 1995 to 2021, ARIMA was employed (Autoregressive Integrated Moving Average) to estimate 2023 values. The extensive time series, which spanned 26 years of historical data, rendered ARIMA particularly well-suited for this imputation, as it is adept at capturing both trends and seasonal patterns inherent in the data. Given the generally stable and progressive nature of intangible investment patterns, this statistical forecasting approach provided reliable estimates for the missing years.

To address missing data in **R&D** and **Data & equipment** investments from Eurostat, particularly for countries where disaggregated asset data were unavailable, a country-clustering imputation approach was implemented. This method relies on the economic and structural similarities between EU countries to estimate missing values while accounting for differences in economic scale. Specifically, for each country with missing data (see Table 3.3. Missing value imputation for Eurostat data), a pair of reference countries with similar economic characteristics (development level, regional proximity, and economic structure) were identified. Only public sector data was missing from the dataset for 2023, so public-private sector ratios for each investment item with missing data were calculated. The average of these ratios was then applied to the investment of the country with missing data. This approach assumes that countries with similar economic structures and development levels are likely to have comparable public investment patterns. For example, missing data for Germany was approximated using public-private ratios from Austria and Sweden, while missing data from Poland were estimated using Czech and Slovak data. This method provides estimates that are more economically sound than simple averages, as it accounts for both structural similarities while taking into account the data available for that country.

Table 3.3. Missing value imputation for Eurostat data

	Missing values
R&D	Bulgaria, Cyprus, Poland
Computer hardware	Bulgaria, Germany, Croatia, Hungary, Poland
Software and databases	Bulgaria, Cyprus, Croatia, Poland
Telecommunications equipment	Bulgaria, Germany, Croatia, Hungary, Poland

Notes: Only public sector disaggregation were missing for these countries, total investment for each category was available and used for imputation.

In order to address the issue of missing data concerning **Academic teacher compensation** after 2021, a forward-fill approach was initially implemented, under the assumption that the 2021 values would remain constant through 2023 for the variables with available data. This assumption, while strong, was deemed necessary in light of the limitations in the data. For the residual missing values, a GDP-based country-clustering imputation approach was employed, leveraging economic and structural similarities between European countries.

AI-intensity coefficients

This methodology operates at the macro level since granular firm-level data on AI expenditures are not readily available. Thus, it relies on two key assumptions about market dynamics. First, the structure of technology demand is assumed to mirror the structure of technology supply. For example, if 20% of available software products in the market incorporate AI capabilities, it is assumed that approximately 20%

of corporate software spending is AI-related. Secondly, patent data are used to approximate the supply structure. For instance, if 15% of software patents is AI-related, it is assumed that a similar proportion of the value of software products in the market is AI-related.

These assumptions have a direct impact on the estimation of AI investments. When the AI intensity coefficients are applied to total investment figures, it is assumed that the share of AI in these broader categories follows the same distribution as the proxy indicators. For instance, if AI-related patents represent 5% of a country's total patents, it is assumed that 5% of that country's R&D expenditure is AI-related. While this approach offers a systematic method for estimating AI investments across countries, it has limitations. It might not capture market-specific dynamics such as accelerated AI adoption in certain sectors, temporary AI hype effects, or the gap between patented technologies and their actual market implementation. However, in the absence of detailed firm-level data on AI spending, these assumptions provide a reasonable framework for approximating AI investments at the national level.

The **AI patent data** used in this analysis come from (OECD, 2025[18]), and they are based on Patent Cooperation Treaty (PCT) applications filed between 2018 and 2021, extracted from the PATSTAT Global 2023 Autumn database. Due to the inherent lag in patent reporting and processing, the analysis uses 2021 data as the most recent observation point for AI intensity calculations. The identification of AI patents follows a dual approach: patents are classified as AI-related if they either belong to specific "core AI" Cooperative Patent Classification (CPC) groups (such as machine learning or pattern recognition) or appear in AI-related groups while containing relevant AI keywords in their title or abstract. Overall, this is in line with the GPT nature of AI. It is necessary to acknowledge the pivotal role these patent-based AI coefficients play in the final investment estimates of this analysis, as they function as multipliers for several major investment categories, including R&D, data and equipment, and intangible assets.

Several countries do not have AI-related patents, and it is therefore assumed that no investment expenditure in the corresponding categories is AI-related. This is a potential drawback with our framework, and variations in patent-based AI coefficients can substantially impact our final estimates.

The mapping between AI intensity coefficients and investment categories is based on economic and technological rationales. The ratio of **AI patents to total patents in a country**, when applied to R&D, Training, and Other intangible investments, serves as a proxy for AI-related expenditure in these categories. This approach relies on the assumption that a country's patent portfolio structure reflects the distribution of its innovation and development activities across different technological domains.

For digital infrastructure investments (Computer hardware, Software and databases, Telecommunications equipment), the **ratio of AI patents to ICT patents** was applied. The reasoning is that ICT patents represent the universe of available digital technology products and solutions, and thus the share of AI patents within ICT patents indicates the relative importance of AI within digital technologies. This provides a reasonable approximation of what portion of digital infrastructure related investments is likely AI-focused.

For ICT specialist compensation, the analysis uses the direct **ratio of AI ICT specialists to ICT specialists**, which most accurately reflects the share of the technical workforce dedicated to AI development and deployment. AI ICT specialists' data at the country level were not directly available. Therefore, these were proxied by the number of available places in university programmes with AI content (JRC, 2022[2]). Data were available for EU Member States for the 2020-21 Academic year. The number of ICT specialists was obtained from Eurostat (isoc_sks_itspe). Selection was limited to specialists with tertiary education.

The use of the **AI publications ratio** as an additional weight for R&D expenditure acknowledges that scientific research output is a particularly relevant indicator for fundamental technological development in AI. The AI intensity coefficient is calculated as the ratio of AI-related publications to total research publications for each country, using data from OpenAlex.

Finally, the **ratio of AI university programmes in a country's total university programmes** was applied to the Compensation of academic teachers. Studyportals, a global platform that consolidates information on English-taught study programs, compiles data on AI university programs worldwide. The 2023 dataset was filtered and categorised by country. To maintain consistency, AI courses offered through online platforms were excluded, as their enrolment and geographic distribution could not be accurately tracked. Data on the total university courses across the world were not available. Hence, the study uses a proxy by re-elaborating data on the total number of universities per country provided by the World Higher Education Database (World Higher Education Database, 2024[19]). The number of universities – public and private – in each country was multiplied by the average number of courses that universities worldwide offer. The absence of a definitive figure led to the examination of the average courses offered by a sample of universities across the EU, which resulted in the conclusion that 200 was an adequate amount. The ratio between AI-related courses and total courses was subsequently computed.

Table 3.4. Descriptive statistics of the AI intensity coefficients

	min	mean	median	max
% AI ICT specialists in country's total number of ICT specialists	0	0.156	0.150	0.568
% of AI university programmes in country's total programmes	0.0002	0.004	0.002	0.025
% of AI patents in country's number of patents	0	0.031	0.027	0.082
% of AI patents in country's total number of ICT patents	0	0.279	0.207	1.33
% of AI publications in country's total number of publications	0.099	0.140	0.141	0.227

Notes: For patents coefficients, 2021 is the reference year. Other descriptive statistics for the remaining coefficients are for the year 2023. AI patents are defined separately from ICT ones. ICT patents are based on a selection of technology classes, as described in Inaba and M. Squicciarini (2017[20]). AI patents rely on a mixed approach looking at a selection of keyword in the patent abstract and classification codes. This allows for the % being >1.
Sources: Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

4 Results

EU27 level

The analysis indicates that the aggregate amount of investments in AI across the EU in 2023 ranged between 220 and 294 billion euros, as illustrated in Table 4.1. Private sector investment in AI significantly outweighs public investment across the EU27, accounting for approximately 73% of total AI investments in 2023. In absolute terms, private sector AI investments reached 188 billion euros, compared to 69 billion euros from the public sector.

Table 4.2 shows that Skills constitute the largest share of total AI investment at 40.97%, totalling 105 278 million euros, followed closely by Data and equipment (95 359 million euros).

Table 4.1. AI investment highlights in 2023 for EU27

EU27	Total (billion euros)
Baseline scenario	257
Min scenario	220
Max scenario	294

Note: For methodological details concerning the min-max scenario, see Chapter 5.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Table 4.2. AI investment by category in 2023 for EU27 under the baseline scenario

Category	% of total	Million euros
R&D	12.99	33 393
Data and equipment	37.11	95 359
Other intellectual property products	8.93	22 943
Skills	40.97	105 278

Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

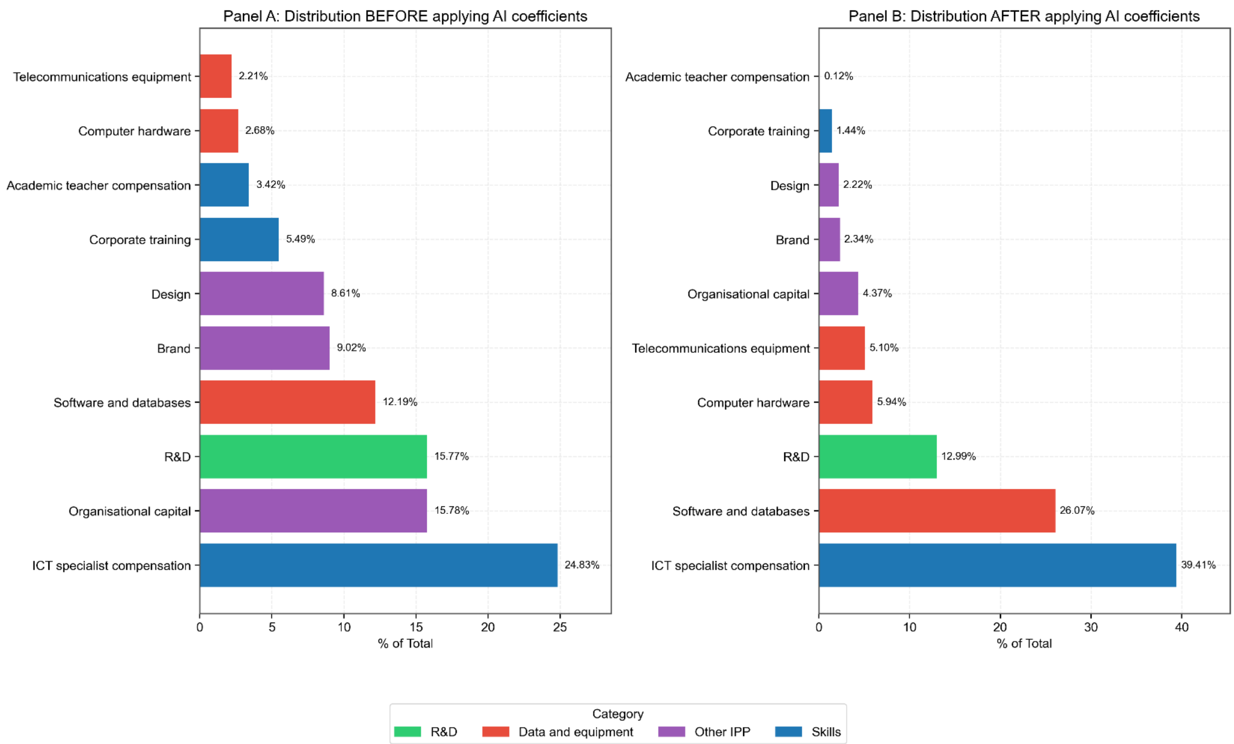
Table 4.3. EU27 AI investments in 2023 by category (percentage)

	R&D	Data and equipment			Other intellectual property products			Skills			
Investment items	R&D	Computer hardware	Software & databases	Telecommunications equipment	Brand	Design	Organisational capital	ICT specialist compensation	Teacher compensation	Training	**Grand Total**
Private	10.89	4.86	22.99	4.64	2.21	2.07	3.92	20.56		1.01	73.14
Public	2.11	1.07	3.09	0.46	0.13	0.15	0.45	18.86	0.12	0.43	26.86
Grand Total	12.99	5.94	26.07	5.10	2.34	2.22	4.37	39.41	0.12	1.44	100.00

Note: Values are percentages. Baseline scenario. Values may not add up exactly to the Grand Totals due to rounding. Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), Identifying emerging AI technologies using patent data: A semi-automated approach (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Table 4.3. EU27 AI investments in 2023 by category (percentage) further disaggregates investments, showing that within the Skills category, ICT specialist compensation dominates at 39.41% of the total, while Teacher compensation and Corporate training contribute minimally (1.56% combined). In Data and equipment, Software and databases lead with 26.07%, predominantly from the private sector (22.99% of the total investments), underscoring their critical role in AI development. R&D investments also show a stronger presence in the private sector, accounting for 10.89% of total investments, compared to a smaller 2.11% in the public sector.

Figure 4.1. EU27 AI investment distribution by items

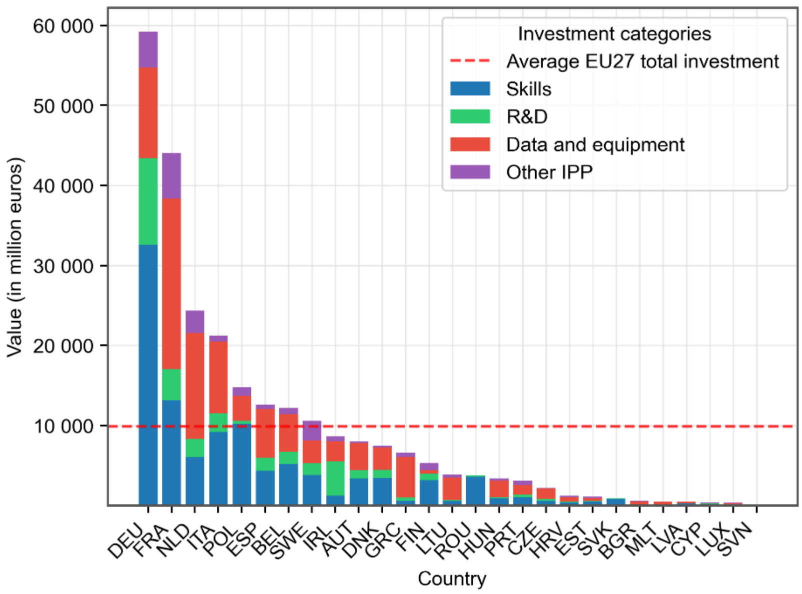


Note: Baseline scenario. IPP category refers here to Design, Brand, and Organisational capital. Panel A displays the raw distribution of investments across various categories before accounting for AI-specificity, reflecting general economic expenditure patterns. Panel B reveals the transformed distribution after applying AI intensity coefficients, illustrating the actual AI-relevant portion of each investment category and demonstrating how certain areas (notably Software and databases, and R&D) disproportionately contribute to AI investment compared to their overall economic footprint. Panel B also demonstrates the sensitivity of the measurement framework to the applied AI intensity coefficients, showing how these coefficients significantly reorder investment priorities.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

The comparison of investment distributions before and after applying AI intensity coefficients reveals significant shifts in the relative importance of different investment categories. Software and databases emerge as one of the dominant AI investment category after coefficient application, increasing from 12.19% to 26.07% of total AI investment. Conversely, Organisational capital's contribution decreases substantially from 15.78% to 4.37%. R&D remains similar after adjustment (15.77% to 12.99%), underscoring the significance of research activities in AI development. Overall, the results demonstrate that AI intensity varies considerably across investment categories, with technical components like Software and databases and R&D capturing a disproportionately large share of AI-specific investment compared to more general investments in Brand, Design, and Academic teacher compensation, the latter diminishing from 3.42% to a mere 0.12% after AI-specificity adjustment.

EU Member States level

Figure 4.2. AI investments in the EU Member States by category

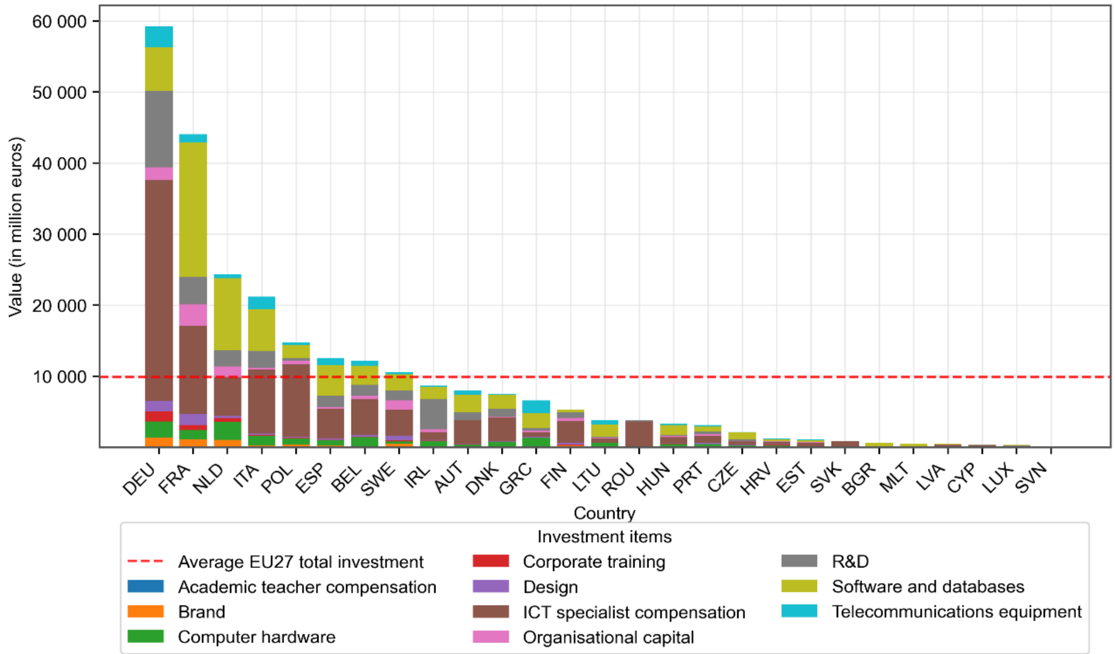


Note: Baseline scenario, 2023. IPP category refers here to Design, Brand, and Organisational capital.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Figure 4.2 reveals significant heterogeneity in AI investments across EU countries, with Germany leading at over 59 229 million euros, predominantly driven by Skills, followed by France and Poland, heavily weighted toward Data and equipment. Skills investments are consistently prominent across most countries, while R&D and Other intellectual property products contribute modestly.

Figure 4.3 complements the broader categorisation in Figure 4.2 by offering insight into which assets are prioritised within each country's AI investment strategy. For example, Germany features a significant concentration of investments in ICT specialist compensation, highlighting a strong emphasis on human capital. Across most EU countries, ICT specialist compensation emerges as a dominant investment item. Meanwhile, categories such as Corporate training, Software and databases, and R&D vary in prominence depending on national priorities and economic structures.

Figure 4.3. AI investments in EU Member States by investment items



Note: Baseline scenario, 2023.

Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

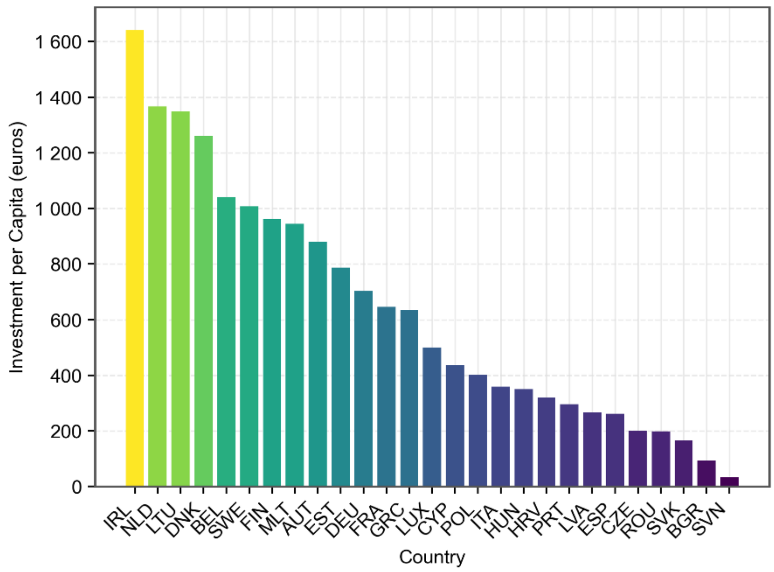
Figure 4.4. Public vs private AI investments by EU Member State

Note: Baseline scenario, 2023.

Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Figure 4.4 highlights varying sectoral contributions across EU27 countries. Private sector investments dominate in most nations, often accounting for 60–80% of total AI investment, as seen in Germany, France, and Sweden.

Figure 4.5. AI investments per capita in EU Member States



Note: Baseline scenario, 2023.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

The distribution of AI investments shifts significantly when examined on a per capita basis (Figure 4.5). Ireland emerges as the top investor, allocating more than 1 600 euros per capita to AI-related expenditures. Overall, there is substantial variation in per capita AI investment across EU Member States.

Table 4.4. AI Investments by EU Member State and by investment item

Country	Brand	Computer hardware	Design	ICT specialist compensation	Organisational capital	R&D	Software and databases	Academic teacher compensation	Telecommunications equipment	Training	Grand Total
AUT	86.48	276.76	67.20	3309.76	61.77	1048.66	2465.56	9.58	628.62	51.99	8006.38
BEL	174.94	1237.91	199.40	5113.19	435.33	1537.60	2716.50	9.66	740.79	50.66	12215.98
BGR	21.58	12.07	18.78	15.31	48.92	48.13	409.30	0.09	10.60	14.11	598.87
CYP	47.13	14.67	5.64	168.82	41.68	65.69	43.23	0.36	11.58	3.79	402.61
CZE	15.37	264.60	16.72	539.75	17.21	271.39	952.44	2.26	80.85	3.46	2164.04
DEU	1283.67	2286.87	1440.06	31103.19	1761.84	10809.52	6076.56	69.38	2970.59	1427.92	59229.60
DNK	69.08	620.04	82.95	3390.47	103.11	1042.59	2025.44	6.01	96.20	40.99	7476.87
ESP	205.05	776.72	136.23	4271.60	166.80	1615.29	4340.63	28.76	995.29	41.28	12577.63
EST	51.42	69.17	24.05	509.32	53.01	49.55	231.86	0.37	70.42	15.57	1074.74
FIN	215.64	50.77	273.81	3038.38	439.91	820.10	350.62	5.94	47.30	106.49	5348.97
FRA	1088.22	1296.53	1547.70	12433.14	3046.59	3898.28	18868.60	17.16	1182.31	698.37	44076.91
GRC	144.76	1150.53	154.06	581.20	277.53	365.67	2118.96	1.22	1775.77	29.97	6599.67
HRV	51.23	209.15	56.00	276.02	59.32	96.03	185.50	0.13	156.80	143.71	1233.88
HUN	50.87	401.85	60.52	880.91	143.07	160.67	1429.05	1.00	204.90	24.21	3357.05
IRL	138.41	686.25	71.95	1104.66	382.12	4273.60	1707.17	24.23	161.23	100.07	8649.70
ITA	222.84	1330.88	187.56	8982.40	316.33	2329.94	5828.56	26.75	1832.74	156.04	21214.05
LTU	151.38	428.80	48.49	564.55	180.93	62.33	1737.87	0.96	659.07	16.39	3850.77
LUX	27.43	18.32	3.90	25.33	18.98	126.26	80.50	0.61	25.64	3.51	330.48
LVA	21.62	44.68	6.92	247.38	31.21	22.50	93.00	0.13	32.38	2.44	502.25
MLT	22.76	24.53	2.15	42.24	25.65	5.35	379.40	0.79	8.13	1.27	512.28
NLD	951.99	2569.27	333.63	5467.64	1484.83	2243.36	10180.46	61.67	542.24	505.06	24340.14
POL	353.67	908.67	185.61	10145.23	544.62	400.49	1777.97	1.10	384.18	55.34	14756.87
PRT	174.35	240.75	119.92	1024.12	254.46	319.79	752.65	1.44	180.19	43.17	3110.84
ROU	0.00	0.00	0.00	3610.15	0.00	167.70	0.00	1.01	0.00	0.00	3778.86
SVK	0.00	0.00	0.00	817.72	0.00	82.85	0.00	0.16	0.00	0.00	900.74
SVN	0.00	0.00	0.00	0.00	0.00	69.29	0.00	0.12	0.00	0.00	69.41
SWE	444.36	331.64	657.19	3616.06	1333.41	1459.96	2250.93	25.09	307.79	168.13	10594.55
Grand Total	6014.23	15251.42	5700.44	101278.55	11228.64	33392.60	67002.77	295.97	13105.60	3703.93	256974.14

Note: Baseline scenario, in million euros, 2023.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Table 4.5. AI intensity coefficients by EU Member State

Country	AI patents over ICT patents (2021)	AI patents over total patents (2021)	AI publications over total publications (2023)	AI specialists over ICT specialists' (2021)	AI degrees over total degrees (2023)
AUT	0.185	0.017	0.145	0.172	0.002
BEL	0.265	0.021	0.141	0.153	0.003
BGR	0.333	0.029	0.149	0.005	0.000
CYP	0.167	0.045	0.182	0.095	0.002
CZE	0.088	0.004	0.122	0.067	0.002
DEU	0.205	0.025	0.151	0.243	0.002
DNK	0.213	0.012	0.127	0.237	0.003
ESP	0.157	0.010	0.104	0.067	0.004
EST	0.278	0.063	0.167	0.309	0.004
FIN	0.087	0.045	0.158	0.218	0.005
FRA	0.207	0.027	0.124	0.093	0.001
GRC	0.831	0.077	0.157	0.150	0.001
HRV	0.500	0.077	0.114	0.101	0.001
HUN	0.500	0.031	0.124	0.166	0.002
IRL	0.319	0.034	0.130	0.058	0.009
ITA	0.167	0.010	0.137	0.227	0.005
LTU	1.333	0.082	0.129	0.194	0.005
LUX	0.095	0.007	0.227	0.008	0.025
LVA	0.250	0.027	0.100	0.192	0.001
MLT	0.333	0.021	0.142	0.077	0.013
NLD	0.331	0.040	0.148	0.105	0.011
POL	0.405	0.030	0.103	0.293	0.000
PRT	0.190	0.043	0.129	0.105	0.001
ROU	0.000	0.000	0.147	0.568	0.001
SVK	0.000	0.000	0.154	0.203	0.000
SVN	0.000	0.000	0.130	0.000	0.001
SWE	0.104	0.050	0.141	0.101	0.009

Note: Baseline scenario. Rounded to three decimals.
Sources: OECD calculations based on Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

The distribution of AI-related investments across European countries reveals interesting patterns that reflect their industrial specialisations and technological capabilities. The Netherlands demonstrates particularly strong investment in Computer hardware (2 569 million euros) and Software/databases (10 180 million euros), which can be attributed to its prominent position in the semiconductor industry, notably through ASML's leadership in AI-enabled chip manufacturing equipment. This technological advantage is further reinforced by substantial Brand investments (952 million euros).

Germany's investment pattern emphasises its industrial strength, with the highest ICT specialist compensation (31 103 million euros) and R&D investments (10 810 million euros). Similarly, France's investment in Software and databases (18 869 million euros) and Organisational capital (3 047 million euros) can be explained by its thriving AI startup ecosystem.

Poland's high investments, particularly in ICT specialist compensation (10 145 million euros) can be explained by several factors. First, the country has emerged as a major IT outsourcing and shared services centre for Europe, attracting significant technology investment. Second, Poland's large population and growing tech workforce have made it an attractive location for multinational companies' AI development centres.

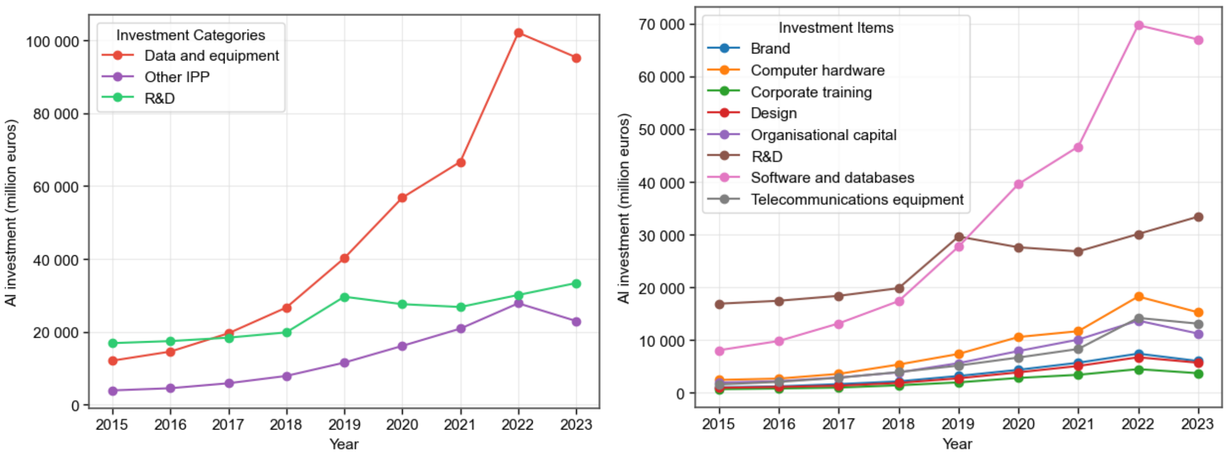
Nordic countries display distinct patterns, with Sweden showing balanced investments across categories but particularly strong in Design (657 million euros) and Organisational capital (1 333 million euros).

EU AI Investment dynamics

This analysis of AI investment trends from 2015 to 2023 reveals a dynamic evolution in both the scale and composition of investments across the EU27. While the early period (2015-2018) showed modest but steady growth, the post-2019 era marked a significant acceleration in AI investments across all categories. This section examines these temporal patterns, highlighting turning points and structural changes in both public and private investments, while decomposing growth across different investment categories and EU Member States.

The exclusion of ICT specialist compensation and Academic teacher compensation from the Skills category in the following analysis stems from data limitations. The AI intensity coefficients, specifically "% of AI university programmes in country's total programmes" and "% AI ICT specialists in country's total number of ICT specialists," are only available for 2023, preventing the construction of a time series for 2015–2023. Until alternative data sources are identified, these items are omitted to maintain analytical consistency.

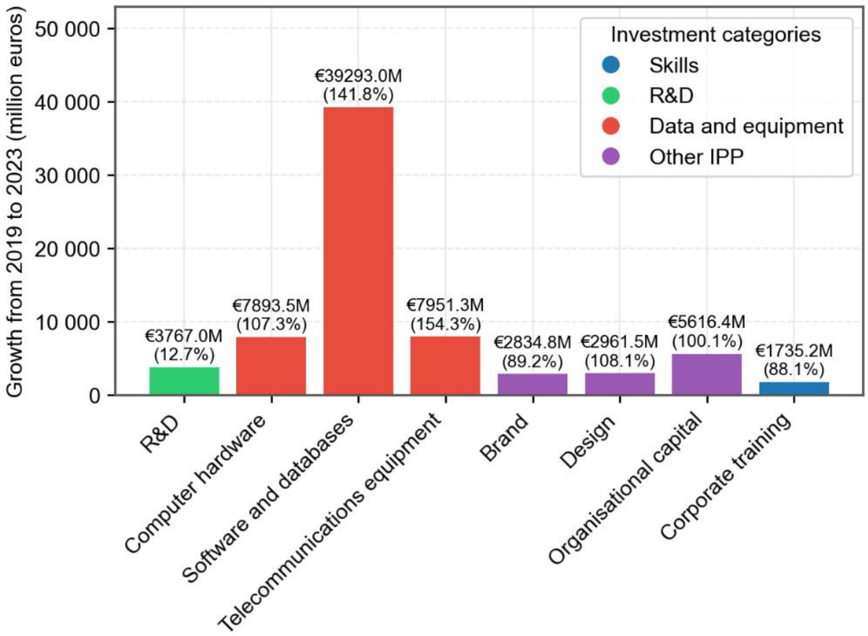
Figure 4.6. EU27 AI investment changes by category from 2015 to 2023



Note: Baseline scenario, two different breakdowns. IPP category refers here to Design, Brand, and Organisational capital
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Figure 4.6 depicts the evolution of EU27 AI investments from 2015 to 2023 under the baseline scenario, excluding skills-related investments, shown in two breakdowns: by category and by investment item. In the left panel, Data and equipment investments exhibit the most significant growth, rising from approximately 20 000 million euros in 2015 to just under 100 000 million euros in 2023, indicating its critical role in AI infrastructure. The decline in 2023 in the Data and equipment as well as in the Other IPP categories is largely the result of a decline in the share of AI patents.

Figure 4.7. EU27 AI investment change between 2019 and 2023



Note: Baseline scenario.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Figure 4.7 shows a remarkable expansion in AI investment across multiple categories from 2019 to 2023, with Software and databases experiencing the most substantial growth both in absolute (39 billion euros) and relative (141.8%) terms. This reflects the increasing centrality of software development, cloud-based AI models, and large-scale databases in Europe's AI ecosystem.

The second most striking development is the 154.3% growth in telecommunications equipment investments, signalling a major push towards AI-enabling infrastructure. This growth is likely driven by both public and private sector efforts to enhance AI computing capabilities, including expanding high-performance computing (HPC) clusters and 5G networks to support AI applications. The European Commission has been promoting AI research and innovation through Horizon Europe, which funds projects in areas such as edge AI, federated learning, and AI-driven cloud computing. The rise in telecommunications infrastructure investment suggests that EU27 countries are scaling the necessary hardware to support these developments, possibly linked to European ambitions to reduce dependency on non-EU cloud and compute providers.

Investments in Computer hardware have also surged with a staggering 107.3% growth rate. This rise could reflect increased procurement of GPUs, TPUs, and other AI-optimised hardware to reduce reliance on American and Asian semiconductor firms. The EU's Chips Act, which aims to strengthen Europe's semiconductor supply chain, is likely contributing to this trend, although the bulk of AI compute investments still depend on external providers.

R&D in AI remains a fundamental pillar of investment, with 3.7 billion euros in additional spending and a 12.7% increase. While this growth is significant, it is notably lower than that of Software, Hardware, and Infrastructure.

Intellectual property products, including Brand, Organisational capital, and Design, have seen moderate but consistent growth. The doubling of Organisational capital investment (100.1%) suggests businesses are restructuring to integrate AI.

Finally, regarding the Skills category, while Training investments grew by 88.1%, this remains the smallest category in absolute terms.

5 Robustness checks

The compilation of AI intensity coefficients with actual investment data generates our baseline scenario, which represents our central estimates of AI-related investments. It is imperative to acknowledge the sensitivity of these results to the AI intensity coefficients, which function as multipliers in our calculations. While the relative rankings and proportions among countries remain fairly stable, the absolute values of AI investments can vary significantly based on these coefficients. Given this sensitivity and the inherent uncertainty in measuring AI intensity, the baseline scenario is complemented with additional scenarios to provide a more comprehensive view of possible investment levels. Ultimately, these analyses show that findings vary depending on the measurement assumptions, but are similar enough to suggest that the baseline results are meaningful.

AI coefficients

The baseline estimation of investment relies heavily on patent data. This dependence leads to low levels of AI investment across multiple categories in countries with negligible AI patents. While this is plausible, it is also subject to differences in patent application regulation and culture, open-source publication, business environments, and market structures that may not accurately reflect AI investments. To add some control and arrive at alternative estimates, the exposure of the model is reduced by taking averages with other coefficients, such that Table 3.2 is redefined as follows:

Table 5.1. Overview of the alternative data for the AI intensity coefficients

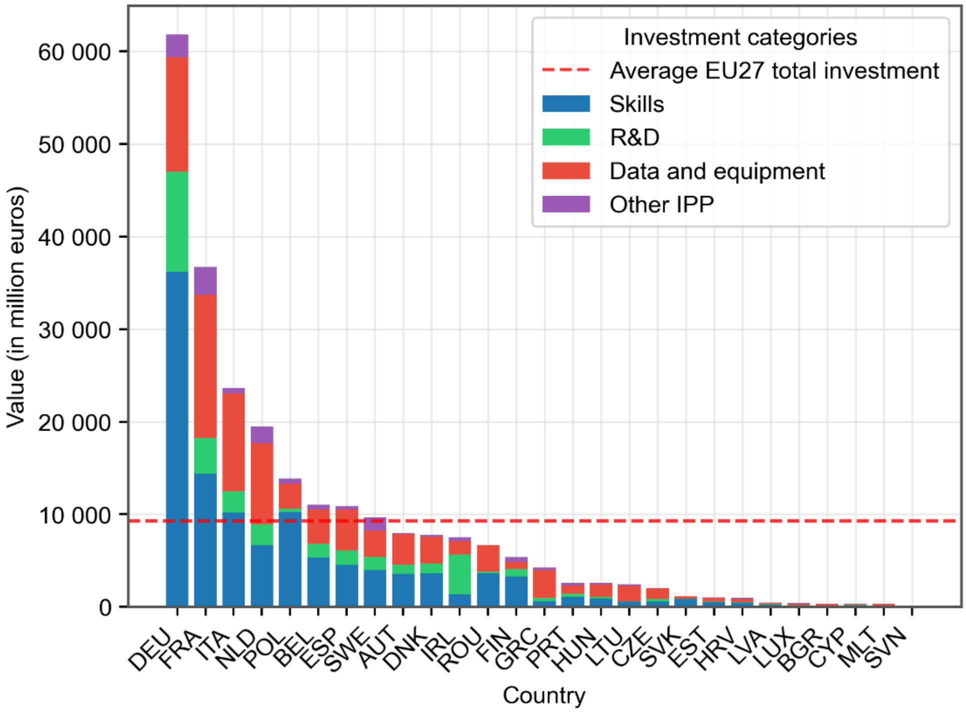
Category	Investment Item	AI intensity coefficient applied	Dataset
Skills	ICT specialist compensation	% AI ICT specialists in country's total number of ICT specialists	JRC and Eurostat
	Academic teacher compensation	% of AI university programmes in country's total programmes	StudyPortals and World Higher Education Database (WHED) Portal
	Corporate training	% of AI patents in country's total number of patents AND % of AI publications in country's total number of publications	OECD based on OpenAlex, and PATSTAT
R&D	Research & Development		
Other intellectual property products	Organisational capital	% of AI patents in country's number of patents **AND** **% of AI university programmes in country's total programmes**	
	Brand		
	Design		
Data and equipment	Computer hardware	% of AI patents in country's total number of ICT patents **AND** **% AI ICT specialists in country's total number of ICT specialists**	
	Computer software and databases		
	Telecommunications equipment		

Note: Changes compared with Table 3.2 are in bold.

The arguments for this alternative are intuitive and are meant to complement the original calibration. Here, it is still assumed that the structure of technology supply is similar to demand. However, in the case of Data and equipment, an adjustment is introduced to reflect that employers hire AI specialists roughly proportional to the targeted AI capital formation. For Other intellectual property products, the additional control is added that the educational and skill attainment of individuals approximately matches the corporate priority for AI. Lastly, Training provided by employers is assumed to also be related to the expertise available in the country, as proxied by publications.

The alternative calibration of AI coefficients alters the findings in several ways. Firstly, several countries have large changes in total AI investment (Figure 5.1). These differences highlight the sensitivity of the methodology to estimates of AI intensity. Notably for Romania, some relative rankings also change due to lower reliance on patent data.

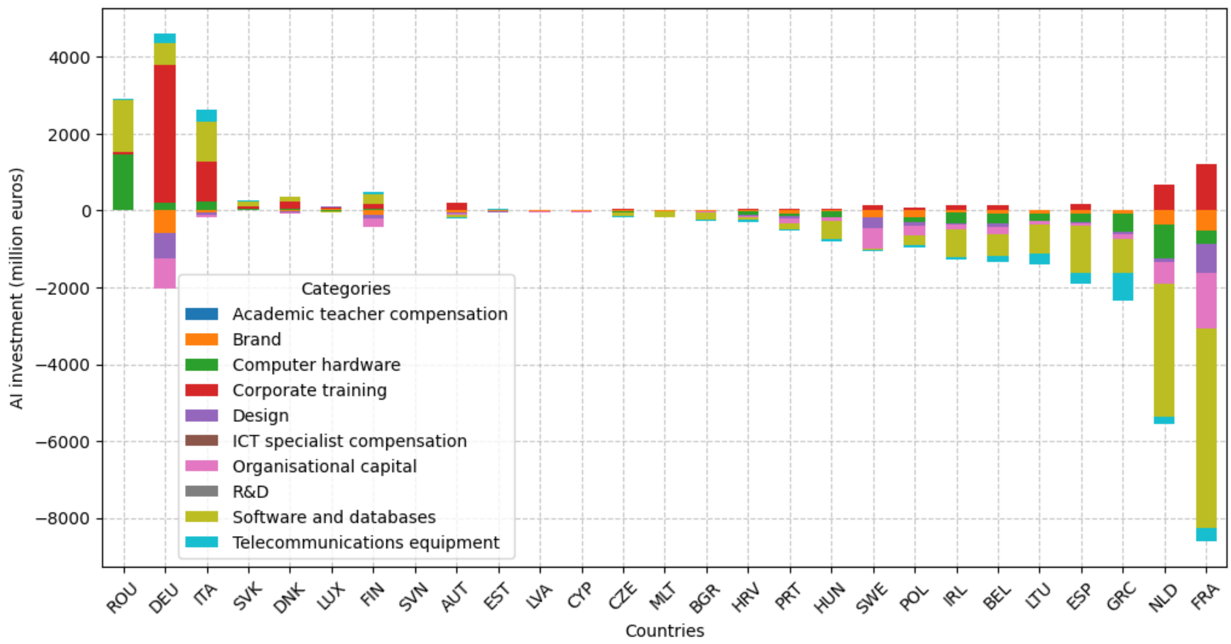
Figure 5.1. AI investments in EU Member States with alternative AI coefficients



Note: Alternative scenario, 2023. IPP category refers here to Design, Brand, and Organisational capital.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Secondly, when the alternative coefficient is applied, the total investment across all countries and categories is 6% lower than the baseline results. The biggest contributors to the change were lower Software and databases investment in France and the Netherlands due to a relatively low shares of AI ICT specialists. This was only partially offset by large positive changes in AI investment from Germany and Romania.

Figure 5.2. Differences from baseline scenario using alternative AI coefficients



Note: The baseline AI investment results were subtracted from the scenario using coefficients calculated as per Table 5.1. Overview of the alternative data for the AI intensity coefficients.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

Lastly, while the issue of some countries having null values for AI coefficients is alleviated, Slovenia's AI ICT specialist share is also 0%, resulting in no investments for Data and equipment categories (Table 5.2). Similarities in results with the baseline scenario, such as this, reinforce our findings but may still benefit from further investigation.

Table 5.2. AI Investments by EU Member State and by investment item with alternative coefficients

Country	Brand	Computer hardware	Design	ICT specialist compensation	Organisational capital	R&D	Software and databases	Academic teacher compensation	Telecommunications equipment	Training	Grand Total
AUT	49.18	267.08	38.22	3309.76	35.13	1048.66	2379.32	9.58	606.63	242.37	7985.93
BEL	99.39	977.66	113.29	5113.19	247.33	1537.60	2145.40	9.66	585.06	192.84	11021.42
BGR	10.86	6.12	9.45	15.31	24.63	48.13	207.65	0.09	5.38	43.90	371.52
CYP	24.79	11.50	2.97	168.82	21.92	65.69	33.91	0.36	9.09	9.49	348.55
CZE	12.37	233.43	13.45	539.75	13.84	271.39	840.23	2.26	71.32	57.82	2055.85
DEU	703.24	2496.59	788.91	31103.19	965.20	10809.52	6633.83	69.38	3243.01	5008.34	61821.23
DNK	43.62	654.96	52.38	3390.47	65.11	1042.59	2139.51	6.01	101.62	242.92	7739.19
ESP	137.42	555.68	91.30	4271.60	111.79	1615.29	3105.37	28.76	712.05	225.64	10854.89
EST	27.29	73.00	12.76	509.32	28.14	49.55	244.70	0.37	74.32	28.33	1047.77
FIN	118.72	89.37	150.74	3038.38	242.19	820.10	617.19	5.94	83.27	238.94	5404.85
FRA	566.62	939.59	805.87	12433.14	1586.33	3898.28	13673.95	17.16	856.81	1924.69	36702.45
GRC	73.65	679.37	78.38	581.20	141.19	365.67	1251.21	1.22	1048.56	45.55	4266.00

Country	Brand	Computer hardware	Design	ICT specialist compensation	Organisational capital	R&D	Software and databases	Academic teacher compensation	Telecommunications equipment	Training	Grand Total
HRV	25.79	125.71	28.19	276.02	29.86	96.03	111.50	0.13	94.25	177.37	964.85
HUN	26.85	267.62	31.94	880.91	75.51	160.67	951.69	1.00	136.46	60.95	2593.59
IRL	86.87	405.07	45.16	1104.66	239.83	4273.60	1007.69	24.23	95.17	240.96	7523.25
ITA	165.04	1567.30	138.91	8982.40	234.28	2329.94	6863.94	26.75	2158.30	1183.43	23650.30
LTU	80.33	245.61	25.73	564.55	96.01	62.33	995.44	0.96	377.51	21.16	2469.62
LUX	63.25	9.95	8.98	25.33	43.76	126.26	43.73	0.61	13.92	59.30	395.10
LVA	11.19	39.50	3.58	247.38	16.15	22.50	82.23	0.13	28.63	5.66	456.95
MLT	18.44	15.09	1.74	42.24	20.77	5.35	233.40	0.79	5.00	4.93	347.75
NLD	600.31	1692.87	210.39	5467.64	936.32	2243.36	6707.83	61.67	357.28	1178.49	19456.15
POL	179.78	783.33	94.35	10145.23	276.85	400.49	1532.72	1.10	331.18	123.56	13868.59
PRT	89.85	186.60	61.80	1024.12	131.14	319.79	583.37	1.44	139.66	85.52	2623.30
ROU	1.21	1475.04	1.81	3610.15	4.27	167.70	1356.12	1.01	19.15	39.69	6676.15
SVK	0.37	59.77	0.35	817.72	0.89	82.85	126.82	0.16	36.10	38.70	1163.74
SVN	0.39	0.00	0.31	0.00	0.12	69.29	0.00	0.12	0.00	24.01	94.24
SWE	262.25	326.78	387.86	3616.06	786.95	1459.96	2217.93	25.09	303.28	322.60	9708.77
Grand Total	3479.07	14184.59	3198.83	101278.55	6375.51	33392.60	56086.70	295.97	11493.00	11827.18	241611.99

Note: Estimates using alternative AI intensity coefficients.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

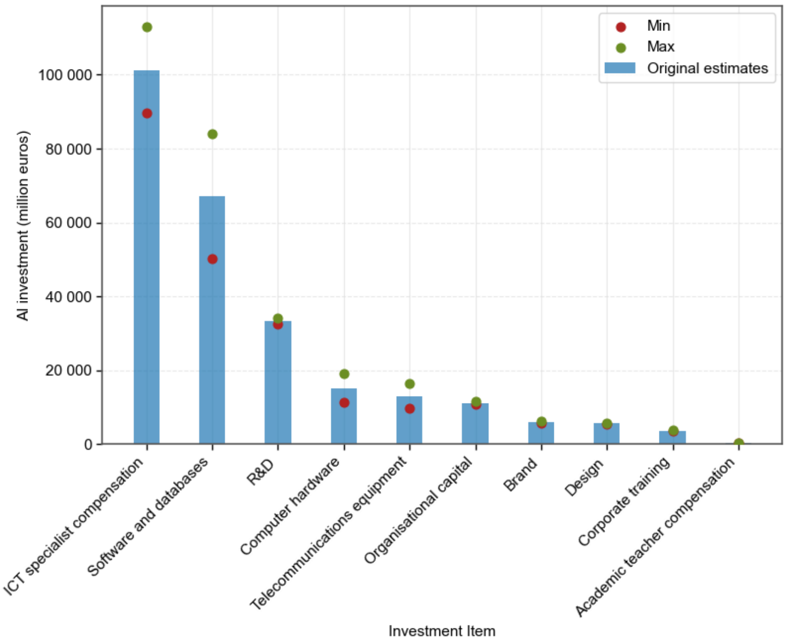
Min-Max scenarios

To further account for the inherent uncertainty in estimations, a sensitivity analysis was also implemented using min-max scenarios. To address uncertainty, two scenarios were created by varying these coefficients using their cross-country standard deviation for the given year. The maximum scenario, where coefficients are multiplied by one plus their standard deviation, represents a more optimistic view of AI intensity in investments, while the minimum scenario, where coefficients are multiplied by one minus their standard deviation, represents a more conservative estimate.

This sensitivity analysis provides a range of plausible values around our baseline scenario and is derived from the cross-country distribution of investment by category. Here, it is assumed that the cross-country variation is reflective of the degree of uncertainty in the AI coefficients.

For R&D, Other intellectual property products, and Teacher compensation, the min-max range is very small (Figure 5.3). However, for the Data and equipment categories, the range is +/-25% due to the large variation in the patent data used for the AI coefficient for that category.

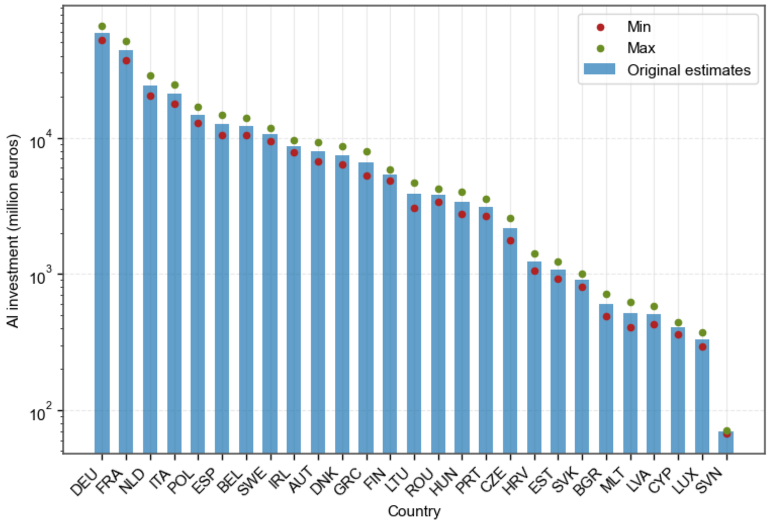
Figure 5.3. AI investments in EU Member States by investment category: Min-max scenario



Note: Alternative scenarios for 2023.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

There was much less variation at the country level, given that the alteration to AI coefficients was applied as a percentage of the original estimate. Countries with a larger amount of investment in equipment and databases were impacted more by this scenario given the large standard deviation of patent data. The smallest range was with Slovenia (+/-2.4%), because the coefficients remained 0 for several investment items. The largest range was with Malta (+/-21.5%) due to its high share of Software and databases.

Figure 5.4. AI investments in EU Member States: Min-max scenario



Note: 2023 data. Logarithmic scale used; actual investment gaps between countries are substantially larger than they appear visually and would be imperceptible on a linear scale.

Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

6 Comparing EU AI investment with selected third countries

This section extends the measurement framework to compare AI investments in the EU with those in select third countries: the United States, the United Kingdom, Canada, and Japan.

Due to data constraints and considerations of statistical consistency, the comparative analysis is necessarily limited to key investment categories, specifically R&D expenditures and investments in Data and equipment. While the original EU analysis relied on Eurostat's National Accounts data, this cross-country comparison uses the "Annual capital formation by economic activity" (DSD_NAMAIN10@DF_TABLE8) dataset in the OECD's Annual National Accounts database, which maintains methodological consistency with the Eurostat framework while offering broader geographical coverage. The OECD dataset adheres to the same NACE Rev.2 classification system used in the original methodology, ensuring conceptual alignment in sectoral breakdowns. To facilitate direct comparison, investment values from non-eurozone countries were converted to euros using the European Central Bank's nominal exchange rates (e.g., EXR.A.GBP.EUR.SP00.E for British pounds), based on annual average spot exchange rates. For AI intensity coefficients, comparable time-series patent data were obtained for these third countries, allowing the application of the same two-step weighting procedure described in the primary methodology.[3] This approach, despite its narrower scope compared to the comprehensive EU analysis, enables a methodologically consistent international comparison of AI investment patterns across these selected economies.

Table 6.1. Investment in AI R&D in 2023

Region	Total AI investment R&D	% public	% private
EU27	33 393	16%	84%
CAN	2 578	46%	54%
GBR	4 980	43%	57%
JPN	10 526	11%	89%
USA	89 838	26%	74%

Note: Baseline scenario, in million euros.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_p5); OECD Data Explorer (DSD_NAMAIN10@DF_TABLE8); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); OpenAlex data available at OECD.AI (https://oecd.ai/en/data); European Central Bank's exchange rates (ECB) (https://www.ecb.europa.eu/mopo/eaec/eer/html/index.en.html).

Table 6.2. AI investment estimates for selected third countries in 2023

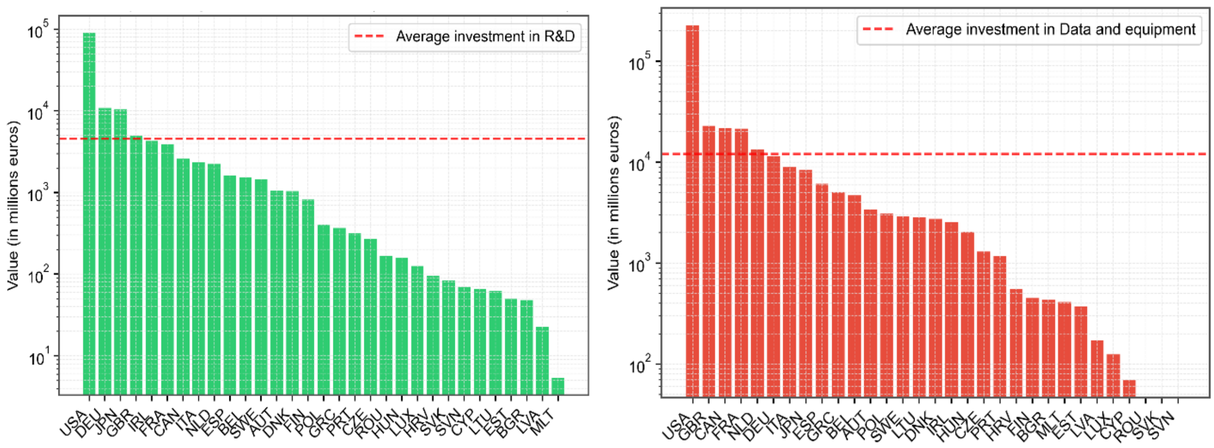
Country	Computer hardware	R&D	Software and databases	Telecommunications equipment	Grand Total
EU27	15 251	33 393	67 003	13 106	128 752
CAN	3 628	2 578	15 534	2 619	24 361
GBR	3 942	4 980	16 998	1 863	27 785
JPN	No data	10 526	8 330	No data	N/A
USA	31 506	89 838	161 984	30 563	313 893

Note: Baseline scenario, in million euros.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_p5); OECD Data Explorer (DSD_NAMAIN10@DF_TABLE8); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); OpenAlex data available at OECD.AI (https://oecd.ai/en/data); European Central Bank's exchange rates (ECB) (https://www.ecb.europa.eu/mopo/eaec/eer/html/index.en.html).

Table 6.1 reveals significant disparities in AI R&D investment volumes and public-private compositions across selected economies in 2023. The public-private composition exhibits marked structural differences, with Canada and the UK maintaining relatively balanced distributions (46% and 43% public sector involvement respectively), while the EU27, Japan, and particularly the USA show stronger private sector concentration. Table 6.2 provides a more granular view across key investment categories, highlighting the comprehensive AI investment landscape beyond R&D.

The cross-country comparative analysis of AI investment reveals pronounced heterogeneity in both R&D and Data and equipment allocations for 2023 (Table 6.1). The logarithmic scale of the visualisations accentuates the substantial disparities between leading and trailing nations. In AI R&D investment, the United States demonstrates exceptional commitment, approximately 90 billion euros - nearly an order of magnitude higher than Germany, Japan, and the United Kingdom, which follow with an allocation of approximately 10 billion euros each. A similar pattern emerges in Data and equipment investment, where the United States maintains primacy at approximately 200 billion euros, while the United Kingdom, Canada, and France invest between 20 and 25 billion euros. The distribution follows an exponential decay pattern, with investment levels decreasing progressively across countries, creating a gap of two to three orders of magnitude between leading and trailing nations. This stratification suggests the emergence of AI capability concentration among a select group of countries.

Figure 6.1. AI investments in R&D and Data & equipment in 2023



Note: Baseline scenario. Logarithmic scale used; actual investment gaps between countries are substantially larger than they appear visually and would be imperceptible on a linear scale

Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_p5); OECD Data Explorer (DSD_NAMAIN10@DF_TABLE8); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); OpenAlex data available at OECD.AI (https://oecd.ai/en/data); European Central Bank's exchange rates (ECB) (https://www.ecb.europa.eu/mopo/eaec/eer/html/index.en.html).

7 Discussion

These findings on AI investments are grounded in a transparent methodology built on clear hypotheses and open data sources, ensuring replicability and robustness. By adopting a broad definition of AI, aligned with the OECD classification and operationalised through an innovative AI patent definition and time series, these estimates may appear higher than those typically reported. This reflects a more comprehensive view of AI-related activities but also underscores differences in scope compared to other studies. A key limitation of any approach is the missingness of data, particularly for certain public and private expenditures. However, our imputation methods are transparent, relying on well-documented assumptions and sensitivity analyses to mitigate uncertainties.

Future work will focus on broadening the geographical scope of this analysis. This will include extending coverage to relevant non-EU AI economies, such as China, and will enable global comparisons and a deeper understanding of relative investment dynamics.

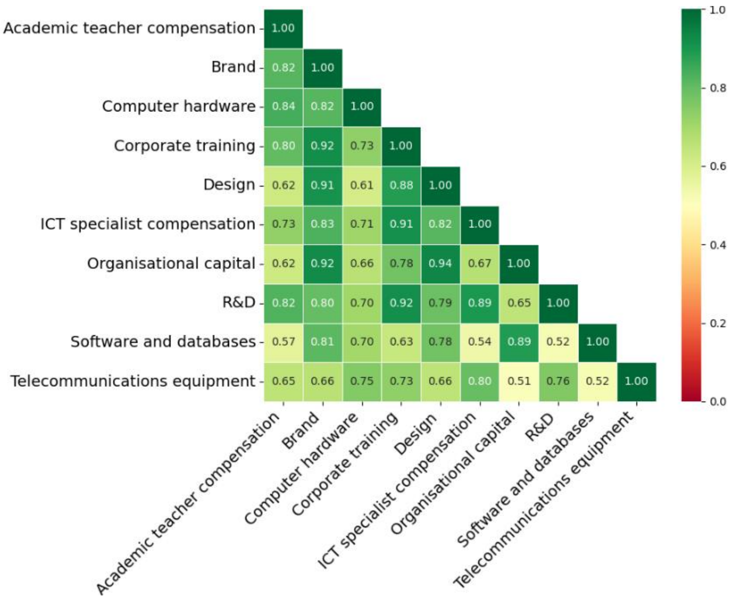
Expanding the scope of AI investments may also provide crucial insights into the AI ecosystem. Notably, investments in energy are an essential component of the training and use of AI models that were excluded from this analysis. This was done partially to contain the definitional scope of AI investment, but also due to the extra complexity this category would introduce. Work to isolate the portion of investments in energy infrastructure dedicated to AI would be valuable, but would likely require an additional layer of estimation not found in the methodology of this paper.

Efforts to more accurately calibrate AI intensity coefficients may also be beneficial. Due to data constraints, assumptions on the percentage of activities that are AI-related are approximate. Our assumption of a one-for-one pass-through of proportional investments to patents, particularly during the current phase of development for AI technologies, may not be completely accurate. This has large implications for the results. Other data gaps exist as well. For example, ICT services imported by firms in countries with a less prominent AI-producing sector may still be considered investment in infrastructure and skills for AI specialists and would not be well captured in the estimates.

There are also merits in pursuing different methodological approaches. Advanced data-mining techniques applied to large-scale databases on R&D projects expenditure and public procurement contracts could improve the granularity of AI-related spending categories, ensuring better calibration of our own estimates. Moreover, leveraging machine learning models to classify AI-related expenditures with greater accuracy could refine sectoral breakdowns and identify underreported areas of AI investment. Finally, this research aims to contribute to more accurate and policy-relevant AI investment tracking by continuously improving data sources' quality and methodological soundness.

Annex A. Additional robustness check

Figure A.1. Correlation matrix for AI expenditure categories



Note: Baseline scenario.
Sources: OECD calculations based on Eurostat National Accounts (nama_10_a64_e, nama_10_a64_p5, lc_lci_lev, isoc_sks_itspe, educ_uoe_fini01); EUKLEMS & INTANProd (https://global-intaninvest.luiss.it/); Joint Research Centre (JRC) (https://ai-watch.ec.europa.eu/ai-watch-index-2021/s-societal-aspects/s6-university-places-ai-content-eu_en); OECD (2025), *Identifying emerging AI technologies using patent data: A semi-automated approach* (https://doi.org/10.1787/d17e9a1a-en); StudyPortals (https://studyportals.com); World Higher Education Database (WHED) Portal (www.whed.net/home.php); OpenAlex data available at OECD.AI (https://oecd.ai/en/data).

The correlation matrix reveals several interesting patterns in the relationships between different AI investment categories. First, strong positive correlations (>0.8) among several investment items appear. This suggests a comprehensive complementarity in AI investments, indicating that countries investing heavily in one of these areas tend to invest substantially in others as well. Notably, the strongest correlations appear between:

- Corporate training and R&D (0.92)
- ICT specialist compensation and Corporate training (0.91)
- ICT specialist compensation and R&D (0.89)
- Software and databases and Organisational capital (0.89)

These results also show that tangible ICT investments (Computer hardware, Telecommunications equipment) do may be a substitute for spending on labour, with Software and databases correlating weakly with ICT specialist compensation (0.54) and Telecommunications equipment weakly correlating with Organisational capital (0.51).

Overall, these correlation patterns suggest that AI investments tend to form a highly interconnected ecosystem rather than distinct clusters, with particularly strong complementarities Corporate training and Brand investments and all other investment categories.

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Endnotes

[1] For the purpose of this paper, *third countries* refer to countries outside of the European Union. In particular, the selection included Canada, Japan, the United Kingdom and the United States.

[2] This report purposefully uses the term *intangible assets/capital*, to capture both the SNA standard *intellectual property products* as well as human capital and skills.

[3] Differences in patentability are particularly relevant for these comparisons. European patent regulations and culture are more aligned with each other than with the other jurisdictions examined in this chapter.