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EU POLICY ON ARTIFICIAL INTELLIGENCE INTEGRATION IN MANUFACTURING

EU policy in the field of artificial intelligence (AI) is becoming an important instrument for industrial modernization, enhancing competitiveness, and ensuring technological sovereignty. We base our work on the idea that EU public policies directly drive technology adoption among manufacturing firms. To test this, we combine normative-doctrinal, comparative, and economic-statistical methods. This approach makes it easier to follow changes in policy decisions over time. It also helps us see how different industrial sectors actually adopt AI tools. It has been established that EU policy in the field of AI during the period 2018–2025 evolved through stages ranging from strategic positioning to institutional and infrastructural consolidation, as well as industrialization and large-scale deployment of technologies. The share of enterprises using at least one AI technology increased from 6.93 % in 2021 to 17.27 % in 2025. The highest growth was observed in the pharmaceutical industry, the production of computer products, the chemical and metallurgical industries, and the manufacture of coke and refined petroleum products. These findings suggest that Ukraine can actively use European frameworks to shape its domestic AI agenda. To succeed, this

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ПОЛІТИКА ЄС ЩОДО ІНТЕГРАЦІЇ ШТУЧНОГО ІНТЕЛЕКТУ В ПРОМИСЛОВІСТЬ

Політика ЄС у сфері штучного інтелекту (ШІ) дедалі більше стає важливим інструментом модернізації промисловості, підвищення конкурентоспроможності та забезпечення технологічного суверенітету. З огляду на припущення, що публічна політика ЄС безпосередньо впливає на впровадження технологій у виробничих компаніях, для перевірки виконано поєднання юридичного аналізу документів, порівняльні дослідження та економіко-статистичні методи. Такий підхід дозволяє простежити, як змінюються політичні рішення з часом, а також показує, як різні виробничі сектори реально впроваджують інструменти ШІ. Дослідження показало, що європейська політика у сфері ШІ протягом 2018–2025 рр. пройшла кілька чітких хвиль: від перших стратегічних планів до побудови реальних інституцій, цифрової інфраструктури та запуску технологій безпосередньо у виробництво. За цей час частка підприємств ЄС, які інтегрували бодай один інструмент ШІ, помітно підскочила – з 6,9 % у 2021 р. до 17,27 % у 2025 р. Найшвидше технології опанували високотехнологічні сектори, зокрема фармацевтика, виробництво комп'ютерної техніки, хімічна й металургійна галузі, а також підприємства з переробки нафти й



strategy must span a complete governance cycle: framing policy goals, applying specific regulatory mechanisms, and running regular evaluations. Building this comprehensive structure helps make local technology governance more coordinated and efficient.

Keywords: AI adoption, EU industrial policy, manufacturing subsectors, digital transformation, technological innovation, NACE classification.

JEL Classification: C18, L60, O31, O32.

коксу. Отримані цифри підтверджують, що Україна може активно спиратися на європейський досвід для формування власної стратегії розвитку ІІІ. Для успіху така стратегія має охоплювати весь цикл управління: визначення цілей політики, застосування конкретних регуляторних механізмів і регулярну оцінку результатів. Побудова такої комплексної системи допомагає зробити управління технологіями на місцевому рівні більш узгодженим та ефективним.

Ключові слова: впровадження ІІІ, промислова політика ЄС, підсектори виробництва, цифрова трансформація, технологічні інновації, класифікація NACE.

Introduction

Global technological competition makes artificial intelligence (AI) very important for industrial and economic policy. Today, AI is not only a general-purpose technology; its actual use directly affects productivity, industrial structures, and the digitalisation of manufacturing. In the European Union, AI policy is part of broader plans to boost technological independence and modernise industries.

Ursula von der Leyen, President of the European Commission, noted that "European AI is critical to our strategic independence and will drive the development of key sectors of industry and society" (European Commission, 2025a). This shows that the EU does not see AI just as a technical tool; rather, it is treated as a strategic instrument to support industrial modernisation and long-term technological growth.

Ukraine is moving closer to the EU and developing its own industrial and economic policy. Because of this, the European experience in digitalisation and the use of AI in industry is very important for the country. For these reasons, it is useful to examine how EU policies influence industrial digitalisation and how businesses adopt AI technologies in their operations.

Hulok (2025) studies the institutional aspects of AI regulation in the EU. This author describes EU digital laws as a "digital constitution," which helps make the use of technology more predictable. On the other hand, Cancela-Outeda (2024) examines how supranational and national bodies cooperate within the EU's multi-level AI governance system.

Some researchers also analyse regulatory and ethical issues. For example, Bolgouras et al. (2025) argue that clearer regulation can improve transparency, accountability, and public trust. Vannuccini (2025) notes that it is important to balance technological autonomy with competitiveness and the public interest. These studies show that regulation is not only a technical problem, but also a strategic question.

At the same time, some studies focus on the use of AI in industry, particularly in smart manufacturing and supply chain optimisation within Industry 4.0 (Zeba et al., 2021; Samuels, 2025; Nurainia & Apriadi, 2025). However, there is still not enough research on how AI adoption interacts with business processes at the firm level.

In Ukraine, AI research is generally more applied. Studies have examined areas such as judicial practice (Tsuvin, 2025), digital marketing (Ponomarenko, 2024), accounting automation (Korol & Romashko, 2024), and the digital transformation of the economy (Bashlay & Yaremko, 2023). These publications demonstrate that Ukrainian research is strongly practice-oriented. However, there remains a lack of institutional and strategic analysis of AI adoption.

Bazhal (2025) substantiates the expediency of applying the neo-Schumpeterian approach to the use of AI as a driver of economic growth that shapes a new technological paradigm for the development of production systems. In this context, the author considers AI a key driver of innovation that transforms the cost structure, reduces the cost per unit of useful effect, contributes to the emergence of new products and the improvement of traditional ones, and shapes the long-term dynamics of sectoral development within the life cycle of technological transformation.

Some studies point out that AI technologies create several important challenges for the global economy. These challenges include privacy concerns, economic inequality, job losses in certain professions, and issues related to intellectual property rights (Pereguda & Chaliuk, 2026). Chabanna (2025) suggests that the European approach to AI policy – which relies on ethical rules and human-centric principles – can serve as a useful example for regulation in other countries.

At the same time, Buchynska (2025) examines the institutional and legal aspects of EU policy. She emphasises the importance of balancing innovation with public trust in digital technologies.

The literature review shows that although many studies examine EU AI policy, research on its actual effects on industrial digitalisation remains quite limited. Therefore, it is important to study the role of EU policy instruments in supporting the integration of AI into business processes and manufacturing systems of industrial enterprises.

The aim of this article is to examine how EU AI policy has evolved, to assess AI adoption in the EU manufacturing sector using available empirical data, and to consider how European experience could be applied in Ukraine.

The hypothesis of this study is that the EU's emphasis on integrating AI into industry has contributed to the faster, more gradual adoption of these technologies by companies. Consequently, a growing number of enterprises have started using AI in their activities.

The empirical base of this study includes strategic and regulatory documents of the European Commission and the European Parliament. We also used statistical and analytical data from Eurostat.

In this study, we examine EU AI policy as a multi-level system. This system brings together strategic, regulatory, and infrastructural mechanisms to create conditions for industrial digital transformation. Its development – from strategic initiatives to risk-based regulation – shows a clear shift toward the practical use of AI in industry. These mechanisms help reduce barriers to technology adoption and increase regulatory certainty. This, in turn, makes it easier for enterprises to integrate AI into their production processes.

As a result, AI technologies are unevenly diffused across the corporate sector, depending on both the functional areas of activity and the technological complexity of the solutions. Eurostat statistical data reflect this pattern and serve as a quantitative measure of the effectiveness of EU AI policy.

The suggested analytical model ‘policy – mechanisms – implementation – indicators’ is designed to link the institutional and regulatory aspects of EU policy with the practical processes of digital transformation in industrial companies.

In this study, we use a combination of normative-doctrinal, comparative, functional, and economic-statistical approaches. The data are classified according to NACE Rev. 2. A limitation of the study is that Eurostat data are aggregated, and differences in digital development across EU countries may affect the interpretation of the findings.

The article is organised into three parts: first, an analysis of the evolution of EU AI policy; second, an empirical assessment of AI adoption in the EU manufacturing sector; and third, a discussion of how the European experience can be applied in Ukraine.

1. The evolution of EU AI policy: a focus on the industrial sector

This study uses a functional approach to analyse EU AI policy in the context of industrial development. The empirical base consists of EU regulatory and strategic documents selected for their relevance to the research problem. In the first stage, these documents were systematised and analysed through content analysis.

The analysis of EU documents reveals three main directions: global positioning, coordination among Member States, and support for an innovation-investment cycle. Naturally, not all regions were equally ready for digital transformation; some developed quickly, while others moved much more slowly.

1.1. Formation of the strategic framework for AI policy (2018–2020)

One of the first steps was the EU strategy Artificial Intelligence for Europe (European Commission, 2018a), which outlined priority areas such as industry, transport, energy, healthcare, and public administration. However, in practice, implementation in these sectors was uneven. Public-

private partnerships, data platforms, and innovation hubs frequently encountered delays, and in some Central and Eastern European countries, including Bulgaria and Romania, projects took considerably longer than in older Member States.

At the company level, AI adoption also varied. Some enterprises, such as Siemens in Germany (van Giffen et al., 2023), experimented with new technologies almost immediately. They were quick to implement predictive maintenance tools, although initial difficulties revealed that staff required additional training. Smaller companies, in contrast, often need several years to catch up because they face more practical challenges than larger firms. This structural gap emphasises why a company's – or even a country's – capacity to absorb new knowledge is so critical. Absorptive capacity involves recognising useful external information, learning from it, and applying it to products or business processes. Achieving this is not always straightforward, and no single document fully captures these local challenges.

To address these differences, the EU introduced the Coordinated Plan on AI (European Commission, 2018b). Germany and the Netherlands were quick to launch industrial AI programs, while Belgium and Sweden placed greater emphasis on developing data platforms and innovation hubs. In contrast, countries such as Bulgaria and Romania encountered administrative barriers that slowed down progress. These variations suggest that local readiness and the capacity to absorb knowledge strongly influence how effectively a country can turn policy objectives into actual economic outcomes. This also raises questions about whether it is realistic for all national innovation systems to develop at the same pace.

The European Parliament (2019) clarified the role of AI in economic transformation. Industry is one of the main areas where new technologies are introduced alongside human-centred approaches. The pace of adoption depends on both the technology itself and how ready people and organisations are for change. When preparation is insufficient, implementation tends to be slower. Companies that are better prepared usually manage to integrate new tools more quickly.

Building a supportive ecosystem for AI remains a key priority. This system brings together different elements that can be used in healthcare, industry, and public services. Some digital innovation hubs give small companies the opportunity to experiment with new solutions. Gradual adoption allows both businesses and society to adjust to new tools, which helps increase trust in AI.

Regulatory "sandboxes" provide a controlled space for testing. They allow organisations to evaluate risks and assess performance while adapting rules. Sandboxes are applied in areas such as autonomous transport, telemedicine, energy, and industrial systems. Experience from Germany shows that combining technical skills with ethical principles can make implementation both more effective and safer.

The 2019 update of the Coordinated Plan (European Commission, 2019) focused on AI integration, particularly in industry. One of the first steps was

to create a network of digital centres, which gave companies – including small and medium-sized ones – access to technologies, data tools, and testing spaces. This contributed to the modernisation of production, though some firms adopted new tools faster than others. High-performance computing (EuroHPC) proved important for handling large datasets and training algorithms. In general, the technology itself and the readiness of the local environment determine whether AI succeeds in a region. Some areas catch up quickly, whereas others progress more slowly.

The White Paper on AI (European Commission, 2020) introduced a more integrated approach by linking technological development, economic tools, and regulatory measures. Because manufacturing is a priority area for AI, this framework tries to balance innovation with public trust. However, actual industry practice shows that smaller companies face more practical challenges than larger corporations. This approach relies on existing EU infrastructure, including high-performance computing, robotics, and industrial datasets. In practice, AI tools help to improve production, logistics, and engineering. For example, predictive maintenance reduces machinery downtime, while precision farming saves natural resources.

Yet, access to shared data and skilled workers varies across regions, leading to different adoption speeds. For instance, a medium-sized German manufacturer reported deployment delays due to older factory machinery. Key industrial applications include digital twins, predictive maintenance, and the optimisation of resource flows. Instead of relying on abstract theories, companies use digital twins as virtual models of physical systems to anticipate technical problems and improve factory operations. Still, coordinating shared datasets and keeping algorithms reliable remain difficult tasks. Larger companies adapt to these tools more quickly, while smaller firms often need additional institutional support. Investment strategies focus on scaling up technology deployment through public-private partnerships and industrial testing facilities. In practice, whether AI is adopted smoothly depends on company readiness and local economic conditions. These factors also influence whether different regions can benefit equally from the policy. The White Paper establishes a framework to increase production capacity and support SMEs, though local industrial circumstances continue to play a decisive role.

1.2. Formation of the institutional and infrastructural foundation (2021–2024)

At this stage, the EU framework for AI developed into a more systematic structure. The emphasis shifted from basic strategic planning to building real institutions and the infrastructure needed for technology adoption.

Regulatory, innovation, and infrastructural instruments were consolidated within an integrated ecosystem that combines technological development, trust-building, and the creation of conditions for the industrial

scaling of AI. A key feature of this period is the establishment of the dual architecture of AI policy based on the interaction between the "ecosystem of excellence" and the "ecosystem of trust." The former is aimed at stimulating research, innovation, and the commercialisation of technologies, particularly through the Horizon Europe and Digital Europe programmes.

The second set of documents focused on rules and values for AI, covering safety, fundamental rights, and ethical responsibilities. These elements were meant to work together, though coordination was sometimes difficult. At that time, the European Approach to AI (European Commission, 2021, COM (2021) 205 final) became an important reference. It brought together earlier EU initiatives and aimed to make the policy more coherent, forming a connected ecosystem. The approach highlighted both the opportunities and risks of AI and suggested actions for the EU and member states, such as mobilising investments, aligning policies, and developing digital infrastructure. In practice, implementing these measures was not always straightforward. Some regions moved quickly, while others needed more time, and coordinating all actions could be challenging.

The infrastructural dimension of policy was further strengthened, within which access to data, computing resources, and a unified digital environment came to be regarded as a fundamental prerequisite for the development of industrial AI. In this context, the European Alliance for Industrial Data, Edge and Cloud was established to coordinate investments in critical digital infrastructure. This initiative is complemented by the development of sectoral Data Spaces, which ensure the integration of industrial data into a common European digital space.

This stage concluded with the adoption of Regulation (EU) 2024/1689, known as the AI Act (European Union, 2024), which moved AI policy toward harmonised regulatory governance. The Act sets out a risk-based model for classifying AI systems into four categories: unacceptable, high, limited, and minimal risk. This allows regulatory measures to vary according to the potential impact of each technology.

High-risk systems – especially in industry, energy, robotics, employment, and public services – face stricter requirements regarding data quality, transparency, cybersecurity, human oversight, and risk management. Their phased rollout in 2026–2027 lays the groundwork for building trust in AI. Ultimately, this transparency and regulatory clarity determine whether the technology can achieve wider use in industrial applications.

The European Commission set up the European Artificial Intelligence Office (European Commission, 2024a) to oversee the AI Act. Its tasks include coordinating the application of the regulation, supporting national regulatory authorities, and developing technical standards and codes of practice, particularly for general-purpose AI (GPAI) models. In industry, these processes create a clearly defined framework for the use of AI in production systems, energy, robotics, and engineering technologies. This framework helps companies scale digital solutions, improve technological capabilities, and align regulatory, innovation, and industrial policies across the EU.

In summary, the years 2021–2024 marked a shift toward an institutional and infrastructural approach to AI development in the EU. During this period, the EU established regulatory, organisational, and technological foundations that paved the way for wider industrial use and the systematic scaling of AI technologies. The year 2024, in particular, represents a transitional phase, as the EU concluded much of its institutional setup while beginning to roll out tools for the industrial deployment of AI.

1.3. Industrialisation and scaling (2024–2025)

In summary, the years 2021–2024 marked a shift toward an institutional and infrastructural approach to AI development in the EU. During this period, the EU established regulatory, organisational, and technological foundations that paved the way for wider industrial use and the systematic scaling of AI technologies. The year 2024 represents a transitional phase, as the EU concluded much of its institutional setup while beginning to roll out tools for the industrial deployment of AI.

By 2024, EU AI policy had started to emphasise the industrial use of AI, paying close attention to how these technologies are integrated into production lines and value chains. The agenda moves beyond preparing the ground for innovation, focusing instead on putting AI to work in real-world applications across the economy. The document *Boosting Startups and Innovation in Trustworthy AI* (European Commission, 2024b) describes an innovation ecosystem intended to help startups and small and medium-sized enterprises bring AI solutions to market. In this context, the industrial sector is the primary arena for these technologies, especially generative AI, which companies can use to improve efficiency and remain competitive.

The core of this approach is the GenAI4EU initiative, which focuses on expanding the use of generative AI and integrating it into manufacturing and engineering processes. This reflects a move toward an applied innovation model, in which technologies are evaluated based on their practical performance in industry and their potential for rapid adoption.

The infrastructural side of the policy is supported by the establishment of AI Factories and European Data Spaces, offering access to computing power, industrial datasets, and development environments. Together, these efforts provide a coherent foundation for connecting innovation actors with industrial ecosystems and help speed up the transfer of technologies into production and value chains.

The "AI Continent Action Plan" (European Commission, 2025b) builds on previous EU initiatives and introduces a platform approach to developing AI. At its core is a system that integrates computing resources, data, and innovation environments, enabling industries to use these elements effectively. The plan focuses on strategic sectors such as advanced manufacturing, energy, transport, and robotics. To make this work, European institutions combine research projects with innovation support and infrastructure development. These efforts help new AI technologies reach production quickly and support their adoption across industrial sectors.

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The AI Application Strategy (European Commission, 2025c) focuses on moving from creating conditions for technological development toward putting AI into practical use. The strategy encourages the systematic integration of AI into production processes and value chains. Applied AI cases—such as robotics, cobots, digital twins, and predictive analytics—help increase operational efficiency and optimise production systems. Specialised support for SMEs provides easier access to technologies, infrastructure, and financial resources, promoting a more balanced digital transformation. Policies now guide AI toward large-scale industrial use, consolidating a model in which these technologies are embedded directly into production systems.

A synthesis of EU AI policy reveals the distinct milestones of its long-term transformation. Each period reflects clear changes in the Union's approach: starting with defining AI as a strategic driver of economic development, moving to building regulatory and infrastructural structures, and finally leading to the real use of technologies within production systems. This progression highlights how theoretical goals gradually turned into practical frameworks across three chronological steps.

From 2018 to 2020, the EU set basic goals to apply AI in traditional industries. European officials identified industry as the main area for AI tools and started the first innovation cycles by connecting research with market deployment. Constructing digital infrastructure became a priority, including early data sharing, regional innovation hubs, and EuroHPC systems. At the same time, Member States aligned national rules and adjusted investment priorities, while the European Commission issued initial guidelines to ensure that AI development adhered to ethical and safety standards.

Between 2021 and 2024, the focus shifted toward strengthening regulations and building administrative bodies to manage technology adoption. Different countries introduced risk-based rules for AI, and shared standards, ethics, and harmonised regulations helped build trust. Technology programs expanded digital infrastructure through Data Spaces, cloud systems, and edge platforms. The AI Office and industrial alliances improved coordination, allowing policymakers to connect innovation directly with the practical needs of manufacturing.

From 2024 to 2025, EU policy emphasised the large-scale industrial use of AI in factories and production lines. AI Factories became the primary infrastructure for deploying new tools, and companies began applying generative AI to engineering and manufacturing processes. Technology

initiatives concentrated on sectors such as advanced manufacturing, energy, transport, and robotics. EuroHPC provided the computing backbone, and EU initiatives supported the broader adoption of AI across industries, helping companies stay competitive in a rapidly evolving global market

2. Empirical analysis of the scale and dynamics of AI adoption in the EU manufacturing industry

2.1. Data sources and methodological approaches to assessing AI adoption

For the empirical part of this study, we use data provided by Eurostat. As part of the EU digital statistical system, this platform regularly monitors how enterprises digitalise their operations and adopt AI tools. The main source is the annual survey "ICT Usage and e-commerce in Enterprises" (Salikhov, 2025). This database ensures cross-country comparability and allows us to track the long-term dynamics of how the EU economy undergoes digital transformation.

Starting in 2023, Eurostat integrated a specialised AI module into its statistical system. This update enables regular measurement of AI use at the company level, covering areas such as data analysis, forecasting, process automation, and decision-making support. This lets us see which AI tools companies actually use. Currently, Eurostat distinguishes eight specific domains of AI application. These include text data analysis (AI_TTM), speech recognition (AI_TSR), natural language generation (AI_TNLG), image processing (AI_TIR), and machine learning (AI_TML). The system also tracks decision automation (AI_TPA), autonomous systems (AI_TAR), and generative AI (E_AI_TPVSG). This last category was added in 2024 to reflect the newest technological wave.

The functional dimension of AI use is defined through nine business domains: marketing and sales (E_AI_PMS), production (E_AI_PPP), business administration (E_AI_PBA), enterprise management (E_AI_PME), logistics (E_AI_PLOG), ICT security (E_AI_PITS), HR (E_AI_PHR), finance and controlling (E_AI_BNU), and R&D (E_AI_RDI). This approach allows us to evaluate how deeply AI is integrated into the core functions of enterprises.

For the empirical analysis, we focus on EU manufacturing firms (NACE Rev. 2, Manufacturing, with 10 or more employees). The main metric we use is the proportion of firms that have adopted at least one AI technology.

2.2. Dynamics and sectoral features of AI adoption in the EU manufacturing industry

The statistical results show a clear upward trend in the adoption of AI tools by EU manufacturing companies. Based on the figures in Table 3, the percentage of enterprises using at least one AI technology rose from 6.93% in 2021 to 17.27% in 2025. We observe a minor slowdown in 2023, with the indicator dropping slightly to 6.79% (see Table 1).

Table 1
Adoption dynamics of artificial intelligence tools across EU manufacturing subsectors

Industry Sector (NACE Rev. 2)	Year 2021 – % of Enterprises Using AI	Year 2023 – % of Enterprises Using AI	Year 2024 – % of Enterprises Using AI	Year 2025 – % of Enterprises Using AI	Net Change 2021–2025 (p. p.)
C – Total Manufacturing	6.93	6.8	10.57	17.3	10.34
C10–C12 – Food, Beverages, Tobacco	5.04	5.42	6.79	12.47	7.43
C13–C15 – Textiles, Apparel, Leather	3.66	4.2	5.98	12	8.35
C16–C18 – Wood, Paper, Printing & Related	6.35	5	9.37	15.63	9.28
C19 – Coke and Refined Petroleum Products	17.81	13.9	20.35	30.41	12.6
C20 – Chemicals and Chemical Products	9.77	11.1	16.7	28.45	18.68
C21 – Pharmaceuticals & Preparations	15.73	17.32	25.8	41.3	25.59
C22–C23 – Rubber, Plastics & Non-Metallic Minerals	7.91	7.68	11.98	16.77	8.86
C24–C25 – Basic and Fabricated Metals (Excl. Machinery)	5.94	5.7	8.59	14.33	8.39
C26 – Computers, Electronics, Optical Products	16.83	16.9	25.29	37.44	20.61
C27 – Electrical Equipment	10.39	10.64	16.37	25.9	15.5
C28 – Machinery and Equipment n.e.c.	11.85	9.83	14.85	25.45	13.6
C29–C30 – Motor Vehicles, Trailers, Transport Equipment	11.39	11.58	14.59	23.86	12.47
C31–C33 – Furniture, Jewellery, Toys & Misc. Manufacturing	4.7	5.21	11.45	17.16	12.46

Source: compiled by the authors based on data from the Eurostat (n. d.).

This dip suggests that companies needed some time to adjust their internal processes and adapt to new regulations. However, from 2024 onward, the growth resumed, reaching 10.57%. This recovery quickly led to rapid expansion by 2025.

Overall, the observed trajectory is consistent with the phased evolution of EU policy – from the strategic formation of the framework, to the institutional and infrastructural model, and subsequently to the industrialisation of AI.

The empirical data show that different manufacturing subsectors adopt AI tools at markedly different rates. In 2021, the highest proportion of companies using these tools was found in coke and refined petroleum production (C19) and the computer and electronics sector (C26). High adoption rates also characterised pharmaceutical manufacturing (C21), machinery and equipment (C28), and the automotive industry (C29–C30). These industries started earlier due to their reliance on advanced technologies and stronger innovation capacity.

Between 2021 and 2025, AI adoption expanded significantly across all studied subsectors. The most rapid growth occurred in pharmaceutical manufacturing (C21), where the indicator surged to 41.32% by the end of the period. High growth rates were also visible in the computer and electronics industry (C26), which reached 37.44%, and in coke and refined petroleum production (C19), at 30.41%. Additionally, sectors such as chemicals (C20) and electrical equipment (C27) showed strong upward trends, climbing to 28.45% and 25.90%, respectively.

The empirical data show that AI adoption strongly depends on enterprise size. Large companies form the innovation core of the economy. They drive AI adoption because they have better access to infrastructure, skilled personnel, and financial resources. Medium-sized firms adopt AI less actively, and small enterprises often lag behind (Polozova & Salikhov, 2025; Polozova & Salikhov, 2026a).

This structural gap leads to a high concentration of AI technologies within certain fields. Consequently, some sectors embrace these tools more readily, becoming early hubs of innovation, while others remain slower to implement them.

The empirical data highlight that the pharmaceutical sector has the highest concentration of enterprises using AI. This pattern reflects a growing demand for machine learning and deep learning applications. In practice, companies use these technologies to speed up drug development and model complex molecular interactions. They also rely on algorithms to optimise compound structures and identify the best candidates for clinical trials.

The pharmaceutical industry's high technological intensity is reinforced by the large share of big companies in this sector. Their presence further strengthens this field's leading position in AI adoption.

The empirical data show that the computer, electronic, and optical products sector uses AI mainly to improve operational efficiency. Companies apply it for predictive maintenance and automated quality checks. They also process production data in real time and adjust technological processes using

machine learning and computer vision. These patterns suggest that sectors with complex production systems and advanced technologies adopt AI more readily than others.

The European Green Deal also plays a role in shaping AI adoption. It encourages companies to use AI to save energy, reduce emissions, and make better use of resources, especially in the chemical and metallurgical sectors. Overall, AI adoption across EU industries is uneven. This pattern depends on a mix of company size, technological complexity, and policy incentives.

The data show that AI adoption in EU manufacturing has been growing steadily. This growth is influenced by both the technological evolution of enterprises and the gradual rollout of European AI policies between 2018 and 2025. These policies combine support for innovation, investment in infrastructure, and regulatory measures, creating a three-level framework that guides the industry's adoption of AI tools.

2.3. Technological structure of AI adoption

As illustrated in *Figure 1*, AI adoption in EU manufacturing shows clear differences across sectors. Cognitive software tools are spreading faster than technologies that require heavy infrastructure. In 2021, only 1.6% of companies used text analysis (AI_TTM), but by 2025 this figure had grown to 9.4%. Natural language generation (AI_TNLG) started at 0.9% and reached 7.1% in 2025. These increases reflect the gradual prioritisation of automating tasks such as document handling, analytics, and managerial communications. Companies often begin with these cognitive functions before applying AI to more complex production processes.

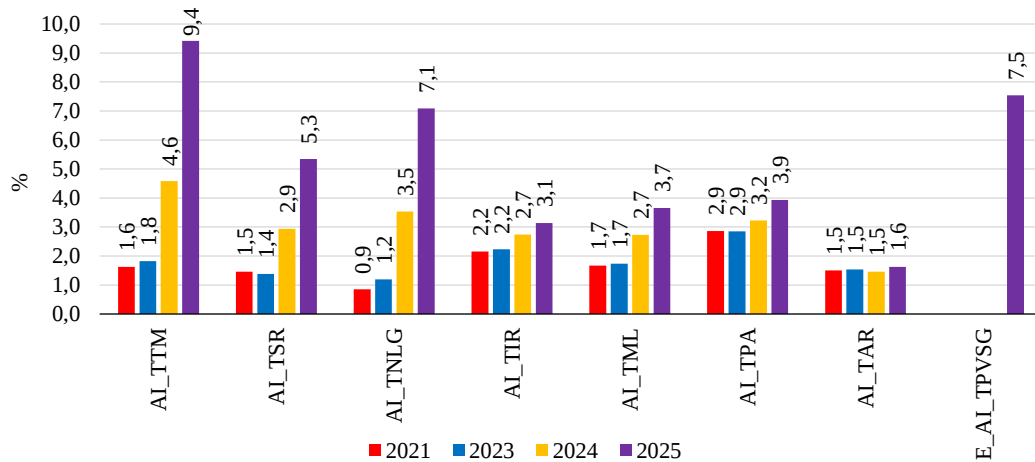


Figure 1. Technological Structure of AI Implementation in the EU Manufacturing Sector.

Source: compiled by the author based on data from the Eurostat (n. d.).

High growth rates were also recorded in the segment of speech recognition (AI_TSR), where the level of use increased from 1.5% to 5.3% (+3.8 percentage points), as well as in machine learning (AI_TML), which rose from 1.7% to 3.7% (+2.0 percentage points) (Eurostat, n. d.). The digital

maturity of enterprises has been steadily improving. Companies are increasingly able to incorporate algorithmic models into both production workflows and managerial decision-making.

Moderate dynamics are characteristic of image recognition technologies (AI_TIR), where the indicator increased from 2.2% to 3.1% (+0.9 percentage points), and of process automation and decision-support technologies (AI_TPA), which grew from 2.9% to 3.9% (+1.0 percentage points). AI adoption is gradually spreading across factory operations, but overall growth is still modest. Interestingly, autonomous systems and transport solutions (AI_TAR) show very slow progress. Between 2021 and 2025, the share of companies using these tools rose only from 1.5% to 1.6% (Eurostat, 2025). Deploying automated vehicles or robots requires large capital investments, careful integration into production lines, and strict safety testing, which limits their adoption.

Notably, generative AI tools (E_AI_TPVSG), which appear in EU statistics from 2025, already reached 7.5% usage. This early uptake indicates that software-based cognitive solutions spread faster than hardware. Across the sector, factories increasingly focus on language- and text-oriented AI models. While software-driven analytics continue to expand dynamically, heavy automated equipment remains at an early stage due to high financial and operational barriers.

2.4. Functional structure of AI adoption

An analysis of the dynamics of AI technology use in the manufacturing industry indicates a gradual expansion of the integration of digital solutions into the functional areas of enterprise activity during the period 2021–2025.

As *Figure 2* shows, the most pronounced growth is observed in the area of marketing and sales (E_AI_PMS), where the level of AI use increased from 0.94% in 2021 to 5.25% in 2025 (+4.31 percentage points). AI adoption is particularly noticeable in customer-oriented and analytical business functions. Companies increasingly apply AI in demand forecasting, tailoring offerings to clients, and improving communication strategies (Eurostat, 2025).

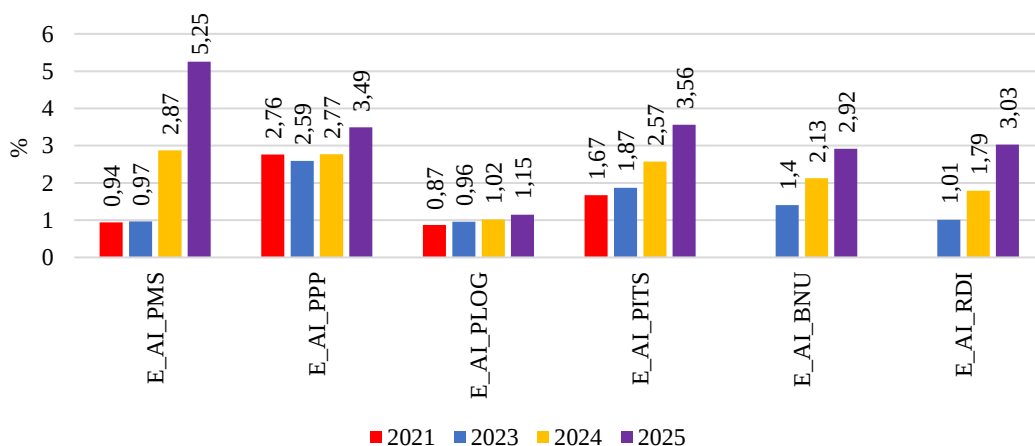


Figure 2. Functional distribution of AI adoption across EU manufacturing subsectors

Source: compiled by the author based on data from the Eurostat (n. d.).

Overall, the empirical evidence indicates that AI adoption in EU manufacturing has moved beyond the initial stage of experimentation and entered a phase of broader diffusion. At the same time, this process remains structurally uneven. Differences are observed across manufacturing industries, AI technologies, and business functions, suggesting that the pace of adoption is determined not only by technological availability but also by sectoral characteristics, enterprise innovation capacity, implementation costs, and the broader institutional environment. The results therefore indicate that AI adoption in manufacturing should be viewed as part of a wider process of industrial transformation rather than as the diffusion of individual digital technologies. In this context, the effectiveness of AI increasingly depends on the coherence between industrial policy, digital infrastructure, and firms' ability to absorb and integrate new technological solutions into production.

3. Adaptation of EU AI policy instruments for Ukraine

An analysis of Ukraine's strategic and policy documents (Polozova & Salikhov, 2026b) indicates the formation of a consistent state policy in the field of AI aimed at the digital transformation of the economy. At the same time, its industrial dimension remains limited. Institutional, regulatory, and infrastructural components dominate the action plans, whereas mechanisms for the direct implementation of AI in production processes (robotisation, digital twins, smart manufacturing, industrial clusters) remain in their early stages of development. This creates a gap between the development of digital infrastructure and the actual use of AI in the manufacturing sector, thereby limiting the possibilities for its scaling. At the same time, the development of infrastructural and regulatory preconditions alone does not ensure economic impact unless they are integrated into production processes. In view of the above, recourse to the EU experience appears justified, as the European model, as demonstrated by this study, reflects a gradual transition from the creation of foundational conditions to the integration of AI into industrial policy and the diffusion of technologies across manufacturing industries.

Policy works best when specific instruments are not only present but also coordinated within a single regulatory framework. At the same time, transferring European experience directly remains difficult, as national innovation systems differ in how quickly they can absorb new technologies. For example, established industrial ecosystems in the EU support fairly rapid technological diffusion. In Ukraine, this process is still fragmented.

To improve the situation, AI policy should focus on selecting and combining practical elements of the European model, taking into account national limitations and the current technological readiness of local industry. In practice, this means creating a policy framework in which regulation, data infrastructure, computing resources, and manufacturing applications work together seamlessly.

A coherent governance cycle—covering policy design, instruments, implementation, and regular review—helps keep actions practical and consistent. Building industrial data infrastructure, expanding computing resources, and establishing testing centres are crucial steps that enable companies to move from initial experiments to broader, systemic use of AI across production.

The institutional strengthening of this process presupposes the creation of a coordination capacity (including a national AI office) and the introduction of a risk-based regulatory model with mechanisms for auditing and certification, which reduce uncertainty and increase the predictability of the regulatory environment.

An important direction is the development of a policy for the industrial deployment of AI as a distinct strategic block oriented toward the integration of technologies into the logic of Industry 4.0, including robotisation, digital twins, and predictive analytics.

Thus, the effective adaptation of the European experience lies not in the fragmented borrowing of individual instruments, but in the formation of a comprehensive AI policy architecture in which institutional, infrastructural, and production components function as interconnected elements of a unified system of economic transformation.

Conclusions

The analysis makes it possible to draw three principal conclusions corresponding to the objectives of this study.

EU AI policy did not evolve as a single regulatory project. Over 2018–2020, the main effort was directed toward agenda-setting, coordination among Member States, and the formation of an initial regulatory basis for AI. In 2021–2024, this agenda was translated into a more institutionalised framework through the development of European Data Spaces, the expansion of data and cloud infrastructure, and the adoption of the AI Act. By 2024–2025, however, the centre of gravity had shifted more clearly toward industrial deployment. Initiatives such as AI Factories and GenAI4EU linked AI policy with practical applications in manufacturing, transport, and energy, extending it beyond general strategic coordination toward the creation of instruments for broader industrial use. This evolution created the institutional and policy conditions for the wider industrial deployment of AI.

The empirical evidence presented in this study shows that AI adoption in EU manufacturing has expanded substantially, although the pace and pattern of diffusion remain uneven across subsectors, technologies, and business functions. The share of manufacturing enterprises using at least one AI technology increased from 6.93% in 2021 to 17.3% in 2025. This trajectory was not linear: after a temporary decline to 6.8% in 2023, the indicator recovered to 10.57% in 2024 and accelerated further in 2025. In sectoral terms, the highest adoption rates in 2025 were recorded in pharmaceutical manufacturing (41.3%), computers, electronics and optical products (37.44%), coke and refined petroleum products (30.41%),

chemicals (28.45%), and electrical equipment (25.9%). This sectoral pattern indicates that AI has spread most rapidly in technologically intensive industries, where innovation activity is stronger and production processes rely more heavily on digital and data-based solutions.

The aggregate dynamics conceal important technological and functional differences. Diffusion in EU manufacturing has so far been driven mainly by software-based and cognitive applications, whereas capital-intensive autonomous systems have spread much more slowly. Between 2021 and 2025, the share of firms using text mining increased from 1.6% to 9.4%, natural language generation from 0.9% to 7.1%, and speech recognition from 1.5% to 5.3%, while the use of autonomous systems changed only marginally, from 1.5% to 1.6%. A similar asymmetry is visible across business functions. AI expanded most rapidly in marketing and sales, where adoption rose from 0.94% to 5.25%. In production processes, the increase was more moderate, from 2.76% to 3.49%, while logistics remained the least digitalised area, with growth from 0.87% to 1.15%. Taken together, these patterns show that the spread of AI in manufacturing is shaped not only by access to technology but also by the cost and organisational complexity of implementation, the technological profile of production, and the innovation capacity of firms. AI diffusion therefore reflects broader structural characteristics of manufacturing rather than the availability of digital technologies alone.

For Ukraine, the practical value of the European experience lies not in a ready-made set of instruments to be copied, but in the policy logic behind them. Ukrainian AI policy is still concentrated mainly on institutional, legal, and infrastructural foundations, whereas the instruments needed for practical deployment in manufacturing remain weakly developed. This applies, in particular, to industrial data ecosystems, digital twins, smart manufacturing solutions, testing environments, and broader automation tools. As a result, the creation of enabling digital conditions has not yet been matched by the spread of AI in production processes. For Ukraine, the key lesson from the EU experience is the need to build an integrated policy architecture in which regulation, industrial policy, data infrastructure, computing capacity, financing mechanisms, and deployment tools operate as interconnected elements of a single system. Without such a link, AI policy risks remaining largely institutional in form while producing only limited effects for industrial modernisation.

The results support the proposed hypothesis, though not in a simplified causal sense. The EU experience shows that integrating AI into industrial policy creates more favourable conditions for the gradual diffusion of AI technologies in manufacturing, but does not by itself guarantee rapid firm-level adoption. The pace and scale of diffusion depend on a broader combination of factors, including regulatory certainty, access to data and computing infrastructure, the technological profile of industries, and the absorptive capacity of enterprises. In other words, industrial AI deployment is shaped not by regulation alone, but by the coherence of the wider policy

framework within which strategic priorities, industrial instruments, infrastructure, and implementation capacity are aligned.

Further research appears most relevant in two interconnected areas. One concerns the development of an integrated AI policy model for Ukraine that would link strategic priorities with concrete instruments of industrial deployment and institutionalise the governance cycle "policy – instruments – implementation – evaluation." The other concerns the quantitative assessment of the factors shaping the intensity of AI adoption in manufacturing, in particular regulatory certainty, access to data and computing resources, and the innovation capacity of enterprises.

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Conflict of interest. The authors certify that don't they have no financial or non-financial interest in the subject matter or materials discussed in this manuscript; the authors have no association with state bodies, any organizations or commercial entities having a financial interest in or financial conflict with the subject matter or research presented in the manuscript. The authors are not affiliated with an institution that is structurally connected to the journal publisher.

The authors did not receive direct funding for this research.

Polozova, T., & Salikhov, M. (2026). EU policy on artificial intelligence integration in manufacturing. *Scientia fructuosa*, 4(168), 32–51. [http://doi.org/10.31617/1.2026\(168\)03](http://doi.org/10.31617/1.2026(168)03)

Received by the editorial office 11.05.2026.

The article has been revised 14.06.2026.

Accepted for printing 10.07.2026.

Publication online 07.09.2026.