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AI Watch: AI uptake in Manufacturing

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Joint Research Centre

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Foreword

This report is published in the context of AI Watch, the European Commission knowledge service to monitor the development, uptake and impact of Artificial Intelligence (AI) for Europe, launched in December 2018. AI Watch monitors European Union's industrial, technological and research capacity in AI; AI-related policy initiatives in the Member States; uptake and technical developments of AI; and AI impact. AI Watch has a European focus within the global landscape. In the context of AI Watch, the Commission works in coordination with Member States. AI Watch results and analyses are published on the AI Watch Portal.

From AI Watch in-depth analyses we will be able to better understand European Union's areas of strength and areas where investment is needed. AI Watch will provide an independent assessment of the impacts and benefits of AI on growth, jobs, education, and society. AI Watch is developed by the Joint Research Centre (JRC) of the European Commission in collaboration with the Directorate General for Communications Networks, Content and Technology (DG CONNECT).

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Abstract

This AI Watch report analyses AI uptake in manufacturing. It recognizes that AI can empower a variety of applications in the manufacturing sector and it can impact all stages of production; in particular a major role for AI lies in blending data from different processes, factory floors or production sites to enable holistic optimizations. However, there is a strong need to access data and, furthermore, the need for quality data. Furthermore, standardization of data formats and of communication protocols will be a fundamental enabler for data sharing. Involving human resources in the AI uptake process is also an essential need in manufacturing, both at the workforce and management level.

The current report shows that AI uptake in manufacturing has accelerated over the last decade, but it is still at its early stage: for instance, In the last five years, the annual VC investment in AI and manufacturing has accounted for up to 15% of the total VC investment in the sector. At EU27 level, we observe that Germany, France, Italy and Spain lead in all the rankings of AI uptake in manufacturing, indicating significant disparities with respect to the level of AI uptake in manufacturing across the EU Member States.

Executive Summary

This report presents an analysis of the uptake of Artificial Intelligence (AI) in the manufacturing sector, carried out by AI Watch. Overall, the current report shows that AI uptake in manufacturing has accelerated over the last decade, bringing a large set of opportunities, but it is still at its early stage, hurdled by several challenges. We summarize both, opportunities and challenges, as well as the quantitative results of our analysis here below.

Benefits and challenges of AI Uptake

Benefits AI can empower a variety of applications in the manufacturing sector and it can impact all stages of production: indeed, beyond local deployement in individual processes, a major role for AI lies in blending data from different processes, factory floors or production sites to enable holistic optimizations. For instance, at the organization level, AI can forecast future demands, enabling a more accurate and efficient scheduling of production. At the machine level, AI can anticipate the need for maintenance, reducing downtimes and production disruptions. At the level of inputs and outputs, quality control can be AI-powered too, for instance, by ensuring the quality of the final product or of the raw material to be processed.

The strive for optimizing processes, reducing waste in a general sense, be it energy or resources, has **a natural beneficial impact on the sustainabilty of manufacturing processes**. However, the transition to “greener” practices cannot emerge solely as a byproduct of the deployement of AI and digital technologies in general. On the contrary, sustainability concerns must be there from the start of the digital transformation, since a local optimization entailed by AI may not necessarily result in an overall reduction of environmental impact, which in turn requires an holistic approach.

Challenges A central and recurring challenge to AI uptake is **the need to access data** and, furthermore, the need for quality data. Furthermore, as one the strengths of AI lies in performing holistic optimizations across processes and machines, the **standardization of data formats and of communication protocols** will be a fundamental enabler for this data sharing. **Involving human resources in the AI uptake process** is also an essential need in manufacturing, both at the workforce and management level. In particular, upskilling and training of human resources should be planned both to ensure an AI deployement apt to meet workers’ needs, in terms of workflow management, and to ensure best results by leveraging tacit domain knowledge held by workers.

AI in manufacturing: scientific research, innovation and start-up activity

Scientific research In terms of scientific publications, our analysis shows a steep increase in AI and manufacturing since 2014, from around 5% to peak in 2019 at around 25% of the year’s publications. The EU27 holds a position of leadership in terms of scientific output, with approximately 20% of manufacturing publications delving into the application of AI. China and the US follow with approximatively 1000 publications each in AI and manufacturing, accounting approximately for 15% and 20% of their scientific output in manufacturing. At the EU Member State level Germany, France, Spain and Italy stand out in terms of scientific output and participation in EU-funded R&D projects. Furthermore, these countries share strong ties in scientific collaboration, both with shared publications and joint H2020 projects.

Innovation In terms of technological innovation, we analysed patent data which are a key instrument for the protection of the innovation carried by new products and processes. China holds the majority of patents in absolute numbers but, when we restrict our analysis to the most cited patents, which is a measure of influence, US holds the largest share, followed by EU27. Furthermore, our analysis of patent citations reveals relatively strong bilateral knowledge transfers between the US and EU27; on the other hand, Chinese patents seem to mostly cite other Chinese patents. Within the EU27, Germany holds the largest number of EU patents in AI and manufacturing, followed by the Netherlands and France, with the top assignees being mostly large firms, such as Siemens, a German manufacturer delving into healthcare, energy and industrial devices, and Bosch, a German engineering company.

Start-up activity AI and manufacturing VC investments account for only 12% of global VC investment in the manufacturing sector, indicating an uptake still relatively low. EU27 receives less than 10% of the worldwide investments in AI and manufacturing; on the other hand, US companies receive the largest share with 59%, followed by Chinese ones with 15%. Within the EU, Germany receives most of AI and manufacturing VC funding, with over 45% of the total VC investments and Luxembourg comes second with a share of approximately 10% of the total.

In synthesis, comparing the EU27 with the main global economies using the technological life-cycle framework, we observed that it has a strong position at the initial stages of AI and manufacturing development and research, and that it becomes less prominent in the later stages of the technology lifecycle (innovation and market applications). For example, the EU scientific output is twice that of US or China. However, when looking at the number of patents (as proxy for innovation activity) or VC funding received by start-ups (as a proxy for market application), the EU starts to fall behind the US and China.

1 Introduction

In recent years, Artificial Intelligence (AI) has proven progressively more transformative across the economy and, as with many of those other sectors, Manufacturing can potentially reap large benefits from the uptake of AI to enable more efficient and sustainable production.

The policy context set by the European Commission (EC) sustains this rising trend, aiming to boost the development and uptake of AI technologies for manufacturing while remaining, however, conscious of the pressing environmental needs. Indeed, among the six political priorities of the EC for the period 2019-24[1], two are particularly relevant to future developments in the Manufacturing sector: the European Green Deal[2], which aims at achieving zero net emission of greenhouse gases by 2050, and a Europe fit for the Digital Age[3], which aims at leveraging the digital transformation to increase the EU technological and data sovereignty.

Industry plays a key role in achieving these objectives, and the Industrial Strategy[4] adopted in 2020 aims at strengthening the competitiveness of European industry using the Green Deal, not only as an objective but also as an opportunity to innovate and create new clean technology markets. At the same time, the digital transition is a key aspect of the innovation necessary to achieve the environmental and social objectives of the Green Deal.

The industrial strategy, updated in May 2021[5], features several initiatives for data sharing, testing and supporting the digital transition geared specifically towards manufacturing:

- Establishing a dedicated industrial manufacturing data space as part of the European Strategy for Data. In such data space, key industrial players would share data, under conditions to be agreed, to support the development of AI-based applications and products.
- Supporting the development and deployment of photonics technologies in various fields, including manufacturing,
- Supporting a public-private partnership on Factories 4.0, 'Factories of the Future', which is public-private partnership (PPP) for advanced manufacturing research and innovation under Horizon 2020.
- Establishing a public-private partnership "Made in Europe" for sustainable manufacturing in Europe, including through AI, contributing to a competitive and resilient manufacturing industry in Europe and reinforcing added value in supply chains across sectors
- Co-funding a Testing and Experimentation Facility for AI in Manufacturing under the Digital Europe Programme, with a first call in 2021-22,
- Extending the network of European Digital Innovation Hubs[6], to support the transfer of know-how between research and industry and in particular SMEs.

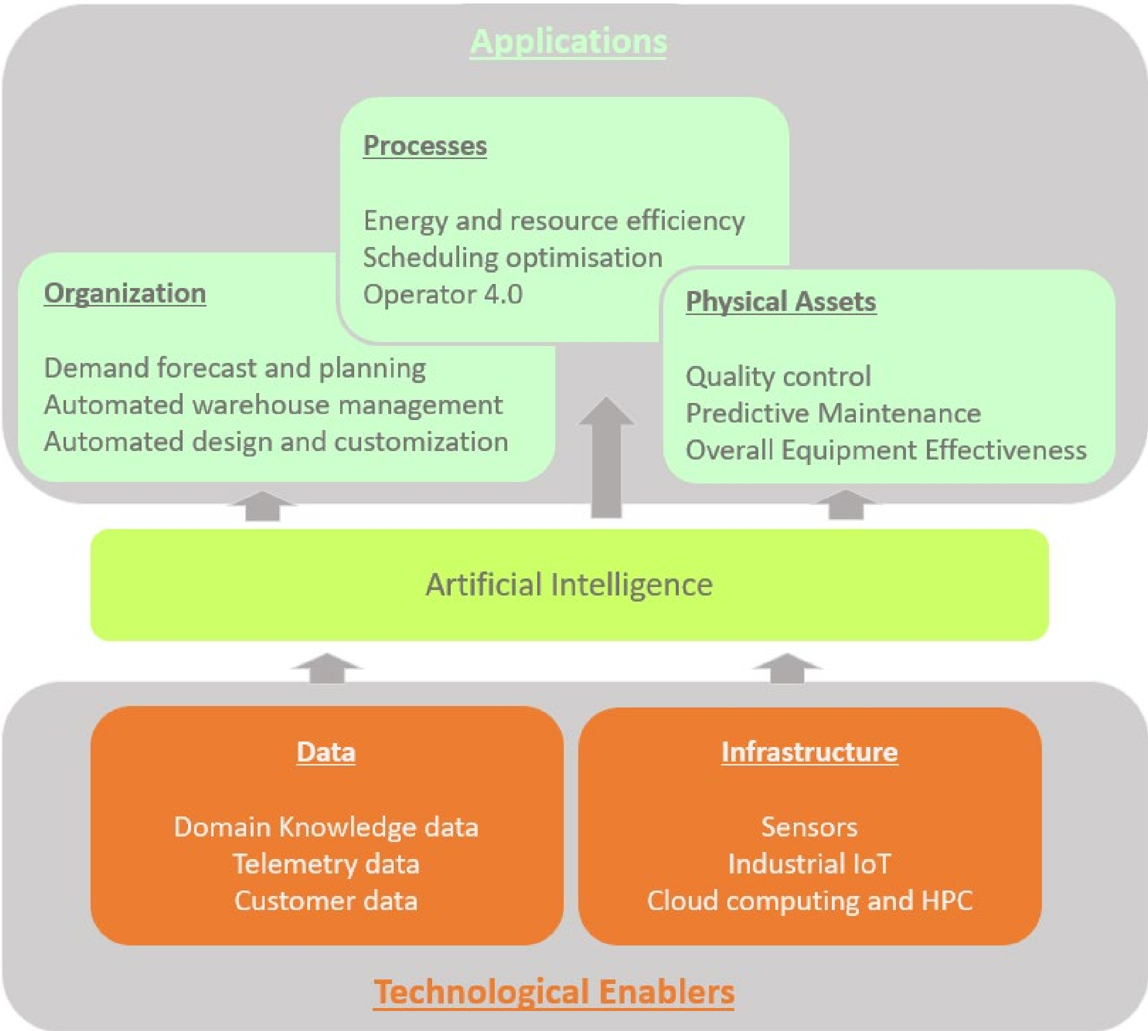
Against this backdrop, this report aims to provide an overview of the current uptake of AI technologies in the manufacturing sector. We adopted a comprehensive approach to analyse the uptake of AI, starting from a more qualitative standpoint with desk research and expert consultations, complemented by using several data sources for a quantitative assessment. For the latter, we followed the technological-innovation lifecycle, starting from an extensive analysis of scientific publications and EU-funded R&D project data, followed by the analysis of Venture Capital investments and innovation activities through patent applications data related to AI and manufacturing, in order to convey the several different facets composing AI uptake.

[1] https://ec.europa.eu/info/strategy/priorities-2019-2024_en
[2] https://eur-lex.europa.eu/resource.html?uri=cellar:b828d165-1c22-11ea-8c1f-01aa75ed71a1.0002.02/DOC_1&format=PDF
[3] https://ec.europa.eu/info/strategy/priorities-2019-2024/europe-fit-digital-age_en
[4] https://eur-lex.europa.eu/legal-content/EN/TXT/?qid=1593086905382&uri=CELEX:52020DC0102
[5] https://ec.europa.eu/growth/industry/policy_en
[6] https://digital-strategy.ec.europa.eu/en/activities/edihs

2 AI in Manufacturing: a mindmap

Our literature review and expert consultations allowed us to gain insight into the deployement of AI in manufacturing. The information we gathered can be organized in two broad categories (Figure 1): **enablers**, on the top of which AI can be deployed, and **applications**, which constitute broad classes of situations in manufacturing where AI is deployed, aiming to generate improvements or outright disruption.

Figure 1. Mindmap of AI in Manufacturing



Source: JRC

Enablers of AI in Manufacturing

As highlighted in the existing literature on AI in Manufacturing, technological enablers comprise all building blocks making up the technological groundwork necessary to make AI applicable in manufacturing, providing the foundations for its deployement.

The following section provides an overview of the main or most commmon technological enablers required to adopt AI in the manufacturing sectors, divided into two main categories: **data** and **infrastructure**.

Data

Conceptually, we differentiate between three different types of **data** which constitute the inputs to applications of AI in manufacturing. These are

- **telemetry data**,
- **customer data**
- **domain knowledge**

Telemetry data

The term telemetry data comprises all types of data collected for the purpose of surveillance and optimisation on machines under operation involved in manufacturing processes. The collection of telemetry data usually involves a sensor, which measures a specific metric, e.g., the temperature of a component. The measurement is transmitted to a recording or visualisation device, evaluated in real time and/or stored for later evaluation (Carden, Jedlicka, & Henry, 2002).

Customer data

In the context of AI in manufacturing, customer data is used for two main purposes. Most importantly, it is used to individualise products based on customers' preferences, physical measurements or design customisation input. In other words, artificial intelligence is used to map the customer's input to the final product. For example, the combination of a customer's recorded preferences regarding the fit of a piece of clothing and physical measurements can be transformed by AI into an individualised cut (Li, Yuan, Kamarthi, Moghaddam, & Jin, 2021).

Second, customer data are used in business analytics along other statistical methods as a general tool for optimisation. More specifically, one application of AI is to forecast demand and consequently optimise the degree of capacity utilisation of machinery to prevent under- as well as overproduction (Seyedan & Mafakheri, 2020) (Kilimci, et al., 2019).

Domain knowledge data

Domain knowledge data refers to knowledge held by experts about specific production processes or the operation of specific machinery. Thus, they serve to tailor AI applications to use-cases and are incremental in moving from general AI solutions stemming from basic research to highly specialised applications. Integrating domain knowledge data can tremendously improve the performance of AI applications. Moreover, for many applications, domain knowledge is necessary to evaluate the performance of the AI methods applied. For example, without domain knowledge, data and computer scientists might not be able to optimise algorithms properly, due to an incomplete or wrong idea of optimal conditions (Li, Yuan, Kamarthi, Moghaddam, & Jin, 2021).

Infrastructure

In addition to data, in order to integrate AI into the manufacturing of products, the gap between machinery and ready-to-use data has to be bridged by adequate **infrastructure**. Besides data-generating infrastructure such as **sensors** and smart meters, other infrastructure is necessary to establish the interconnectivity of physical components, which is required for various technologies commonly included under the umbrella term **internet of things (IoT)**. The way to integrate such physical components into these networks is to create **digital twins**, which enables a seamless digitisation and prevents incompatibility issues. Moreover, as training of AI models and augmenting data tends to be computing-power intensive, the deployment of AI calls for appropriate infrastructure able to cope with such computation tasks. This infrastructure usually relies on computing clusters, i.e., either on in-house solutions or external **cloud computing** services, and **high-performance computing**, which are requested on demand.

Sensors

Sensors represent the first element in the signal transmission chain necessary to bridge the gap between machinery and data evaluation, which makes them essential in recording digital data of machines in operation. For the numerous different metrics to be recorded, a wide range of specialized sensors exist. However, sensors always work in interaction with other electronic components (Sabu, Nguyen, Ahmadi, Farmani, & Yasin, 2021).

IoT

The term internet of things refers to the interconnectedness of physical objects. Once integrated into a network, the objects can exchange information and can be integrated into automated higher-level processes, which involve any number of objects part of the network. AI can be used for processing and interpreting data generated this way. For example, for optimising higher-level processes, for aiding communication amongst objects, and many other applications (Song, Jeschke, & Rawat, 2017).

Industrial digital twins

Industrial digital twins provide the means to integrate otherwise analogue physical objects into digital networks. The term does not describe an exact digital copy of an object, but rather a digitized form, which summarizes information about the physical object being relevant for its functionality in the network. The digital twin might for example contain physical measurements of the analogue object, like weight or volume measurements, which can be used as input by other objects in the network (Pal, et al., 2021)

Cloud and High performance computing

The term cloud computing refers to the provision of computing and data storage services mostly on demand. The cloud infrastructure and maintenance are thus usually provided by the cloud computing provider and not actively managed by the user. Cloud computing services have emerged mainly due to increasing data availability and size, but also due to the increased use of computationally intensive statistical methods, of which some categorize as AI. (Furht & Escalante, 2010). High performance computing refers to computing clusters with extremely high computational power that are able to solve complex and demanding problems, such as fluidodynamics simulations.

Artificial intelligence

In alignment with the research carried out in the context of the AI Watch project (Samoili, 2020), we adopt as operational definition of AI the one proposed by the HLEG on AI:

HLEG definition of AI

"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans[7] that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a

[7] ec.europa.eu/newsroom/dae/document.cfm?doc_id=584

numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.

Applications of AI in Manufacturing

The literature also highlights a broad variety of use cases or applications for AI in Manufacturing. Building on the enablers, this section shows that AI can empower a variety of applications in the manufacturing sector. The following applications do not, however, exaust the space of possibilities because, as was also stressed by several experts during our consultations, AI can impact all stages of production: indeed, beyond local deployement in individual processes, a major role for AI lies in blending data from different processes, factory floors or production sites to enable holistic optimizations.

Organization

Organisation concerns primarily **the internal relationships within the factory and the company** such as responsibilities of personnel, arrangement of machines and planning the schedules for each component, the physical assets and the human reseources, to meet the demand. In this context, we outline here three main applications of AI at the organisation level: **demand forecast and planning, automated warehouse management** and **automated design and customization**.

Demand forecast and planning: Demand forecasting allows to optimise the degree of capacity utilisation in manufacturing and thus is conducted to maximize profits by matching supply with demand. Various statistical and econometric methods are available to forecast demand, of which some classify as AI (Seyedan & Mafakheri, 2020). Because of the agility in a commoditizing market which is transitioning **from mass production to mass customization**, it is very important to apply **AI in a combined cycle** between processes, market demand and market pricing.

Indeed, to maximize profit, companies aim to match output to the demand, since both over-producing and under-producing imply profit losses. In the case of over-producing, companies have to deal with extra costs generated by surplus products, which could involve costs due to disposal, returns from retailers or reductions in prices to prevent the former. When under-producing, firms miss out on potential profits.

Automated warehouse management: Automated warehouse management refers to replacing repetitive tasks that commonly take place in warehouses with automated systems. In general, one can differentiate between digital automation and physical automation. The former involves mostly software solutions, digital databases and the creation of networks (IoT). Physical automation refers to the use of robotics, scanning devices, sorting equipment, etc. Thus, AI can be applied to various tasks to facilitate automation of warehouses in both domains. In the context of digital automation this can be done by optimisation of networks, databases, and maximizing efficiency; in physical automation, by assisting in robot navigation, image recognition (e.g., of barcodes), operation of smart shelves, among others (Hamberg & Verriet, 2012).

Automated design and customisation: Automated design and customisation is the process of automating the incorporation of the customers' specifics in a product design. For instance, some companies offer manufacturing on-demand, with customers making choices about the appearance of products, materials used or physical measurements. In this context, AI algorithms can be used to implement all of these forms of customisation. The same way that AI can be used to transfer styles of one image to another, for example, applying the style of Vincent van Gogh's 'starry night' to another image, it can be used to transfer the 'look' of a customer's input image to the design of a product. Besides aesthetics, physical measurements of products manufactured on-demand are also customizable (Butler & Bright, 2018) (Pathak, Pal, Shrivastava, & Ora, 2019).

Processes

A manufacturing process is the transformation of raw material into the finished product by manufacturing methods, operations scheduling, software, machinery and human operators. In this domain AI can contribute by improving efficiency in several ways, for instance by improving **scheduling optimisation**, the **energy and resource usage** and by supporting human operators in **the operator 4.0** context.

Scheduling optimisation Scheduling optimisation is the process of arranging, controlling and work and workloads of machines and human resources to generate a certain output level while entailing minimal costs and time needed. The term stochastic scheduling is used when random effects are integrated into the optimisation exercise, such as random machine failures or delays. As stochastic and non-stochastic scheduling problems are solved with specialised algorithms, AI is one possible method to solve these optimisation problems (Lee, 2020).

Energy and resource efficiency refers to methods to reduce energy consumption and resource usage in manufacturing processes. For instance, AI in waste management can reduce resource consumption through the use of smart tags to track products and raw materials. Against the backdrop of climate change, efficiency in managing energy and resources is increasingly gaining attention and importance for companies. Stricter regulations, often accompanied by higher energy costs, are increasing the pressure to produce as energy-efficiently as possible. Increasing energy-efficiency often resembles other classic optimisation problems, which can be solved with AI (Lee, 2020).

Operator 4.0 The term operator 4.0 refers to technology-augmented machine operators or other industrial workers. The possibilities of augmenting humans are manifold, however, developments in this area are at an early stage. Areas of application include increased physical ability, augmented or virtual reality, biomarker or health surveillance and collaborative robots (co-bots). Most of these applications have the objective in common to make operators more able, efficient and precise. The exception is health surveillance, whose objective is to protect operators in hazardous work environments (Peruzzini, Grandi, & Pellicciari, 2020).

Physical Assets

In a manufacturing firm, physical assets encompass the **equipment and machine tools** as well as other equipment such computers and hardware components. AI can be deployed at the level of physical assets to monitor and ensure the correct functioning of such equipment in order to reduce or eliminate costly downtimes.

Quality inspection and control One of the essential elements of manufacturing is quality inspection, which refers to the continous monitoring of the product characteristics to ensure it meets quality standards requirements. In many cases, quality inspection resembles at core a pattern recognition-based labelling problem. Since pattern recognition problems are an application where AI does particularly well, quality inspection is an element of manufacturing in which AI is heavily used.

An example would be the use of image recognition algorithms to spot and weed out faulty products. The principle at work in quality control usually is to collect a range of data points about a manufactured product and then to infer an individual label from these data points, such as “meets quality standards”. Many algorithms can be employed for this inference, but the advances in cost and availability of computing resources have favoured AI classification algorithms, such as convolutional neural networks (Escobar & Morales-Menendez, 2018).

Predictive maintenance Predictive maintenance refers to the permanent surveillance of machines using statistical methods, which predict whenever maintenance should be conducted. Defect-induced downtimes of machinery are associated with huge costs for manufacturers. In order to prevent such downtimes, manufacturers conventionally run maintenance schedules of machines. However, regular maintenance can cause inefficiencies. First, since maintenance usually entails additional costs in the form of labour costs, production stops, etc., it is inefficient to conduct maintenance when it is not strictly needed, i.e., without diagnostic findings or reparations. Second, by means of a discrete, regular schedule, anomalies may develop just after maintenance and lead to defect-induced downtime before they are discovered in the following maintenance. Thus, ideally, manufacturers permanently monitor the condition of machinery without interfering with manufacturing processes. For this purpose, sensors are installed at crucial parts of the machine which deliver real time data on the condition of the machine such as temperature, pressure, etc. AI is used to improve the performance of these predictive methods due to its pattern recognition capabilities (Zonta, et al., 2020).

Overall equipment effectiveness The term overall equipment effectiveness (OEE) refers to a measure for productivity for the physical assets used in the manufacturing process. It has three components: quality, performance and availability and, therefore, OEE encompasses both quality control and predictive manteinance mentioned above. Quality is typically defined as the ratio of good parts to total parts produced. Performance refers to the speed of production and is a measure for how close the production runs to maximum speed. Availability refers to the ratio of uptime to total time, i.e., the degree of utilization. AI can be used to improve all three of these measurements: quality can be improved by AI-based pattern recognition, performance can be improved by optimising schedules and availability can be improved via predictive maintenance (Hansen, 2001).

AI and Manufacturing for the Green Deal

As AI can improve the efficiency of production, reducing resource and energy consumption and waste, it can be an enabler for sustainable manufacturing processes. This strong link emerged both from the literature review and expert consultations as well as from the quantitative analysis of several data sources as shown below. The impetus towards sustainability can indeed be enhanced by AI: in (Vinuesa, 2020), the authors identified 128 out of 169 targets of the 2030 Agenda for Sustainable Development for which AI could act as an enabler. Twenty five of them correspond to climate mitigation and environment protection.

A key feature of AI is its capacitiy of improving effectiveness through optimization and, for manufacturing, it can reduce the environmental impacts of the sector by reducing wastes of time, energy and materials: indeed, for instance, computer vision algorithms can avoid unnecessary waste of both raw materials and finished products by improving quality inspection and forecasting enabled by machine learning can help reduce over-production, anticipating demand and matching it more closely with production schedules (see Box 1). Furthermore, the use of digital twins fed with the collected data, can be used for simulations of processes thus allowing an enhanced control over the process management prior to its deployement, reducing the waste of energy and resources due to inefficiencies.

It is however important to note that, as was stressed by several of the experts who participated in our consultations, to support sustainability objectives a holistic optimization is required, taking into account all the steps of the production chain, while local optimizations do not necessarily have a net positive impact when considering counter-balancing effects such as increasing demand leading to an increase in production.

Box 1: AI monitoring performance and improving operating efficiency of industrial machines by Elmodis

From our analysis of AI and manufacturing start-ups, several ones emerged whose activity is geared towards sustainability. As an example, Elmodis is a Polish Industrial Internet of Things (IIoT) Technology company developing solutions based on AI.

Founded in 2015, this provides solutions improving the energy and operating efficiency of electric-powered industrial machines by combining hardware, with IoT, and algorithms that enable manufacturers and end-users to remotely monitor the performance of the machines in real-time.

Their solution for machine monitoring is based on measuring current and voltage from electric motors powering those machines, combining with process parameters to provide a complete picture. Then, from the measurements of electric energy that flows through the machine, it is possible to calculate several parameters in real-time which give the performance and state of the machines. Using such data flow enables machine manufacturers to reduce warranty repair costs, improve the products' quality with, at the same time, an optimization of their energy consumption and preventions of failures from incorrect usage.

The deployment of its AI-enabled solutions in the manufacturing context helped to avoid over 2,000 hours of down time and reduced the level of CO2 emissions by nearly 3 million kilograms since 2015.

The development of this technology was supported by European funding, through the European Fund for Strategic Investments (EFSI), in the frame of a project focusing on preparing and implementing new computational and measurement-based methods for modelling machine and process simulation. These simulations can help predicting the technical condition in order to increase availability of critical equipment and, furthermore, help improving efficiency of energy generation with the use of advanced Distributed Edge Computing technology and the Hybrid Cloud.

3 Expert consultation on the adoption and use of AI technologies and applications in the manufacturing sector

The adoption of AI in manufacturing

During our expert consultations, the emergent topics on adoption of AI in the manufacturing sector were focused along three main axes: a **technical** one, one related to **human resources,** and one related to environmental concerns and **sustainability**.

From the technical standpoint, a recurring topic for AI uptake was **the importance of standards,** as they are key to enable communication between machines, processes and stakeholders in the value chain. Standards can also provide an essential starting point for data sharing and they are seen as crucial to enable applications such as industrial digital twins.

On the link between AI and human resources, **AI is seen as a means to augment human capabilities** (Sahu, 2021): for instance, many tasks in manufacturing, though dangerous and cumbersome, still require a lot of expertise; in this context, AI-powered collaborative robots could take them over, so that the expert operator can focus on tasks with more value added. Furthermore, AI can also assist in the decisional process, by augmenting the operator's assessment capacities with more information.

Human-in-the-loop is regarded as fundamental (Bousdekis, 2021): AI-powered optimization concerns the optimization of the human-machine interaction itself, not just the customization of the workflow over the operators or the optimization of the machine. Thus, to be effective the optimization must encompass the mutual cooperation across the manufacturing process. To this end, trials are already being carried out innovation laboratories on the mutual interaction between algorithms, intelligent machines and workers.

Human-machine collaboration also allows for **breaking silos** (Jarrahi, 2022): many companies face the challenge of losing tacit knowledge regarding machines or the workflow when workers retire or change jobs. This impacts software architectures as well, whose intricacies are sometimes known only by some of the workers, who therefore become critical to the company. AI solutions can help to grasp this tacit knowledge: for instance, solutions exist composed of a speech recognition system connected to a database in the background, allowing experienced workers to orally relate their experience, which is then structured and made available to others. As was noted by the experts who participated in our consultation, this aspect is particularly important for small and medium enterprises, which sometimes have very scarce key personnel to the company.

Lastly, regarding the use of **AI for sustainability** (Mao, 2019), there is a double incentive for the manufacturing industry to adopt AI both to improve the carbon footprint and to reduce waste and inefficiencies, as both of these aims entail economic benefits. As was flagged by some of our experts, Digital Innovation Hubs in synergy with industrial clusters already operate on the ground to raise awareness in this respect.

Barriers and challenges to adoption

Regarding challenges to adoption, we identified concerns around **data** as prominent (Escobar, 2021): while AI demands huge amounts of data, a lot of manufacturing companies either deal with small datasets or face a complete lack of data. As an example, in predictive maintenance, a specific machine could display a certain effect very seldomly, leading to a paucity of such data points. Additionally, it would also be strongly machine-dependent, hindering generalizability: for instance, the data coming from a specific machine model can be affected by differences in setting, parameters and working conditions and, furthermore, a given company may have several machines but only one instance of each type, especially in the SME context. In this respect, the establishment of the Manufacturing Data Spaces, forecast by the Digital Europe Programme, is identified as a possible solution which could help to overcome this scarcity of data.

Furthermore, finding training data that is unbiased or where bias is controlled is extremely difficult for many companies and it creates a strong divide between larger companies, which can access such data to ramp up their AI solutions faster, and small and medium ones which cannot obtain data so easily. A possible solution, as pointed out by the experts, could be to create a standard and a certification to prepare quality training datasets. The variety of machine tools and contexts in manufacturing also leads to **the need for tailoring AI solutions[8] :** as there is no off-the-shelf solution for manufacturing, every application has to be adapted to the situation. This can hinder AI uptake for SMEs, whose IT departments may struggle to carry out the needed tailoring to the company's needs.

Beyond technical hurdles, the success of an AI application in manufacturing depends critically on making it human-centric, by **co-designing together with the workforce the uptake of AI solutions** (Waschull, 2022). This may be achieved by creating synergies, for instance up-skilling the workforce and providing training to master digital tools so that, instead of being passive, users can exert more control on the tools and help their calibration.

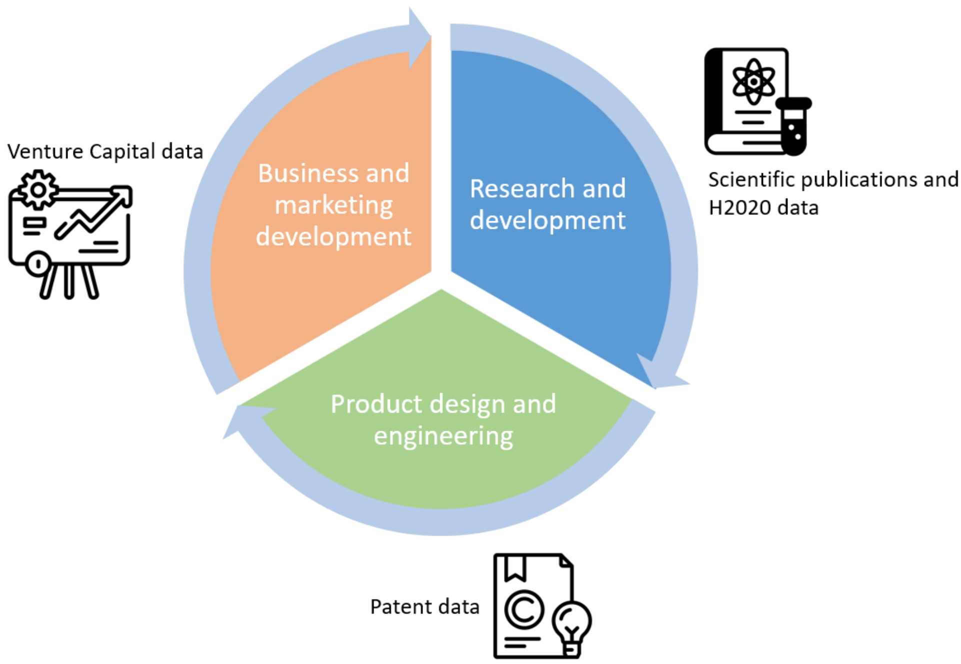
Lastly, **buy-in of management** may pose a challenge to the adoption of AI (Makarius, 2020): several experts pointed to the issue of managers understanding the added value of adopting AI technologies and applications. The perceived lack of understanding stems mostly from the difficulty in grasping whether this type of investment can in the long run bring a bigger return on investment (ROI). Indeed, it is generally difficult to forecast the ROI from AI uptake, which therefore hinders the upfront investment in AI.

[8] https://www.protocol.com/enterprise/landing-mariner-ai-manufacturing-defect

4 Investigating the uptake of AI technologies in the manufacturing sector worldwide and in the EU

To monitor and assess AI uptake in the manufacturing ecosystem, no single knowledge stream can capture all the different facets involved. The approach adopted in this report therefore fuses several data streams, complementing the qualitative research described in the previous sections. We attempt to convey a holistic picture of the technology-innovation cycle of AI uptake, starting with scientific research using data from scientific publications and EU-funded R&D projects, moving to product design with patent data, and reaching marketing and business development using venture capital data (Figure 2).

Figure 2. Representation of the technology-innovation cycle and the data sources used at each step.

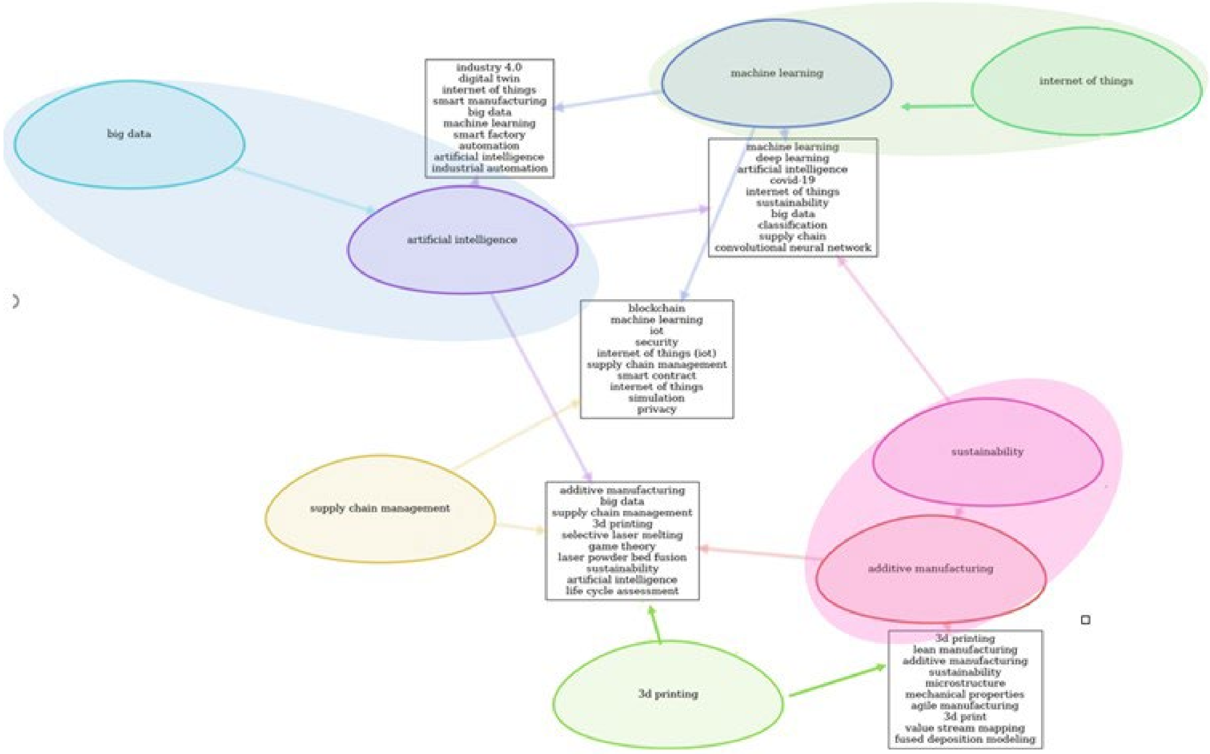


Source: JRC

Scientific research: Scientific publications and H2020 projects

Analysing scientific publications is important to detect the emergence of key innovations and concepts as well as their intra-relationships. Indeed, such understanding of research outputs in terms of scientific publications sheds light on the first stage of the technological-innovation lifecycle. To this end, we queried Scopus, the most comprehensive database for peer-reviewed literature, with sets of keywords related to manufacturing to obtain a sample of relevant publications.

Figure 3. Topics in AI and Manufacturing scientific publications

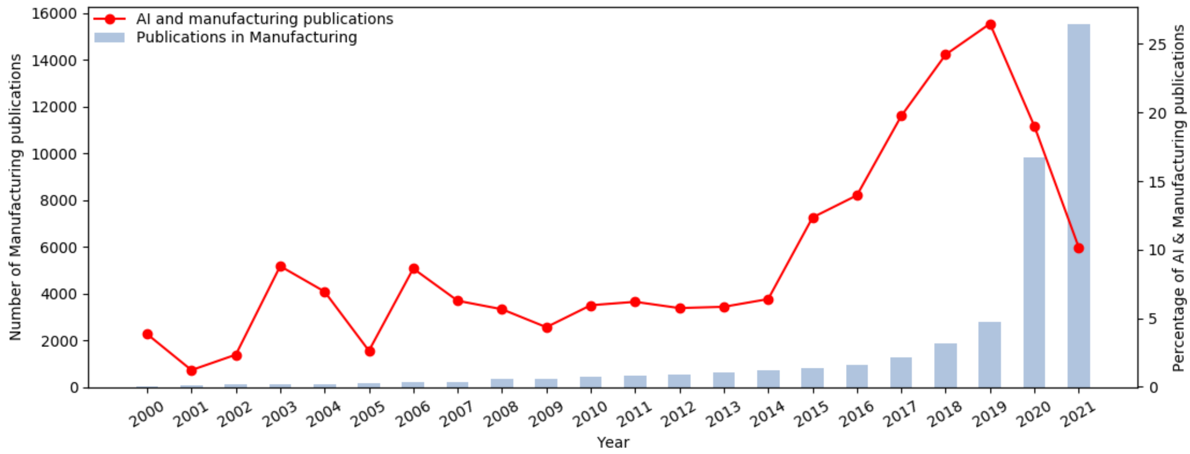


Source: JRC, data: Scopus

To gain insight into the relevant concepts for AI in manufacturing, we first performed a topic analysis, depicted in Figure 3. The emerging topics (the five boxes in the figure) display concepts that most frequently co-appear in scientific publications. As shown in the figure, AI and Machine learning emerge strongly in the manufacturing literature, as do 3d printing, additive manufacturing, sustainability and supply chain management.

In the network of publication we can observe some tightly linked couples of concepts : the two natural associations of AI with big data and IoT with machine learning, confirms the fact, also mentioned by the experts, that AI in manufacturing is intrinsically related to data but also infrastructure (as is the case of IoT). Another strong association is the one between sustainability and additive manufacturing, which corroborates the fact, emerging from our expert consultations, that advanced manufacturing technologies can support efforts towards sustainability.

Figure 4. Temporal evolution of publications in Manufacturing and the share of AI and Manufacturing publications.



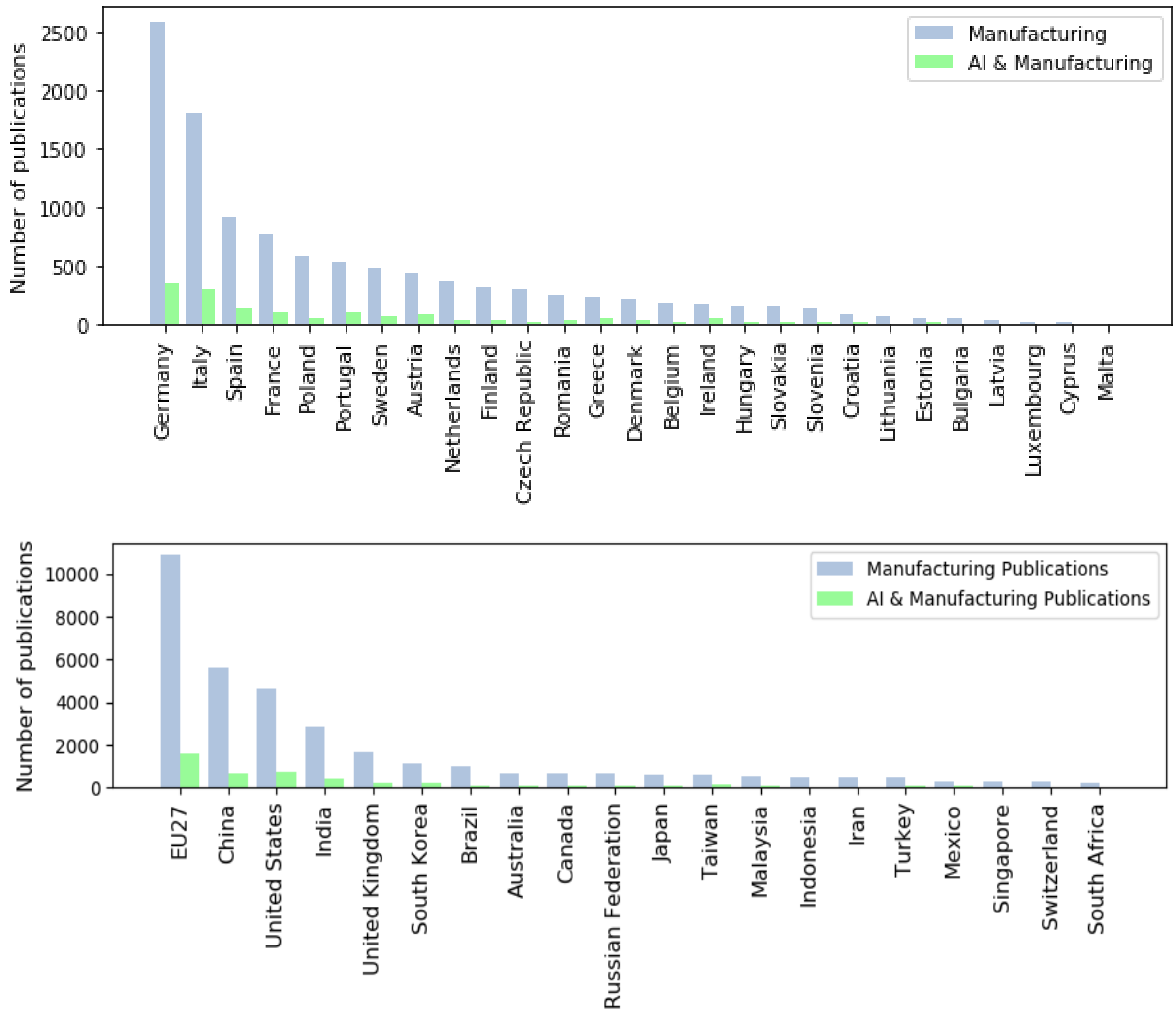
Source: JRC, data: Scopus

The temporal evolution of scientific output, depicted in Figure 4, shows that, although publications in manufacturing increased exponentially since 2018, the share of publications in AI and Manufacturing plummeted after 2019 from more than 25% to around 10%. The reason for this steep decrease can be traced back to a spike in publications related to supply chain management in 2020 caused by the COVID-19 crisis, which did not feature AI-related keywords.

Lastly, in terms of the geographical distribution of scientific output (Figure 5 below), EU27 is leading the rank, with more than 10000 publications in manufacturing, of which 20% delving also into AI. China and US follow albeit with much smaller numbers, around 6000 and 5000 respectively.

At the level of EU Member States (Figure 5), Germany accounts for a fifth of the EU's AI-related scientific output in manufacturing, followed by Italy, Spain and France. For these countries, the percentage of AI and manufacturing related publications accounts for approximately 10-12% of their total output of scientific publications. These four countries contribute up to the 65% of the whole EU27 scientific output in AI-related manufacturing. This ranking is also mirrored by Horizon2020 projects: Germany, Italy, Spain and France coordinate or participate in more than 150 projects each, with again around 10% of them geared towards AI.

Figure 5. Geographical distribution of scientific publications. Top: worldwide, bottom: EU27

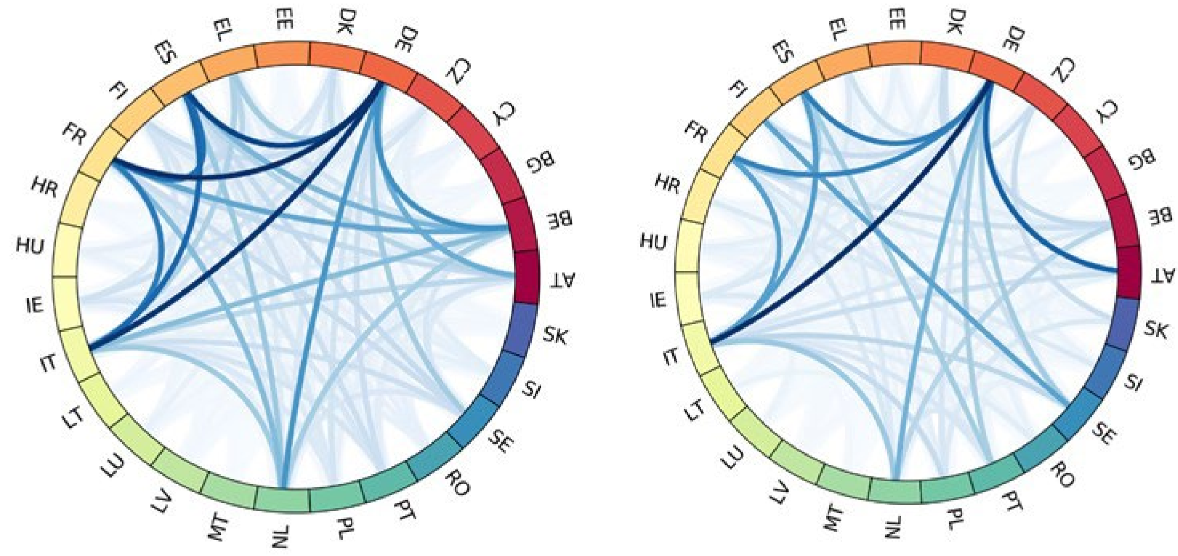


Source: JRC, data: Scopus

From scientific publications and H2020 projects, a more holistic picture emerges if we analyse the patterns of bilateral collaborations, depicted by the chord diagrams in Figure 6 below. Contrasting with Figure 5, we can note that the four countries more active individually also form tight partnerships, both in EU-funded projects (left) and in scientific publications (right).

In Figure 6 we note that there are a larger number of more intense connections between countries on H2020 than in publications. Therefore, H2020 seems to be successful in the aim of networking and connecting the MS. We can futher note that the scientific collaborations are sometimes not closely mirrored by the partnerships in H2020 projects: for instance, Germany shares a strong link with Austria which is not as strong in the H2020 network and the same happens for Sweden and Finland. This phenomenon can be probably traced back to the physical proximity and closeness in culture and language. Furthermore, Italy, France and Spain, despite being still very close collaborators in terms of shared scientific output, do not share links as strong as in the H2020 network.

Figure 6. Networks of bilateral collaboration on H2020 projects (left) and scientific publications (right).



Source: JRC, data: CORDIS

Technological innovation: Patents

Moving one step further in the technological-innovation lifecycle, to product design and engineering, patents are a crucial tool for the protection of the technological innovations carried by new products; therefore, we analyse international patent data to shed light on the innovation landscape driving the uptake of AI in manufacturing. The dimensions of our analysis are chosen to illustrate who the drivers and owners of innovations are, where these drivers and owners are located and what the innovations at the intersection of AI and manufacturing comprise, i.e., what technologies they involve and build on.

The richness of patent data allowed us to distinguish between **enabler patents** and **application patents**: the former, enabling inventions, provide the means for AI to be integrated into systems, e.g., sensors collecting data that will be used by an AI system, whereas the latter, application inventions, are products directly embedding AI for the manufacturing sector.

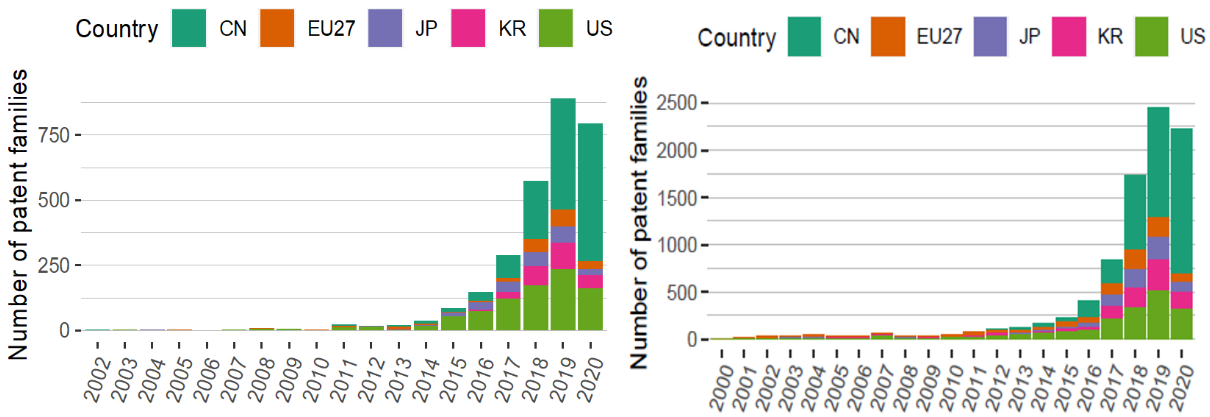
Through this classification of our data, we investigate differences in AI uptake for the two types of innovation activity separately, allowing for a finer-grained analysis.

Looking at the global picture, we observe that four countries stand out in terms of assignee countries of AI in manufacturing patents: China, South Korea, Japan and the US. **Together with the EU27, these countries account for more than 86% of all patent families in the sample.** Figure 7 shows the number of patent families for enabler and application patents filed by the main assignees between 2000 and 2020. We note that the number of patent families has almost exponentially increased over the course of the last decade for both AI enablers and AI applications. China and South Korea have had especially strong growth rates, with China overtaking the US in total patent filings in 2018.

To extend the analysis of absolute patent ownership figures, we analyse the patent citations, with existing patents being cited as prior art in the context of new patents. Thus, the number of citations received by a patent provides information of its importance in terms of innovation and knowledge flows.

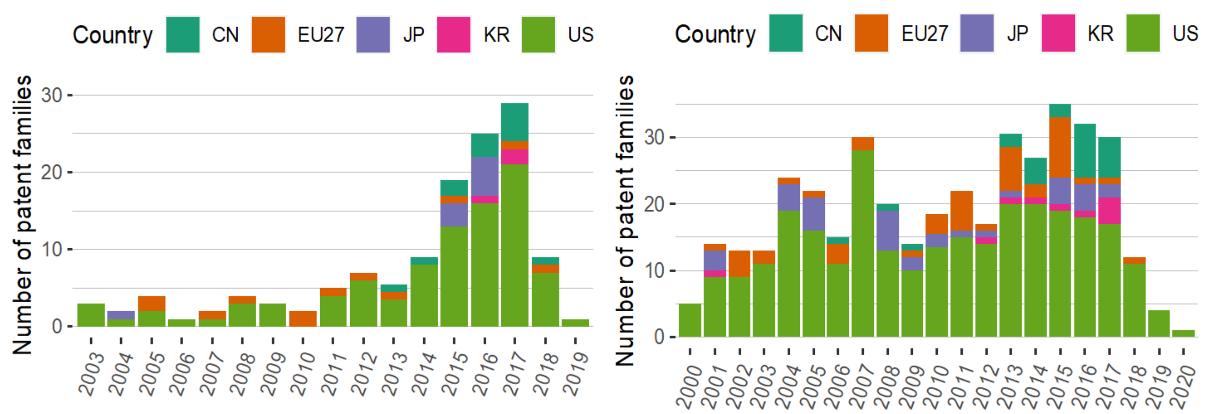
Figure 8 shows the number of patent families for the EU27 and four selected countries for enabler and application patents respectively between 2000 and 2020, based on a subsample of the data which was created by keeping only the top 5% most cited patent families. Comparing with Figure 7, we observe that, while **China dominates patent ownership in absolute terms, the majority of highly cited patents are owned by the US**. Besides the US, also the EU27 gains shares in patent ownership relative to China once the sample is reduced to highly cited patents. This suggests that US is the most influent country with respect to patenting activity in AI and manufacturing.

Figure 7. Temporal distribution of patents filed in AI and manufacturing. Left: Enabler patents, Right: Application patents.



Source: Orbit/Questel, JRC 2022

Figure 8. EU27 in comparison to top assignee countries, subset of 5% most cited patents. Left: AI Enablers, Right: AI Applications.

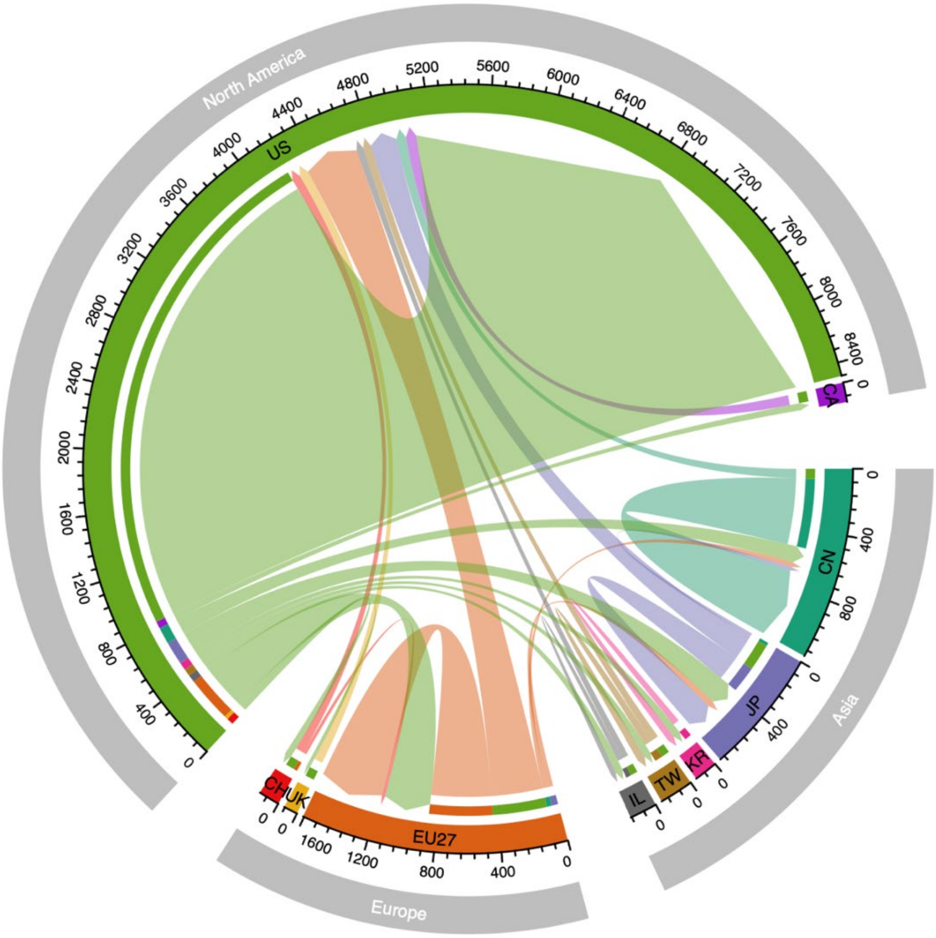


Source: Orbit/Questel, JRC 2022

To further illustrate knowledge flows within and across countries, we represent the data on patent citations in a network in Figure 9 (below). We pool all citations in our 2000-2020 patent data and illustrate the resulting links between countries which exceed 20 citations**. Our analysis reveals relatively strong bilateral knowledge transfers between the US and the EU27. On the other hand, Chinese assignees seem to mostly cite other Chinese assignees.** Besides their links to the US, the EU27 Member States most frequently interact with other EU27 Member States, Switzerland, UK and Japan.

In addition, the citation network analysis reveals that Israel, Taiwan, Korea and Canada are relevant in the citation landscape, with relatively strong bilateral links with the US.

Figure 9. AI in manufacturing, patent citation links, 2000-2020, subset of links with more than 20 citations

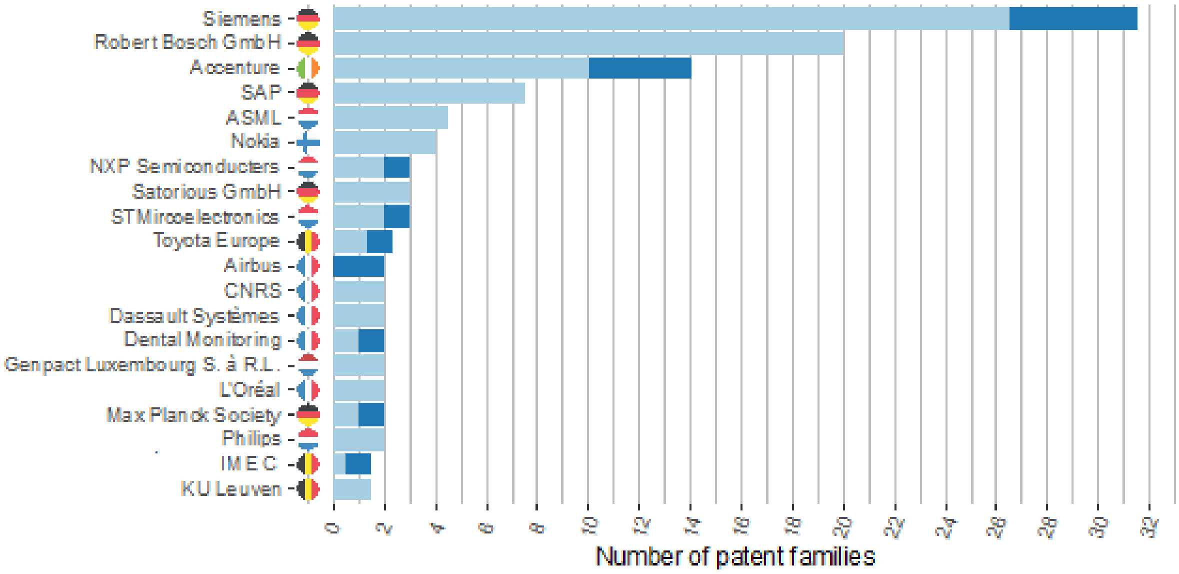


Source: Orbit/Questel, JRC 2022

Focusing on the EU Member State patenting landscape: Figure 10 and Figure 11 below depict the number of patents of the twenty assignees with the largest patent ownership within the EU27 for enabler and application patents respectively. The distinction between granting and pending patents can show how established an assignee already is in AI in manufacturing, As assignees with a relatively large number of granted patents will tend to belong to the early innovators.

In Figure 10 we observe that, among the top twenty EU assignees for enabler patents, 5 have their headquarters in Germany, 5 in France, 4 in the Netherlands and 3 in Belgium. Siemens and Robert Bosch GmbH**, the top two assignees, own more patents in AI in manufacturing than the rest of the top 20 combined**. As both Siemens and Robert Bosch GmbH are German firms, this indicates that Germany is a technology leader within the EU27 in the context of enabler patents in AI in manufacturing. Moreover, in terms of organisation type, only four assignees listed in Figure 10 are research centers, the other sixteen being companies. **Thus, the general innovative power in AI in manufacturing originates more from companies than from independent institutional research facilities.**

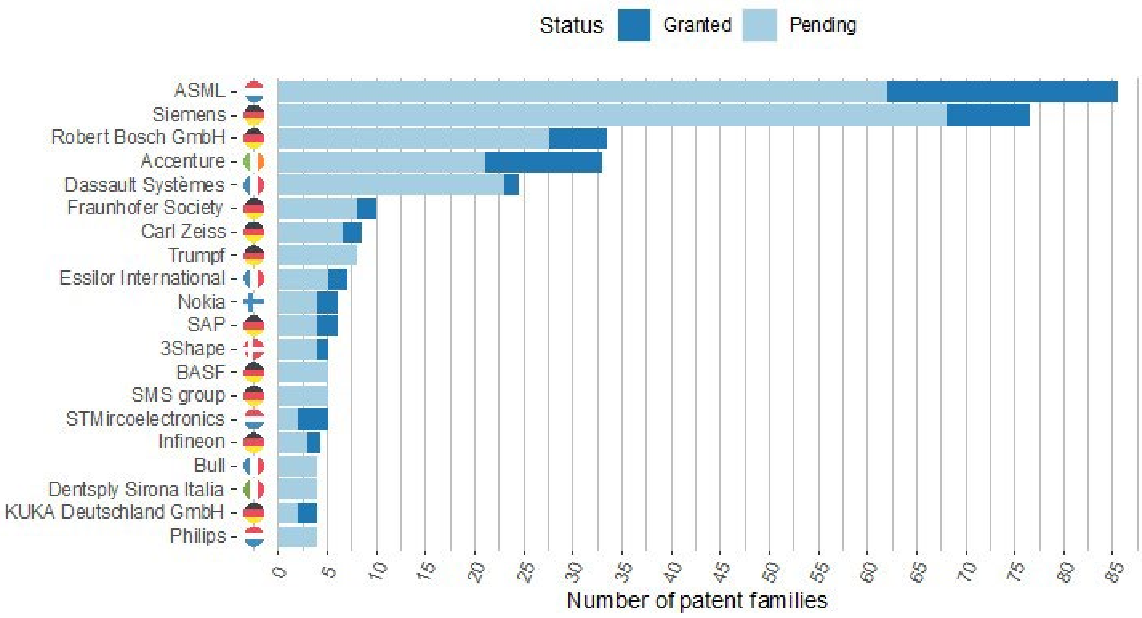
Figure 10. Top enabler patents assignees in the EU27.



Source: Orbit/Questel, JRC 2022

For AI application patents (Figure 11), half of the top 20 assignees have their headquarters in Germany, which is then followed by the Netherlands and France with 3 assignees in the top 20 each. However, the assignee with the single largest patent ownership in AI applications in manufacturing is ASML, a Dutch company whose patents concern the production o semiconductors. **As with AI enabler patents, application patent ownership appears to be concentrated in a few innovative firms**.

Figure 11. Top application patents assignees in the EU27



Source: Orbit/Questel, JRC 2022

Considering that manufacturing encompasses several industrial sectors, we investigated at a finer scale our patent sample in AI and manufacturing to identify sectorial specialisations of EU27 patenting output. To compare the EU27 with the four countries already highlighted in the global comparison, China, US, South Korea and Japan, we calculate the revealed comparative specialisations (RCAs) for each assignee country/region and sectorial domain. The revealed comparative advantage is defined as

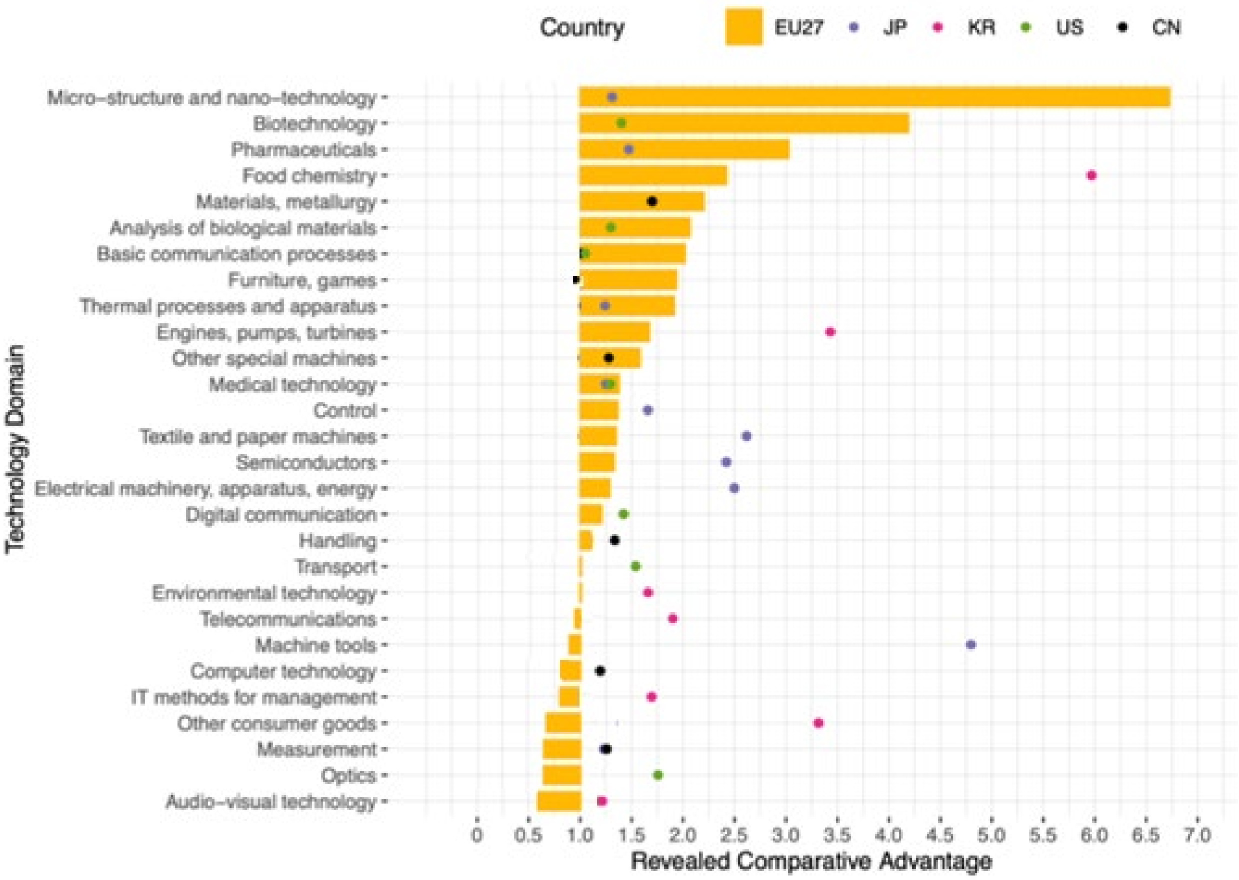
$$RCA_{c_i,k_w} = \frac{\frac{A_{c_i,k_w}}{\sum_w A_{c_i,k_w}}}{\frac{\sum_i A_{c_i,k_w}}{\sum_{i,w} A_{c_i,k_w}}} = \frac{\frac{sum\ of\ activities\ of\ country\ c_i\ in\ a\ sector\ k_w}{sum\ of\ activities\ of\ country\ c_i\ in\ all\ sectors}}{\frac{sum\ of\ worldwide\ activities\ in\ sector\ k_w}{sum\ of\ worldwide\ activities\ in\ all\ sectors}}$$

This index gives us the relative strenght (or weakness) for a country with respect to the others in a given sector. An RCA larger than one means that a country has a relative specialisation in a given sector, while an RCA between 0 and 1 means that the country is less specialised when compared to other countries.

As shown in Figure 12**, EU27 displays a relative specialisation in 20 out of 35 sectors for AI enablers in manufacturing**. "Micro-structure and nano-technology" stands out as the sector with the highest specialisation for the EU27 patenting output, followed by Biotechnology and Pharmaceuticals..

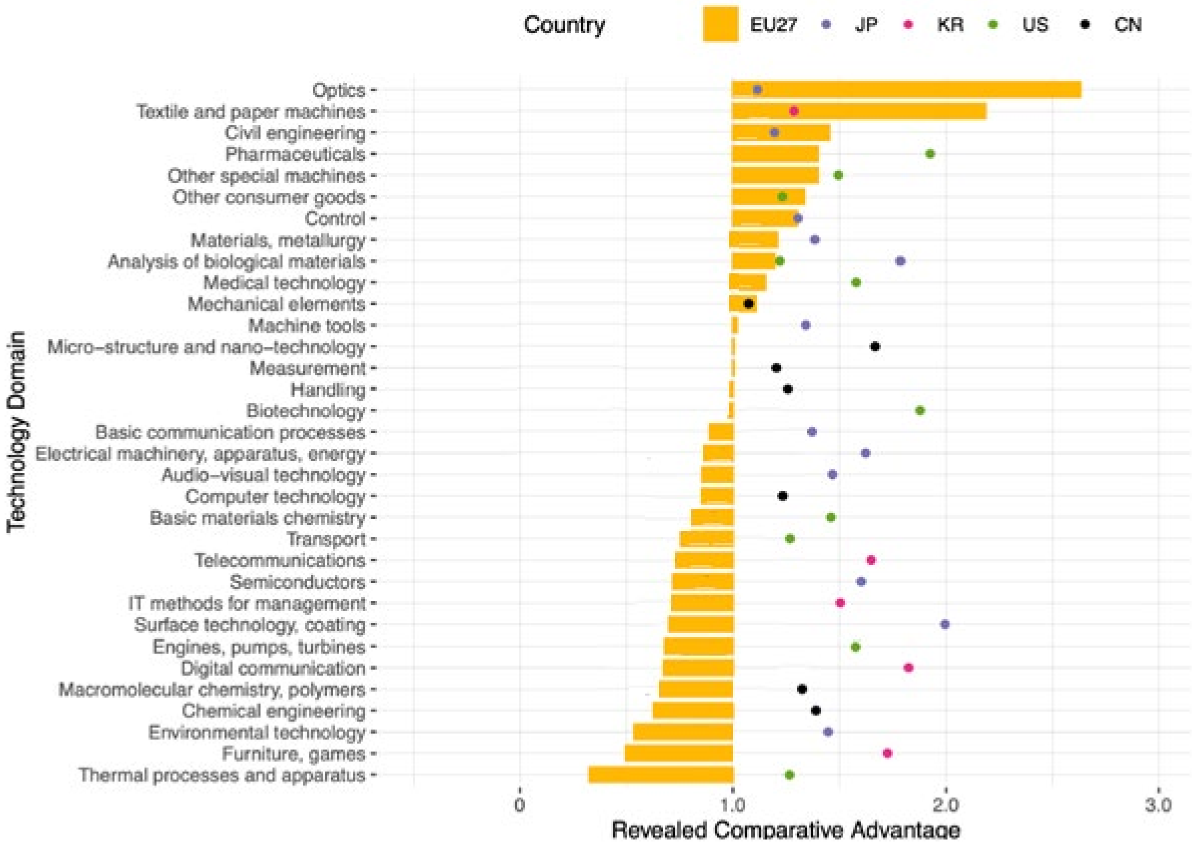
For AI application patents in manufacturing (Figure 13 below), we observe that **EU27 displays a relative specialisation in 13 out of 35 sectors**. Remarkably, we observe an RCA of about one for the EU27 in "micro-structure and nano-technology", implying that the EU27 does not have a relative specialisation in this sub-domain for application patents, even though it appears to specialise in this domain when it comes to enabler patents. Indeed, upon inspection, we uncovered that the assignees for enabler and application patents tend to differ since universities and research centres often are holders of enabler patents, while private companies are more frequent in application patents. Hence, this may suggest that difference between the two RCA rankings for EU27 may be caused by a stronger research landscape over the private sector one in terms of patenting output.

Figure 12. Revealed comparative advantages of the EU27, enabler patents.



Source: Orbit/Questel, JRC 2022

Figure 13. Relative comparative advantages for the EU27, application patents.



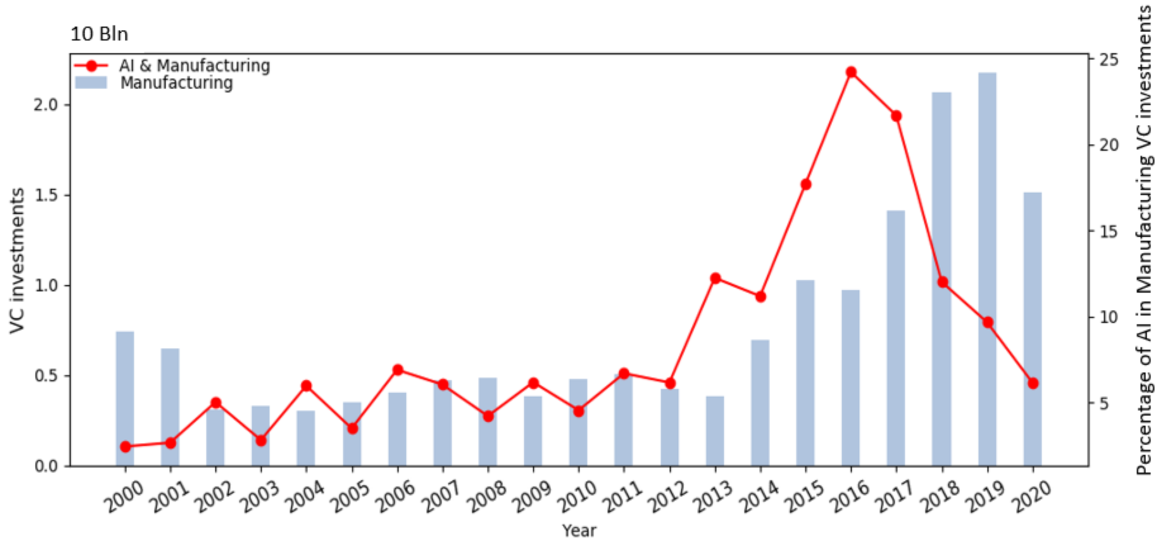
Source: Orbit/Questel, JRC 2022

Start-up Ecosystem: Venture Capital Investments in AI and manufacturing

Arriving to the last step of the technological-innovation lifecycle, business development, we turned to data on Venture Capital (VC) investments as they can provide rich information on the adoption of emerging technologies with the potential to transform industrial sectors. To this end, we merged two datasets, Dealroom and Crunchbase, in order to obtain a final sample with an extensive coverage and identified investments for AI and manufacturing as well as the companies receiving them.

Firstly, from the temporal evolution of investments (Figure 14), we observe that the investments geared towards AI and manufacturing experienced a steep increase over the years 2015-2017, passing from around 12% to almost 25% of overall VC funding for manufacturing. However, upon closer investigation, data shows that such a peak was not the result of a systemic increase of investment in a specific subsector of manufacturing, but rather was caused by massive rounds of investments in two companies, OneWeb (a UK satellite manufacturer) and NIO (a Chinese electric vehicle manufacturer) (Table 1). These two companies together accounted for 1.4 Bln in 2016, more than 60% of global AI and manufacturing VC investments. When analysing the trend without the influence of these two outlier companies, we still notice an increase of investements, starting in 2013, from 6% to 12%. **Since 2013, VC investment in AI and manufacturing has accounted for between 10% and 15% of the total VC investment in the manufacturing sector**.

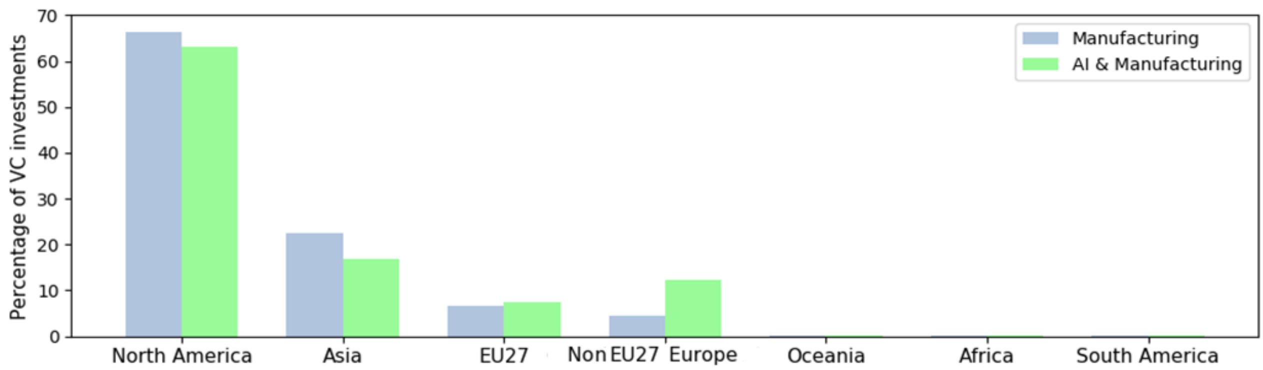
Figure 14. Temporal evolution of VC investments (Bln EUR)



Source: Crunchbase and Dealroom, JRC 2022

Overall, VC investments in the manufacturing sector account for more than 160 Bln EUR, of which almost 18 Bln EUR are for AI and manufacturing investments, 11% of the total. The geographic distribution of AI and manufacturing investments follows closely the one for the total manufacturing investments: **US and China as the largest recipients of VC funding in AI and manufacturing** with a share of 59% and 15%, respectively, while European countries outside of the EU27 (mainly UK) account for 12%, surpassing the EU27 with 7% of global investments in AI and manufacturing (Figure 15). The start-up ecosystem for AI in manufacturing is less concentrated than the overall manufacturing startup ecosystem, indicating a greater geographical spread in participants.

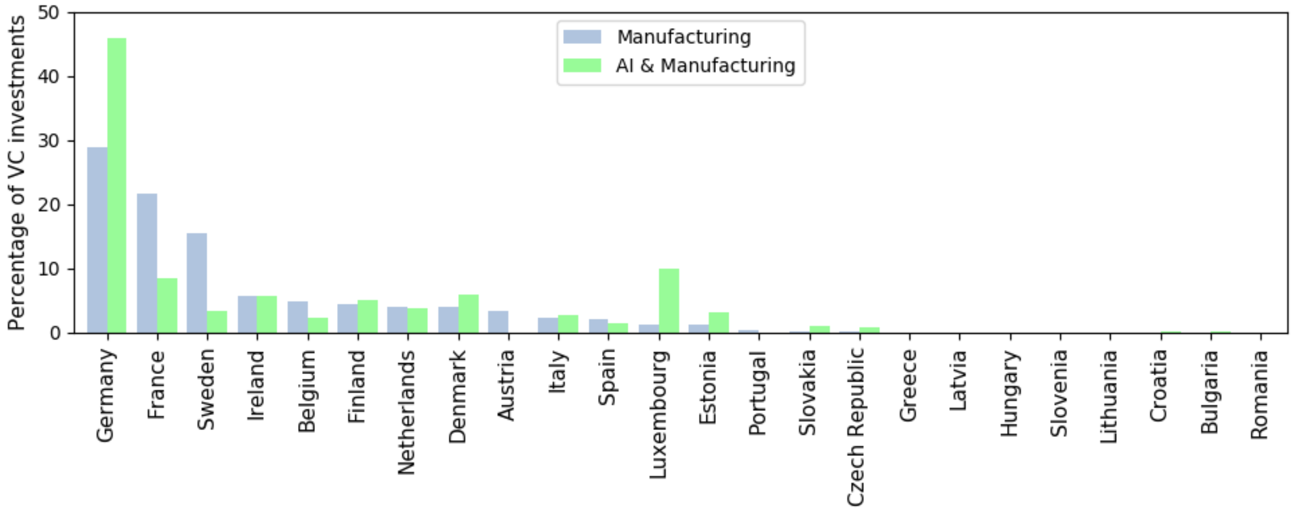
Figure 15. Geographical distribution of VC investments, worldwide.



Source: Crunchbase and Dealroom, JRC 2022

From our analysis at EU27 level (Figure 16), **Germany, France and Sweden lead the ranking**, by cumulatively accounting for more than 65% of the whole VC investments for European manufacturing companies, followed by Ireland (7%), Finland (6%) and the Netherlands (5%). On the other hand, the distribution of AI and manufacturing investments looks very different: Germany receives the largest share, over 45%, followed by Luxembourg (10%) and France (9%). Sweden, on the contrary, which receives more that 15% of overall manufacturing VC investments, accounts for less than 5% of AI and manufacturing investments.

Figure 16. Geographical distribution of VC investments, EU27.



Source: Crunchbase and Dealroom, JRC 2022

An analysis at company level (using the Dealroom database only) offers a finer understanding of the start-ups receiving the flow of VC investment. We created a network by linking companies which have similar description (Figure 17 top).

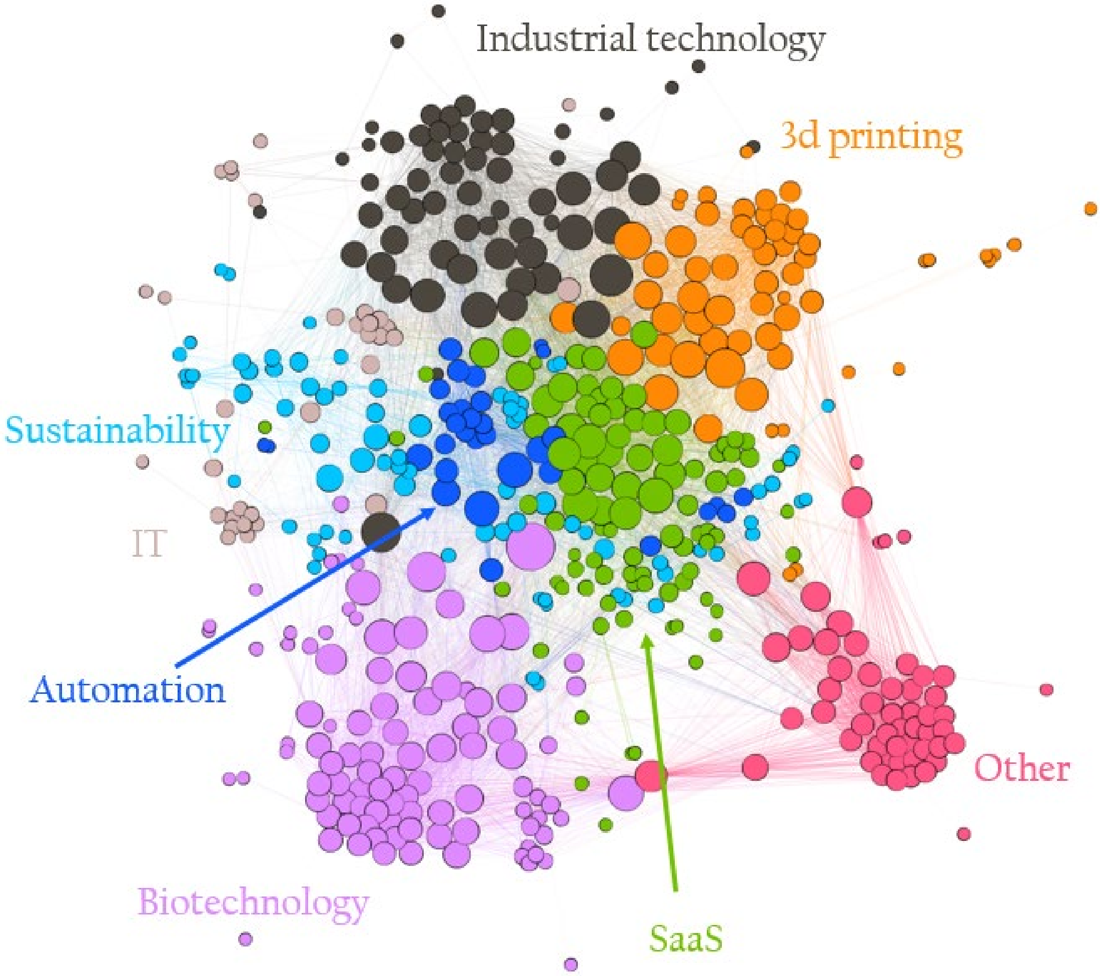
After clustering, the resulting network displays four main communities of companies in the exterior rim corresponding to: industrial technology (which encompasses advanced manufacturing technologies such robotics and digital twins), 3d printing, biotechnologies and the remainder Other cluster of companies which is composed of more traditional companies, such as food manufacturing and construction. At the center of the network, we observe three clusters deeply intermeshed with the first ones, as they are composed by IT and Service-as-a-Service (SaaS) companies and companies working in the realm of automation. Lastly, transversal to the core of the network, is a cluster of companies working in domains closely related to Sustainability such as renewable energy and recycling. It should be noted that the percentage of AI and manufacturing startups in each of the clusters is very variable (Figure 16 bottom): technology-related clusters like 3d printing, automation and industrial technologies tend to feature a higher proportion of AI companies (between 40% and 60% of startups considered); while, at the other end of the spectrum, we find the clusters related to broader sectors such as biotechnologies (where less than 20% of the companies are AI startups). Lastly, in Table 1, we display the startups in AI and manufacturing which are the top receivers of VC investments.

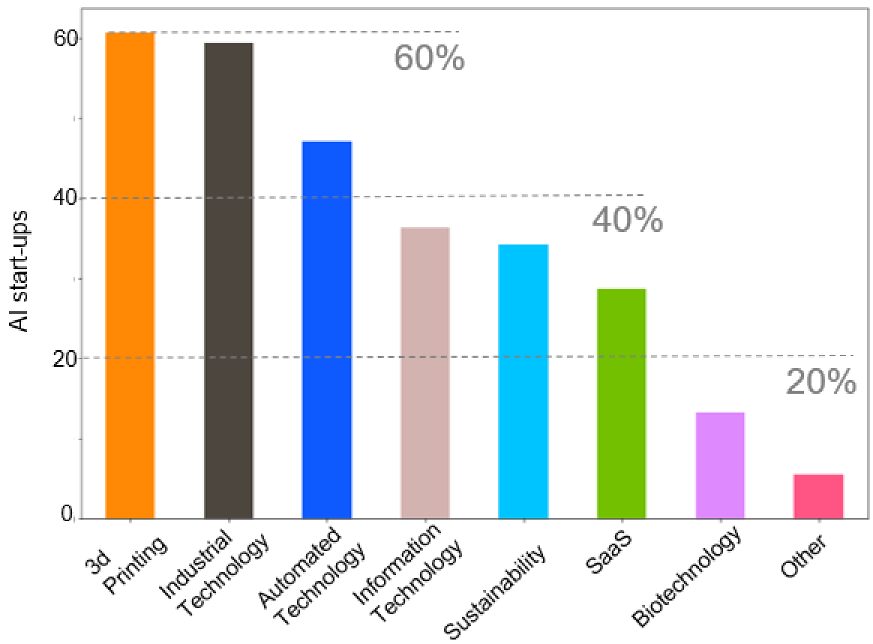
Table 1. Top AI and manufacturing startups.

Region	Name	Raised Amount (Mln EUR)	Country	Description
North America	View Inc.	1270	US	Smart eyewear
	ThoughtSpot	559	US	Search engine for data analytics
	Symphony	388	US	Communication Services
Asia	NIO	2180	CN	Electric autonomous vehicles.
	Preferred Networks	112	JP	Applications of deep learning and robotics
	HeyGears	95	CN	Digital 3D Printing Application Service Provider
EU27	Agile Robots	196	DE	Industrial automation and robotics
	OCSiAl Group	134	LU	Graphene nanotube production
	Spryker Systems	125	DE	Retail and e-commerce technology provider
Other European country	OneWeb	1580	UK	Satellite manufacturer for internet connection.
	Scandit	110	CH	Technology platform for mobile computer vision and augmented reality (AR) solutions for enterprises.
	ONI	92	UK	Microscope manufacturing

Source: Dealroom, JRC 2022

Figure 17. Network of manufacturing startups (top), percentage of AI startups in each cluster (bottom).





Source: Dealroom, JRC 2022

Sustainability in AI and manufacturing: the data perspective

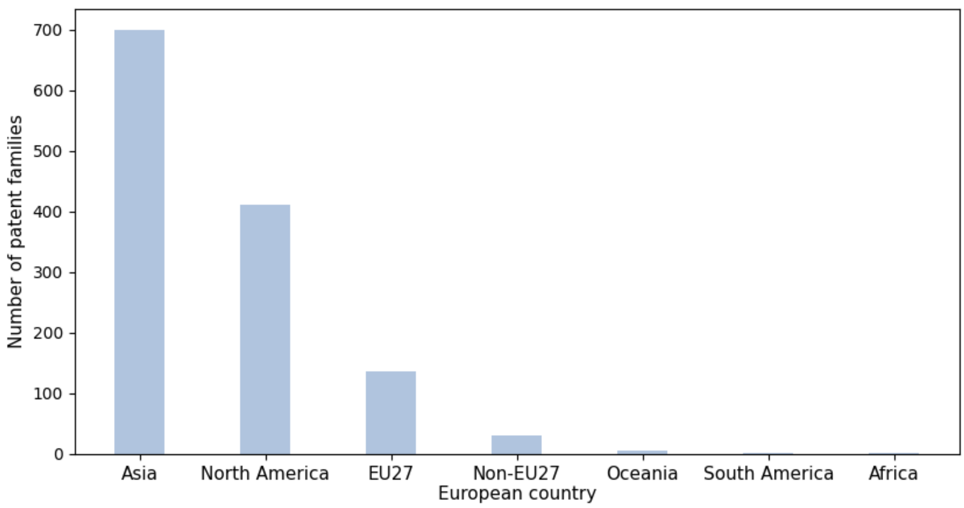
In our data analysis, **sustainability emerged in all the data streams considered**, under different angles, thus highlighting its strong link to AI uptake in manufacturing.

Indeed, we first observed in scientific publication data a strong association between sustainability and artificial intelligence clusters and, furthermore, between sustainability and additive manufacturing (Figure 3), suggesting that these two **technologies are regarded as fundamental drivers of sustainability in the manufacturing-related literature**.

Patent data also points to evidence for the use of AI in manufacturing in the context of sustainability and climate change mitigation. Overall, we observed an **exponential increase of sustainability-related application patents**, starting from around 40 worldwide in 2013 to peak at more than 400 in 2019, a 10-fold increase in six years. On the other hand, less evidence for the emergence of climate change mitigation technologies emerges for enablers patents than in applications ones, sustainability-related enabler patents are in the order of a few tens worldwide. This suggests that the use of AI to solve concrete challenges in the manufacturing sector (e.g. optimization tasks as mentioned above) offers sustainability gains. On the contrary, enablers patents tend to be less manufacturing specific and, therefore, do not appear in the data since they address sustainability challenges beyond the manufacturing context. As to the geographical distribution, Asia, comprising China, Japan and South Korea, holds the largest share of sustainability-related application patents, with 55% of the total, followed by the US with 30% (Figure 18), while EU27 is third with 10%. Compared with the overall geographical distribution of AI and manufacturing application patents, which sees Asia cumulatively holding a share of 63% while US accounts for 24%, we see that US position with respect to climate-related patents is stronger. As for EU27, in both distributions, it accounts for 10%. In terms of growth, Asia is also the fastest growing region, starting from a few patents in 2013 to reach more than 200 in 2019, more than 30-fold increase; while for EU27 and US experienced a 10-fold increase over the same period.

Regarding VC funding, we could find the signature of start-up companies related to sustainability: as shown in Figure 17, a cluster of companies whose business is deeply linked to sustainability objectives, such as waste management, recycling and renewable energy, was identified in the network analysis and, within this cluster, more than 35% of companies use AI in their endeavours. Furthermore, we observe that the cluster of sustainability startups is deeply intermeshed with the SaaS and the Automated technology ones, pointing to **a strong correlation between companies using advanced technologies, such as automation, and sustainability-related ones**.

Figure 18. Geographical distribution of sustainability-related application patents.



Source: Orbit/Questel, JRC 2022

5 Conclusions

In this analysis, we blended two major sources of information to understand the uptake of AI in the manufacturing sector: a more qualitative one, with desk research and expert consultations and quantitative one, building on several data sources. This latter strand follows the technological-innovation lifecycle of AI in manufacturing in analysing the stages of AI development and uptake: publications provides insight into research, patents providing insight into innovation capacity, and venture capital funding and start up ecosystem providing insight into market penetration. Overall, the current report shows that AI uptake in manufacturing has accelerated over the last decade, but it is still at its early stage and, in this section, we summarize its main takeaways.

How is AI used in manufacturing? Enablers and applications

The adoption of AI in manufacturing is enabled by a bundle of digital software and hardware used to collect, store and analyse data. Sensors and smart meters bridge the gap between machinery and data. Connected machinery and other pieces of manufacturing equipment form the internet of things. Digital twins constitute a digital representation of the physical resources and dependencies between them. Depending on the amount of data and computing intensity, running AI models may require the use of cloud computing services and high-performance computing.

At the organization and planning level, AI applications help with demand forecasting allowing to optimise the degree of capacity utilisation or to automate the process of developing new products and adapt it to individual customer needs. At the level of manufacturing processes and shop floor, applications of AI range from scheduling optimisation, increasing the efficiency of resources allocation through supporting tasks performed by humans to oversight of manufacturing equipment and optimising its maintenance schedules, increasing machine longevity and decreasing costs.

AI in manufacturing: a tool for the Green Deal?

The analysis of different metrics of AI uptake in manufacturing shows an increasing trend linking AI with manufacturing and sustainability: for instance, this link strongly emerges in scientific publications in manufacturing, where these two topics, AI and sustainability, frequently co-appear. Similarly, in patent data, we observed a steep increase of climate-related patents filings, leading to a 10-fold increase in the period since 2013.

The areas in which AI and digital technolgies seem to have a positive impact in terms of sustainability include additive manufacturing, waste management, recycling and renewable energy and, from the data related to startup activity, we observed a strong link between companies using advanced technologies, such as automation, and sustainability-related ones. In addition, by optimising production processes and resource use, AI may have positive impacts on energy consumption and waste generation of manufacturing activities. However, to assess the impact of AI on sustainablity, an holistic perspective is required[9], since AI can have a beneficial impact on the energy balance but it is an important carbon emitter by itself, for instance when training of large models is necessary (Dhar, 2020, Strubell, 2019). Hence, future work in this direction should consider the environmental impact and energy consumption of digital infrastructure powering AI applications as well as increased demand driven by lower prices and new products developed with the help of AI.

Uptake in the AI and manufacturing innovation lifecycle: research, innovation and market application

We observed an exponential increase of AI in manufacturing scientific publications since 2014. This coincides with advances in deep learning and increasing interest in 3D printing and additive manufacturing. Slightly later, the rate of AI in manufacturing innovative activities also began to increase, as demonstrated by increased patenting activity: since 2016, there has been a surge in patents concerning both enablers and applications of AI in manufacturing. Venture Capital funding of

[9] https://medium.com/@AINowInstitute/ai-and-climate-change-how-theyre-connected-and-what-we-can-do-about-it-6aa8d0f5b32c

start-ups offering AI-driven products and business models in various domains of manufacturing has also increased since 2016. In the last five years, the annual VC investment in AI and manufacturing has accounted for up to 15% of the total VC investment in the sector, with a significant share of these investments going to industrial automation start-ups, including robotics, digital twins and 3D printing solutions.

Europe's position in the global AI and manufacturing landscape

Comparing the EU27 with the main global economies using the technological life-cycle framework, we observed that it has a strong position at the initial stages of AI and manufacturing development and research, and that it becomes less prominent in the later stages of the technology lifecycle (innovation and market applications). For example, the EU scientific output is twice that of US or China. However, when looking at the number of patents (as proxy for innovation activity) or VC funding received by start-ups (as a proxy for market application), the EU starts to fall behind the US and China. Especially in terms of patent applications, Asia broadly leads, with South Korea and Japan significantly increasing their position in the last decade, and China overtaking the US in total patent filings in 2018. It is worth nothing, however, that China's leadership in patents is moderated when the quality of patents is considered, as measured by inter-patent citation, where the US still has the highest share of the most cited patents indicating that it is the source of the most innovative enablers and applications of AI in manufacturing.

Looking at the final stage of the technology lifecycle, i.e. commercialisation and market uptake of AI in manufacturing, one can observe that the US (59%) and China (15%) account for most of the VC funding for AI in manufacturing start-ups. EU27 start-ups receive only 7% of the total funding in this domain, while the UK and Switzerland together account for 12%.

The EU's shortcomings in transforming scientific output into commercial applications is illustrated by its revealed comparative advantage (RCA) in distinct technological fields of enablers and applications of AI in manufacturing. For example, compared to the main global economies, the EU displays a high degree of specialisation for enablers in AI in manufacturing in the field of Micro-structure and nano-technology. However, this advantage diminishes in AI in manufacturing applications in this domain. Considering that the origin of AI in manufacturing enablers are universities and research centres and applications mostly come from private companies, this exemplifies the weak commercial uptake of AI in manufacturing in the EU.

Within the EU27, Germany, France, Italy and Spain lead in all the rankings of AI uptake in manufacturing. This indicates that there are significant disparities in the level of AI uptake in manufacturing across the EU Member States.

Challenges to AI uptake in manufacturing

As illustrated by the case of the EU, scientific leadership and advanced manufacturing base in the economy are not a guarantee to transform research results into commercially viable AI-enabled products and services. A central and recurring theme in the literature and in our expert consultations was the **need to access data** and, furthermore, the need for quality data to train AI models and this data scarcity affects SMEs harder. In this sense, the establishment of the Manufacturing Data Spaces and the Testing Experimentation Facilities by the European Commission could help to address this barrier, allowing also smaller actors to deploy AI solutions. If compared to other sectors like health or smart mobility (De Nigris et al., 2020; De Nigris, Hradec, Craglia, & Nepelski, 2021), data presents less sensitivities in the context of manufacturing, this does not make AI uptake easier. Non-technological elements play a critical role, for example, as AI adoption requires **re-thinking and re-designing existing processes, structures and business models, with the participation of both workforce and management** appears crucial. To this end, initiatives to raise awareness about opportunities by giving practical examples, providing demonstrations and showcases and sharing best practices could help filling this need. Furthemore, to bridge the gap between research and business, activities geared towards providing information could be beneficial, such as easing access to expert networks, events and publications.

Regarding management buy-in, however, it is often unclear which benefits AI can bring on the ground and, moreover, it can still be difficult to quantify the return on investment of adopting AI in manufacturing. Hence, there is a **clear need for training and raising awareness at the management level**. On the other hand, at the level of the workforce, AI delivers its best results when deployed in synergy with the operator, who holds vast process knowledge and experience. This domain knowledge may go untapped if the synergy is not established or lost if the operator retires or switches jobs. Hence, **upskilling and training the workforce must be planned** both to ensure an AI deployement apt to meet their needs (e.g. in terms of workflow management), and to ensure the best results by leveraging the tacit domain knowledge held by the operators.

Annexes

Annex A. Methodology for Elsevier SCOPUS data analysis

We have obtained the complete metadata for articles concerning manufacturing and AI from the Elsevier API. We queried papers with a combination of the following keywords :

- **Manufacturing keywords**:

MANUFACTURING OR INDUSTRIAL AUTOMATION OR MACHINERY MANUFACTURING OR SUPPLY CHAIN MANAGEMENT OR INDUSTRY 4.0 OR FACTORY 4.0 OR ADDITIVE MANUFACTURING OR INDUSTRIAL ANALYTICS OR SMART MANUFACTURING OR AUTOMATION INDUSTRY OR "3D" PRINT+ OR LEAN MANUFACTURING OR ROBOTIC PROCESS AUTOMATION OR PROCESS AUTOMATION OR SMART FACTORY OR WORKFLOW AUTOMATION OR INTELLIGENT AUTOMATION OR THREE DIMENSIONAL PRINT+ OR DISCRETE MANUFACTURING OR PROCESS MANUFACTURING OR AGILE MANUFACTURING OR PREDICTIVE MAINTENANCE OR PREVENTIVE MAINTENANCE OR PRODUCTION LINE OR FABRICATION OR MANUFACTURING EXECUTION OR ASSEMBLY LINE

- **AI keywords**:

artificial intelligence, deep learning, machine learning, neural network, reinforcement learning

After cleaning the data for removal of duplicates, we had N = 48299 records.

The topic clustering was performed using Latent Dirichelet Allocation (LDA). We investigated the performance of the algorithm on our data by imposing 5,10,15 and 20 topics and we manually inspected the quality of the topics obtained, lastly setting for 5 as displayed in Figure 3.

Annex B. Methodology for Orbit patent data analysis

For patent data, we mined a comprehensive patents database using Orbit Intelligence software by Questel. This database comprehends the World Intellectual Property Organization (WIPO), the European Patent Office (EPO) and the national authorities in UK, Canada, France, Germany, China, Japan, South Korea and India, totalling over 100 patents authorities.

The database records come in the form of 'FamPat family numbers': such families of patents are invention-based, so that all the publication stages of an invention as well as documents from different patenting authorities are associated to only one FamPat number.

In order to isolate relevant patents in the Orbit database, we performed the following steps:

1. We first used the advanced search tool of Orbit software, looking for the co-presence of the AI-related and manufacturing-related keywords listed above in Annex A.

3. The above steps of advanced keyword search and removal of technological domains were applied to perform two searches:

- One search, called "Pure", restricting the search to just the most relevant patents fields: Title, Abstract, Claims, Object of Invention.
- The second search, called "Extended", included also the field Concepts, beyond the aforementioned Title, Abstract, Claims and Object of Invention.

4. We built a classifier which tags the patent as follows:

    - Application: patents where AI and manufacturing keywords and concepts appear with equal weight.

- Enablers: patents mostly featuring AI related concepts and keywords, but which could we used in the context of manufacturing, albeit not exclusively. It is often the case, for instance, of smart sensors.
- Spurious: patents where the presence of the AI and manufacturing keywords is very weak.

6. The resulting dataset is the union of the Pure and Extended dataset, once both have been filtered by the classifier. The resulting cohorts contained N = 3201 records for Enabler patents and N=9442 records for Application patents.

Annex C. Estimation of false positive and false negatives for API queried databases.

False positives: After several cleaning and validation rounds, the share of false positives in our datasets is below 5%.

False negatives: For Scopus and patent data from Orbit having a precise estimation of false negatives is challenging as both datasets are queried via an API; hence, there may be records which are not captured by our queries and, not having access to the entirety of the datasets, their quantification remains imprecise.

Hence, to palliate to this intrinsic limitation, we perform queries to the APIs as general and as comprehensive as possible to circumscribe large swaths of the datasets, which we then clean afterwards to remove the false positives. Furthermore, we adopt a hybrid strategy for curating the queries, both supervised (with experts validating the keywords) and unsupervised (by using topic modelling from different sources like for instance Twitter to further uncover keywords).

Annex D: Dealroom and Crunchbase data analysis

In order to look at the level of AI uptake among start-ups in the manufacturing sector, venture capital (VC) investment was analysed using two datasets provided by Dealroom[10] and Crunchbase[11].

For our analysis, we first filtered in the datasets the manufacturing related records. This selection was made by filtering the companies that are either in the “manufacturing” industry or that feature the manufacturing related keywords in the “Tags” or the “Descprition” fields and whose funding is compatible with being a start-up[12].

Furthermore, we mined in the first selection the companies featuring AI-related keywords in their description to isolate a subset of companies which, furthermore, were backed by VC between 2000 and 2020, either by angel investors or by venture capital funds.

As we merged two different datasources, we made futher checks using several fields such as the domain to isolate companies in the intersection of the two datasets in order to count them only once. The resulting dataset contains N = 19467 VC deals.

Lastly, to build the network of the different specializations in manufacturing start-ups, we linked every company to similar ones, according to the similarity in their description and we then clustered the resulting network using the Force Atlas 2 algorithm.

10 https://app.dealroom.co/
11 https://www.crunchbase.com/
12 Specifically, companies whose funding rounds were of the type: 'angel', 'seed', 'early VC', 'series a-i' and 'late VC'.

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List of abbreviations

AI	Artificial Intelligence
HPC	High Performance Computing
IoT	Internet of Things
VC	Venture Capital

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