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Progress by innovation

Mapping European Best Practices for AI Uptake in Industry

UNIDO REPORT. MAY 2026

ACKNOWLEDGEMENT

This report has been prepared by the Centre for European Policy Studies (CEPS) for the United Nations Industrial Development Organization (UNIDO) within the project "Supporting the reconstruction and development of industrial sectors in Ukraine by fostering digital transformation and the innovation ecosystem", funded by the Governments of Austria and Bulgaria and implemented under the UNIDO Green Industrial Recovery Programme for Ukraine (2024-2028) in partnership with the Ministry of Economy, Environement and Agriculture of Ukraine and the Ministry of Digital Transformation of Ukraine. It forms part of a series of joint CEPS–UNIDO outputs[1] supporting Ukraine's recovery and industrial reconstruction and EU accession process.

The report contributes to UNIDO's work on digital transformation, artificial intelligence, and innovation ecosystems, and was prepared under the overall guidance of the Division of Digital Transformation and Artificial Intelligence (TCS/DAI). The Division promotes digital transformation and AI, as well as associated technologies, within innovation ecosystems that span manufacturing, services, and digital firms. Its objective is to strengthen the competitiveness of industries and manufacturing enterprises in Member States. The Division supports industries in leveraging rapid advances in digital and convergent technologies associated with the Fourth Industrial Revolution (4IR), ensuring a smooth transition toward safe and secure cyber-physical industrial systems and a smart society, while mitigating potential adverse effects on employment and the quality of work. Through its services, the Division supports productive transformation by integrating industrial businesses, dynamic entrepreneurship, and acceleration mechanisms, and by applying technological innovation to sectors such as smart manufacturing, smart energy, and smart agribusiness, particularly in developing, transition, and emerging economies.

The report documents European experience with AI adoption across seven priority innovation sectors identified in Ukraine's WINWIN Global Innovation Strategy 2030: agritech, textiles, wood processing, medtech, automotive and autonomous vehicles, semiconductors, and energy. For each sector, it examines the conditions that enabled AI to progress from pilot to operational deployment in European practice, and what these findings imply for Ukraine's sectoral priorities.

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The publication represents a collaborative effort and has benefited from valuable inputs from both UNIDO and CEPS colleagues. In particular, we would like to thank **Mr. Tomoyoshi Koume, Mr. Andrea Renda, Mr. Andrii Zablovskyi** and **Mr. Oleksandr Soshnikov** for their substantive contributions and technical reviews, which supported the refinement and finalisation of the report.

Ukrainian policymakers, industrial stakeholders, and international partners working on the reconstruction agenda are the primary audience. The report is organised for practical use: each sector chapter can be read independently, and the synthesis in Chapter 3 brings together the cross sectoral findings for readers interested in the broader picture.

SUPPORT RESOURCES

Download on your Desktop for best viewing and active interactive elements.

Knowledge graph: Mapping EU AI best practices for Ukraine (interactive .html)
AI technology stack: As seen in European best practices (interactive .html)

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Executive Summary

This report analyses how European industry has adopted artificial intelligence (AI) across seven sectors that Ukraine designates as priority innovation areas under its **WINWIN Global Innovation Strategy 2030.**[2] Based on 18 case studies of operational AI implementations and a systematic review of the OECD's assessment of EU Member States' progress in implementing the Coordinated Plan on AI[3], it identifies the conditions under which AI adoption moves from pilot to sustained operational deployment, and draws implications for Ukraine's reconstruction-era industrial strategy.

Key findings

1 AI ADOPTION IS PREDOMINANTLY VENDOR-MEDIATED

Across all seven sectors, most documented deployments rely on external AI systems, commercial platforms, or specialist technology partners rather than internally developed algorithms. Large firms with substantial in-house capability still find it more efficient to access AI through the ecosystem. For Ukraine, this shifts the strategic question from building AI development capacity sector by sector, to reducing barriers to technology access and partnership formation.

2 DATA INFRASTRUCTURE IS THE GATING CONDITION

In every sector surveyed, the absence of appropriate data at operational quality was the most consistent point of failure for AI projects. Satellite imagery for forest monitoring, annotated clinical datasets for diagnostic AI, sensor telemetry for predictive maintenance, integrated production data for quality control: in each case, the data pipeline had to be in place before AI could function, and not assembled alongside it. Ukraine's sectoral data infrastructure investment priorities should reflect this sequencing.

3 TESTING AND EXPERIMENTATION FACILITIES (TEFS) AND EUROPEAN DIGITAL INNOVATION HUBS (EDIHS) ARE THE CRITICAL ACCESS MECHANISM FOR SMALLER ENTERPRISES

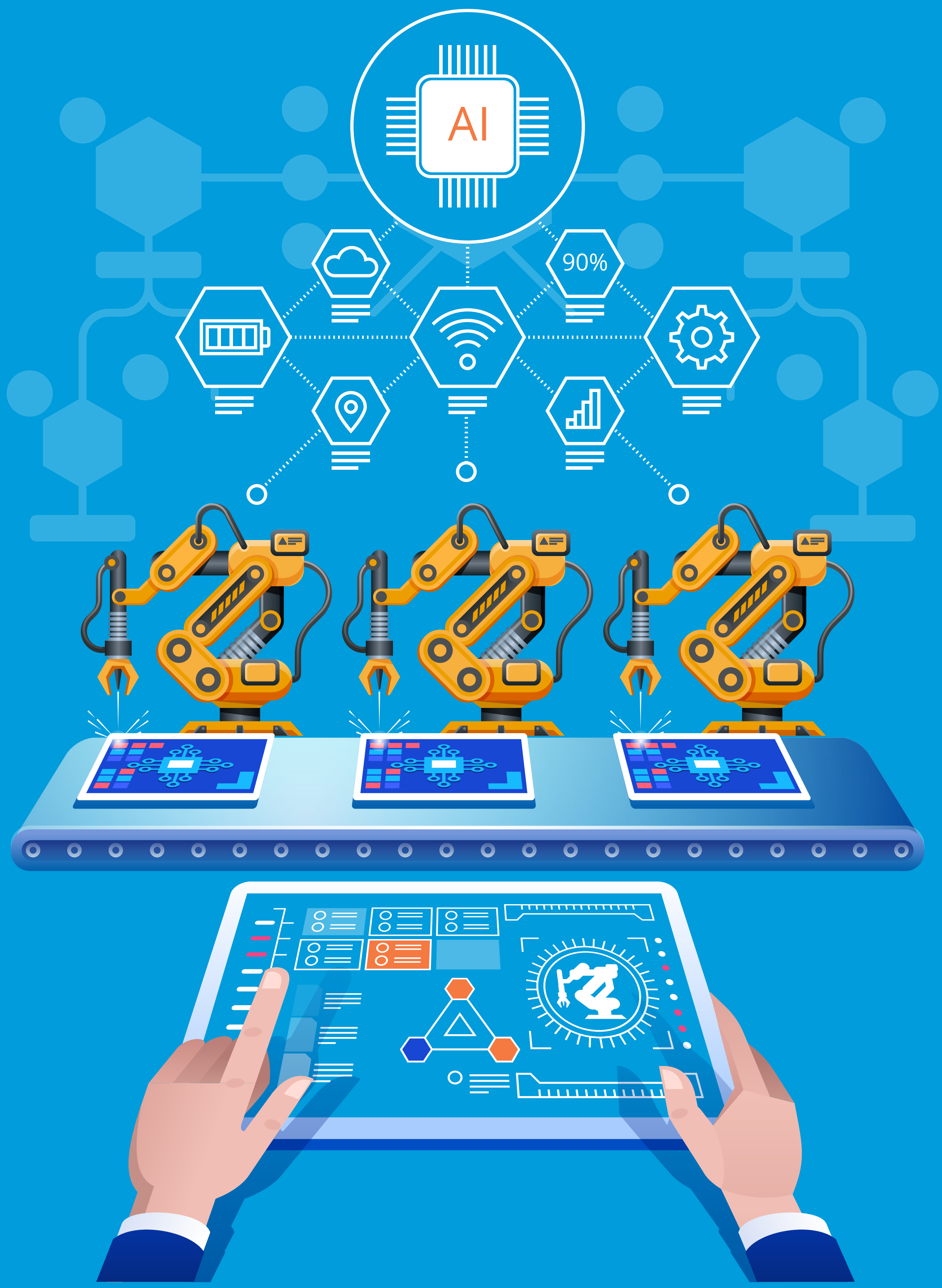
TEFs and EDIHs provide validation environments and certification support that allow smaller enterprises to move from proof-of-concept to operational deployment without bearing the full compliance cost independently. For example, a Dutch startup reached safety certification for autonomous agricultural machinery through the agrifoodTEF, or a major European semiconductor fab moved a predictive maintenance project from concept to production through the testbed. Access to equivalent infrastructure is among the most actionable near-term priorities for Ukraine.

4 PILOT DISCIPLINE IS MORE DECISIVE THAN INVESTMENT SCALE

Cases that successfully transitioned from pilot to operational deployment consistently started with a specific, bounded operational problem, defined measurable success criteria in advance, and demonstrated return on investment before seeking wider rollout. The scale of initial investment was less consistently differentiating than the rigour of problem definition and outcome measurement.

5 EU ACQUIS ALIGNMENT IS AN AI ADOPTION ENABLING CONDITION

it is not only a trade or accession requirement. In medtech, automotive, and energy, the degree of alignment with EU regulatory frameworks determines which certification pathways are available and whether tools validated in the EU can be extended to Ukraine without full re-validation. Regulatory credibility, built through compliance, functions as a market access credential in these sectors.



Sector highlights

In **agritech**, cloud-based precision farming platforms requiring only drone access and internet connectivity show that high-value AI adoption is achievable at modest cost. Ukraine's existing satellite imaging capacity is a deployable comparative advantage. The binding constraint for most use cases is rural connectivity, not algorithmic sophistication.

In **textiles**, the retrofit computer vision model, layering AI onto existing machinery, maps directly onto Ukraine's SME-dominated, export-oriented textile sector. Documented payback periods of 5 to 24 months in Portuguese deployments provide the financial case. EU sustainability compliance requirements create the adoption incentive for producers integrated into EU supply chains.

In **wood processing**, two distinct adoption models emerge: satellite-based forest monitoring, accessible through vendor partnership with public imagery data; and greenfield sawmill co-design, where AI integration from inception produced a 3x productivity premium over conventional facilities. The second model is time-limited: the option exists only at the investment planning stage.

In **medtech**, the CE marking pathway rewards evidence quality over firm size. A Lithuanian startup deployed across NHS-scale networks by investing in multi-site clinical validation before seeking regulatory approval, competing successfully against global incumbents. Ukrainian medtech companies with strong research partnerships are structurally positioned to follow this route.

In **automotive and AUV**, Ukraine's WINWIN strategy's focus on autonomous systems at the software and algorithmic layers aligns with where Ukraine's IT sector has established strengths. The binding constraint is access to regulatory testing environments: European autonomous vehicle deployments consistently required sandbox infrastructure before reaching market readiness.

In **semiconductors**, commercial AI-driven electronic design automation tools, deployed on cloud infrastructure, delivered a 3x productivity improvement on chip design without requiring proprietary AI development. The fabrication AI case showed that EDIH testbed access was the gating condition for moving past proof of concept.

In **energy**, predictive maintenance AI for distribution grids and generation equipment is operationally mature in Europe, with documented outcomes including a 30% reduction in cable outages and annual savings from equipment monitoring. The enabling condition is sensor and telemetry infrastructure, which reconstruction investment can build in directly.

Implications for Ukraine

1. First, integration into the EU's **EDIH and TEF networks** is a near-term institutional target: these facilities provide the validation infrastructure that de-risks AI adoption for enterprises that lack the capacity to navigate certification and compliance independently.

2. Second, Ukraine's **agricultural** and **medical** imaging AI research output represents an asset for commercialisation partnerships rather than a starting point for platform building.

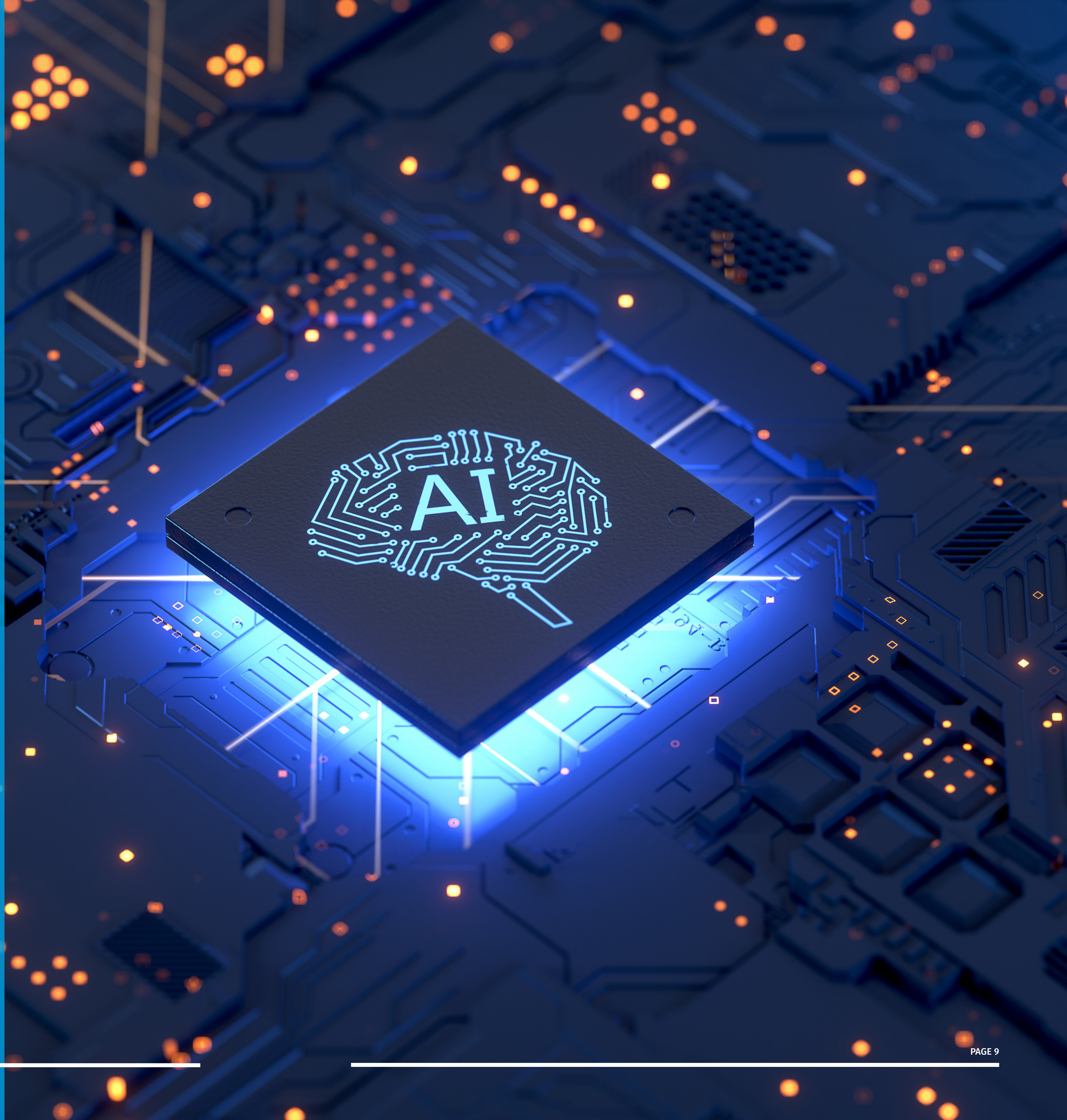
3. Third, **energy** presents the clearest case for AI investment aligned with reconstruction priorities: enabling conditions identified in European deployments serve reconstruction priorities directly while creating the data infrastructure AI adoption requires.

The WINWIN strategy's horizontal commitments to EU acquis alignment, innovation cluster development, and EDIH network integration address the right enabling conditions. Ukraine's newly adopted ***Strategy for the Development of Artificial Intelligence until 2030***[4] reinforces this direction with concrete targets: enterprise AI usage rising from 5% to 75% by 2030, 100 AI-ready priority datasets, 50 petaflops of computational infrastructure, and an **Operational Plan** committing to EDIH cooperation for at least 200 enterprises and a regulatory sandbox for AI solutions by 2028. The sectoral analyses in Chapter 2 provide an evidence base for translating these commitments into concrete, sector-specific actions.

1

Introduction

Ukraine's industrial recovery and reconstruction coincides with two concurrent transformations in European industry: the transition to a data-driven, AI-enabled production model and the realignment of supply chains and industrial ecosystems accelerated by the EU accession process. This report addresses the first transformation with direct implications for the second.



1.1 RESEARCH OBJECTIVES AND SCOPE

Ukraine's industrial recovery and reconstruction is taking place at a moment when European industry is itself undergoing a substantial shift: AI is moving from experiment to operational infrastructure across manufacturing, agriculture, energy and healthcare. What works, what it costs, and what conditions it requires are now documented across enough European deployments to be analytically useful for reconstruction planning.

The WINWIN Global Innovation Strategy 2030, adopted by Ukraine's Ministry of Digital Transformation in late 2024, designates seven sectors among others as priority innovation areas: agritech, textiles, wood processing, medtech, automotive and autonomous vehicles, semiconductors, and energy. For each, the strategy sets innovation targets and outlines integration pathways into European ecosystems. This report provides the European evidence base those targets can be measured against.

The analysis draws on 18 case studies of operational AI deployments across the seven sectors. Cases were selected for documented, measurable outcomes rather than technical novelty, and cover a range of organisational types, from large incumbents to startups, and adoption models, from vendor-mediated platforms to greenfield co-design and multi-partner consortia. The selection prioritised cases where the conditions of success were clearly traceable, since the goal is to understand what enabled adoption, not to showcase the technology itself. Where the report references Ukrainian institutional frameworks, it reflects the current architecture.

1.2 METHODOLOGICAL NOTE

The analytical framework is drawn from the OECD's assessment of EU Member States' progress in implementing the Coordinated Plan on AI. The OECD structures AI adoption analysis across two dimensions: enabling conditions (governance, data infrastructure, compute, skills) and lab-to-market pathways (research investment, TEF and EDIH infrastructure, scaling mechanisms). These categories provide a viable organising logic for the adoption pathways analysis in each sector chapter.

The OECD framework is used as an analytical scaffold, and not as a set of findings to be reproduced. Where OECD data on adoption rates, skills gaps, or investment patterns illuminate a sector analysis, they are cited directly. Gaps in the OECD coverage, notably for wood processing and semiconductors, are flagged in the relevant sections with alternative sources used.

Company names are anonymised in the adoption pathway analyses and used in full in the case study descriptions. The distinction matters: the pathway sections aim to identify generalised patterns of successful deployment, while the case studies provide the specific evidence behind those patterns. Readers should treat the case studies as the primary empirical material and the pathway analyses as the interpretive layer above them.

WHAT 'BEST PRACTICES' MEANS HERE

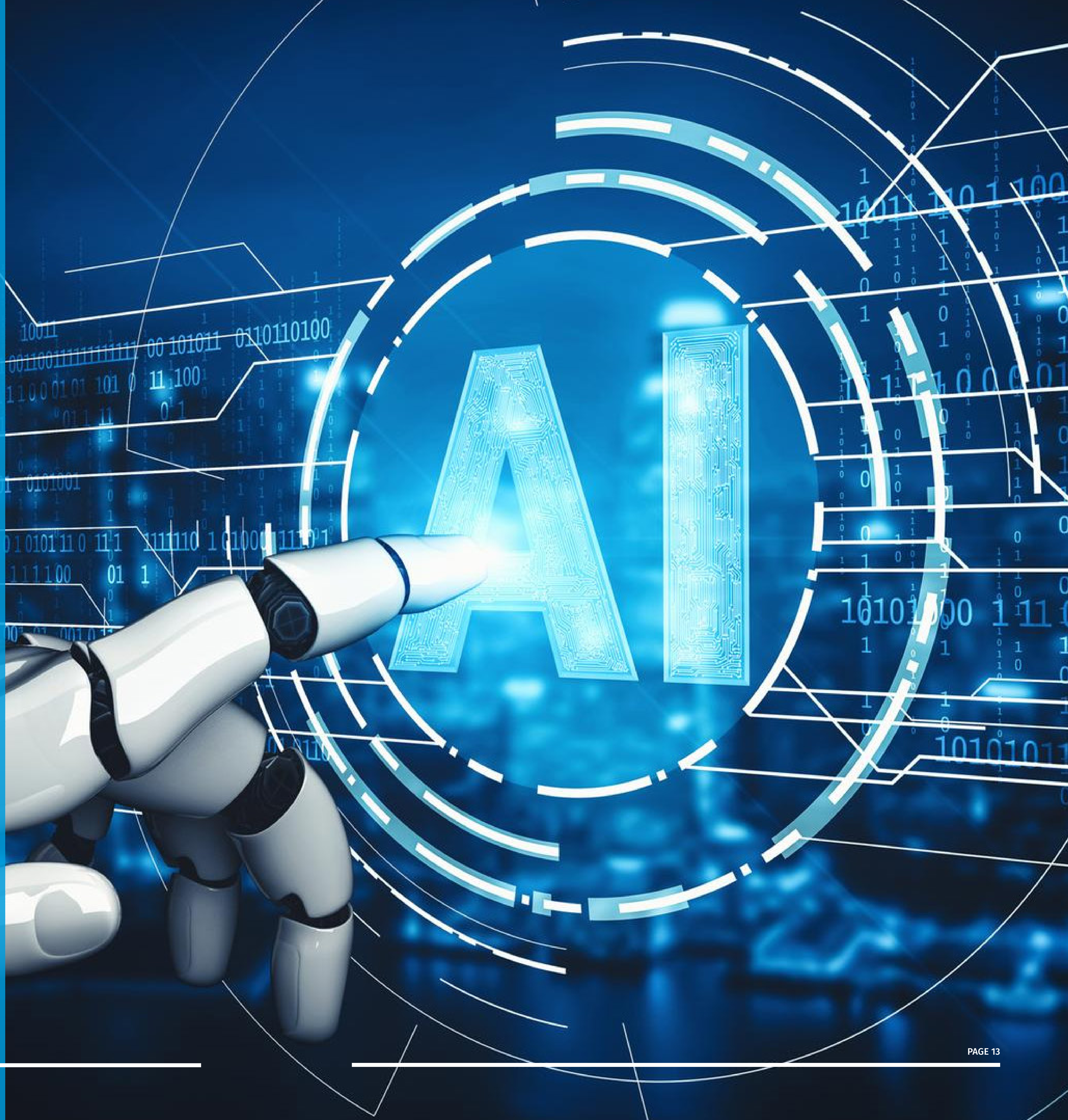
The phrase is used pragmatically. A best practice in this report is an AI implementation that moved from pilot to sustained operational use, with outcomes documented well enough to assess what made it work. The cases are not necessarily the most technically advanced deployments in Europe, nor the most widely replicated. They are deployments from which adoption lessons are extractable.

The European context is relevant to Ukraine because the enabling conditions these cases required, and the sequence in which those conditions had to be assembled, are informative for designing investment and policy environments that produce similar results. Direct transfer of any specific model is rarely feasible; the conditions that made the model work are the transferable element.

2

Sectoral case studies

This chapter presents the adoption pathways analysis and case studies for each of the seven priority innovation sectors. Each sector section opens with an overview of the EU ecosystem and relevant national initiatives, Ukraine's sectoral strategy and EU alignment, and the principal AI applications in the sector.



This chapter presents the adoption pathways analysis and case studies for each of the seven priority innovation sectors. Each sector section opens with an overview of the EU ecosystem and relevant national initiatives, Ukraine's sectoral strategy and EU alignment, and the principal AI applications in the sector. The adoption pathways analysis follows, identifying deployment patterns and the policy context and enabling conditions that shaped them. Case studies then illustrate the patterns identified analytically. Each section closes with an assessment of adoption dependencies and diagnostic indicators for the Ukrainian context.

Context for the sectoral analyses that follow is provided: AI adoption rates across EU manufacturing sub-sectors in 2024 (OECD, 2026). Two of the sectors covered in this report (textiles and wood processing) sit at the lower end of the spectrum, with 6% and 9% respectively of enterprises using AI, against a manufacturing average of 11%. This does not reflect the potential of AI applications in these sectors, but the enabling conditions that are currently in place.

Table 1 provides a reference overview of all 18 case studies documented in this report, including the primary adoption pathway each demonstrates.

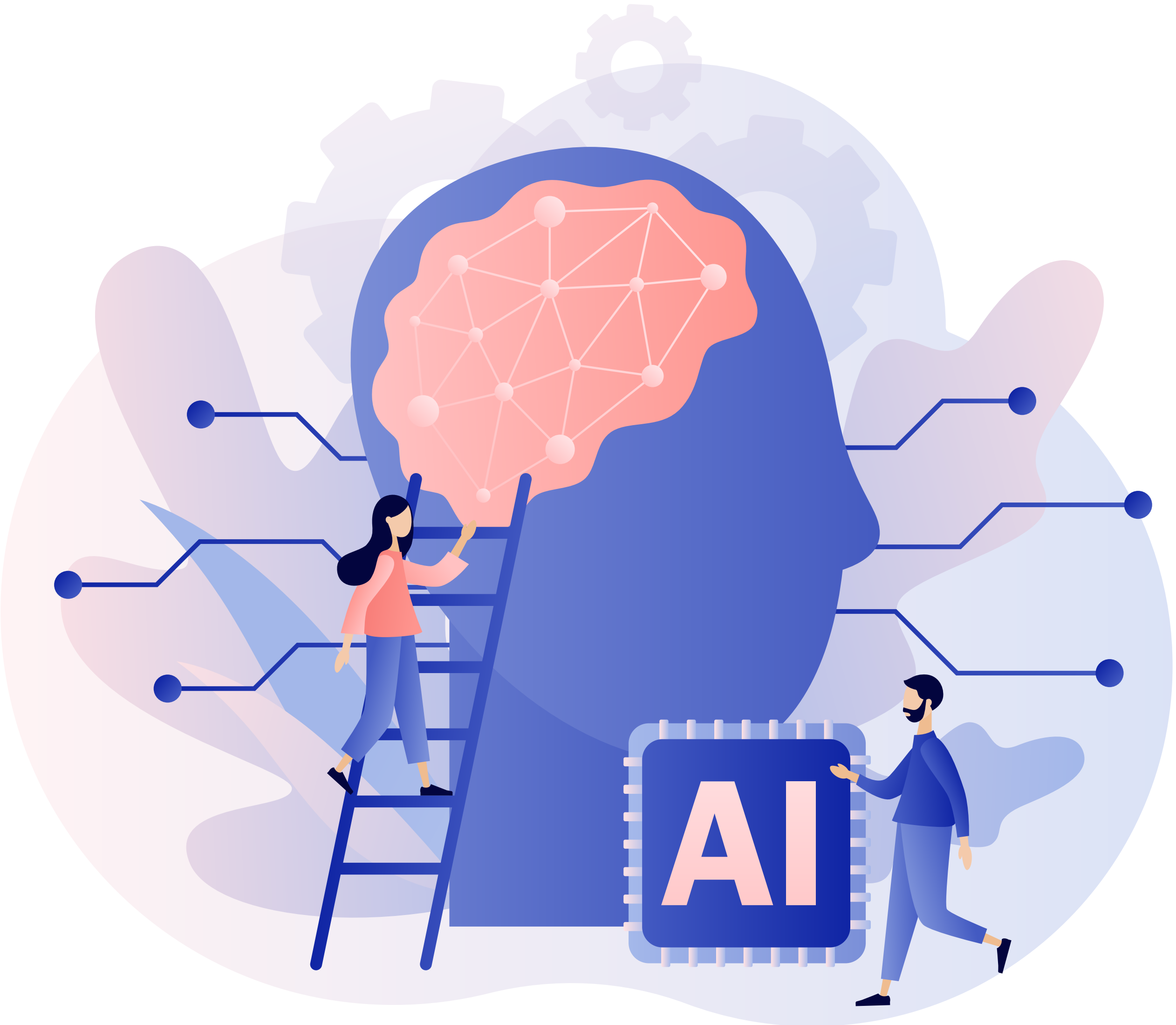


TABLE 1: Overview of all 18 case studies documented in this report.
Cases were selected for documented operational deployment with measurable outcomes

Sector	Case	Country	Org. type	Pathway	Key outcome documented
Agritech	Skymaps (CultiWise)	Czech Republic	Startup	Vendor-mediated	Cloud precision farming; drone + subscription; variable-rate prescription maps
Agritech	Eco Clipper / agrifoodTEF	Netherlands / Sweden	Startup + TEF	Consortium R&D	Safety certification (EN ISO 25119) for autonomous mowing via agrifoodTEF
Textiles	Smartex	Portugal	Startup	Vendor-mediated	Payback 5-24 months; up to 80% defect reduction; 22 Portuguese sites; €24.7M Series A
Textiles	Monforts Montex	Germany	Large enterprise	Vendor-mediated	100% real-time machine data mapping; cloud-connected stenter retrofit
Wood processing	Stora Enso / Sogeti	Sweden	Large enterprise + partner	Vendor-mediated	Bark beetle detection across 200,000 ha; Sentinel-2 + deep learning; operational since deployment
Wood processing	ABB / Metsä Fibre Rauma	Finland	Large enterprise + integrator	Greenfield co-design	€260M sawmill; 3x European productivity benchmark; 40 logs/min at 250m/min
Medtech	Oxipit ChestLink	Lithuania	Medical AI company	Vendor-mediated	~200,000 X-rays; 99.8% sensitivity; CE Class IIA/IIB; deployed in UK, Finland, Denmark
Medtech	Siemens Healthineers / MVZ	Germany	OEM + radiology network	Consortium R&D	18-month co-development; 14 imaging systems; results within 2 min in PACS workflow
Medtech	Ossur prosthetics	Iceland	Large OEM	Vendor-mediated	70% fewer falls; AI across IP management, product development and embedded device
Automotive & AUV	Renault Refactory Flins	France	Large OEM	Greenfield co-design	Circular economy factory; 45,000 vehicles/yr refurbished; AI control tower for 650+ presses
Automotive & AUV	Stellantis Factory Booster	Multinational	Large OEM	Open innovation ecosystem	80+ technology partners; $2M saved in first 50 days at one facility
Automotive & AUV	BMW / NVIDIA Omniverse	Germany	Large OEM + tech partner	Greenfield co-design	31 facilities; 30% planning efficiency gain; 2,100 configurations managed digitally
Semiconductors	STMicroelectronics / Synopsys	Netherlands	Large enterprise	Vendor-mediated	3x chip design productivity; Arm Cortex-A510; deployed on Azure cloud
Semiconductors	GlobalFoundries Dresden	Germany	Large fab + consortium	Consortium R&D	2.15x MTBF; ~62% transport loss reduction; ~8,000 maintenance hours saved
Energy	E.ON / Schleswig-Holstein Netz	Germany	Major utility	Open innovation ecosystem	2–3x defect prediction accuracy; up to 30% cable outage reduction; operational since 2018
Energy	ENGIE Digital (Robin / Agathe)	France (multinational)	Energy company + digital unit	Open innovation ecosystem	1,000+ ML models; 10,000 equipment targets; €800K annual savings documented
Energy	D-HYDROFLEX consortium	EU-wide (17 partners)	Horizon Europe consortium	Consortium R&D	Digital twin toolkit for legacy hydropower; 5 demo sites across 4 EU Member States

2.1 AGRITECH

2.1.1 Overview: AI Applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

Uses for AI in agriculture

AI in agriculture covers a wide and uneven range of applications. The more established end includes drone-based crop monitoring, computer vision for pest and disease identification, precision irrigation, and GPS-guided autonomous field machinery. At earlier stages there are AI-driven livestock health monitoring, soil analysis, and predictive yield modelling. Across these, the common enabling architecture combines IoT sensors, wireless connectivity, and cloud or edge computing under a unified management interface.[5]

Advances in the EU's coordinated plan on AI in agriculture

The EU Coordinated Plan on AI recognises agriculture as a priority domain, and EUR 175 million has been allocated to Horizon agricultural digitalisation research since 2020.[6] Two-thirds of EU Member States have launched AI agriculture initiatives, though most remain focused on research and testing rather than operational deployment. Fourteen Member States report 25 active initiatives, covering testing hubs, digital innovation hub networks, and cross-sector collaboration. National programmes include Austria's AI for Green initiative, Czechia's EUR 32.4 million investment in agricultural robotics, and Ireland's EUR 17.6 million CONSUS research programme.[7] Seven Member States use EDIHs for agricultural AI knowledge transfer, but only five have targeted agricultural data-sharing initiatives – a recognised gap for scaling adoption beyond isolated deployments.

The agrifoodTEF, the EU's Testing and Experimentation Facility for Agrifood Innovation, provides physical and digital infrastructure for validating AI and robotics solutions in real agricultural conditions. Its role extends beyond equipment testing to regulatory navigation: helping companies meet the Machinery Regulation and the EU AI Act requirements that are a significant constraint for agricultural robotics developers.[8]

The Apply AI Strategy proposes a new agrifood AI platform to support discovery, integration and trust-building for AI-enabled farming tools, alongside sector-tailored AI literacy training through the AI Skills Academy.[9]

Ukraine's agritech strategy and EU alignment

Agriculture accounts for over 10% of Ukraine's GDP and 41% of exports.[10] The WINWIN strategy designates agritech as a priority innovation sector, targeting precision farming, drone-based monitoring, and automated harvesting as core AI-enabled use cases. Ukraine's comparative strength in satellite imaging is already deployable; its development in robotics, precision livestock technology, and advanced precision farming trails behind.

The structural constraints are documented in the CEPS-UNIDO 2024 baseline:[11] limited innovation culture in the sector, financing gaps that inhibit scaling, and a shortage of technology skills. Land mining and equipment damage from the war add operational constraints specific to Ukraine. The WINWIN strategy's emphasis on the AgroFoodTech Centre of Excellence as a testing and validation hub, and on participation in EDIH networks, aligns with the enabling infrastructure that European cases show matters most.

Ukraine's satellite imaging strength is also a two-way asset: Ukrainian comparative advantages in this domain have potential value within broader European agritech ecosystems, not only as a domestic foundation.

AI applications in the sector

The main operational AI applications in European agritech are at present:

- **Precision farming platforms:** drone or satellite imagery processed through computer vision to generate prescription maps for variable-rate application of seeds, fertiliser, and herbicides. Reduces input costs and environmental footprint with measurable ROI at farm level.
- **Autonomous field machinery:** GPS, camera, and sensor-equipped equipment for tillage, sowing, harvesting, and mowing. AI handles obstacle detection, geofencing, and operational safety. Requires functional safety certification under EU standards.
- **Pest and disease detection:** AI models trained on imagery to identify crop stress, pest presence, or disease at early stages, enabling targeted intervention before yield loss occurs.
- **Livestock monitoring: sensor-based health tracking combined with AI behaviour analysis for early detection of illness**, heat cycles, and feed efficiency anomalies.

2.1.2 Adoption pathways analysis

The two case studies cover cloud-based precision farming using aerial imagery and computer vision, and the autonomous operation of field machinery with AI-enabled safety systems. These are among the more common AI applications in European agriculture, though they represent only a portion of the use cases gaining traction across the sector, which also include predictive analytics, livestock monitoring, and soil management.[12]

Europe's agricultural AI adoption remains at an early stage overall; as of 2024, comparable adoption rates for agriculture are not systematically measured at sector level, though uptake appears limited and uneven across Member States.[13] Two-thirds of EU Member States have launched AI agriculture initiatives, but most remain focused on scientific and industrial research rather than operational deployment.[14]

Sectoral deployment patterns

Both surveyed cases process sensor-generated data through AI models to produce actionable outputs for farm operators. In the drone-based precision farming case, aerial imagery is uploaded to a cloud platform and processed through a pre-trained computer vision model; outputs are prescription maps compatible with variable-rate farm equipment. In the autonomous mowing case, continuous input from cameras, GPS, and environmental sensors feeds an on-device system that handles safety decisions in real time. Both workflows are designed for non-specialist users: AI complexity is handled within the product, not by the operator.

The two cases represent distinct adoption models. The precision farming platform is vendor-mediated: a startup packages the AI capability as a cloud service, and the farmer's entry requirements are a commercially available drone and internet connectivity. The autonomous mowing case is consortium-based: a startup without the resources to navigate functional safety certification independently assembled a network of partners, including a safety software developer, an autonomous systems firm, and the Swedish node of the agrifoodTEF, to reach market readiness under EN ISO 12100 and EN ISO 25119.[15]

Both cases crossed from pilot to operational deployment in part because they connected AI outputs to demonstrable economic return. The precision farming platform reduces input costs through targeted application; the autonomous mower addresses the labour cost and safety liability of manual turfgrass management. Linking AI capability to a clear financial case is consistent with the broader OECD finding that return-on-investment uncertainty remains a primary barrier to farmer adoption.[16]

Cloud computing underpins the precision farming case; edge computing underpins the autonomous mowing case. The difference has practical implications for connectivity requirements: cloud-based advisory applications need reliable rural internet access; edge-based operational applications do not. Both cases built adaptability to local conditions into their design — trainable species models in one case, configurable geofencing in the other — which helps avoid the performance degradation that generic models can exhibit outside their training environments.

Europe's agricultural AI adoption overall remains at an early stage. Most Member State activity is concentrated in research and testing phases rather than operational deployment, and VC investment in EU agricultural AI reached only USD 57 million in 2024, representing approximately 0.6% of total EU AI venture investment.[17] Public funding plays a correspondingly large role, and both cases here are connected to publicly supported infrastructure.

Policy context and enabling conditions

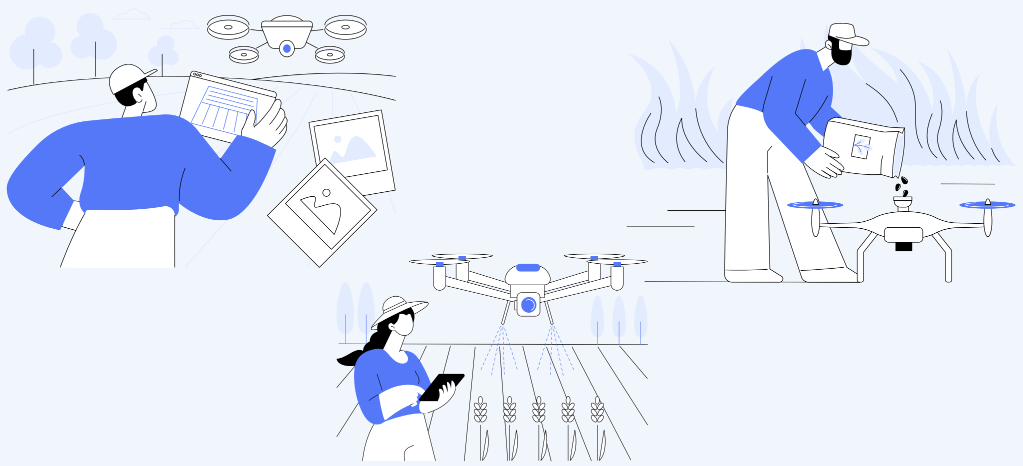
1 DATA, COMPUTE AND SKILLS

The **Common European Agricultural Data Space**[18] aims to create a secure framework for cross-border agricultural data sharing, but implementation is at an early stage. The EU Data Act (applicable from September 2025) establishes farmers' rights to access and share data generated by connected machinery, addressing vendor lock-in concerns that currently limit data portability. Rural broadband coverage remains uneven across Member States despite 5G and edge cloud investment; targeting underserved rural areas is a recognised policy priority. Skills gaps are significant. Vocational programmes covering AI and digital tools for farming are limited in coverage. The approaches recommended in the OECD assessment include hands-on demonstrations, peer learning through farmer networks, and 'farmer ambassador' schemes; the Apply AI Strategy adds sector-tailored micro-credentials through the AI Skills Academy.

2 R&D AND SCALING-UP INITIATIVES

The agrifoodTEF was directly involved in one of the surveyed cases, providing risk assessment, safety function definition, and compliance verification against EN ISO 12100 and EN ISO 25119. This illustrates the de-risking function that TEFs serve for SMEs that cannot independently absorb the cost of navigating the Machinery Regulation and **EU AI Act** requirements.[19] Seven Member States have used EDIHs to transfer AI knowledge to the agricultural sector, though agricultural coverage within the EDIH network remains limited . The Apply AI Strategy signals an intention to relaunch EDIHs as 'experience centres for AI' and to invite European companies to share AI models through the network.[21]

Venture capital investment in EU agricultural AI reached **USD 57 million** in 2024, representing **0.5-0.6%** of total EU AI VC funding.[22] This is consistent with a sector still in early-stage transition from research to commercial deployment, and it means public funding plays a correspondingly large role in enabling development. **Horizon Europe** projects have supported the development of multi-robot systems, precision spraying technologies, and digital innovation hub networks in the sector.[23] The Apply AI Strategy proposes a new flagship action: an agrifood AI platform to support discovery, integration, and trust-building for AI-enabled farming tools.



High-level assessment

These two case studies suggest that AI uptake in agriculture does not uniformly depend on large-scale investment or advanced technological infrastructure. The enabling conditions that mattered differed between the two cases.

The precision farming case shows that considerable value can be generated by applying existing technologies, specifically drone imagery, computer vision and cloud processing, within an accessible workflow. The investment required at the farm level is modest: a commercially available drone, internet connectivity, and a subscription to the platform.

What appears to have mattered more than the scale of resources was the design of the workflow itself: AI is embedded in a practical, ROI-linked process with adaptability to local conditions. The startup operated in a national context with targeted public support for agricultural innovation, and the cloud-based delivery model reduces the dependency on rural broadband that constrains real-time on-field applications. The platform also addresses the persistent skills barrier through its design: it requires no AI expertise from the farmer, which helps mitigate the digital literacy gaps that vocational training programmes have yet to close.

The autonomous mowing case suggests that institutional infrastructure and targeted policy support can be important enabling factors for certain types of deployment. The agrifoodTEF's testing and certification services appear to have played a significant role in helping the startup achieve the safety compliance needed for market deployment.

The enabling conditions here map onto the EU's lab-to-market infrastructure: TEFs provided the validation environment, cross-border partnership provided the technical expertise, and harmonised safety standards provided the regulatory target. The EUR 175 million in Horizon 2020 agricultural digitalisation funding and the agrifoodTEF network represent the type of public investment that this category of deployment appears to depend on.

2.1.3 Towards EU best practices

Ukraine's agritech sector has deployable strengths in satellite imaging and a large agricultural market that could support vendor ecosystem development. The WINWIN strategy's targets in precision farming, drone-based monitoring, and automated harvesting align with the application types where European evidence is most developed. The constraints are structural: limited testing infrastructure, rural connectivity gaps, and a skills shortage that vocational programmes have not yet addressed at scale.

Adoption dependencies

Vendor-mediated cloud adoption depends on rural connectivity being in place first. Without reliable internet access in farming regions, cloud-based precision farming platforms cannot function regardless of their quality. The satellite imaging pathway is an exception — it does not require on-farm connectivity at the moment of capture — and this is where Ukraine's existing capacity is concentrated.

Safety-certified autonomous machinery adoption depends on accessible testing and validation infrastructure. European evidence shows that startups cannot reach commercial deployment under functional safety standards without a facility that absorbs the certification cost. Where no such infrastructure exists, this adoption pathway stalls at proof-of-concept regardless of technical readiness.

Scaling from isolated deployments to sector-level adoption requires agricultural data governance frameworks. Individual vendor-mediated deployments can proceed without cross-farm data sharing; sector-level AI improvement from pooled data requires it. Ukraine's planned national platform for land users and soil data is aligned in direction with the EU's Common Agricultural Data Space.

Diagnostic indicators

- Rural connectivity investment is reaching farming regions, including areas affected by the conflict.
- An agricultural testing facility with commercial SME access mandates is being established or accessed through EU network participation.
- EU agritech vendors are engaging the Ukrainian market through distributors or partnership programmes.
- The WINWIN national agricultural data platform is progressing in a form interoperable with the EU Common Agricultural Data Space.

2.1.4 Case studies

CultiWise
Sometimes, less is more

Case study 1

Skymaps (CultiWise) — Drone-based AI prescription farming[24]

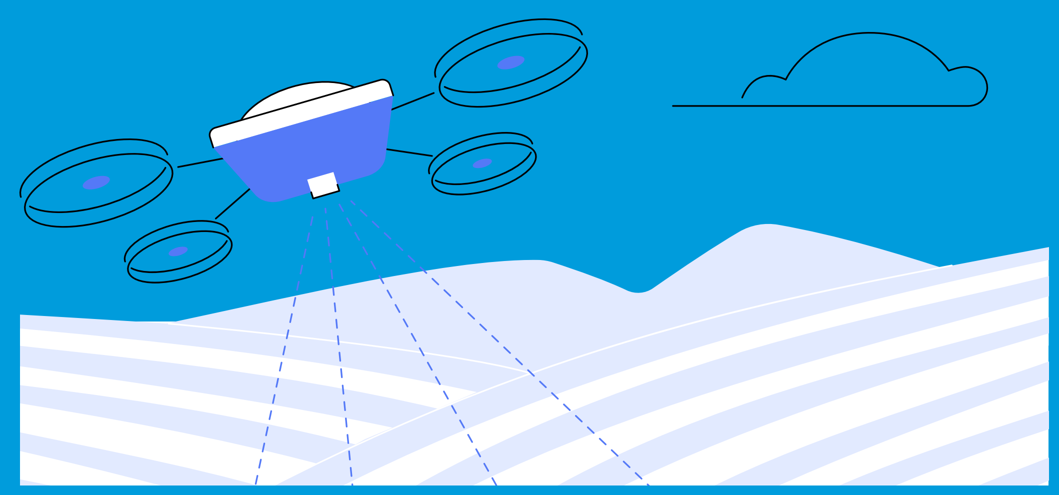
Czech Republic | Startup

Implementation

Czech startup Skymaps Agrimatics provides a cloud-based precision farming platform combining drone imagery with computer vision and AI to generate prescription maps for variable-rate agricultural applications. Its core product, Zoneye, is an AI model pre-trained on 37 common weed species that farmers can further train to recognise weeds specific to their region. Farmers capture fields with drones, upload imagery to the platform, and receive classified prescription maps for targeted re-seeding, fertiliser adjustment, herbicide spot spraying, and recovery treatments. Parameters are customisable to local field conditions and management preferences. Outputs can be exported directly to farm equipment, enabling immediate operational use.

Adoption pattern demonstrated

This case illustrates the vendor-mediated adoption pathway: a startup absorbs AI complexity and delivers it as an accessible cloud service to non-specialist end users. The enabling factors include user-centred design minimising technical barriers for farmers, adaptability to local conditions through trainable models rather than a rigid generic approach, and a potential link between technology use and measurable cost reduction through targeted input application. The approach is replicable in contexts with drone availability and basic internet connectivity; no advanced computing infrastructure is required at the farm level.
This connects to the WINWIN strategy's priority areas of sensor technologies, satellite imagery for crop monitoring, and precision farming.



Source: https://cultiwise.com/about/

Case study 2

Eco Clipper — AI safety certification for autonomous mowing[25]

Netherlands, Denmark, Sweden (agrifoodTEF)[26] | Startup consortium

Implementation

Dutch manufacturer Eco Clipper developed a fully autonomous mowing solution for high-capacity turfgrass production, integrating propulsion, mowing, and safety systems into a single platform. The autonomous mower series features obstacle detection, geofencing, and capacity of up to 6 hectares per hour using 5.13-metre mowing decks. To achieve safety compliance, Eco Clipper partnered with Thorsen Teknik (semi-autonomous precision agriculture solutions) and AgriRobot (certifiable safety software), and accessed the Swedish node of the agrifoodTEF for testing and validation. The TEF provided risk assessments, safety function definition, and compliance verification against EN ISO 12100 and EN ISO 25119, enabling the integration of AI-driven safety features for operation across dynamic environments.

Adoption pattern demonstrated

This case study illustrates the consortium co-development pathway: a small startup accessed specialised capabilities through partnerships rather than developing them in-house. The agrifoodTEF appears to have been a key enabling factor, providing testing and certification support that would likely have been prohibitively expensive for a startup to develop independently. In agricultural robotics, regulatory compliance and safety validation are a significant constraint on deployment, and TEFs can help address this. The case connects to the WINWIN strategy's priority area of automated harvesting systems and its ambition for Ukraine to become a testing centre for agritech solutions.

Sources: https://agrifoodtef.eu/success-stories/autonomous-mowing-eco-clipper-thorsen-teknik-and-agrirobot-enhance-safety

2.2 TEXTILES

2.2.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The EU Strategy for Sustainable and Circular Textiles[27] provides the overarching policy framework for the sector's digitalisation. It explicitly promotes digital precision technologies to optimise manufacturing processes, reduce inefficiencies, and enable supply chain transparency. The strategy's plans for a Manufacturing Dataspace[28] and European Green Deal Dataspace provide the data-sharing infrastructure that makes AI-generated quality data commercially useful beyond the individual factory, enabling standardised records to flow across supply chain steps rather than remaining siloed.

At Member State level, national strategies translate these EU-level ambitions into targeted investment mechanisms. Germany's National Circular Economy Strategy, adopted in December 2024, allocates research funding for AI and generative AI applications in textile design optimisation and process efficiency, with parallel investment in automated sorting technologies using machine learning for fibre identification. Italy's Piano Transizione 5.0, a EUR 6.3 billion cross-sectoral programme, provides tax credits for Industry 4.0 investments including AI-enabled production systems, automated quality control, and digital finishing.[29] By subsidising adoption through tax incentives rather than grant programmes requiring competitive application, it removes a key friction point for enterprises that have the internal capability to evaluate and implement AI systems but lack the capital to absorb upfront costs.

The EU's regulatory agenda functions as a demand-side driver for AI adoption among textile suppliers. The Ecodesign Regulation, the Corporate Sustainability Reporting Directive (CSRD), Extended Producer Responsibility frameworks, and Green Public Procurement criteria all require suppliers to provide standardised, verifiable production data. Suppliers who generate this data through AI quality inspection become commercially de-risked partners for EU brands; those who cannot face exclusion from supply chain relationships.[30]

Ukraine's textile sector and EU alignment

Ukraine's textile and clothing sector is SME-dominated, with around 14,600 registered business entities, the majority micro-enterprises operating primarily in clothing production.[31] Annual exports reach approximately USD 460 million, mostly to EU buyers, giving the sector direct exposure to the EU regulatory compliance pressures that are one of the primary adoption drivers in Europe.

Ukraine's first dedicated initiative for textile digitalisation is the Green and Digital Transformation in Textile (GDT Textile) project, launched in 2025 with UNDP support.[32] It draws on the EU's Advanced Manufacturing methodology, enabling Ukrainian enterprises to benchmark their Industry 4.0 readiness against European counterparts. The resulting roadmap specifies 80 initiatives across six areas of transformation: industrial ecosystems, technologies, production methods, human capital, eco-factory practices, and support tools, with implementation targets extending through 2027. Its headline AI-related use cases include AI-enabled quality inspection and defect detection, predictive maintenance via IoT-connected sensors, AI demand forecasting, digital twins for process management, and ERP-MES integration with real-time production data. These map directly onto the two European deployments examined in this section. The roadmap's targets include at least 150 enterprises receiving twin transition services, 50 or more pilot projects, and a 25% increase in productivity among participating enterprises.

Ukraine's alignment with the EU regulatory environment is further supported by the EU-Ukraine Cluster Partnership Programme, launched in 2024, which has established six partnerships to strengthen value chain linkages and accelerate single market integration.[33] The 3T Alliance (Twin Transition in Textile), established under the GDT project, brings key sectoral stakeholders together to coordinate implementation. Most production management in Ukrainian textile firms still relies on manual processes, and ERP and cloud adoption rates are substantially below EU norms — which is precisely the starting point from which the European retrofit model operates.

AI applications in the sector

The principal AI applications gaining commercial traction in European textiles include:

Real-time quality inspection: computer vision and machine learning retrofit onto existing circular knitting machines, inspecting 100% of production in real time for defects including contamination, elastane irregularities, and needle malfunctions. Outputs integrate directly with factory ERP systems.

Process digitalisation and digital twins: cloud-connected control systems capturing 100% of machine data in real time, creating a virtual representation of equipment for process reproducibility, remote diagnostics, and energy management.

Predictive maintenance: IoT sensor networks on production equipment feeding machine learning models for early fault detection and condition-based maintenance scheduling.

Automated sorting: machine learning applied to fibre identification and material classification for recycling and circular economy applications.

2.2.2 Adoption pathways analysis

The textile case studies examined here represent two distinct but complementary modes of AI-enabled transformation in European manufacturing: real-time computer vision quality inspection deployed at the fabric formation stage, and cloud-connected process digitalisation applied to fabric finishing.[34] Both share the defining characteristic that they achieve digital transformation through replacing existing assets rather than through augmenting them, layering sensing, data capture, and analytical capability onto machinery already on the factory floor. These are not greenfield deployments; they are retrofit interventions calibrated to an industry operating on margins that leave little room for large-scale capital replacement.

The OECD finds that only 6% of textile and apparel enterprises currently use AI,[35] among the lowest rates in manufacturing, yet the deployments examined demonstrate that even at these early levels, well-structured implementation generates returns substantial enough to justify rapid scaling.

Sectoral deployment patterns

1 RETROFIT AS STRATEGIC LOGIC, NOT COMPROMISE

The dominant implementation pattern in both cases is retrofit integration with existing machinery. A startup retrofitted high-resolution cameras and advanced lighting directly onto operational circular knitting machines, enabling real-time defect detection without requiring machine replacement. A German equipment manufacturer enabled equivalent digital transformation of fabric finishing lines by equipping existing stenter frames with modern control cabinets, programmable logic controllers, standardised machine interfaces, and cloud connectivity — no new physical infrastructure was required at customer sites.

Academic analysis of the quality inspection deployment identifies a structural parallel to the Toyota Production System's Jidoka principle, the concept of 'automation with a human touch', in which machines are empowered to detect deviations and pause operation pending human review.[36] Where traditional lean systems respond to defects after they occur, AI-enabled retrofit systems act on real-time data to stop defect propagation at the moment of detection. The retrofit model is the technically appropriate response to a sector in which a single rejected roll of fabric can require ten subsequent successful sales to recover the loss, and where deals are routinely lost over price increases of one or two cents per kilogramme.

2 DATA QUALITY AS THE FOUNDATIONAL PREREQUISITE

Across both cases, AI deployment is inseparable from the generation of verifiable, objective, real-time data — what practitioners in the sector term 'golden data'. Industry analysis confirms that most textile supply chains still rely on manually inputted, non-standardised data shared in fixed formats such as PDFs or handwritten records, rendering it inaccurate, slow to communicate, and unusable for operational decisions.[37] The quality inspection system addresses this directly: alongside defect detection, it generates roll-by-roll grading data and production metrics integrated with factory ERP systems, automatically creating standardised records that serve purchasing, compliance, and sustainability reporting requirements simultaneously. The fabric finishing system captures 100% of machine performance data in real time via a digital twin model, enabling process reproducibility and machine-to-business-system integration across sites.[38]

Crucially, the data generated as a byproduct of AI quality inspection is the same primary data now required by EU brands for supply chain compliance under the Ecodesign Regulation, CSRD, Green Public Procurement criteria, and Extended Producer Responsibility frameworks.[39] Suppliers who can provide this data become commercially de-risked partners; those who cannot face exclusion from supply chains. Real-time data collection is therefore not only an operational improvement — it is the first step in a factory's modernisation sequence, unlocking data-driven decision-making, ERP integration, and measurable resource efficiency simultaneously. This positions AI adoption for EU-facing suppliers as a commercial enabler, with compliance data as a byproduct.

3 RETURN ON INVESTMENT AS THE ADOPTION TRIGGER

The evidence base across multiple Portuguese installations makes clear that demonstrable financial return is the proximate driver of SME adoption. Payback periods range from 5 to 24 months, with verified returns of between 1.5 and 7 times the investment across different facility types and scales.[40] The shortest paybacks, 5 to 7 months at the most defect-intensive sites, occurred where defect detection was most closely matched to the factory's highest-cost operational problem. The OECD notes that seemingly small marginal improvements in quality control, a 3% reduction in defect rates, can nearly double operational profits in high-volume settings, precisely the kind of outcome that compresses pilot-to-deployment timelines.[41] Sustainability co-benefits, reductions in water use, energy consumption, and CO2 emissions across documented sites support adoption decisions but do not initiate them. Technology vendors in this sector must be capable of calculating and communicating total cost of ownership and ROI from the outset; systems that require external compliance pressure to justify their cost remain fragile as adoption models.

4 ON-SITE IMMERSION AS A DEPLOYMENT REQUIREMENT

A consistent finding across quality inspection deployments is that remote-only technology rollout fails in this sector. The successful scaling model required direct physical presence at customer facilities: on-site installation, operator training in the local workforce's language, immersive engagement with factory management, and in-person problem resolution. Circular knitting machine environments vary significantly in lighting conditions, machine age, vibration profile, and defect type distribution; effective calibration requires expertise on the factory floor. Machine operators, trained in analogue inspection routines, require not only technical instruction but practical demonstration that AI-generated quality signals are more reliable than experienced human judgement. Where vendors have treated deployment as a remote technical problem, uptake has stalled; where they have treated it as an immersive human engagement on a par with a major customer relationship, results have been consistent and replicable across geographically diverse sites.

5 **SME ACCESS AND THE PILOT-TO-OPERATIONAL TRANSITION**

The retrofit architecture of both systems directly addresses the primary SME access barrier: upfront capital exposure. By avoiding machinery replacement costs and enabling implementation at the level of individual machines, the entry point is calibrated to the financial capacity of enterprises operating on thin margins. In textiles, most enterprises fall into the ‘laggard’ category: firms that have not yet recognised AI’s potential or lack the skilled workforce to evaluate it.[42] Short, structured pilot studies, **four weeks to three months** in the documented cases, proved decisive in converting managerial scepticism to operational commitment. Pilots scoped to a single production line with clearly defined success metrics enabled decision-makers to assess ROI from direct evidence at their own facility. The transition from pilot to operational deployment was, in practice, an economic rather than a technological decision, driven by the clarity of the financial case generated during the pilot phase.

Policy context and enabling conditions

1 **EU-LEVEL AND NATIONAL AI STRATEGIES ACROSS DATA, COMPUTE, AND SKILLS**

The EU Strategy for Sustainable and Circular Textiles[43] provides the overarching policy framework within which both cases operate, explicitly promoting digital precision technologies to optimise manufacturing processes, reduce inefficiencies, and enable transparency. The strategy’s plans for a ‘manufacturing dataspace’ and ‘European Green Deal dataspace’ are directly relevant to the data interoperability challenge identified across the cases: the absence of standardised, machine-readable data formats across supply chain steps is one of the most significant structural barriers to scaling AI-generated quality data from individual factory installations to system-level supply chain intelligence. The EU’s regulatory agenda, Ecodesign, CSRD, Extended Producer Responsibility, and Green Public Procurement, functions in this context not as a compliance burden but as a demand-side driver that creates commercial value for AI-generated primary data, accelerating the adoption calculus for supplier enterprises.

At Member State level, national strategies[44] translate these ambitions into targeted investment mechanisms. Germany’s National Circular Economy Strategy, adopted in December 2024, allocates research funding for AI and generative AI applications in textile design optimisation and process efficiency, with parallel investment in automated sorting technologies using machine learning for fibre identification. Italy’s Piano Transizione 5.0, a EUR 6.3 billion cross-sectoral programme, provides tax credits for Industry 4.0 investments including AI-enabled production systems, automated quality control, and digital finishing, precisely the categories into which both case study technologies fall. This represents one of the most significant demand-side interventions available to SMEs: by subsidising the cost of AI adoption through tax incentives rather than grant programmes requiring competitive application, Piano Transizione 5.0 removes a key friction point for enterprises that have the internal capability to evaluate and implement systems but lack the capital to absorb upfront costs.

The OECD’s assessment reveals significant gaps at the skills level. AI-skilled professionals constitute[45] less than 2% of the manufacturing workforce across most EU Member States, and textiles, at 6% overall AI adoption, sits at the lower end of the manufacturing spectrum, behind food processing, basic metals, and wood and paper. The skills challenge in this sector is compounded by its operational context: what is needed is not data scientists but professionals combining domain knowledge of textile production with the capacity to interpret and act on AI-generated outputs. The successful deployments examined here suggest that workforce development in textiles AI is best achieved through structured operator-level training embedded in the deployment process itself, rather than pre-deployment upskilling programmes. Training that is abstract and separated from the production environment does not transfer; training conducted on the factory floor with the actual installed system does. This has implications for how workforce support programmes are designed: EDIH-delivered training that connects operators to running demonstrations on comparable equipment will be more effective than classroom instruction.[46]

2 **R&D AND SCALING-UP INITIATIVES**

The European Commission’s direct R&D support for the Portuguese quality inspection startup, one of the enabling conditions cited in the company’s development trajectory, illustrates the role that public R&D funding plays in de-risking the development of technically complex systems that the private market alone would not fund at early stages. The startup’s subsequent USD 24.7 million Series A raise in 2022, with investors including a major European fashion retailer and a sustainability-focused fashion innovation fund, demonstrates the lab-to-market pathway in practice[47]: public R&D de-risks technical development; private capital scales proven systems. The OECD identifies this sequencing as a general feature of successful AI adoption in manufacturing, noting that the gap between academic AI research and deployable industrial systems remains a primary bottleneck, and recommending that Member States invest in accelerators specifically designed to bridge research output and enterprise deployment.

The EU Apply AI Strategy's manufacturing flagship directly addresses this gap. The strategy commits Commission support for AI agent development adapted to manufacturing environments, data pooling through trusted third parties via the manufacturing dataspace, and dedicated 'Acceleration Pipelines' designed to move AI solutions from research labs to operational deployment.[48] For the textile sector, the manufacturing dataspace is particularly significant: interoperable, standardised data exchange between supply chain steps is a prerequisite for AI-generated quality data to be utilised across the value chain, rather than remaining siloed at individual factory installations. Without this infrastructure, the 'data highway' that supply chain analysis identifies as essential remains fragmented, relying on non-standardised PDF and Excel transfers that render data commercially unusable at scale.

No dedicated TEF currently exists for the textile sector, unlike, for example, agrifood or robotics. This gap is significant: TEFs provide the validated, neutral testing environments in which SMEs can evaluate AI systems against their own production profiles without committing to purchase. In the absence of a textile TEF, the Apply AI Strategy's repositioning of EDIHs as 'experience centres for AI', with 250+ hubs covering over 85% of EU regions, provides the most accessible alternative.

EDIHs can serve as demonstration and knowledge-transfer environments, enabling enterprises to assess systems against comparable production contexts before committing capital. Their effectiveness in this role depends, however, on whether they are equipped with technology demonstrations relevant to textile production environments, a level of sector-specificity that has not been consistently achieved across the network. The OECD recommends fostering data-sharing within and across sectors and promoting interoperable standards through industry consortia as complementary measures; in textiles, this would translate to national cluster organisations and sector associations taking an active role in coordinating demonstration access and knowledge transfer among their members.

High-level assessment

The textile deployments examined point to a disaggregated picture of what drives successful AI adoption, one in which sophisticated technology and large-scale investment are enabling conditions for some components of the adoption pathway, but not for others. The technical systems themselves are sophisticated: computer vision, machine learning-based defect classification, real-time sensor fusion, and cloud-connected digital twins represent genuine AI capability. However, the enabling factors that determined whether these systems were adopted and sustained were largely non-technical. The clarity of the financial case, the physical presence of the technology vendor, the design of the pilot study, and the operator-level training embedded in deployment all proved more decisive than the technical specification of the AI system itself. In this sense, the barrier to adoption in textiles is not primarily a technology gap, it is a deployment methodology and business case communication gap.

Where investment did prove central was in the scaling phase rather than the proof-of-concept phase. Moving from 22 Portuguese installations to 100 global factories required capital that only private equity and strategic investors could provide. And the development of the data infrastructure, the manufacturing dataspace, interoperable ERP integrations, and standardised quality data formats, requires coordinated public investment that no individual enterprise can provide. The most effective policy interventions observed are those that absorb upfront financial risk for SMEs: Italy's tax credit mechanism and the EC's direct R&D support function in this way, lowering the capital commitment required to initiate deployment without distorting the commercial discipline that forces vendors to demonstrate ROI.
The broader lesson is that AI uptake in textiles does not require frontier research capability or greenfield infrastructure; it requires deployment methodology that is honest about financial returns, physically present, and calibrated to the constraints of a high-volume, low-margin sector.

2.2.3 Towards EU best practices

Ukraine's textile and clothing sector is SME-dominated and export-oriented, with around 14 600 registered business entities, mostly micro-enterprises, operating primarily in clothing production. Annual exports reach approximately USD 460 million, mostly to EU buyers. Most production management still relies on manual processes; ERP and cloud adoption rates are well below EU norms. Wartime pressures on workforce availability and energy supply further constrain investment capacity.

The WINWIN strategy does not designate textiles as a standalone priority innovation sector, but its horizontal commitments to Industry 4.0 practices and digital transformation apply. Ukraine's Roadmap for the Twin Transition of Ukrainian Textile Industry SMEs (December 2024) sets a more specific three-year programme targeting AI-enabled quality inspection, predictive maintenance, digital twins for process management, and ERP-MES integration as key use cases.

1 ADOPTION DEPENDENCIES

The ROI-first adoption model depends on enterprises being embedded in EU supply chains. The financial case for AI quality inspection rests substantially on the compliance data value it generates for EU buyers under the Ecodesign Regulation, CSRD, and Extended Producer Responsibility frameworks. Ukrainian producers integrated into EU supply chains face this compliance pressure and are therefore positioned to access the same adoption incentive. Producers without EU buyer relationships face a weaker financial case.

Physical vendor presence is a technical requirement, not a preference. European evidence consistently shows that remote-only deployment fails in this sector because of machine environment variation and the need to build operator trust in AI-generated quality signals. Ukrainian deployment depends on whether EU or EU-adjacent technology vendors are willing to operate physically in the Ukrainian market, including under wartime conditions.

2 DIAGNOSTIC INDICATORS

- The depth of EU supply chain integration among Ukrainian textile enterprises, as EU-integrated producers have the compliance-driven adoption incentive that is the primary driver in European cases.
- Whether pilot support programmes under the GDT Textile roadmap require vendors to be physically present during deployment, since programmes that fund remote rollouts are likely to produce stalled implementations.
- Whether the Twin Transition Roadmap's targets of 150 enterprises and 50+ pilot projects are being implemented with the bounded, ROI-first pilot structure that European evidence associates with successful operational transition.
- Whether EDIH network access for Ukrainian textile enterprises is being developed with sector-specific demonstration equipment.

2.2.4 Case studies

SMARTEX.AI

Case study 1

Smartex — AI-powered real-time fabric quality inspection[49]

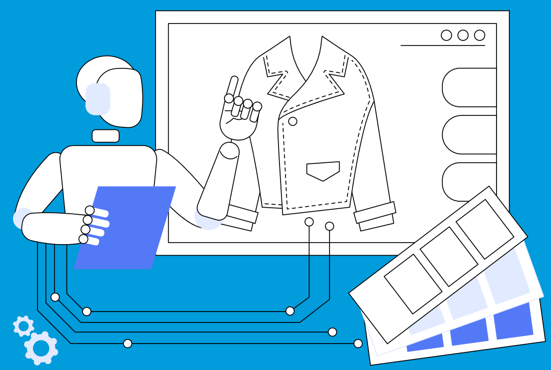
Portugal | Startup

Implementation

A Portuguese startup developed an AI-powered fabric quality inspection system that retrofits high-resolution cameras with advanced lighting analysis onto existing circular knitting machines. Computer vision and machine learning algorithms analyse imagery in real time to detect and classify defects including oil contamination, holes, elastane irregularities, and needle malfunctions. When the system identifies abnormalities, it triggers warning alerts or automatically halts machine operation to prevent continued defective production. Alongside defect detection, the system generates roll-by-roll grading data and real-time production metrics integrated with factory ERP systems, creating standardised, verifiable quality records that serve both purchasing decisions and regulatory compliance requirements. Documented results across 22 Portuguese installations include payback periods of 5 to 24 months. Tintex, a Portuguese fabric manufacturer, documented savings of over 50,000 litres of water, 2 772 kWh of electricity, and 532 kg of CO2 over a 70-day study, with a 3x return on investment. Impetus Textiles Group reported a 50% reduction in rolls requiring manual inspection. Familitex achieved 2x ROI over 14 months. Ekoten achieved an 80% reduction in defective fabric production

Adoption pattern demonstrated

This case study illustrates the vendor-mediated adoption pathway applied to the ROI-first logic specific to the textile sector: the startup packages AI complexity into a cloud service calibrated to the financial constraints and operational context of family-owned SMEs. The enabling factors are user-centred design that minimises technical barriers, adaptability to local machine environments and defect profiles, and a financial case communicated in terms of rejected-roll economics and payback periods rather than technological capability. The compliance data generated as a byproduct of quality inspection connects to WINWIN's industry modernisation priorities and the EU regulatory framework that drives adoption incentives for EU-integrated producers.



Source: n.a.

Case study 2

Monforts Montex — Cloud-based textile finishing digitalisation[50]

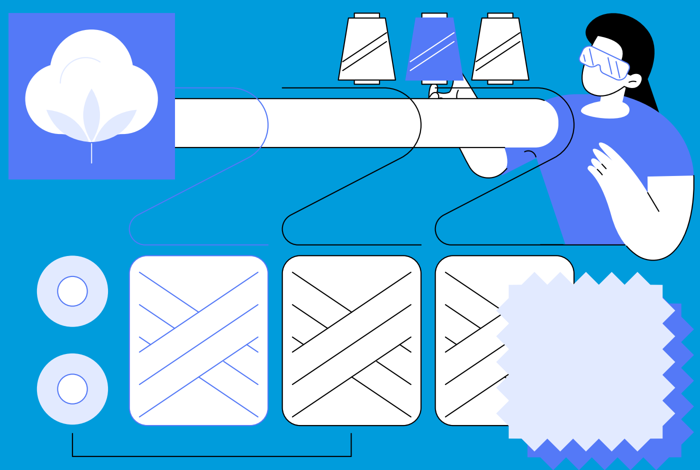
Germany | Large enterprise (equipment manufacturer)

Implementation

A German equipment manufacturer implemented comprehensive digitalisation across its stenter range for fabric finishing through the Qualitex 800 control system and associated cloud infrastructure. The system uses advanced sensor technology to virtually map 100% of machine data in real time, creating a digital twin of the physical equipment accessible through integrated applications for monitoring machine performance, process parameters, and production status. Automation covers both production and maintenance: the control system adjusts fan speeds and temperature settings automatically, reducing energy use without requiring manual oversight. Remote diagnostics allow the manufacturer's technical team to identify and resolve issues from any location, reducing service response times. The system enables recipe data management, supporting process reproducibility across production runs and multiple sites. Cloud connectivity allows fabric finishing customers to adopt digital process control by retrofitting existing stenter frames with modern control cabinets, standardised machine interfaces, and cloud connectivity, without replacing the machinery itself.

Adoption pattern demonstrated

This case study illustrates the vendor-mediated retrofit model from the equipment manufacturer's side: AI and cloud capability is delivered to the customer as an upgrade to existing machinery rather than requiring capital replacement. The enabling factors are the standardised machine interface that makes cloud connectivity compatible with existing stenter frames, and the remote diagnostics model that lowers the ongoing operational cost of the technology relationship. For EU-integrated producers facing supply chain data and compliance reporting requirements, the 100% real-time machine data capture serves as the data infrastructure that more complex analytics and compliance reporting depend on. This connects to WINWIN's emphasis on digital transformation of industrial processes and energy efficiency.



Source: n.a.

2.3 WOOD PROCESSING

2.3.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The European ecosystem and EU and national initiatives

The EU forest-based sector employs 4 million workers across the extended value chain, generating over EUR 165 billion in gross value added (GVA) annually.[51] The forestry and logging segment contributed EUR 27.9 billion in GVA in 2022, with Finland (EUR 4.4 billion), France (EUR 3.9 billion), and Germany (EUR 3.2 billion) leading among Member States. The sector occupies a strategic position in European climate and bioeconomy policy: the EU Forest Strategy 2030,[52] adopted as a flagship of the European Green Deal, explicitly promotes digital wood traceability systems, IoT platforms for automated carbon reporting, and AI-enabled monitoring tools aligned with EU data governance frameworks.

Horizon Europe Cluster 6 (food, bioeconomy, natural resources, agriculture and environment), budgeted at EUR 9 billion for 2021-2027, provides the primary R&D funding mechanism for the sector.[53] Illustrative EU-funded initiatives include the DigiForest project, which is developing heterogeneous robot teams combining ground-based and aerial platforms to generate and update 3D forest data for machine learning-based precision silviculture; the Forest 4.0 Centre of Excellence in Lithuania (EUR 9.9 million), connecting three universities to develop IoT and AI competences for smart forestry; and the ROSEWOOD4.0 Thematic Network, which promotes digital tool adoption and innovation transfer across five regional forestry hubs. At national level, Finland's National Forest Strategy and Sweden's Mistra Digital Forest programme both position digital transformation as central to forestry competitiveness. The multi-country CEI-Bois TIMBIM initiative develops common data structures for wood product information across timber associations in Switzerland, Austria, Finland, and Sweden.

The EU's Forest Information System for Europe (FISE) provides publicly available satellite-based data on forest condition and biodiversity.[54] This public data infrastructure underpins commercial AI development for forest monitoring, creating a foundation that private actors can build on without duplicating the data acquisition cost — as the Stora Enso case directly illustrates.

Ukraine's wood processing sector and EU alignment

Ukraine ranks sixth in Europe in timber reserves (approximately 2.2 billion cubic metres) and tenth in total forest area (9.7 million hectares).[55] The sector's contribution to GDP is modest at 0.26-0.37%, though it generates significant tax revenue relative to state forest management allocations. War damage to forest ecosystems during 2022-2024 reached approximately EUR 540 million, with additional losses in equipment (EUR 11.5 million) and real estate (EUR 32.5 million). Roundwood production volumes decreased 15% in 2022.[56] Ukraine's WINWIN Global Innovation Strategy 2030 does not designate wood processing as a standalone priority innovation sector, but positions forestry-related innovation within its greentech focus area, with bioenergy development and cascading use of biomass as explicit priorities.[57] The strategy's broader emphasis on Industry 4.0 practices, digital transformation, and integration into European innovation ecosystems applies to the sector. Ukraine's export structure in wood processing is notably strong: trade data shows a 5.4-to-1 export surplus in wood processing, with exports broadly distributed across EU Member States, making it the most pan-European export footprint of any Ukrainian sector.[58] Import composition is healthy, comprising mainly capital equipment and precision woodworking technology from Germany, Poland, Czechia, France, and Italy.

AI applications in the sector

The main operational AI applications in European wood processing:

- **Satellite and aerial forest monitoring:** deep learning applied to Sentinel-2 and commercial satellite imagery for pest detection, health monitoring, and forest inventory at landscape scale. Enables detection at the resolution of groups of four to five trees across hundreds of thousands of hectares.
- **Machine vision quality control:** convolutional neural networks detecting and classifying wood defects (knots, cracks, resin pockets, discolouration, warping) with 98% accuracy, substantially exceeding the approximately 90% achievable through manual inspection. Systems operate at industrial speeds for real-time grading and routing.
- **Sawing pattern optimisation:** machine learning combined with 3D laser scanning to maximise timber yield by accounting for internal defects invisible to surface inspection.
- **Integrated facility control and digital twins:** holistic optimisation of sawmill operations through integrated monitoring, AI-driven process control, and predictive maintenance of equipment.
- **Drone-based inventory:** computer vision for tree species classification, standing timber quality assessment, and disease vector detection at individual-tree resolution.

2.3.2 Adoption pathways analysis

The two case studies examined in this sector represent two distinct positions within the wood processing value chain: AI-powered satellite forest monitoring deployed at landscape scale, and a fully integrated AI and robotics platform embedded into a new large-scale sawmill. Both have reached operational deployment, though through markedly different investment profiles and implementation logics. Wood and paper products sit at 9% AI adoption among EU manufacturing enterprises, tied with basic metals and above textiles, reflecting a sector where specific high-value applications have reached commercial scale, but where broader uptake remains limited.[59]

Sectoral deployment patterns

The satellite forest monitoring case and the automated sawmill case share a common analytical feature: both address challenges of scale and complexity that exceed the capacity of conventional manual approaches. A large Swedish forestry company monitoring 200,000 hectares for bark beetle infestations across multiple annual swarm cycles cannot rely on manual satellite imagery review; a Finnish sawmill processing 40 logs per minute across a 130-metre line coordinated by six robots and 1,000 variable speed drives cannot be managed through conventional instrumentation. In both instances, AI is the enabling technology for an operational problem defined by volume and speed, not by algorithmic novelty.

The implementation approaches diverge significantly. The forest monitoring system represents a data-overlay model: AI is applied to publicly available satellite imagery using proprietary deep learning algorithms, with no new physical infrastructure at the forest level. The technology provider (Sogeti/Capgemini) developed and operates the AI system; the forestry company contributed domain knowledge about pest behaviour and operational response protocols. The result is a capability delivered as a service, accessible without capital investment in hardware. This is a vendor-mediated adoption pathway, and its low entry barrier is relevant: even large companies with substantial in-house technical capacity opted for external AI development rather than building internally, reflecting the specialist skills required for satellite imagery processing and deep learning model development.

The sawmill represents the opposite end of the capital spectrum. At EUR 260 million, the Metsä Fibre facility at Rauma is Finland's largest sawmill investment to date.[60] It was designed from inception to integrate AI, machine vision, and robotics throughout the production process rather than layering these onto existing infrastructure. ABB served as systems integrator, bringing automation, power distribution, and control room expertise; Metsä Fibre contributed process knowledge and operational requirements. The result is a productivity level three times higher than typical European outputs, achieved because the AI systems and the physical facility were co-designed rather than sequentially combined. This greenfield co-design model generates the highest performance outcomes but requires both capital availability and strategic commitment to digital integration at the investment planning stage.

SME access is structurally limited in both cases. Neither deployment was initiated or led by a small enterprise: Stora Enso is one of Sweden's largest forest owners; Metsä Fibre is a major Finnish forestry company backed by a cooperative. The satellite monitoring pathway is in principle more accessible, since it does the AI development requires technical partnership with specialist firms. The EDIH network could in principle serve as an access pathway for smaller forestry enterprises seeking to adopt comparable monitoring approaches, though the OECD assessment notes that EDIH coverage for forestry-specific applications remains limited.[61]

Both deployments moved beyond pilot to operational use through different mechanisms. In the satellite monitoring case, the expanding threat window created by climate change, with bark beetles now swarming multiple times per year rather than once, generated the operational urgency that made a reliable automated monitoring system commercially necessary rather than merely useful. In the sawmill case, the full integration logic meant that the AI system was operational from the facility's launch: there was no pilot phase, as the technology was embedded in the design from the outset.

Policy context and enabling conditions

1 EU-LEVEL AND NATIONAL AI STRATEGIES ACROSS DATA, COMPUTE AND SKILLS

The EU Forest Strategy 2030 provides the overarching policy orientation, explicitly promoting digital wood traceability, IoT platforms for carbon reporting, and AI-enabled monitoring.[62] This policy direction has created a governance context within which both deployments fit, even though neither was directly funded by forest strategy instruments. The broader Manufacturing-X initiative in Germany and comparable national digitalisation programmes in Finland and Sweden create the ecosystem conditions within which technology providers and industrial partners develop the capabilities that forestry companies then deploy. Horizon Europe Cluster 6 funding has supported the DigiForest project, the Forest 4.0 Centre of Excellence in Lithuania, and the ROSEWOOD4.0 network, all of which contribute to the knowledge infrastructure that underpins commercial AI adoption in the sector.

Skills requirements differ between the two application domains. Satellite forest monitoring requires data science expertise and computer vision capabilities that are not sector-specific: the talent pool is shared with other industries deploying remote sensing AI. Sawmill automation at the level documented at Rauma requires a combination of industrial automation engineering, machine vision, and process expertise specific to wood processing. The AI talent concentration in wood and paper manufacturing remains below 2% across most EU Member States, consistent with the broader manufacturing pattern.[63] The Rauma case addressed this through ABB's systems integration role, externalising the AI and automation engineering expertise rather than building it in house.

Data infrastructure requirements also differ. Satellite monitoring relies on publicly available imagery (Sentinel-2 and commercial providers), combined with proprietary AI models: the data supply chain is external and robust. Manufacturing AI at Rauma depends on integrated sensor networks generating operational data from the production line; ABB's information systems integration was explicitly designed to maximise automated data collection, treating data infrastructure as a production facility requirement from the design stage.

2 R&D AND SCALING-UP INITIATIVES

No dedicated TEF exists for the wood processing sector, unlike agrifood or robotics. The Apply AI Strategy's repositioning of EDIHs as experience centres for AI provides the most accessible alternative pathway for smaller enterprises.[64] Horizon Europe Cluster 6 has funded relevant R&D, including multi-robot systems for forest data collection and digital innovation hub networks. The sector's capital intensity in manufacturing means that public R&D support typically functions as a complement to private investment at the design and validation stage rather than as the primary funding source for deployment. The satellite monitoring model, by contrast, is more suited to public R&D support structures, as the AI development cost is modest relative to the value protected.

The EU Forest Strategy's digital tools include the Forest Information System for Europe (FISE), which provides satellite-based data on forest condition and biodiversity. This public data infrastructure underpins commercial AI development for forest monitoring, creating a foundation that private actors can build on without duplicating the data acquisition cost.

High-level assessment

The wood processing cases illustrate a sector where AI adoption has followed two very different enabling logics. In upstream forest monitoring, the primary enabling factor was access to external AI expertise through partnership, combined with publicly available satellite data infrastructure. The capital requirement at the point of adoption was low; what mattered was the availability of a technology provider capable of developing the specific deep learning application and the operational urgency created by climate-driven pest pressure. In downstream manufacturing, the enabling factors were capital availability, strategic commitment to co-design, and a systems integrator with the breadth to cover automation, robotics, power distribution, and control systems simultaneously. These are high-resource requirements, but the productivity gains are commensurately high.

The sector overall is not at the frontier of EU AI adoption. Wood and paper sit at 9% enterprise-level AI adoption, considerably below pharmaceuticals (26%) or electronics (25%) in the manufacturing spectrum.[65] The two documented cases are among the most advanced deployments in the sector: both involve large companies with substantial technical and financial resources. The adoption pathway for smaller forestry enterprises, which represent most of the sector by enterprise count, has not yet been consistently defined or enabled.

2.3.3 Towards EU best practices

Ukraine holds the sixth-largest timber reserves in Europe and significant processing capacity, though war damage to forest ecosystems between 2022 and 2024 reached approximately EUR 540 million.[66] Production volumes fell 15% in 2022. The CEPS-UNIDO connections analysis finds a 5.4-to-1 export surplus, with exports distributed broadly across EU Member States, making wood processing Ukraine's most pan-European export footprint. WINWIN positions the sector within its greentech focus area rather than as a standalone priority, emphasising bioenergy and biomass.

1 ADOPTION DEPENDENCIES

The satellite forest monitoring pathway depends on two conditions that are separable from capital intensity. Forest management organisations need the operational capacity to act on AI-generated outputs: the monitoring insight has no value if the organisational response capability is absent or damaged. Ukraine's State Forest Agency has experienced significant wartime disruption; operational restoration that incorporates data processing protocols is a prerequisite for this adoption pathway to generate value. The second condition is access to a technology partner capable of developing and maintaining the satellite imagery processing pipeline. EU technology firms active in this domain represent the most direct route to accessing this capability.

Greenfield sawmill co-design carries a fundamentally different dependency structure: capital availability at reconstruction investment scale, digital integration written into facility design mandates rather than treated as optional, and a systems integrator with breadth across automation, robotics, and control systems. The productivity differential between co-designed AI integration and retrofitted AI in manufacturing is documented in the European evidence: the 3x productivity premium at Rauma is achievable only when the design commitment is made before capital is committed. Once facilities are built without digital integration mandates, this option closes.

These two dependency profiles suggest a practical sequencing. Satellite monitoring and similar data-overlay applications are accessible using existing organisational capacity and external partners, and do not require new physical infrastructure. Manufacturing AI integration is available as a reconstruction-era design choice, but only if that choice is embedded in capital investment frameworks before facility designs are finalised. The second pathway is time sensitive in a way the first is not.

2 DIAGNOSTIC INDICATORS

- State Forest Agency operational capacity is being restored with data processing and response protocols incorporated, not only physical infrastructure.
- EU technology partners active in forest monitoring AI are engaging the Ukrainian market or participating in Ukrainian forestry partnerships.
- Reconstruction investment frameworks for wood processing facilities include requirements or incentives for digital integration at the design stage.
- EDIH network access for Ukrainian wood processing enterprises is being developed with relevant demonstration capability.

2.3.4 Case studies

Case study 1

Stora Enso / Sogeti — AI-powered satellite forest monitoring[67]

Sweden | Large enterprise + technology partner

Implementation

A major Swedish forestry company partnered with a technology services firm (part of the Capgemini Group) to deploy an AI-powered monitoring system covering 200,000 hectares of managed forest. The system combines satellite imagery with deep learning algorithms to automatically detect bark beetle infestations at the resolution of groups of four to five trees. Prior to deployment, detection relied on manual expert review of imagery, which was insufficient given that climate change has driven bark beetles to swarm multiple times per year rather than once, expanding the threat window substantially. The automated system enables rapid identification of infection sites and more efficient targeting of intervention resources. Detection is based on spectral signatures in publicly available satellite data processed through proprietary convolutional neural network models trained on annotated historical imagery.

Adoption pattern demonstrated

This case study illustrates the vendor-mediated adoption pathway for AI in environmental monitoring: the AI capability was developed and delivered by an external technology partner, with the forestry company contributing domain knowledge and operational requirements. The enabling conditions include access to publicly available satellite data infrastructure, availability of specialist computer vision expertise through partnership, and operational urgency created by climate-driven intensification of the pest threat. The implementation required no capital investment in ground-level hardware, making it accessible without large upfront commitment. It connects to WINWIN's greentech priorities around sustainable forest management and ecosystem monitoring.

Source: https://www.sogeti.com/client-story/stora-enso-tracks-bark-beetle-activity-using-satellite-imaging

Case Study 2

ABB / Metsä Fibre — Integrated AI sawmill at Rauma[68]

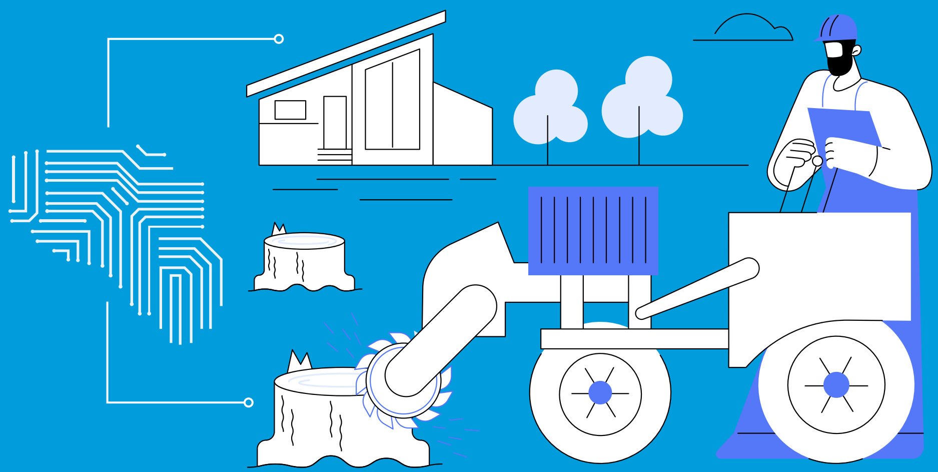
Finland | Large enterprise + systems integrator

Implementation

A Finnish forestry company invested EUR 260 million in a new sawmill facility designed from inception around integrated AI, machine vision, and robotics. The facility processes 40 logs per minute on a 130-metre sawline at maximum speeds of 250 metres per minute, with six robots equipped with machine vision working alongside 1,000 variable speed drives managed from a centralised control room. The systems integrator (ABB) provided automation, power distribution, and control room technologies, developing information systems infrastructure to maximise automated data collection and treat the sawmill operation with the reliability standards of a process industry plant. Productivity levels are approximately three times higher than typical European sawmill outputs. By-products including wood chips, sawdust, and bark are directed to pulp and bioenergy production, embedding circular economy integration into the facility's operational logic.

Adoption pattern demonstrated

This case illustrates the greenfield co-design pathway, in which AI capability is embedded in facility architecture at the investment planning stage rather than retrofitted to existing operations. The enabling conditions are capital availability (EUR 260 million investment), strategic commitment to digital integration from project inception, and access to a systems integrator capable of delivering automation, robotics, and AI across the full facility scope. The productivity gains are substantially higher than retrofit approaches but require that digital integration be a design priority rather than an afterthought. For recovery and reconstruction contexts, this case is relevant as a benchmark for what is achievable when AI systems and physical infrastructure are co-designed.



Source: https://new.abb.com/news/detail/114420/abb-control-room-power-distribution-and-robotics-technologies-help-metsa-fibre-mill-excel-in-productivity-and-efficiency

2.4 MEDTECH

2.4.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The European Commission's July 2025 Communication 'Choose Europe for life sciences' articulates an ambitious vision to position the bloc as the world's most attractive destination for life sciences by 2030. Responding to a sector employing 29 million people and generating EUR 1.5 trillion in value added, the strategy acknowledges persistent structural barriers including fragmented research ecosystems and, critically, the underuse of data and artificial intelligence.[69] Digitalisation and AI integration feature prominently, with EUR 50 million committed to multi-modal generative AI in biomedical research, EUR 25 million for genomic data infrastructure, and the AI Factories initiative dedicating at least ten facilities to life sciences applications including drug discovery and genome analysis. The European Health Data Space Regulation[70] provides the legal architecture for secure health data access, while the EU Biotech Act and proposed simplification of medical device regulations aim to balance innovation facilitation with patient safety.

On the national level, Denmark's November 2024 Strategy for Life Science towards 2030 emphasises leveraging the country's unique health data assets through strengthened IT infrastructure to accelerate AI deployment and drive innovation – positioning digital capabilities as a differentiator for attracting foreign investment.[71] France's Innovation Santé 2030 strategy commits EUR 7.5 billion to health innovation, establishing 12 new Instituts Hospitalo-Universitaires and five globally-scaled bioclusters designed to concentrate academic, hospital, and industrial actors around specific therapeutic themes, with digital health and AI in healthcare constituting one of four strategic research priorities receiving EUR 550 million in dedicated funding.[72]

Ukraine's Medtech strategy and EU alignment

Ukraine's WINWIN strategy designates medtech as a priority innovation sector, targeting AI-enabled diagnostics, remote patient monitoring, and clinical workflow automation.[73] The country has built a functional national eHealth system storing data on 35 million patients, and a growing startup ecosystem producing AI-based diagnostic tools, clinical decision-support systems, and remote monitoring solutions. Data interoperability across healthcare information systems is estimated at around 30% of organisations, and over 80% of components for medical devices, including prostheses, are imported.[74]

The WINWIN medtech strategy identifies four priority areas: modern prosthetics production, mental health and PTSD solutions, rehabilitation infrastructure, and integrated diagnostics platforms leveraging IT for clinical decision support. Ukraine's existing strengths include developed IT infrastructure, a functioning e-health system, and a dynamic startup ecosystem. Key gaps include a regulatory framework that does not yet align with EU medical device certification standards, limited dedicated medtech funding, and the absence of high-tech production capacity for devices.[75] Ukraine's strategic commitment to harmonising with EU medical device classification standards and creating regulatory sandboxes provides the policy alignment framework; the operational gap is between that commitment and the institutional infrastructure to implement it.

Innovative uses of digital technology in Ukrainian healthcare provide early evidence of adaptive capacity: UAV-based transport of donor organs between medical institutions and drone delivery of medicines under the 'Affordable Medicines' programme to remote areas demonstrate that the country's IT and robotics competences are being applied to healthcare logistics alongside the clinical AI priorities that the strategy targets.[76]

AI applications in the sector

The main operational AI applications gaining traction in European medtech:

- **Autonomous diagnostic imaging AI:** platforms that automatically analyse medical images and generate reports for studies with no significant findings, allowing radiologists to concentrate on clinically relevant cases. Validated to clinical-grade accuracy standards under EU MDR Class IIA/IIB.
- **AI-assisted radiology companions:** systems integrated within PACS workflows that analyse imaging studies for specific findings and return structured results within the radiologist's standard working environment. Designed to operate across multiple imaging equipment vendors without hardware standardisation.
- **Embedded AI in medical devices:** microprocessor control and real-time sensor algorithms integrated directly into devices such as prosthetics, enabling adaptive behaviour responses in real time.
- **AI in R&D and regulatory processes:** commercial AI tools applied to patent search, requirements management, and regulatory documentation traceability within medical device development pipelines.
- **Remote patient monitoring:** AI-driven analysis of continuous patient data from connected devices, supporting clinical decision-making outside hospital settings.

2.4.2 Adoption pathways analysis

The European medtech case studies collectively illustrate a sector in which AI adoption has progressed from validation to operational deployment in two distinct domains, clinical workflow automation in medical imaging, and intelligence-embedded medical devices, while remaining fragmented and institution-specific rather than system-wide.

A Lithuanian medical AI company and a German radiology network have each achieved operational AI integration into frontline diagnostic workflows, with documented clinical performance at scale. An Icelandic prosthetics manufacturer has embedded AI across both its product development processes and in the devices themselves, delivering measurable patient outcome improvements. Together, these cases mark a sector in which the prerequisites for AI deployment are now well understood, and in which the challenge has shifted from proof-of-concept to the conditions required for broader uptake.

Sectoral deployment patterns

1 **THE EVIDENCE-FIRST DEPLOYMENT LOGIC**

The most consistent pattern across the European medtech case studies is that rigorous clinical evidence generation precedes deployment, and that this sequencing is structural rather than incidental. A Lithuanian medical AI startup built its entire commercialisation strategy around retrospective clinical trials at major teaching hospitals before seeking market access. The UK's largest retrospective radiology AI trial, processing nearly 200,000 chest X-rays and achieving 99.8% sensitivity with a 1% discordance rate after expert review, was conducted as a pre-deployment confidence-building exercise, not a post-market study.[77] A German radiology network co-developed its AI imaging system with a technology partner over 18 months, contributing over 100,000 annotated training images before the system entered routine clinical use.[78] The regulatory logic underlying this pattern is clear: EU Medical Device Regulation (MDR) requires clinical evidence of safety and efficacy before market authorisation, and 18-to-36-month approval timelines are standard. What the case studies reveal, however, is that leading adopters treat this requirement not as a barrier to be navigated but as a strategic asset: clinical validation data build institutional trust and overcome professional scepticism in conservative clinical environments.[79]

A critical operational lesson embedded in this pattern is the value of staged deployment sequencing. Shadow mode operation, in which an AI system produces outputs that are reviewed but not acted upon, preceded autonomous or semi-autonomous reporting in both imaging cases. This sequence allowed clinical staff to calibrate trust in the system's outputs, identify edge cases, and develop familiarity with the tool's behaviour before the organisation committed to deploying it in safety-critical contexts. Across a sector where professional resistance and liability concerns are significant adoption barriers, this staged approach is not a workaround: it is the pathway through which pilot implementations become operational deployments. Institutions that skipped this sequence reported higher rates of abandonment or underutilisation.[80]

2 WORKFLOW INTEGRATION OVER PARALLEL SYSTEMS

A second consistent pattern is integration into existing clinical infrastructure rather than introduction of parallel or replacement systems. The cloud-based imaging AI deployed by the German radiology network returns structured findings within approximately two minutes, displayed directly within the radiologist's standard working environment alongside the original scan, not in a separate interface. The system operates across 14 different imaging devices from multiple manufacturers without requiring hardware standardisation.[81] This interoperability with existing picture archiving and communication systems (PACS) is architecturally deliberate: the OECD's assessment of AI adoption in EU radiology identifies PACS integration failure as one of the leading implementation barriers, and designs that eliminate this friction have demonstrably reached operational scale while those requiring separate workflows have not.

The practical implication for the sector broadly is that AI solutions designed to retrofit into existing clinical infrastructure, operating as an additional analytical layer within established workflows rather than demanding new ones, have substantially higher probability of sustained deployment. Total cost of ownership calculations is directly affected by this architecture choice: systems requiring workflow redesign, staff retraining, or parallel data management impose ongoing costs that erode operational ROI and trigger organisational resistance over time. By contrast, the German case study documents radiologists specifically valuing the tool during night and weekend shifts, when less experienced clinicians benefit most from additional analytical support, a differential value proposition that emerged from workflow integration rather than from the algorithm's performance characteristics alone.

3 MULTI-LAYER AI ADOPTION IN DEVICE MANUFACTURING

The specialist prosthetics manufacturer case demonstrates a distinct but instructive model: AI adoption layered across the entire innovation pipeline rather than concentrated in a single application. Upstream, AI-powered image search for patent identification has reduced search time from days to hours while substantially improving coverage, achieved by a lean IP team using a commercially available tool, not proprietary infrastructure.[82] Automated requirements management systems have shortened product development cycles and improved traceability across complex regulatory documentation requirements. Downstream, microprocessor control and real-time terrain-sensing algorithms are embedded directly in prosthetic devices, with clinical outcomes including a 70% reduction in reported fall rates over four-week user trials, and measurable improvements in quality-of-life scores on standardised assessments.

This distributed model, repurposing commercially available AI tools for internal processes while simultaneously developing proprietary embedded intelligence in products, does not require wholesale organisational transformation or large-scale AI infrastructure investment. It is a practical architecture for specialist manufacturers operating at manageable scale, and one that demonstrates genuine commercial returns at each layer. The integration of clinical outcome measurement across both upstream efficiency gains and downstream patient impact also reflects a measurement discipline that enables continuous improvement: each component of the AI stack has defined and tracked performance indicators, creating an evidence base that supports both internal decision-making and external market positioning.

4 SME ACCESS AND THE CE-MARKING PATHWAY

The presence of a small Lithuanian AI startup deploying across NHS-scale hospital networks, competing with global medtech incumbents, demonstrates that SME-level innovators can secure competitive market positions in this sector. The route was through regulatory credibility: CE Class IIA/IIB certification, achieved through rigorous multi-site clinical validation, functions simultaneously as a market access credential, a trust signal to clinical procurement, and a barrier to undifferentiated competition. Once achieved, CE marking enables cross-EU deployment across a market of 450 million patients.[83] The regulatory pathway rewards evidence quality over firm size, which is the structural characteristic that makes this sector accessible to smaller innovators with strong research capacity.

Policy context and enabling conditions

1 EU-LEVEL AND NATIONAL AI STRATEGIES: DATA, COMPUTE, AND SKILLS

The European healthcare AI landscape is characterised by substantial policy ambition that is not yet matched by uniform deployment at scale. The Apply AI Strategy's flagship actions for healthcare designate the sector as a strategic priority, committing to establish European AI-powered advanced screening centres and a European Network of Expertise on AI Deployment in Healthcare, both of which respond directly to documented structural gaps.[84] The strategy acknowledges that AI uptake in clinical workflows across the EU remains limited and uneven, with barriers spanning data availability, infrastructure heterogeneity, and limited AI literacy among healthcare professionals. This candid assessment is corroborated by the OECD: among healthcare AI use-cases, medical imaging AI is described as among the most advanced in the EU, yet national-level rollouts remain the exception, with implementation still concentrated in individual hospitals or health regions rather than across systems.[85]

The data infrastructure supporting clinical AI is the most advanced enabling condition across the sector. The European Health Data Space Regulation entered into force in March 2025, establishing federated architecture principles for secure secondary use of health data, a legal and institutional framework that the co-development model in the German radiology case which structurally changes the conditions for future scaling. As of mid-2024, twelve EU Member States have operational health data access bodies, with ten more establishing them, though five remain behind.[86] National-level health data systems in Denmark and Finland, countries where digital health infrastructure is well-established and interoperability is advanced, are assessed by the OECD as among the most capable in Europe. Lithuania's participation in the EU eHealth Digital Service Infrastructure reflects how smaller Member States connect to the broader European data architecture, relevant context for understanding how a Lithuanian AI startup could develop and validate clinical AI at EU-competitive level.[87]

The compute requirements for diagnostic imaging AI are less demanding than for large-scale pharmaceutical AI or genomics applications: the deployed imaging systems in both cases operate on cloud infrastructure with sub-two-minute turnaround, with PACS integration rather than dedicated HPC as the critical infrastructure dependency.[88] The Apply AI Strategy's AI Factories initiative, which commits dedicated compute capacity to life sciences, is better suited to upstream drug discovery and genomics applications than to the clinical deployment use cases documented here. At the device level, embedded AI in prosthetics operates on microprocessors within the device itself, driven by product architecture decisions rather than public compute infrastructure. The infrastructure gap most relevant to the cases is not compute but interoperability: the continued absence of harmonised PACS standards and EHR interoperability across EU health systems limits the scalability of any imaging AI solution that achieves certification in one institutional context.[89]

The skills dimension is the most structurally underdeveloped enabling condition in the sector. OECD data on AI talent concentration in hospitals and healthcare, measured through LinkedIn workforce analysis, show growth across all EU Member States between 2018 and 2024 but describe overall levels as remaining relatively low compared with sectors such as finance and IT.[90] An OECD forthcoming report on AI and the healthcare workforce finds that all surveyed countries are using AI to reduce administrative burden, the lowest-friction entry point, but that bridging the broader skills gap requires coordinated action across healthcare organisations, universities, and industry that is not yet institutionalised in most Member States. The Apply AI Strategy's cross-cutting workforce provisions, AI Skills Academy, sector-specific upskilling through the Pact for Skills, and hybrid AI/sector training programmes, address this at framework level. The OECD's Vol 1 assessment notes that more than half of Member States are implementing eHealth upskilling programmes, but flags the absence of standardised EU-wide quality indicators as a gap that limits the transferability of national models.[91]

2 R&D AND SCALING-UP INITIATIVES

The R&D ecosystem for healthcare AI in Europe is characterised by high activity at the startup level but modest venture capital investment relative to other sectors. Annual VC funding for EU healthcare AI, drug discovery, and biotech startups reached approximately USD 670 million in 2024, the strongest year on record, rising from near-negligible levels before 2018. This trajectory reflects growing investor confidence in the commercial promise of AI-driven life science innovation. However, healthcare represented only 7% of total VC investment in EU AI startups in 2024, considerably lower than financial services, energy, and IT. The OECD also notes that EU health companies lag behind their US counterparts in absolute R&D investment levels, even as the health sector accounts for 19.3% of total investment among the top 800 EU-based R&D investors.[92]

The Apply AI Strategy's flagship healthcare actions are explicitly structured around scaling validation infrastructure, a direct response to the most consistent bottleneck identified in the OECD assessment. The proposed network of AI-powered advanced screening centres addresses the absence of structured real-world clinical validation mechanisms that can generate generalisable evidence rather than institution-specific pilot data. The European Network of Expertise on AI Deployment in Healthcare targets the deployment playbooks gap, the absence of consolidated guidance on local validation, post-deployment monitoring, and workflow integration that currently forces each implementing institution to build its own approach from scratch. This repeats a significant inefficiency across EU health systems: the German radiology case study's 18-month co-development period, while producing a well-validated and clinically integrated tool, reflects the current absence of shared validation frameworks that would make such development more efficient and more replicable.

The EU EDIH network plays a cross-cutting enabling role for medtech SMEs and startups. The Apply AI Strategy's refocusing of EDIHs as experience centres for AI creates access points through which smaller innovators can engage with the European AI ecosystem without managing country-by-country relationships independently. For clinical AI companies seeking to move from national to EU-wide deployment, EDIHs can provide structured support in navigating the regulatory environment, accessing clinical partners, and building the evidence base that CE marking requires.[93] The OECD's key recommendations for the healthcare sector additionally call for an EU registry of CE-marked healthcare AI solutions, modelled on the FDA device listing, to reduce due diligence costs in hospital procurement and increase market transparency. In the current absence of such a registry, procurement decisions are complicated by the difficulty of comparing certified and uncertified solutions, which creates friction that delays both adoption and market development.[94]

The dual regulatory burden of MDR compliance and EU AI Act requirements remains the sector's most significant structural friction point for scaling. The OECD's Vol 2 assessment identifies the overlap between the two frameworks, each requiring risk assessment and clinical evidence, with partially inconsistent procedural requirements, as a source of increased complexity, cost, and time-to-market that disproportionately affects smaller innovators. The Apply AI Strategy's commitment to streamlining market entry for AI medical devices without compromising safety addresses this directly, and the EU medtech industry has strongly advocated for alignment between MDR and AI Act compliance pathways. The operational implementation of consolidated guidance has not yet materialised. In the interim, the CE marking pathway continues to function as the primary scaling mechanism for medtech AI: once achieved, it enables cross-EU deployment across a market of 450 million patients, and the cases confirm that even small companies can leverage it to achieve disproportionate market reach.

High-level assessment

The European medtech cases reveal a sector in which evidence generation was structurally necessary and there is no shortcut to regulatory credibility. Deploying autonomous diagnostic AI at clinical scale required large-scale annotated datasets, 18 to 36-month certification processes, and sustained institutional partnerships with teaching hospitals. This investment is non-negotiable.

In other dimensions, significant and measurable impact was achieved without requiring substantial new resources. A lean IP team achieved material productivity improvements by repurposing a commercially available patent search tool. Multi-site imaging AI deployment was enabled by designing for PACS interoperability rather than requiring new hardware investment. Shadow mode deployment built institutional trust without requiring additional technical capability. Sequencing and integration strategy consistently mattered more than investment scale.

The most durable deployments shared three characteristics: regulatory credibility (CE marking as a trust mechanism), workflow fit (integration into existing PACS and clinical environments), and clinical ownership (practitioner champions who vouched for safety and performance). Where all three were present, AI moved from validation to operational deployment. Where clinical ownership was absent, technically capable solutions remained in pilot. The EU policy architecture is increasingly oriented towards creating the conditions for these factors to converge at scale; the current challenge is consistent implementation across Member States.

2.4.3 Towards EU best practices

Ukraine's medtech sector has a strong research base, with the CEPS-UNIDO baseline identifying significant clinical AI publication activity and a pool of software engineering talent that several EU-aligned startups have drawn on. Clinical infrastructure is variable, with PACS and electronic health record adoption uneven across hospital networks. WINWIN designates medtech as a priority innovation sector, targeting AI-enabled diagnostics, remote patient monitoring, and clinical workflow automation as key use cases.[95]

1 **ADOPTION DEPENDENCIES**

European medtech AI adoption shows a dependency that runs counter to what capital-intensive sectors might suggest: regulatory credibility precedes market access, and evidence quality determines regulatory credibility. The Lithuanian startup's ability to deploy across NHS-scale networks in the UK, competing with global incumbents, followed from its investment in multi-site clinical validation and CE Class IIA/IIB certification. Capital was not the differentiating factor; the evidence base was. This means the dependency for clinical AI deployment is not primarily financial: it is access to clinical research partnerships with hospitals whose validation data will be accepted by regulators.

A second dependency involves PACS infrastructure. The most common integration pathway for diagnostic imaging AI, adding an analytical layer within the radiologist's existing working environment, requires interoperable PACS. The German radiology network case succeeded specifically because it designed for PACS compatibility across 14 different imaging systems from multiple manufacturers. Where PACS infrastructure is absent or fragmented, this pathway is blocked regardless of the AI capability available.

A third dependency is the shadow-mode deployment sequence. Clinical AI requires a trust-building phase before it operates autonomously or semi-autonomously in safety-critical contexts. This is not optional and cannot be shortened significantly: it is the mechanism through which professional resistance is addressed and liability concerns are managed. Any deployment plan that skips this phase is more likely to stall at the institutional level than to fail technically.

A fourth dependency, the least developed in the European evidence and the most relevant for Ukraine, is clinical leadership capacity. The documented cases consistently show that technical AI implementation without corresponding clinical adoption capacity results in underutilisation or abandonment. What differentiates successful deployments is the presence of clinician champions who understand the AI system's capabilities and limitations, can integrate its outputs into clinical decision-making, and take professional responsibility for the workflow changes it requires. Ukraine's AI Strategy 2030 addresses workforce development broadly, but the European evidence suggests that medtech requires a sector-specific approach: clinical leadership programmes embedded in teaching hospital partnerships, designed around the specific AI tools being deployed, not generic digital skills training.

2 **DIAGNOSTIC INDICATORS**

- Ukrainian clinical AI companies have established multi-site clinical research partnerships with EU-recognised hospitals, as these partnerships generate the validation data CE marking requires.
- Hospital network infrastructure investment includes PACS interoperability standards, which is the gating condition for the most common EU imaging AI deployment pathway.
- Ukrainian medtech firms have initiated CE marking processes, since certification progress indicates that the regulatory credibility pathway is being actively pursued.
- Clinical outcome measurement is built into Ukrainian AI deployments from the outset, enabling the evidence base that both EU regulatory pathways and procurement decisions require.

2.4.4 Case studies

Case study 1

Oxipit — Autonomous AI for chest X-ray analysis[96]

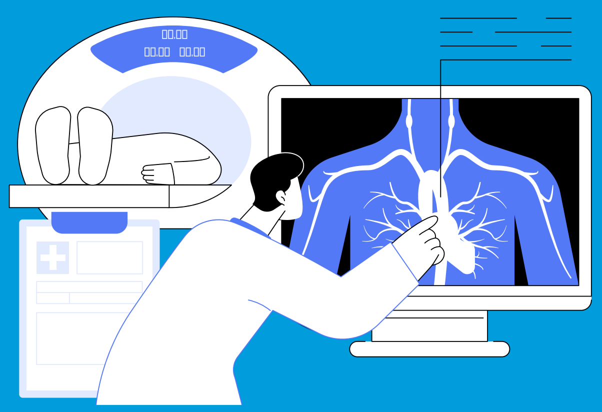
Lithuania (deployments in UK, Finland, Denmark) | Medical AI company

Implementation

A Lithuanian medical AI company developed ChestLink, a CE-marked (Class IIA/IIB) autonomous AI platform for chest X-ray analysis that automatically identifies and reports studies with no significant findings, allowing radiologists to focus on clinically relevant cases. The University Hospital Birmingham 2024 study, the UK's largest retrospective radiology AI trial, processed nearly 200,000 chest X-rays, automating 10.5% of total workload with 99.8% sensitivity and a 1% discordance rate after expert review. Finland's Oulu study (2020) demonstrated that 36.4% of normal chest X-rays were correctly ruled out. Independent Danish multicentre validation (2023) across four hospitals with 2,040 consecutive patients confirmed performance. The company's commercialisation strategy was built around clinical validation before market access: retrospective trials at major teaching hospitals preceded regulatory certification, and CE marking then enabled deployment across EU markets with a 450 million patient reach.

Adoption pattern demonstrated

This case study illustrates the evidence-first deployment logic specific to medtech: regulatory credibility, built through rigorous clinical validation, is the market access mechanism. An SME-scale company competed successfully with global incumbents by investing in the evidence base rather than in capital or scale. The shadow-mode deployment sequence, producing outputs reviewed but not acted upon before autonomous reporting began, was central to building clinical trust. The enabling factors are access to clinical research partnerships with EU-recognised teaching hospitals, willingness to absorb extended certification timelines, and a regulatory framework (MDR) that rewards evidence quality over firm size. This pathway connects to WINWIN's medtech priorities and to the broader pattern that CE marking unlocks EU-wide deployment from any Member State context.



Source: n.a.

Case study 2

Siemens Healthineers / MVZ — AI-assisted radiology at network scale[97]

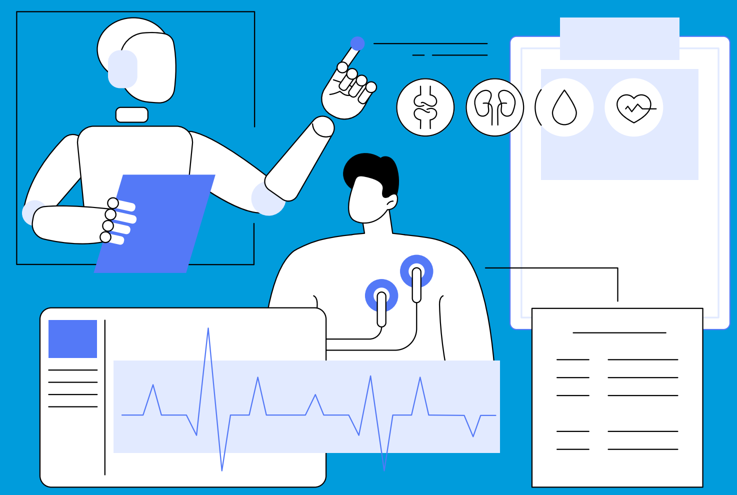
Germany | Large enterprise (technology partner) + regional radiology network

Implementation

A major North Rhine-Westphalia radiology network operating 13 locations, around 270,000 annual examinations including 30,000 chest X-rays across 14 imaging systems from multiple manufacturers, co-developed an AI chest X-ray companion with a global technology partner over 18 months, contributing over 100,000 annotated training images. Introduced into routine practice in 2020, the cloud-based system automatically analyses chest X-rays for five findings, returning results within approximately two minutes displayed directly within the radiologist's standard working environment alongside the original scan. The system functions across different imaging equipment brands without requiring hardware standardisation. Radiologists reported particular value during night and weekend shifts, when less experienced clinicians benefit from additional analytical support. The 18-month co-development period and 100,000-image training contribution illustrate the investment required to build clinical-grade AI at deployment scale.

Adoption pattern demonstrated

This case study illustrates the co-development pathway in medtech: a clinical network contributes annotated data and operational access in exchange for a validated AI system calibrated to its specific context. The enabling factors are PACS interoperability designed to work across 14 different imaging systems, workflow integration that returns results within the radiologist's existing environment rather than requiring a separate interface, and a clinical ownership structure in which practitioners vouched for safety and performance. The 18-month timeline and annotated dataset requirement indicate that this pathway requires institutional commitment and data infrastructure that is not universally available. The case connects to WINWIN's medtech priorities around AI-driven diagnostics and to the broader evidence that PACS interoperability is the gating condition for imaging AI deployment.



Source: n.a.

Case study 3

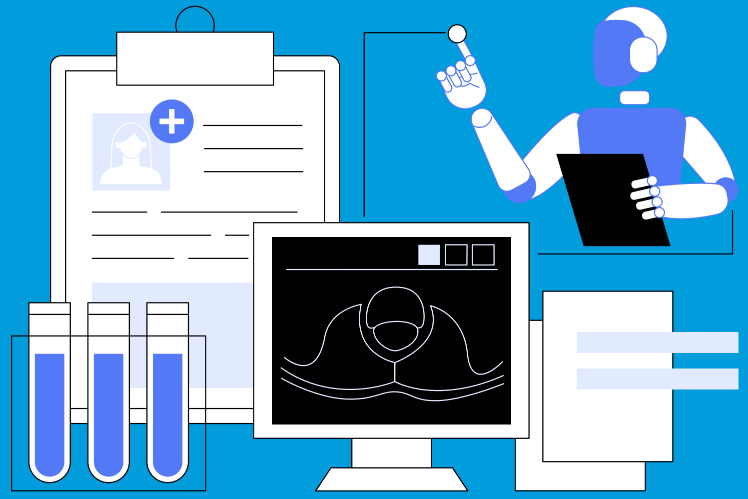
Ossur — AI across the medical device innovation pipeline[98]
Iceland | Large medical device OEM

Implementation

An Icelandic prosthetics manufacturer integrated AI across its innovation pipeline from R&D through to embedded device intelligence. Upstream, AI-powered patent image search reduced patent search time from days to hours while improving coverage, achieved by a lean IP team using a commercial tool. Automated requirements management systems shortened product development cycles and improved traceability across regulatory documentation requirements. At the device level, microprocessor control and real-time terrain-sensing algorithms are embedded in prosthetic products: the Proprio Foot adjusts ankle position automatically on slopes and stairs, and the i-Digits Quantum system translates muscle signals into independent finger control through pattern recognition. Clinical outcomes include a 70% reduction in reported fall rates over four-week user trials and measurable improvements in quality-of-life scores.

Adoption pattern demonstrated

This case study illustrates the distributed AI adoption model: commercially available tools are applied to internal processes, and proprietary embedded intelligence is developed for the product itself. Neither component required wholesale organisational transformation or large-scale AI infrastructure investment. The enabling factors are a measurement discipline that defines performance indicators at every layer of the AI stack, a regulatory environment that rewards evidence quality (the CE marking pathway applies to the embedded device AI as well as to software-only products), and a product design philosophy in which clinical outcome measurement is built into the development process. This pattern, repurposing available tools for high-value internal problems while developing proprietary capability selectively, is accessible at scales well below those of large pharmaceutical or imaging AI companies.



Source: n.a.

2.5 AUTOMOTIVE AND AUV

2.5.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The European ecosystem and EU and national initiatives

The European automotive industry accounts for over 7% of EU GDP and provides direct and indirect employment to 13.8 million Europeans.[99] The sector is navigating a structural twin transition towards electrification and digitisation, driven by competitive pressure from software-defined vehicle (SDV) ecosystems emerging from China and the US. The EU Sustainable and Smart Mobility Strategy targets at least 30 million zero-emission vehicles in operation by 2030. Supporting this, the EU Battery Regulation mandates a digital battery passport by 2027, requiring AI-driven data traceability across the full vehicle lifecycle.[100]

Research and innovation are primarily channelled through Horizon Europe's Cluster 5 (Climate, Energy and Mobility), specifically the Connected, Cooperative and Automated Mobility (CCAM) partnership, which co-ordinates public-private funding to move autonomous driving technologies from pilot phases to large-scale cross-border demonstrations.[101] At national level, France's France 2030 programme has committed significant funding within its EUR 54 billion budget to the automotive sector, targeting domestic production of two million electric and hybrid vehicles by 2030.[102] Germany complements this with data ecosystem initiatives including Manufacturing-X and the Catena-X automotive data network, a federally supported project creating an interoperable data space for secure supply chain data sharing among manufacturers and suppliers: a prerequisite for AI deployment in logistics and carbon footprint tracking.[103]

More than half of EU Member States (17 of 27) have launched initiatives to foster AI adoption in mobility, covering automated vehicles, urban mobility transformation, and digital infrastructure. Eleven Member States have reported dedicated autonomous vehicle initiatives, encompassing testing environments, regulatory adaptations, and AI safety and verification programmes (OECD, 2025). Austria's Automated Transport Innovation Labs, Belgium's Mobilidata 2 Proloog for remote driving trials, and Sweden's Drive Sweden national platform involving over 200 stakeholders represent the diversity of these approaches.[104]

Ukraine's automotive strategy and EU alignment

Before 2022, Ukraine was integrated into the European automotive supply chain as a significant Tier-2 manufacturing hub. Analysis indicates that Ukraine supplied approximately 7% of wiring harnesses imported into the EU, with around 60,000 employees across 38 plants for major global suppliers.[105] This provides a brownfield industrial base, albeit one concentrated in manual assembly rather than high-value design or systems integration.

The WINWIN Global Innovation Strategy 2030 signals an intended shift from this assembly-based model. The strategy identifies unmanned technologies and autonomous systems (AUV) as a standalone priority innovation sector, explicitly targeting a position as an innovation hub for autonomous robotics and logistics solutions.[106] This is reinforced by the greentech focus on a sustainable battery value chain leveraging Ukraine's lithium reserves, and the cross-cutting application of AI in industrial contexts. Ukraine's strategic priorities map to the EU's SDV roadmap at the software and algorithmic layers, where its IT sector has established comparative advantages, rather than at the regulatory and capital-intensive infrastructure layers where the EU focuses its CCAM partnership investment.

AI applications in the sector

The principal AI applications gaining operational traction in European automotive:

- **Advanced driver assistance systems (ADAS):** neural networks processing inputs from LiDAR, radar, and cameras for real-time navigation and obstacle avoidance. Classified as high-risk AI under the EU AI Act, requiring conformity assessment before deployment.
- **Digital twins for factory planning:** virtual facility models enabling simulation of production layouts, logistics flows, and equipment configurations before physical construction. Bridges multiple industrial software environments into unified collaborative platforms.
- **Open innovation AI ecosystems:** structured programmes through which OEMs scout, pilot, and deploy AI from external technology partners across quality control, predictive maintenance, and workforce training.
- **Circular economy operations:** AI-driven coordination of vehicle refurbishment, battery diagnosis, material recovery, and process monitoring across heterogeneous activity centres.
- **Predictive maintenance:** real-time sensor analytics on production equipment for condition-based maintenance and reliability management at network scale.

2.5.2 Adoption pathways analysis

The three case studies examined in this sector represent three distinct models of AI adoption in European automotive manufacturing: circular economy repurposing of a legacy site (France), collaborative ecosystem-based integration of multiple AI applications across a global production network (multinational), and greenfield co-design of a comprehensive digital twin platform for factory planning (Germany). Together they reflect an industry in which AI adoption has reached production scale at large OEMs, though the OECD's assessment of mobility AI notes that deployment remains concentrated among incumbents with the data infrastructure, capital, and integration capacity to implement at scale.[107]

Sectoral deployment patterns

A consistent pattern across all three cases is the use of AI to manage industrial complexity that has grown beyond the capacity of conventional planning or control systems. A German automotive OEM managing 31 production facilities, 2.5 million vehicles annually, and 2 100 possible configurations per model cannot optimise factory layouts through manual CAD workflows: the digital twin platform enables simulation of millions of variables before any physical commitment. A multinational automotive group with operations across multiple continents cannot maintain consistent predictive maintenance coverage through centralised monitoring teams: AI-powered sensor analysis operating in real time at individual facility level makes system-wide reliability management feasible. A French OEM repurposing a 237 hectare legacy site for circular economy operations cannot co-ordinate vehicle refurbishment, battery diagnosis, dismantling, and innovation incubation without AI-driven process visibility across all activity centres simultaneously.

In all three cases, the AI capability was assembled through ecosystem partnerships rather than developed entirely in-house. The German OEM partnered with a major technology platform provider (NVIDIA) for the foundational digital twin infrastructure, and developed proprietary extensions on top of it. The multinational automotive group's Factory Booster programme structured this as a deliberate innovation scouting model, engaging over 80 technology partners annually to identify and integrate AI applications across quality control, predictive maintenance, and workforce training domains. The circular economy facility hosts over 30 startup incubators on-site, embedding external innovation capacity within its operational structure. This reliance on external technology ecosystems reflects a structural feature of AI adoption in automotive manufacturing: the specialist capabilities required across AI-driven electronic design automation (EDA) tools, computer vision, sensor analytics, and digital twin platforms are not concentrated within any single OEM.

The pathway from concept to operational deployment differs across cases. The digital twin platform was implemented as a production system from inception, with no separate pilot phase: factory planning tools are either used or not. The predictive maintenance implementations followed a structured pilot-to-scale logic, with initial deployments at specific facilities generating the performance data and business case that justified network-wide rollout. The circular economy facility underwent a multi-year conversion, with AI systems introduced as part of the broader operational repurposing rather than as standalone projects. In all cases, measurable operational outcomes were defined and tracked: the 30% planning efficiency improvement attributed to the digital twin, the USD 2 million saved in the first 50 days of predictive maintenance at one facility, and the reduction of vehicle refurbishment turnaround from 21 days to 6-8 days.[108, 109, 110]

SME access to AI in automotive is structurally limited by the sector's capital intensity and the data infrastructure requirements of the most valuable applications. Digital twin platforms and AI-driven production systems presuppose existing investments in connectivity, sensor networks, and enterprise data systems that smaller suppliers typically lack. The OECD identifies data-sharing frameworks, specifically programmes like Catena-X for secure supplier data exchange, as important enabling conditions for broadening AI adoption beyond OEMs to the supplier ecosystem (OECD, 2025). Without standardised, interoperable data exchange, AI applications that depend on supply chain data remain accessible primarily to OEMs with the leverage to mandate data sharing from their suppliers.[111]

Policy context and enabling conditions

1 **EU-LEVEL AND NATIONAL AI STRATEGIES: DATA, COMPUTE, AND SKILLS**

The regulatory environment is a defining enabling condition for AI in automotive. The EU AI Act classifies autonomous driving systems as high-risk AI under Annex III, requiring conformity assessment, technical documentation, and registration before deployment.[112] The UNECE WP.29 framework establishes international approval requirements for AI-equipped vehicles, including cybersecurity management system requirements.

These frameworks create a compliance pathway that, while demanding, also functions as a market access standard that harmonises requirements across EU Member States and reduces the regulatory fragmentation that would otherwise impede cross-border deployment. The OECD assessment notes that 49 AI-driven mobility initiatives have been reported across EU Member States, but that data sharing for mobility remains at an early stage: the absence of standardised vehicle data ecosystems is identified as a primary constraint on scaling AI applications that depend on fleet-level data.[113]

The Catena-X programme and the Manufacturing-X initiative address data sovereignty at the national level, creating infrastructure that enables AI deployment across value chains through secure, standardised data exchange.[114] The EU Battery Regulation's Digital Battery Passport requirement will extend data traceability requirements to the full automotive value chain by 2027, creating a regulatory driver for AI-based data management systems across OEMs and suppliers.[115]

Skills at the intersection of automotive engineering and AI remain a recognised bottleneck. The OECD assessment of mobility AI finds that AI talent concentration in transport and automotive has grown between 2018 and 2024 across EU Member States, but that the supply of professionals combining domain expertise with AI and data science competencies remains limited.[116] The cases addressed this through external partnership rather than internal workforce development as the primary mechanism.

2 **R&D AND SCALING-UP INITIATIVES**

The CCAM partnership under Horizon Europe provides the primary EU R&D funding mechanism for autonomous and connected mobility, with a focus on safety validation and cross-border testing.[117] Austria's ALP.Lab, Belgium's Mobilidata 2 Proloog, Slovenia's SRIP ACS+ partnership, and Sweden's Drive Sweden platform represent the national testing infrastructure through which AV technologies move from concept to real-world validation. These ecosystems directly reduce the cost and risk of pre-deployment validation for companies developing AI-driven mobility solutions.

The Apply AI Strategy's mobility flagship designates connected and automated mobility as a priority domain, with planned actions including support for AI applications in traffic management, logistics optimisation, and autonomous transport.[118] The OECD recommends establishing regulatory sandboxes and cross-border testbeds to allow cities, regions, and logistics operators to experiment with AI solutions under controlled conditions.[119] The EU's AI Continent Action Plan's AI Factories initiative provides compute infrastructure relevant to the training requirements of autonomous driving perception systems.

VC investment in EU automotive AI reflects the sector's capital intensity and the long commercialisation timelines for AV technologies. EU automotive AI startups raised significant funding through 2023-2024, concentrated in perception systems, software-defined vehicle platforms, and fleet management AI. The OECD notes that while AV adoption is expected to grow across all major economies, Europe is projected to progress at a slower pace than China, which is driving ADAS adoption at scale through consumer acceptance and OEM investment (OECD, 2026).

High-level assessment

AI adoption in the European automotive sector is characterised by high investment thresholds, ecosystem dependency, and concentration among large OEMs. None of the three cases was initiated by an SME; all involved large organisations with existing digital infrastructure and the leverage to engage specialist technology partners. The most significant enabling factors were not algorithmic novelty but system integration capability: bridging multiple industrial software environments (digital twin), structuring open innovation partnerships at scale (ecosystem), and redesigning an entire industrial facility around circular economy and AI principles (circular economy conversion).

The most durable deployments in this sector are those tied to strategic business model changes rather than point-solution efficiency gains. The digital twin platform is a prerequisite for managing mass customisation at scale, not a cost-saving tool. The circular economy facility is a new operational model enabled by AI, not an AI pilot attached to an existing operation. The predictive maintenance ecosystem is a systematic approach to reliability at network level, not a standalone project. In each instance, AI is embedded in a larger industrial logic that defines its value and sustains its use beyond the initial deployment phase.

2.5.3 Towards EU best practices

Before 2022, Ukraine supplied approximately 7% of EU wiring harnesses, employing around 60,000 people in manual assembly across 38 plants.[120] This integration has been substantially disrupted. WINWIN targets the software and algorithmic layers of autonomous systems, where Ukraine's IT sector has comparative advantages, and positions AUV as a standalone priority innovation sector rather than treating it as an extension of legacy manufacturing.[121]

1 **ADOPTION DEPENDENCIES**

Ecosystem-based AI adoption requires an anchor organisation with sufficient network reach to attract and integrate a large number of technology partners. Without an OEM or equivalent platform organisation at scale, there is no structure for a startup ecosystem to connect to. This is a dependency that policy instruments cannot substitute for: the anchor organisation's existence and its willingness to open its network are the preconditions.

Ukraine's automotive sector, however, as noted above, consists primarily of SMEs and Tier-2 component suppliers rather than large-scale OEMs. This means the European adoption models documented in the case studies, which centre on OEM-driven digital twin platforms and large-scale factory reorganisation, are not directly transferable. The relevant European pathways for Ukrainian firms are those that enable supply chain participants to adopt AI without OEM-scale resources: vendor-mediated platforms that abstract complexity from end users (as in the textile quality inspection case), EDIH-supported pilot projects that de-risk experimentation for smaller firms (as in the semiconductor case), and supply chain data standards like Catena-X that enable Tier-2 suppliers to participate in AI-enabled supply chains by meeting interoperability requirements rather than building proprietary systems.

Digital twin adoption for factory planning depends on prior factory digitisation. The BMW case succeeded because existing industrial software infrastructure created a context in which adding a unified digital twin layer was tractable. Where factory management relies on manual processes or disconnected legacy systems, a digital twin platform solves a problem that does not exist yet in a form it can address.

For AUV specifically, the European evidence consistently shows that access to regulatory testing environments is the gating condition for commercial readiness. Autonomous systems require validated performance in controlled conditions before public deployment. The 11 EU Member States with dedicated AV testing environments all established these as preconditions for commercial deployment, not as consequences of it . Without equivalent sandbox infrastructure, AUV development can advance technically but cannot reach certified market readiness. Ukraine's AI Strategy 2030 Operational Plan commits to establishing a regulatory sandbox for testing AI solutions by June 2028, which could serve this function if designed to accommodate autonomous systems testing.

2 **DIAGNOSTIC INDICATORS**

- Ukraine's AUV and defence technology companies are establishing formalised EU partnership frameworks that could serve as the basis for ecosystem-based adoption, including the three strategic international agreements WINWIN targets.
- Regulatory sandbox provisions for autonomous systems are being developed in alignment with EU safety standards and UNECE WP.29 requirements.
- Reconstruction investment in industrial sites includes digital-first design mandates, creating the foundation for digital twin adoption in new or converted facilities.
- UNECE WP.29 regulatory alignment is progressing, which would indicate that the certification pathway for AI-equipped vehicles is being opened.

2.5.4 Case studies

Case study 1

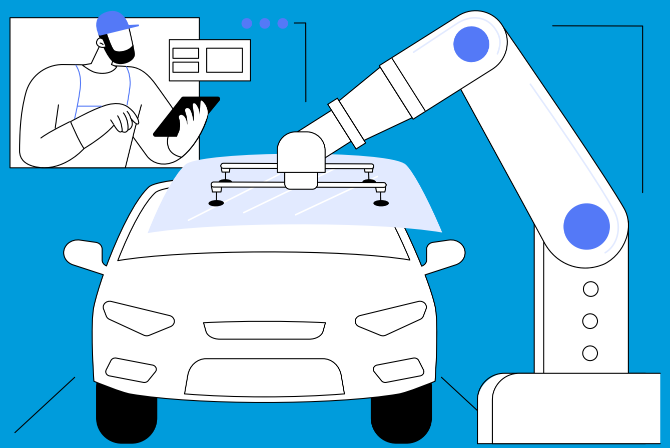
Renault Refactory Flins — Circular Economy Automotive Conversion[124]
France | Large automotive OEM

Implementation

A major French automotive manufacturer converted a legacy 237 hectare production site, originally opened in 1952, into Europe's first facility entirely dedicated to circular economy mobility operations. The facility is structured around four activity centres covering vehicle refurbishment (reducing turnaround from 21 days to 6-8 days for up to 45,000 vehicles annually), battery diagnosis and second-life applications, end-of-life vehicle dismantling and material recovery, and an innovation incubator hosting over 30 startups. An industrial control tower monitors 650+ stamping presses across the group's global factory network in real time, using data analytics to detect potential breakdowns and anticipate maintenance. Over 200 robots were refurbished on site in 2024 before returning to production lines. The model is being replicated at other group sites.

Adoption pattern demonstrated

This case study illustrates the brownfield repurposing pathway, in which AI and automation are used to transform an existing industrial site rather than replace it. The enabling conditions include strategic commitment to circular economy business model transformation, existing manufacturing expertise that can be redirected, and AI-based process control tools that make co-ordination of heterogeneous activities (refurbishment, recycling, battery diagnosis, incubation) operationally feasible. This pathway is relevant in contexts where greenfield investment is constrained but existing industrial infrastructure can be repurposed. It connects to WINWIN's cross-cutting AI and greentech priorities around sustainable industrial transformation.



Source: https://www.renaultgroup.com/en/group/refactory

Case study 2

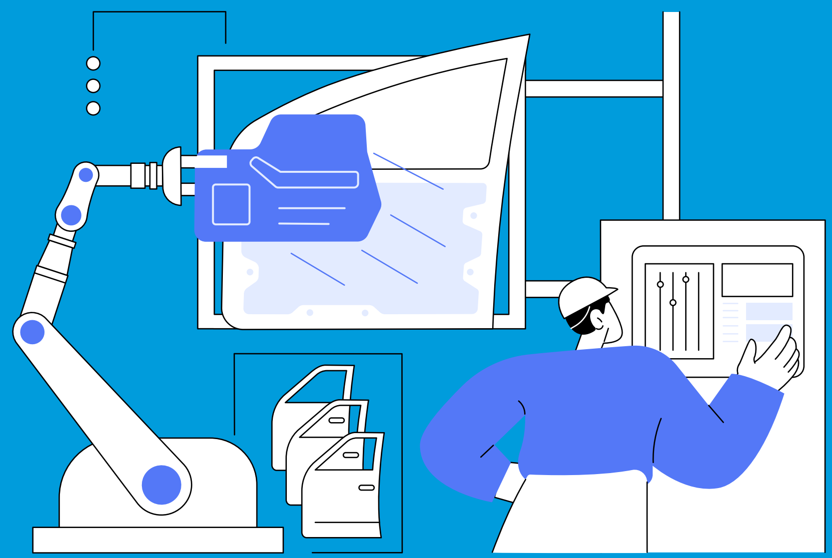
Stellantis Factory Booster — Ecosystem-Based AI Integration[125]
Global (Italy innovation centre) | Large automotive OEM

Implementation

A major multinational automotive group has structured AI adoption in its manufacturing network around a systematic open innovation programme, now in its tenth annual edition, engaging over 80 technology partners annually to identify and deploy 100+ innovations across quality, efficiency, and sustainability domains. Documented implementations include AI-powered predictive maintenance in paint shops using real-time sensor data from pumps, fan units, and oven exhaust systems (with an estimated USD 2 million saved in the first 50 days at one facility); machine vision systems performing over 50,000 daily fastener-installation inspections at assembly plants with automated repair alerts; VR forklift training using AI-generated hazard scenarios; and an SDV architecture enabling over-the-air product updates.

Adoption pattern demonstrated

This case study illustrates the open innovation ecosystem pathway, in which a large OEM accelerates AI adoption by systematically scouting and integrating external technology capabilities rather than relying on internal R&D. The enabling conditions are the scale and global network of the OEM, structured partnership management processes, and a deployment philosophy that prioritises measurable operational ROI from focused applications before seeking network-wide rollout. The skills and integration capability required to manage 80+ technology partnerships simultaneously is itself a core organisational competence that differentiates this approach.



Source: https://www.media.stellantis.com/em-en/corporate-communications/press/stellantis-2025-factory-booster-day-showcases-100-technology-driven-manufacturing-innovations

STELLANTIS

Case study 3

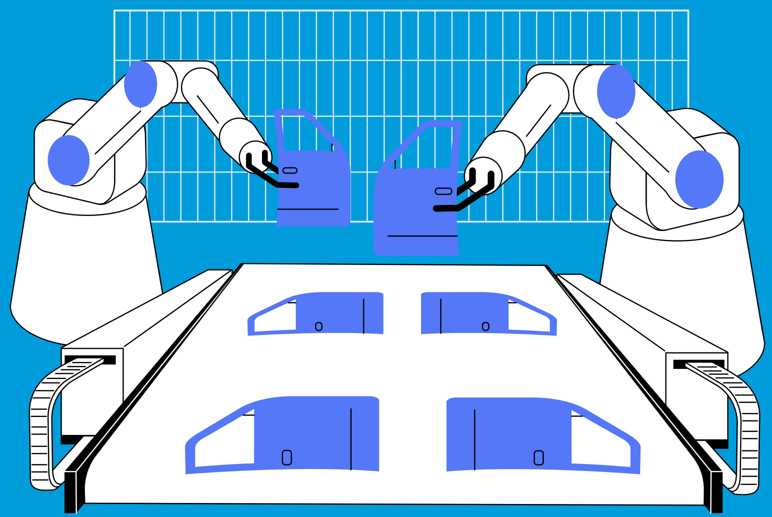
BMW Group / NVIDIA Omniverse — Factory Digital Twin Platform[126]
Germany (global deployment) | Large automotive OEM + technology platform provider

Implementation

A major German automotive manufacturer implemented a comprehensive digital twin platform for factory planning and optimisation across 31 production facilities globally. The platform enables factory planners to design, simulate, and optimise facilities in virtual environments before any physical construction, bridging multiple industrial software tools (including process simulation, CAD, and logistics planning systems) into a unified collaborative environment where teams across geographies work simultaneously on shared factory models. The manufacturer claims 30% more efficient planning processes. A custom internal application was developed on the platform's SDK, with specialised extensions for collision detection, factory filtering, and logistics planning tailored to the complexity of producing 2.5 million vehicles annually across 40+ models with 2 100 possible configurations. Digital twin capabilities span the full facility lifecycle including building structure, robotics simulation, product-process integration, and human ergonomics modelling using motion capture data.

Adoption pattern demonstrated

This case study illustrates the greenfield co-design pathway for digital twin adoption: the platform became operational infrastructure for planning rather than a separate project with a defined pilot phase. The enabling conditions are existing digital infrastructure maturity, the strategic necessity of managing mass customisation complexity at global scale, and access to a platform provider capable of supporting the integration of multiple industrial software environments. The 30% planning efficiency gain is credible precisely because the complexity being managed, simultaneous design changes across 30 factories producing 2 100-configuration vehicles, is genuinely unmanageable through conventional workflows.



Source: https://www.nvidia.com/en-us/customer-stories/bmw-group-develop

2.6 SEMICONDUCTORS

2.6.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The European ecosystem and EU and national initiatives

The European semiconductor industry, currently holding about 9% of global market share, is a critical leader in specialised equipment, materials, and automotive/industrial chips.[127] It is currently undergoing a strategic transformation through the EUR 43 billion European Chips Act, aimed at doubling its share to 20% by 2030.[128] A major driver is AI demand, as semiconductors are essential for frontier AI training, yet Europe significantly lags behind in the supply chain of advanced chips, with the exception being Netherlands-based ASML, leading in advanced chipmaking equipment.

The geographic concentration in the chips market creates vulnerabilities to economic shocks and geopolitical tensions, prompting major economies to bolster domestic chip manufacturing capacity through strategic investments. Beyond the EU Chips Act, over half of EU Member States support semiconductor R&D or manufacturing through national strategies or participation in the IPCEI (Important Project of Common European Interest) on Microelectronics and Communication Technologies. Examples for the former include Czechia's EUR 45 million national strategy targeting threefold sector growth by 2029 focused on research, exports and talent, and Poland's strategy supporting investment across the entire semiconductor value chain. Examples for participation in the IPCEI ME/CT include the Slovak Republic, supporting four Slovak companies involved in the IPCEI with EUR 200 million; and Slovenia, supporting involved companies through both annual funding (EUR 1.2 million) and project-based co-financing (EUR 1.5 million), with its initiative Čip is covering not only company support but talent support and infrastructure.[129]

Ukraine's semiconductor strategy and EU alignment

Historically, Ukraine held significant capacity in microelectronics, producing 40% of the USSR's total volume in the early 1990s. It has lost market share since and has a small domestic market, but it aims to leverage its legacy experience and its large pool of specialists working in global chip design companies to re-establish its relevance in the European ecosystem.[130] Key priorities include the development of manufacturing capacities and its integration into the global supply chain. The Innovation strategy emphasises partnership and integration with European initiatives, with one of its strategic goals being signing memorandums with the EU and companies for joint projects, investment programmes, and involvement in the European Chips Act implementation. It prioritises tasks related to boosting manufacturing capacities but also includes R&D initiatives.

Ukraine's semiconductor strategy aligns with the EU Chips Act by pursuing many of the same core goals: expanding manufacturing capacity, reintegrating into global and European supply chains, and strengthening R&D and talent to support a resilient, innovation-driven chip ecosystem. As with EU Member States' use of national strategies and IPCEI participation, Ukraine's plan explicitly seeks legal and financial frameworks, innovation clusters, and memorandums with the EU and companies, so it can participate in Chips Act projects and co-investment mechanisms rather than developing a parallel, isolated ecosystem.

AI applications in the sector

The semiconductor sector has a distinctive double relationship with AI: it produces the chips that AI systems run on, and it applies AI internally to improve the efficiency of chip design and manufacturing. The two surveyed cases address both sides of this relationship at the operational stage where European evidence is most developed.

- **AI-driven electronic design automation (EDA):** machine learning applied to optimise power, performance, and area (PPA) metrics in chip design, automating iterative parameter exploration across search spaces too large for manual methods. Reinforcement learning algorithms explore design configurations that experienced engineers would not attempt through conventional workflows.[131]
- **Predictive maintenance in fabrication:** acoustic and optical sensor data from fab equipment processed through machine learning to identify anomalous patterns indicating wear or impending failure, shifting maintenance from scheduled to condition-based approaches.[132]
- **Quality control and yield optimisation:** AI-powered computer vision systems inspecting wafers to identify and classify defects, operating at production speeds with accuracy levels that exceed manual inspection.[133]
- **Process monitoring and equipment control**: machine learning models applied to equipment process data for real-time anomaly detection and parameter optimisation across complex multi-step fabrication processes.

2.6.2 Adoption pathways analysis

The surveyed case studies illustrate two principal domains where AI is gaining traction in the European semiconductor sector: chip design optimisation and predictive maintenance in fabrication. In design, AI-driven EDA tools are enabling engineers to explore parameter search spaces that would be infeasible using traditional methods, delivering measurable productivity gains. In manufacturing, machine learning applied to acoustic and optical sensor data is shifting maintenance from scheduled to condition-based approaches, reducing unplanned downtime and production losses. Both applications rely on cloud computing infrastructure for scalable processing and on multi-partner collaboration to assemble the necessary expertise. Europe's uptake in these areas, though concentrated among large firms with established fab or design operations, points to adoption patterns that may be relevant beyond the immediate cases studied.

Sectoral deployment patterns

The two case studies address distinct stages of the semiconductor value chain, which share several features that point to broader deployment patterns in the sector. The most prominent is the reliance on third-party AI solutions and ecosystem partnerships rather than in-house algorithm development. In chip design, a European semiconductor company adopted a commercial AI-driven design space optimisation tool developed by an external EDA vendor, deploying it on a major cloud platform to explore 180 permutations across 3,000 runs and achieve a 3x productivity improvement . In fabrication, a large European fab partnered with four external organisations, spanning digital transformation, electronic manufacturing services, microelectronics networking, and optical solutions, to develop and implement an acoustic monitoring system for its overhead wafer transport vehicles.[135]

Cloud infrastructure was a prerequisite in both instances. For design optimisation, the cloud-based deployment saved compute resources and set-up time, enabling scalable processing and remote collaboration across distributed teams through a common data structure supporting easy database export and import. For fab predictive maintenance, AWS was used to build a software environment integrating sensor data into a dashboard, processing the large volumes of acoustic and optical information generated by over 900 automated transport vehicles operating across a 23-kilometre system. In both cases, the cloud served as the enabling infrastructure for large-scale deployment.[136]

The pathway from proof of concept to operational deployment in the manufacturing case is instructive. The fab used a Testbed IoT lab within an EDIH to advance the project beyond its initial proof-of-concept stage. The EDIH facility provided data collection kits, IoT infrastructure, optical sensor integration, and the environment for enhancing the machine learning algorithms with additional data inputs. This intermediate step, moving from a narrowly scoped proof of concept through a dedicated testing facility before full operational deployment, appears to have been central to the project's progression. The design optimisation case followed a different path, with the AI tool integrated directly into the production workflow through the vendor-mediated model.

Both implementations started with focused, bounded use cases rather than attempting broad AI transformation. The design case targeted a specific Arm core project with well-defined parameters. The predictive maintenance case targeted a specific operational bottleneck: transport vehicle reliability in the fab. One project lead reflected that the project succeeded precisely because it was a focused, manageable AI use case with demonstrable return on investment, which in turn built organisational support for broader AI adoption. The measurable outcomes, including a 2.15x increase in mean time between vehicle faults, an approximately 62% reduction in transport-related production losses, and around 8,000 hours saved in corrective maintenance, provided the internal business case for continued and expanded investment. This incremental approach, delivering verifiable results on a contained problem before seeking wider application, was a factor in moving beyond pilot status.

The skills requirements are different for the two application domains. AI-assisted chip design demands a combination of semiconductor design expertise and familiarity with AI-driven EDA tools, a skillset that exists primarily within established design houses. Predictive maintenance in manufacturing requires sensor and IoT engineering, data science for acoustic and optical pattern recognition, and domain knowledge of fab operations. In the latter case, these competencies were assembled through the multi-partner consortium rather than residing within a single organisation, suggesting that the skills barrier can be addressed through collaboration structures even where individual firms lack the full range of required expertise.

Policy context and enabling conditions

1 **DATA, COMPUTE AND SKILLS**

EU Member States increasingly address computing infrastructure through national AI strategies, though access remains uneven, and SME access to AI is predominantly enabled through cloud platforms rather than internal development.[137] For semiconductors specifically, the capital intensity of the sector means that AI adoption presupposes significant existing digital infrastructure, making compute access less of a barrier for large fabs and design houses than it is for smaller firms in less capital-intensive sectors.

Skills gaps are a persistent constraint. The semiconductor sector requires specialised expertise at the intersection of chip engineering and AI/data science. While most Member States have introduced AI-related education and training programmes, the supply of specialists with combined domain and AI competencies remains limited. The surveyed cases addressed this through partnerships with specialised vendors and multi-partner consortia rather than internal workforce development alone. WINWIN's target of training 500+ new specialists and retraining engineers in the sector acknowledges this gap directly.[138]

2 **R&D AND SCALING-UP INITIATIVES**

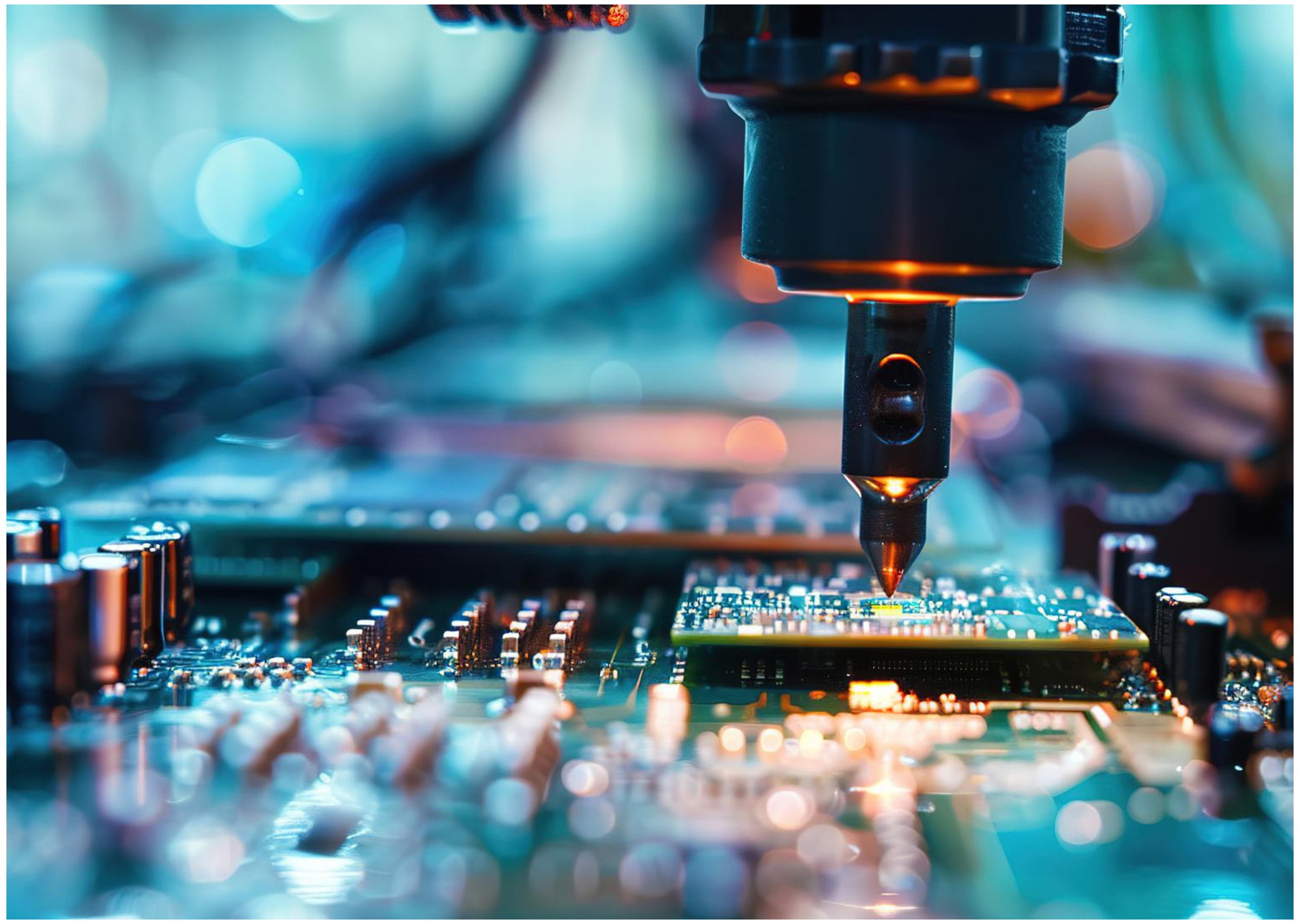
The EU's R&D and scaling infrastructure has played a direct role in the semiconductor AI applications surveyed. The GlobalFoundries predictive maintenance project used the EDIH Saxony Testbed IoT lab to advance from proof of concept to operational deployment. EDIHs, established under the Digital Europe Programme, provide testing, experimentation, and skills development services to firms, with a particular mandate to support SME access to digital technologies. In the semiconductor context, the EDIH model functions as an intermediary that de-risks innovation: a fab with an identified operational problem can use the testbed to develop and refine a solution without committing to full-scale deployment before validation. The Apply AI Strategy identifies EDIHs and TEFs as cross-cutting instruments for accelerating AI adoption across sectors, and the Chips Act further reinforces this by supporting pilot lines and design infrastructure that connect R&D to manufacturing readiness.[139, 140]

The IPCEI on Microelectronics and Communication Technologies provides another scaling pathway. STMicroelectronics' cloud-based design optimisation deployment aligns with IPCEI priorities for scalable R&D ecosystems and talent integration, illustrating how the combination of EU-level frameworks and commercial cloud infrastructure can support design-stage AI adoption.[141] At the national level, programmes such as Germany's microelectronics research investments and Saxony's positioning as a semiconductor hub, where the Smart Systems Hub innovation network operates, create the regional ecosystem conditions within which these projects emerged. Horizon Europe and the Digital Europe Programme provide funding mechanisms for collaborative R&D, though the semiconductor sector's high capital intensity means that public R&D support typically complements, rather than substitutes for, substantial private investment.

High-level assessment

AI adoption in the European semiconductor sector is characterised by high investment thresholds, significant technical specialisation, and concentration among large firms with existing fabrication or design infrastructure and cloud access at scale. The design optimisation case required a commercial AI-driven EDA tool, cloud compute, and deep semiconductor design expertise. The predictive maintenance case required sensor infrastructure, a multi-partner consortium, and an EDIH testbed facility.

What the case studies also demonstrate is that successful AI uptake did not depend on developing novel AI capabilities. The design optimisation case used an existing commercial tool; the productive step was integrating it effectively into the design workflow and providing the cloud compute to make it tractable at scale. The predictive maintenance case combined off-the-shelf sensor technology and machine learning techniques within a focused application. The value came from disciplined application of available tools to well-defined problems, supported by the right partnerships and infrastructure. The role of ecosystem infrastructure, including EDIHs, cloud platforms, and collaborative partnerships, was at least as important as the AI technology itself. Even in a capital-intensive sector, accessible testing facilities and partnership structures can be as decisive as the scale of investment.



2.6.3 Towards EU best practices

Ukraine retains a pool of chip design specialists with experience in international firms, representing a genuine foundation for the vendor-mediated design pathway that the STMicro case demonstrates. WINWIN's explicit targeting of EU Chips Act participation and the development of a national centre for microelectronics aligns with the institutional pathway that less-developed EU Member States have used to enter the European ecosystem.[142]

1 ADOPTION DEPENDENCIES

The two European cases show dependency structures that differ by application domain. EDA tool adoption in chip design depends on established design expertise existing before AI augmentation is applied: the reinforcement learning algorithms in the design case amplified a capability that was already present in the engineering team, they did not create it. Ukraine's pool of chip design specialists represents a genuine foundation for this pathway, provided cloud access and commercial EDA tool availability are in place.

EDIH-based adoption for fabrication AI depends on EDIH network access being established. The GlobalFoundries case could not have proceeded without the EDIH Saxony testbed providing the IoT lab, sensor integration, and rapid prototyping environment needed to move past proof of concept. The EDIH's function here was not advisory but infrastructural: it provided the physical and technical environment in which the solution was developed. Where equivalent infrastructure does not exist and EDIH network membership is not in place, this pathway is blocked at the transition from concept to working prototype.

A third dependency concerns ecosystem density. The fabrication case assembled four external partners across digital transformation, electronics manufacturing services, microelectronics networking, and optical solutions. This multi-partner assembly was feasible because an innovation network (Smart Systems Hub) and a regional semiconductor cluster (Saxony) created the institutional density in which these partnerships could form. Replicating this model requires building the ecosystem, not just the individual organisations within it.

2 DIAGNOSTIC INDICATORS

- EDIH network access for Ukrainian firms is being formalised, as this is the gating condition for consortium-based fab AI adoption.
- Chips Act engagement that WINWIN targets is producing co-investment projects, not only memoranda, indicating that the partnership frameworks needed for scaling are being activated.
- The National Centre for Microelectronics that WINWIN envisions includes testing and validation functions equivalent to the EDIH testbed model, rather than being designed primarily as a research facility.
- Innovation cluster development is creating the ecosystem density that multi-partner AI consortia require in fabrication applications.

2.6.4 Case studies

Case study 1

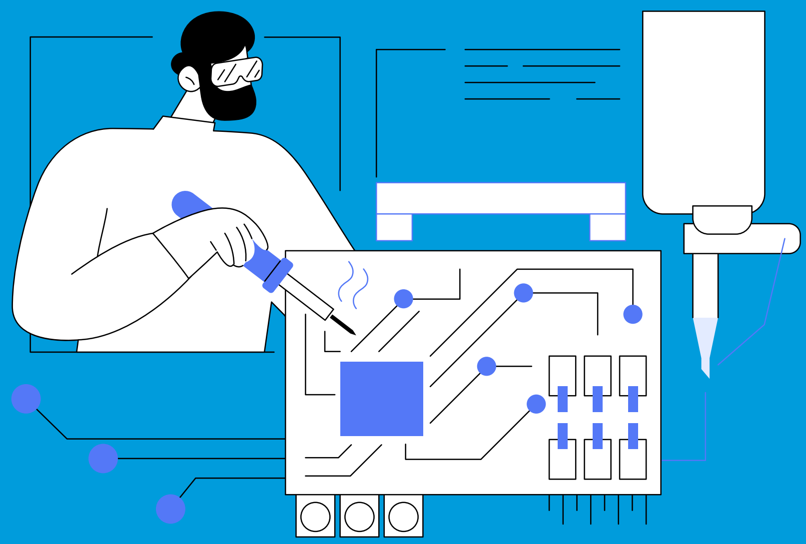
STMicroelectronics - AI for chip design optimisation[143]

Implementation

STMicroelectronics used the Synopsys DSO.ai™ (Design Space Optimization) tool to optimise PPA metrics for the Arm Cortex-A510 chip design. The project involved a large number of design parameters related to memory, floor planning, and group paths, creating a search space that was infeasible to explore using traditional methods. DSO.ai's reinforcement learning algorithms iteratively evaluated parameter configurations, covering the entire search space of 180 permutations within 3,000 runs to reach the targeted frequency and optimal power compromise while maintaining the desired floorplan dimensions. The solution was deployed on Microsoft Azure Cloud, using a common data structure for database export/import and remote task scheduling. Overall productivity increased by 3x.

Adoption pattern demonstrated

This case study illustrates vendor-mediated AI adoption in a high-complexity design environment: a semiconductor firm integrated a third-party AI tool into its existing EDA workflow rather than building proprietary AI capabilities. Cloud infrastructure was the critical enabler, providing scalable compute without requiring on-premises investment. The implementation demonstrates how established design talent, combined with commercial AI tools and cloud access, can achieve substantial productivity gains on well-defined problems. The pattern is relevant to Ukraine's WINWIN semiconductor priorities, particularly the emphasis on leveraging existing design specialists and integrating into European R&D ecosystems through Chips Act partnerships.



Source: n.a.

GLOBALFOUNDRIES

Case study 2

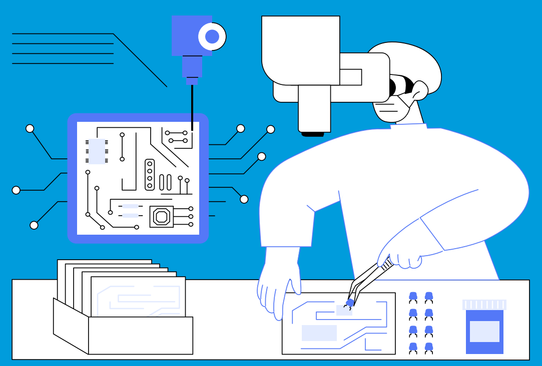
GlobalFoundries - AI for predictive maintenance in semiconductor fabrication[144]

Implementation

GlobalFoundries' Dresden fab, producing around 880,000 wafers annually across 22 nm to 55 nm technologies, implemented AI-enabled monitoring for its overhead transport system of over 900 automated vehicles spanning a 23-kilometre network. An ultrasonic sensor detects approaching transport carts and activates a machine learning-based acoustic analyser, which records sounds transmitted via Wi-Fi to an evaluation centre. The machine learning algorithm filters for anomalous sounds that indicate wear or malfunction. The project used the EDIH Saxony Testbed IoT lab for rapid prototyping, integrating optical sensors and building an AWS-based software environment. Partners included Telekom MMS, DELTEC electronics, Smart Systems Hub, and ZEISS Digital Innovation. Results: mean time between vehicle faults increased by a factor of 2.15; transport-related production losses decreased by approximately 62%; corrective maintenance costs were reduced by around 8,000 hours. The project won the Digital Use Case category at the Lean Automotive Production Award 2024.

Adoption pattern demonstrated

This case study demonstrates consortium-based AI adoption in a manufacturing setting, where no single partner held all the required competencies. The EDIH testbed played a specific role in moving the project from proof of concept to operational deployment, illustrating the function of EU innovation infrastructure in de-risking and validating AI solutions before full-scale implementation. The focused scope of the use case, targeting a specific operational bottleneck with clear metrics, provided the internal business case for broader AI adoption. The pattern connects to the EU Chips Act's emphasis on strengthening manufacturing competitiveness through AI-driven innovation, and to Ukraine's WINWIN goal of establishing cooperation with EU manufacturers through joint projects and involvement in Chips Act implementation.



Sources:
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2.7 ENERGY

2.7.1 Overview: AI applications in the sector, EU and national initiatives, and Ukraine's innovation strategy

The European ecosystem and EU and national initiatives

The European energy sector is undergoing a structural transformation from centralised, steady-state fossil fuel generation to decentralised, variable renewable energy, targeted to reach 42.5% of the mix by 2030. This shift increases grid management complexity beyond conventional operational capacity. The EU Action Plan for Digitalising the Energy System (2022) positions AI not as an optional efficiency tool but as a prerequisite for grid stability, specifically for balancing variable loads and integrating millions of distributed energy resources including electric vehicles, heat pumps, and solar installations.[145]

Horizon Europe's Cluster 5 (Climate, Energy and Mobility) provides over EUR 300 million in 2025-2026 for calls to projects accelerating this transition. The Smart Energy Expert Group advises the Commission on interoperability and data exchange, while the European Electricity Data Space is being developed to enable secure cross-border sharing of consumption and generation data, a critical prerequisite for training AI models on grid behaviour at European scale. The IEA estimates that digital technologies can reduce operational costs in the power sector by up to 25% and extend asset lifetimes, important economic drivers for utilities managing the capital requirements of energy transition.[146]

At Member State level, the Netherlands' EUR 189 million AiNed programme has launched AI Innovation Labs specifically for energy and sustainability.[147] Germany's Energy Research Programme prioritises smart grids and digital twins for Energiewende management. Italy's Piano Transizione 5.0 (EUR 6.3 billion cross-sectoral) includes AI-driven energy efficiency applications. Latvia has deployed the EUR 5.59 million I-NERGY project, and Poland's New Energy programme (EUR 590 million) supports AI-driven smart city energy systems. More than two-thirds of EU Member States have adopted policies supporting AI applications for climate and environmental sustainability, though efforts remain uneven and often fragmented.[148]

Ukraine's energy strategy and EU alignment

Ukraine's energy infrastructure has historically centred on large-scale centralised generation: nuclear, thermal, and hydroelectric. WINWIN marks a pivot towards greentech and decentralisation, explicitly identifying decarbonisation of energy, microgrids, smart grids, and energy storage as priority innovation areas. The Ministry of Energy's Energy Strategy to 2050 envisions full integration into European energy markets. WINWIN's energy targets include construction of 140 GW of wind power plants and 87 GW of solar power plants and launch of 38 GW of energy storage systems, creating conditions where AI-based grid management will become operationally necessary.[149]

WINWIN classifies energy systems as a dual-use priority under both greentech and defencetech, recognising that a digitised, decentralised grid is harder to disable than a centralised one. The IEA's 2025 report on Ukraine's electricity system has elevated distributed energy resources and storage as strategic priorities, a decentralised approach that also creates the technical architecture within which AI grid management tools operate.[150] Ukrenergo, Ukraine's electricity transmission system operator, has been integrating digital tools, including Microsoft Dynamics 365 for operational management, as part of a broader strategy to modernise and align with European grid standards.[151] The WINWIN CoE AI for Energy Competence Center is identified as a priority institutional vehicle, targeting energy security, digital networks, and automated dispatching.

AI applications in the sector

AI applications divide by value chain position:

- **Predictive maintenance in generation:** machine learning applied to sensor data from turbines, valves, pumps, heat exchangers, and rotating machinery to shift maintenance from scheduled to condition-based approaches. Particularly valuable as thermal plants operate increasingly in flexible backup modes complementing variable renewables, creating stress patterns their original designs did not anticipate.
- **Distribution grid optimisation:** machine learning applied to power flows, weather data, and consumption patterns to balance supply and demand in real time, prevent outages, and optimise voltage across medium-voltage networks.
- **Digital twins for grid infrastructure:** simulation of grid behaviour under different generation and demand scenarios, enabling planners to evaluate infrastructure investment decisions and operational configurations before physical commitment.
- **Renewable integration:** AI-driven forecasting of variable generation output and locational risk analysis, reducing curtailment and improving market bidding optimisation.
- **Legacy asset digitalisation:** sensor retrofitting, condition monitoring, and digital twin development for analogue-controlled generation assets such as hydropower plants, enabling AI application where no data infrastructure currently exists.

2.7.2 Adoption pathways analysis

The three case studies examined in this sector represent AI adoption at three distinct points in the energy value chain: AI-driven predictive maintenance at distribution grid level (Germany/Europe), predictive maintenance for power generation equipment at scale (France/multinational), and a Horizon Europe consortium project developing digital twin tools for hydropower plant modernisation (EU-wide). Together they illustrate a sector in which AI adoption in the energy industry is advancing in targeted high-value applications but faces substantial structural barriers in most of the asset base, where analogue infrastructure and the capital intensity of grid assets constrain deployment speed.

Sectoral deployment patterns

A defining characteristic of all three case studies is the management of complex, multi-variable degradation patterns that exceed human analytical capacity. A distribution network operator managing thousands of cable segments, transformers, and switching equipment across a regional grid cannot manually identify which specific components are approaching failure based on their individual degradation trajectories: the combination of thermal cycling history, load patterns, environmental exposure, and equipment age requires analysis at a scale and speed only machine learning can provide. A major energy company operating 1,000+ prediction models across diverse equipment types in multiple power plants, each requiring models calibrated to its specific operational mode (increasingly flexible rather than baseload), cannot manage this complexity through centralised data science teams working on individual assets. In both cases, AI is the enabling technology for maintenance intelligence at scale, not a replacement for domain expertise but an amplifier of it.

The case studies also illuminate the specific challenge of AI deployment on legacy infrastructure. The distribution grid case involves equipment installed over decades of rolling investment, with highly heterogeneous vintage, condition, and data availability. The generation case involves thermal power plants now operating in fundamentally different modes than their original design intent, requiring models trained on new operational data rather than historical norms. The hydropower digitalisation project specifically targets plants over 50 years old operating on fully analogue control systems, where even sensor data collection is a prerequisite investment before AI can be deployed. These scenarios are not edge cases: much of Europe's energy infrastructure falls into this category, and the majority of Ukraine's grid and generation assets share this characteristic.

The scaling pathways differ between cases. The distribution grid AI system was developed internally by a major utility's innovation unit and is being rolled out progressively across the group's European network, following an initial operational deployment from 2018. The generation predictive maintenance platform was built by a dedicated digital subsidiary using cloud infrastructure (AWS), with models developed in collaboration with an AWS consulting partner and progressively extended to cover more equipment types and business units. The hydropower digitalisation toolkit is being developed through an EU research consortium of 17 partners across 7 countries, with demonstration sites at real facilities, representing the publicly funded R&D pathway rather than commercial deployment. The first two cases have demonstrated measurable commercial ROI (30% reduction in cable-related outages; EUR 800,000 annual savings across adopting business units).[152, 153] The third is at development stage, targeting a market of hundreds of similar legacy facilities across Europe.

Cloud infrastructure is a common enabling condition in two of the three cases. The generation predictive maintenance platform runs entirely on AWS, with the cloud's capacity for scalable compute during model training and its geographic reach enabling simultaneous management of equipment in power plants across multiple countries. The distribution grid case integrates with the utility's broader digital infrastructure including smart meter data and SCADA systems. The hydropower case is developing cloud-based tools as part of its modular digital twin framework. For energy sector AI adoption broadly, cloud infrastructure reduces the deployment barrier substantially compared to on-premise alternatives, though data sovereignty requirements for critical infrastructure create regulatory considerations that utilities must navigate.

SME access to energy AI is structurally constrained. All three documented cases involve either large utilities or publicly funded research consortia. The capital and operational complexity of energy infrastructure means that smaller operators face disproportionate barriers: the data infrastructure, the expertise to interpret AI outputs in safety-critical contexts, and the organisational capacity to manage vendor relationships for AI systems all require scale. The EDIH network provides one access pathway, with EDIHs in several Member States supporting energy sector digitalisation, though coverage is uneven. The hydropower consortium model, in which SME operators participate in a multi-partner project without bearing the full development cost, represents an alternative pathway relevant for smaller generation companies.

Policy context and enabling conditions

1 EU-LEVEL AND NATIONAL AI STRATEGIES ACROSS DATA, COMPUTE AND SKILLS

The AI Act's classification of AI systems in critical infrastructure as high-risk creates compliance requirements for energy sector AI that affect deployment timelines and documentation requirements.[154] The energy sector's classification as critical infrastructure under the NIS2 Directive adds cybersecurity requirements for AI-connected systems. These regulatory layers create a compliance environment that is more demanding than in other manufacturing sectors, and that shapes the adoption pathway: utilities deploy AI systems with extensive testing, staged rollout, and audit trails that extend timelines relative to less regulated sectors.

Data infrastructure is the most significant structural enabling condition. The European Electricity Data Space under development, the smart meter rollout across Member States, and SCADA system modernisation all contribute to the data availability that underpins energy AI.[155] The OECD's assessment notes that only a few EU Member States have launched targeted energy AI data-sharing initiatives, despite its recognised importance.[156] The absence of standardised data exchange frameworks across TSOs and DSOs limits the interoperability of AI systems developed in one national context being deployed across borders. Skills represent a recognised gap: AI-skilled professionals in the energy sector remain below 2% of the workforce in most Member States, consistent with the manufacturing benchmark, and the combination of power systems engineering and AI/data science expertise required is scarce.[157]

2 R&D AND SCALING-UP INITIATIVES

The D-HYDROFLEX project illustrates the Horizon Europe consortium model for energy AI development: a 17-partner consortium combining operators, research institutions, and technology providers, with multiple demonstration sites providing real-world validation data. This model distributes development cost and technical risk across partners, making it particularly relevant for legacy infrastructure digitalisation where the commercial market alone would not fund tool development at sufficient scale.

The Apply AI Strategy's energy flagship commits the Commission to deploying AI for energy grid management, smart grid optimisation, and building energy efficiency applications.[158] The Commission's planned Strategic Roadmap on Digitalisation and AI for the Energy Sector will provide further policy direction. Germany's AI-Lighthouses for Environment, Climate, Nature and Resources programme (EUR 150.9 million) and the Netherlands' AiNed energy innovation labs represent the scale of national public investment targeting energy AI.[159]

VC investment in EU climate and environment AI startups, a category that includes energy AI, has reached approximately EUR 700 million since 2019, reflecting growing investor confidence in clean energy applications.[160] The AI Continent Action Plan's compute infrastructure is relevant to the training requirements of large-scale grid simulation and energy forecasting models.

High-level assessment

The energy cases reveal a sector in which AI adoption's enabling conditions are in place for large utilities with digital infrastructure, capital, and data science capacity, but where most of the asset base faces structural barriers that investment and technology availability alone cannot quickly resolve. The distribution grid predictive maintenance system and the generation platform both required years of development, data infrastructure investment, and iterative model refinement before reaching operational scale. Neither was a rapid deployment of off-the-shelf AI.

The most durable energy AI deployments are those anchored in a specific, high-cost operational problem with a quantifiable benefit: reduced cable outages with documented customer and cost impact; avoided unplanned plant shutdowns with a specific annual savings figure. This grounding in measurable operational ROI drives continued investment and organisational commitment beyond the initial deployment. Applications without a clear and trackable benefit have a higher risk of stalling after the pilot phase. The hydropower consortium addresses a different enabling challenge: creating the basic data and digital infrastructure that makes AI optimisation possible for assets where sensor coverage is currently absent, which is the prerequisite investment before any other AI application can follow.

2.7.3 Towards EU best practices

Ukraine's energy infrastructure has suffered systematic damage to generation and transmission assets.[161] Ukrenergo has begun integrating digital tools, including Dynamics 365 for operational management. WINWIN targets microgrids, smart grids, energy storage, and AI-enabled grid management, supported by the WINWIN CoE AI for Energy Competence Center targeting energy security, digital networks, and automated dispatching.[162] The war has created an additional rationale for digitisation that the European transition does not share: decentralisation as a security strategy, not only an efficiency strategy.

1 ADOPTION DEPENDENCIES

Distribution grid predictive maintenance, the most operationally mature AI application in European energy, depends on sensor telemetry being available from the equipment being monitored. Smart metering infrastructure, SCADA systems covering substation equipment, and connected sensors on cables, transformers, and switching infrastructure must be in place before AI models have inputs to work from. The E.ON case succeeded because years of smart meter rollout and SCADA investment had generated the data histories that machine learning required. Where infrastructure is analogue or physically damaged, this dependency is structural: sensor coverage is the prerequisite for predictive maintenance AI, and software cannot substitute for it. Generation equipment AI and digital twins depend on cloud infrastructure and data integration across assets. The ENGIE platform required a centralised data lake aggregating operational telemetry across geographically distributed plants; without cross-asset data architecture, models are limited to single-facility scope and lose the pooled learning that drives performance at scale.

For legacy hydropower specifically, before AI-based optimisation is applicable, analogue control systems must be augmented with digital instrumentation. Hydropower plants operating on fully analogue systems cannot connect to AI platforms regardless of cloud availability or model quality. Digital instrumentation is the prerequisite layer before all others.

For Ukraine, this dependency has immediate practical implications for reconstruction planning. Energy infrastructure being rebuilt or repaired in the aftermath of the armed conflict will operate for 30 to 50 years. If sensor arrays, telemetry systems, and data collection infrastructure are specified in reconstruction design mandates now, the marginal cost is modest relative to the total infrastructure investment. If they are not, retrofitting these systems later follows the European pattern of being three to five times more expensive than incorporating them at inception. The specific requirements are identifiable from the European case studies: smart metering at the distribution level, SCADA coverage of substation and switching equipment, connected sensor arrays on transformable and cable infrastructure, and cloud-compatible data architectures that enable cross-asset telemetry aggregation.

2 DIAGNOSTIC INDICATORS

- Energy infrastructure reconstruction mandates include sensor and telemetry requirements, since retrofitting sensors after reconstruction is more expensive and less effective than building them in at the reconstruction stage.
- Ukrenergo's data architecture is developing in a form that enables cross-asset AI model deployment rather than remaining facility specific.
- TSO-DSO data-sharing frameworks are being developed alongside the grid rebuilding programme, not as a subsequent step.
- The WINWIN CoE AI for Energy Competence Center is progressing with testbed access functions for grid AI applications, rather than being designed primarily as a policy coordination body.

2.7.4 Case Studies

Case study 1

E.ON — AI-Powered Predictive Maintenance for Distribution Grids[163]
Germany (rollout across European network) | Major energy utility

Implementation

A major European energy utility developed and deployed an AI-powered predictive maintenance system for electricity distribution infrastructure, initially operational on medium-voltage grids in Germany's Schleswig-Holstein region from 2018. The system combines historical data including outage records, repair logs, equipment age, environmental exposure, and load patterns with self-learning machine learning algorithms that continuously refine failure predictions as new data accumulates. By analysing sensor telemetry alongside contextual variables, the platform identifies which specific cables, transformers, and grid components are likely to fail before the next scheduled inspection cycle, enabling condition-based maintenance interventions. The utility reports a two-to-three-fold improvement in the probability of accurately predicting defects compared to conventional assessment methods, with potential to reduce cable-related outages by up to 30%. The system integrates with smart meter data, SCADA monitoring, and mobile workforce management tools, forming part of a broader grid digitalisation strategy.

Adoption pattern demonstrated

This case study illustrates the large-utility in-house development pathway, in which AI capability is developed and progressively deployed by the utility's own innovation function with iterative refinement based on operational data. The enabling conditions include an existing smart meter infrastructure providing granular consumption data, SCADA systems generating equipment telemetry, and organisational commitment to multi-year development before full network rollout. The quantifiable operational benefit, reduced cable outages translating to lower emergency repair costs and fewer customer disruptions, provided the internal business case for continued investment. This case is relevant to the Ukrainian context, where distribution grid reliability under stress from infrastructure attacks makes condition-based maintenance a strategic priority, not just an efficiency improvement.

Source: https://www.powerengineeringint.com/smart-grid-td/td-infrastructure/eon-deploys-ai-for-predictive-power-grid-maintenance/

Case study 2

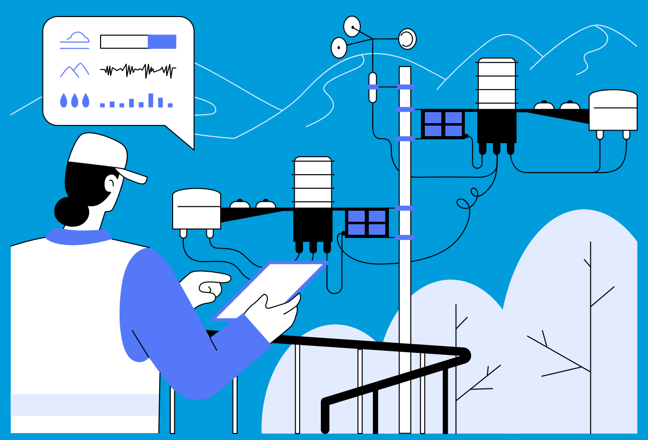
ENGIE Digital — Predictive maintenance platforms for power plant equipment[164]
France (multinational deployment) | Major energy company + digital subsidiary + cloud provider

Implementation

A major European energy company's dedicated digital subsidiary developed two AI-powered predictive maintenance platforms: one for the group's internal thermal power plants (covering early anomaly detection, useful equipment life prediction, and health state estimation), and one offered as a service to B2B customers. The platforms were built using cloud-based machine learning infrastructure, with an AWS consulting partner leading the technical implementation. Over 1,000 prediction models have been developed covering diverse equipment types including valves, pumps, heat exchangers, and ventilation systems. The deployment targets 10,000 connected equipment pieces across the group's power plants and customer facilities, with documented annual savings of EUR 800,000 for adopting business units. The platforms address a specific challenge created by the energy transition: thermal plants now operating in flexible backup mode rather than steady-state baseload experience stress patterns that traditional maintenance schedules, designed for original operating conditions, cannot anticipate.

Adoption pattern demonstrated

This case study illustrates the internal digital subsidiary pathway for AI development at scale, in which a large energy company creates a dedicated software entity to develop AI capabilities that simultaneously serve internal efficiency and external commercial purposes. The enabling conditions include cloud infrastructure providing scalable compute for model training across geographically distributed assets, a specialist consulting partner for machine learning implementation, and a data lake aggregating operational telemetry across the group. The transition of thermal plants to flexible operation created the technical and commercial justification for developing predictive models calibrated to new operational realities. The B2B platform dimension shows that utility AI capabilities developed for internal use can become revenue-generating services.



Sources: https://aws.amazon.com/solutions/case-studies/engie-digital-sagemaker

Case study 3

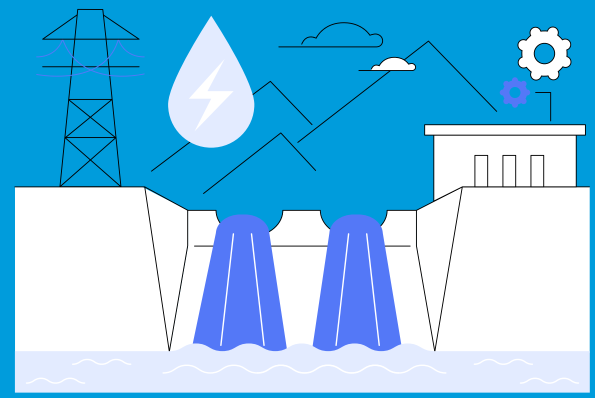
D-HYDROFLEX — Digital twin toolkit for legacy hydropower plants[165]
EU-wide consortium (demonstration site: Poland) | Horizon Europe research consortium, 17 partners

Implementation

A 17-partner EU Horizon Europe consortium (Grant Agreement 101122357) is developing a modular digital twin toolkit for retrofitting existing analogue hydropower plants with digital monitoring, AI-based optimisation, and predictive maintenance capabilities. The consortium includes five power plant operators providing real-world demonstration sites across France, Greece, Poland, Spain, and Romania; six research institutions contributing expertise in turbomachinery, computer vision, and AI algorithms; and seven technology providers covering cloud platform development, sensor integration, and machine learning tooling. The flagship demonstration is at a run-of-river hydropower plant in Poland's Lower Silesia province, commissioned in 1959 and still operating on fully analogue control systems. The toolkit includes modules for turbine condition assessment, 3D computer vision-based dam structural monitoring, and energy flexibility optimisation to support renewable integration. The project responds to a documented challenge: many of Europe's hydropower plants are over 50 years old and require digital modernisation to operate with the flexibility needed to complement variable renewable generation.

Adoption pattern demonstrated

This case study illustrates the publicly funded consortium R&D pathway for legacy infrastructure digitalisation: tool development costs and technical risks are distributed across 17 partners, with real-facility demonstration sites providing validation data that no single partner could generate independently. The enabling conditions are EU Horizon Europe funding, multi-disciplinary expertise assembled through consortium structure, and the availability of plant operators willing to serve as demonstration sites. The pathway from consortium R&D to commercial deployment depends on the modular toolkit's uptake among the broader population of similar legacy plants, which are estimated to number in the hundreds across Europe. For Ukraine, where hydropower capacity requires modernisation and war-damaged energy infrastructure requires reconstruction, the D-HYDROFLEX model is relevant both as a technology source and as a consortium model that Ukrainian research institutions and plant operators could potentially join.



Sources: Horizon Europe Grant Agreement 101122357; D-HYDROFLEX project documentation

3

What Europe's experience means for Ukraine

This chapter draws together the cross-sectoral evidence from Chapter 2 to identify patterns that hold across all seven sectors, examine the policy architecture that sustained successful AI adoption, and characterise the structural dependencies between enabling conditions.

This chapter draws together the cross-sectoral evidence from Chapter 2 to identify patterns that hold across all seven sectors, examine the policy architecture that sustained successful AI adoption, and characterise the structural dependencies between enabling conditions. The goal is not to synthesise findings that are better read in each sector chapter, but to identify what is consistent, what is sector-specific, and what the sequencing logic of adoption looks like when viewed across the full evidence base.

This chapter supports three types of decisions. For investment sequencing, it identifies which enabling conditions must be built first and which can follow. For institutional design, it clarifies which EU mechanisms (TEFs, EDIHs, data spaces) are worth pursuing and what policy alignment they require. For partnership strategy, it specifies the conditions under which European vendors, research partners, and ecosystem actors engage.

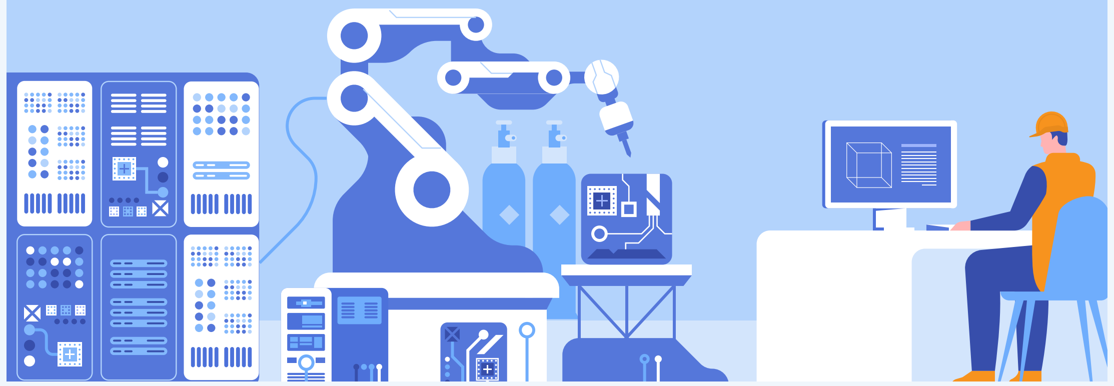
At a glance: what the European evidence shows:

1 ENABLING CONDITIONS THAT RECUR ACROSS ALL SEVEN SECTORS

- Data infrastructure at operational quality is the prerequisite for every documented AI deployment; it must precede, not accompany, AI investment.
- Testing and Experimentation Facilities (TEFs) and European Digital Innovation Hubs (EDIHs) are the mechanism through which smaller enterprises access AI; they absorb the validation and compliance costs that SMEs cannot bear independently.
- Vendor-mediated and ecosystem-based adoption is the dominant pathway; building in-house AI development capacity at the firm level is less effective than reducing barriers to technology access and partnership.

2 SEQUENCING RULES EMERGING THROUGH EVIDENCE

- Data and validation infrastructure come first; platform and vendor engagement second; greenfield co-design only where reconstruction investment windows are still open.
- EU regulatory alignment enables TEF/EDIH network access, which enables SME adoption; each link in this chain depends on the preceding one.
- Pilot discipline (bounded problem, measurable ROI, defined success criteria) is the mechanism that converts experiments into operational deployments; scale of investment is less consistently decisive.



3.1 CROSS-SECTORAL PATTERNS IN AI ADOPTION

Data infrastructure is the prerequisite layer

Across all seven sectors, the most consistent enabling condition for AI adoption is the availability of domain-relevant data at the quality, volume, and accessibility needed to train and operate AI systems in production environments. In each case, the data infrastructure was a prerequisite investment, not a byproduct of implementing AI.[166] Satellite imagery for forest pest detection, annotated clinical datasets for diagnostic AI, sensor telemetry for distribution grid maintenance, ERP-integrated production data for textile quality inspection: in every instance, the data pipeline had to be in place before AI could function at operational scale.

The quantified outcomes across the evidence base confirm that data-ready deployments produce substantial returns: up to 30% reduction in cable outages where smart meter and SCADA data were available for years before AI was applied; EUR 800,000 in annual savings from generation equipment monitoring where a centralised data lake aggregated telemetry across distributed plants; 99.8% diagnostic sensitivity in medical imaging AI where over 100,000 annotated training images were contributed before the system entered clinical use.[167, 168, 169] In each case, the data investment preceded and enabled the AI outcome.

European policy has recognised this sequencing. The European Health Data Space, the Common European Agricultural Data Space, the Manufacturing Dataspace, and the European Electricity Data Space all represent sector-specific public data infrastructure investments intended to create conditions for AI development that the private market alone would not fund.[170, 171] For Ukraine, sectoral data infrastructure should be treated as the first layer of AI investment, before platform selection, before model development, and before procurement of AI tools.

Sectoral data infrastructure investment is the highest-priority enabling condition. The AI Strategy 2030's target of 100 AI-ready priority datasets by 2030 is the right instrument; what matters is whether those datasets are aligned to the sectors where adoption is closest (agritech, energy) and whether they meet the quality and interoperability standards that European AI systems require. Reconstruction-era sensor and telemetry infrastructure, if specified at the design stage, can build this data layer at marginal cost.

Third-party and ecosystem-based adoption dominates

In all seven sectors, most documented deployments rely on external AI capabilities accessed through commercial platforms, specialist technology partners, or consortium structures rather than in-house algorithm development.[172] This reflects the genuine specialisation advantage of AI technology providers and the economics of AI development, where the fixed costs of building domain-specific models are spread across many deployments. Large firms with substantial in-house capacity still find it more efficient to access AI through the ecosystem than to develop it internally: a major German automotive OEM partnered with NVIDIA for digital twin infrastructure; a leading European semiconductor fab used a commercial EDA tool for chip design optimisation; a major French energy company built its predictive maintenance platform with an AWS consulting partner.[173, 174, 175]

The policy implication is direct: instruments that reduce barriers to technology access and partnership formation, through EDIHs, TEF networks, vendor matchmaking, and procurement frameworks, are more leveraged than instruments focused on building in-house AI development capacity at the firm level. The AI Strategy 2030's Operational Plan targets support for at least 200 SMEs through EDIH cooperation by December 2027, and an 'AI for Business' portal with 500+ enterprise self-assessments.[176] These are the right instruments for ecosystem-based adoption. The strategic question is not whether Ukraine can develop its own AI, but whether the ecosystem access mechanisms are in place for Ukrainian firms to adopt European AI effectively.

TEFs and EDIHs as the SME enabling mechanism

Across agritech, semiconductors, textiles, and medtech, TEFs and EDIHs function as risk-absorbing access mechanisms for smaller enterprises. They provide validation environments, certification support, and experimentation infrastructure that allow SMEs to move from proof-of-concept to market-ready implementation without bearing the full compliance cost independently.

The evidence is specific. A Dutch autonomous mowing startup reached safety certification under EN ISO 25119 through the agrifoodTEF, which absorbed the cost of risk assessment, safety function definition, and compliance verification that the startup could not have funded independently.[177] A major European semiconductor fab moved a predictive maintenance project from proof of concept to production through the EDIH Saxony Testbed IoT lab, which provided the physical infrastructure for rapid prototyping and sensor integration that no individual partner in the consortium held independently[178]. In both cases, the facility's function was infrastructural, not advisory: it provided the environment in which the solution was built and validated. TEF and EDIH access is the most actionable near-term target for SME AI adoption. The AI Strategy 2030's Operational Plan commits to launching an 'AI and blockchain solutions sandbox' by June 2028 and to EDIH network cooperation supporting 200+ enterprises. The European evidence suggests that the pathway to this access runs through policy alignment and institutional partnership agreements, which should be prioritised ahead of the infrastructure investments themselves.

Pilot discipline and measurable ROI unlock the operational transition

The transition from pilot to operational deployment is the most consistently challenging phase of AI adoption across all sectors surveyed. Cases that successfully made this transition consistently started with a specific, bounded operational problem, defined measurable success criteria in advance, and demonstrated return on investment before seeking wider rollout.[179] The scale of initial investment was less consistently differentiating than the rigour of problem definition and outcome measurement.

In textiles, payback periods of 5 to 24 months from quality inspection systems generated the internal business case that converted managerial scepticism to operational commitment, and the OECD notes that a 3% reduction in defect rates can nearly double operational profits in high-volume settings.[180, 181] In semiconductors, a project lead explicitly attributed success to the fact that the deployment was a focused, manageable AI use case with demonstrable ROI, which built organisational support for broader adoption.[182] The pattern is consistent across sectors: scoped pilots with clear metrics are the mechanism through which AI moves from experiment to infrastructure.

The AI Strategy 2030's Operational Plan establishes a mechanism for systematic selection, implementation, and scaling of pilot AI projects in the public sector, targeting at least 25 selected and launched pilot projects by December 2027. The European evidence suggests that the selection criteria for these pilots, specifically the requirement for bounded problem definition and measurable ROI, will be more important for their success than the scale of funding allocated to them.

Regulatory environment is the most sector-specific variable

The governance and regulatory environment is the enabling condition that varies most significantly across sectors. EU MDR clinical validation requirements define the medtech adoption sequence. The EU AI Act's high-risk classification of autonomous driving systems determines the automotive adoption pathway. NIS2's critical infrastructure cybersecurity requirements shape energy sector AI deployment.[184, 184] In each case, leading enterprises treat compliance as a strategic asset: regulatory credibility functions simultaneously as a market access credential and a trust signal to professional and institutional buyers. The Lithuanian medical AI startup's CE marking pathway, achieved through rigorous multi-site clinical validation, enabled deployment across a 450 million patient market that would otherwise have been inaccessible.[185] For Ukraine, EU acquis alignment in the sectors covered by this report is therefore an AI adoption enabling condition, not only a trade or accession requirement. Progress on regulatory alignment determines which certification pathways are available to Ukrainian companies and whether tools validated in the EU can be extended to Ukraine without full re-validation.

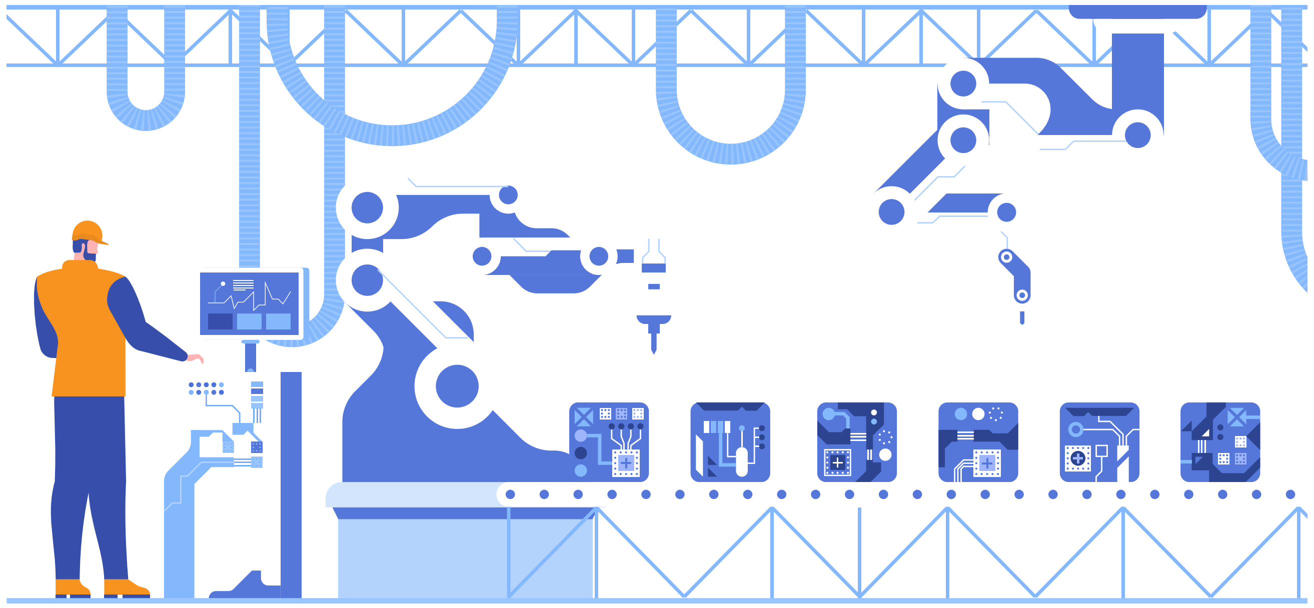
The AI Strategy 2030's Strategic Goal 4 commits to preparing the regulatory framework in accordance with EU requirements and supporting European integration. The Operational Plan targets legal regulation and harmonisation with the European digital space by December 2028. The European evidence confirms that this is not an administrative formality: regulatory credibility directly determines market access and vendor engagement in the sectors where AI adoption is most advanced.

3.2 POLICY MECHANISMS AND ENABLING CONDITIONS

Public R&D investment plays a sequencing role

The European policy architecture supporting AI adoption operates through three distinct types of instrument, each serving a different function in the adoption sequence. Infrastructure instruments (data spaces, TEFs, EDIHs, computing facilities) create the shared resources that individual firms cannot build alone. Demand-side instruments (tax credits, compliance requirements, procurement standards, outcome-based contracting) reduce the cost of adoption or create market conditions that make it investable. Coordination instruments (national strategies, standards, regulatory sandboxes, network agreements) reduce uncertainty for private actors and align investment across the ecosystem. The European evidence shows that all three types are necessary, but they operate at different stages: infrastructure instruments enable the first deployments, coordination instruments shape the environment in which they scale, and demand-side instruments accelerate uptake once the conditions are in place.

For Ukraine, this typology provides a practical framework for mapping which instruments already exist (WINWIN and the AI Strategy 2030 function primarily as coordination instruments), which are being built (the Operational Plan's EDIH cooperation and regulatory sandbox are infrastructure instruments), and which are largely absent (demand-side instruments such as outcome-based procurement templates, tax incentives for AI adoption, and compliance-driven deployment requirements).



National strategies function as coordination signals

National AI strategies contribute to AI adoption primarily through coordination signals that reduce uncertainty for private actors rather than through direct technology provision. Germany's Catena-X programme created the data-sharing standards that made automotive supply chain AI investable; Italy's Piano Transizione 5.0 reduced the upfront capital barrier for SME AI adoption through tax credits rather than grant programmes requiring competitive application; Finland's National Forest Strategy made digitalisation a priority that shaped industry investment decisions across multiple planning cycles.

Ukraine's WINWIN strategy operates at this level of coordination signal. Its most important enabling function is the regulatory and institutional commitments it makes: to EU acquis alignment, to EDIH network integration, to innovation cluster development, to regulatory sandboxes for testing autonomous systems. These commitments reduce uncertainty for European technology partners considering Ukrainian market engagement and for Ukrainian enterprises evaluating whether EU-standard compliance investments are worth making.

Skills gaps are addressable through ecosystem structures

AI talent concentration in manufacturing and energy remains below 2% of the workforce in most EU Member States, and the combination of domain expertise and AI/data science competencies required for sector-specific applications is scarce everywhere. European enterprises have addressed this consistently through partnership structures rather than internal workforce development as the primary mechanism: EDIH-delivered hands-on training embedded in deployment processes, vendor-managed AI tools that abstract complexity from end users, and multi-partner consortia that assemble required competencies across organisations.

Ukraine's 307,000-strong IT workforce and AI research output, ranked second in Eastern Europe, represents assets for partnership-based AI adoption rather than indicators of readiness for large-scale internal AI development at the firm level. The implication for workforce policy is that training programmes designed around deployment and partnership structures, rather than sovereign AI development capacity, are better matched to the actual adoption patterns the evidence documents.

3.3 ADOPTION DEPENDENCIES: WHAT THE EUROPEAN EVIDENCE INDICATES

The following analysis identifies structural dependencies between enabling conditions, as observed across the seven sectoral analyses. It is framed as a diagnostic reading of the European evidence, indicating what conditions must be in place for others to follow, and what indicators are worth tracking in any context where similar adoption outcomes are being pursued.

Data infrastructure enables everything else, and must come first

The strongest dependency in the European evidence is between data infrastructure and all AI application types, and the most irreversible in the European evidence. It applies to all adoption pathways: cloud-based, vendor-mediated, consortium-based, and TEF-validated alike. No documented case achieved operational AI deployment without a preceding data investment measured in years, not months.

The diagnostic question for any sector in Ukraine is: does domain-relevant data exist at the quality, volume, and accessibility that AI systems require? If not, the enabling condition is data collection and governance infrastructure, not AI procurement. The sectors where this dependency is most clearly documented are energy (smart meter and SCADA data accumulated over years before grid AI became operational), medtech (annotated clinical datasets built through multi-year hospital partnerships), and wood processing (satellite imagery archives and real-time sawmill telemetry). In each case, the AI deployment that followed was faster than the data infrastructure that preceded it.

WHAT TO TRACK

Availability of sector-specific datasets at operational quality; data governance frameworks and sharing agreements; connectivity and sensor infrastructure in the relevant sector.

TEF and EDIH access requires a chain of prior conditions

The access mechanism that most consistently unlocked SME AI adoption in the European evidence is TEF and EDIH infrastructure. But access to this infrastructure depends on institutional participation in the EU network, which in turn depends on the policy alignment and partnership agreements that precede it. The chain is: policy alignment enables network membership, network membership enables infrastructure access, infrastructure access enables SME AI adoption. Each link is necessary; none is sufficient on its own.

The practical implication is that TEF and EDIH access is a medium-term target, not an immediate one. The institutional groundwork, the agreements, the legislative alignment, the designated national contact points, must be in place before the testbed access itself is useful. Ukraine's AI Strategy 2030 Operational Plan commits to EDIH cooperation by December 2027, which implies that the policy alignment work should be under way now.

WHAT TO TRACK

Status of partnership agreements with EU TEF and EDIH networks; designated national contact points; legislative alignment with relevant EU facility access requirements.

Vendor-mediated adoption requires market presence, through two routes

The vendor-mediated pathway, the most accessible route to AI adoption for SMEs across most sectors, depends on AI vendors being willing and able to operate in the relevant market. In European cases, vendor presence required a market of sufficient scale to justify localisation investment, a business environment where IP protection and payment systems were reliable, and in several cases direct vendor-customer co-development relationships. Where vendor presence is absent, the platform may exist but the deployment support, calibration, and operator training that European evidence consistently identifies as essential for successful adoption are not available.

For Ukraine, two routes to vendor engagement are available, and they are sequential rather than alternative. The first and faster route is attracting EU vendors through market signals that justify their engagement: anchor procurements by large Ukrainian enterprises or public bodies, risk-sharing arrangements, predictable demand in reconstruction contracts, and procurement frameworks that reduce transaction costs. The second and more durable route is building Ukrainian intermediary and system integrator capacity: local firms that can deploy, configure, calibrate, and support European AI tools in Ukrainian operational contexts, combining domain knowledge with deployment capability. The AI Strategy 2030's commitment to an 'AI for Business' portal and EDIH cooperation supports both routes, but the first requires active market-making that goes beyond information provision.

WHAT TO TRACK

Number of EU or EU-adjacent AI technology vendors active in the Ukrainian market by sector; volume of AI-related procurement by Ukrainian public bodies and major enterprises; number of Ukrainian system integrators with demonstrable AI deployment experience.

Greenfield co-design is a time-limited option

European evidence shows that co-designing AI into facility architecture from inception produces substantially higher productivity outcomes than retrofitting it afterwards. The ABB/Metsä Fibre sawmill achieved 3x European productivity benchmarks because AI systems and physical infrastructure were designed together; the BMW factory digital twin platform delivers 30% planning efficiency gains because it is production infrastructure, not an add-on. These outcomes are not achievable through retrofit approaches, and the European evidence documents the gap.

This dependency has a temporal dimension that makes it distinct from the others. The co-design option exists only at the investment planning stage. Once facilities are designed and built without digital integration mandates, the option closes and the higher-cost, lower-performance retrofit pathway becomes the only one available. For reconstruction-era investment planning in Ukraine, digital integration requirements should be built into capital investment frameworks before facility designs are finalised. This is the most time-sensitive of the dependencies identified here.

WHAT TO TRACK

Percentage of reconstruction capital investment frameworks that include digital integration requirements; number of industrial facility designs incorporating sensor infrastructure, data collection, and AI-ready architecture from inception.

3.4 CONCLUDING OBSERVATIONS

Europe's evidence shows that AI uptake in industry is less about acquiring AI and more about sequencing the enabling conditions that make deployment investable and repeatable. The report documents a consistent logic across seven sectors: data infrastructure enables the first applications; testing and validation facilities de-risk adoption for smaller enterprises; regulatory clarity accelerates deployment rather than impeding it; and pilot discipline, not investment scale, determines whether experiments become operational.

What is sector-specific is not the logic itself but the instruments through which it operates. In medtech, regulatory credibility through CE marking is the mechanism that unlocks the 450 million-patient European market. In agritech, rural connectivity and the regulatory framework for autonomous machinery determine whether precision farming moves beyond satellite monitoring toward field-level automation. In energy, sensor and telemetry infrastructure embedded in reconstruction mandates is the design choice that will shape AI possibilities for decades. In semiconductors, EDIH network access and ecosystem density are the binding constraints. The sector chapters in Chapter 2 provide the evidence behind each pathway.

The trade-offs embedded in these findings deserve explicit statement. Speed of deployment favours vendor-mediated adoption, which is faster but creates dependency; the alternative, building local system integration capacity, is slower but more durable. Pilot breadth is appealing, but the evidence consistently favours pilot discipline: fewer, better-defined pilots with measurable ROI produce more operational deployments than broad experimentation without clear success criteria. EU regulatory alignment involves real compliance costs, but the European evidence shows it functions as a market access credential that pays for itself through certification pathways and vendor engagement.

Ukraine's WINWIN strategy and the newly adopted Strategy for the Development of Artificial Intelligence until 2030 address the right enabling conditions. WINWIN's commitments to EU acquis alignment, EDIH network integration, and innovation cluster development map onto the dependencies this synthesis identifies. The AI Strategy 2030 adds concrete targets: enterprise AI usage rising from 5% to 75% by 2030, 100 AI-ready priority datasets, 50 petaflops of computational infrastructure, and an SME support programme through EDIH cooperation serving at least 200 enterprises by 2027. The Operational Plan establishes a regulatory sandbox for AI and blockchain solutions by June 2028, and a systematic mechanism for selecting, implementing, and scaling AI pilot projects in the public sector.

The contribution this report makes is the analytical connection between those strategic commitments and the sector-specific actions they need to generate: the digital integration mandate in wood processing reconstruction investment, the PACS interoperability standard in hospital network rebuilding, the telemetry requirement in energy infrastructure design, the EDIH membership target in the semiconductor cluster strategy. Build data and validation access first; scale vendor-mediated deployments second; pursue greenfield co-design only where reconstruction investment windows are still open. The opportunity is to embed these conditions into reconstruction choices now, so that AI becomes infrastructure, not another pilot cycle.

3.4.1 What this report does not cover (and why it matters)

This report has focused on the enabling conditions that recur across European examples of operational AI deployment, and on how those conditions translate into actionable priorities for Ukraine's reconstruction-era industrial strategy. As a result, several cross-cutting implementation questions are addressed only indirectly. They are not secondary: in practice, they often determine whether otherwise well-founded pilots can be procured, operated, and sustained at scale.

Procurement, contracting, and financing mechanisms

The evidence base demonstrates where ROI is achievable, but does not specify how public bodies and firms can consistently procure AI: outcome-based contracting, subscription and AI-as-a-service models, vendor liability and warranties, audit rights, and blended finance all shape whether adoption is bankable and repeatable. For Ukraine, where public procurement frameworks are being modernised alongside EU accession preparation, embedding AI procurement templates into reconstruction programmes could significantly reduce transaction costs.

Cybersecurity and operational resilience

In critical sectors, notably energy and healthcare, secure deployment is a gating condition for vendor participation and operational acceptance. Security architecture, supplier assurance, incident response protocols, and continuity planning determine whether digital-first reconstruction increases resilience or introduces new vulnerabilities. Given the context of the armed conflict, this dimension carries particular weight for Ukrainian infrastructure operators and their international partners.

Lifecycle operations and model governance

Many AI deployments fail after initial rollout due to model drift, unclear ownership of system performance, insufficient monitoring, or lack of update and decommissioning processes. Sustained adoption typically requires an operating model for performance monitoring, retraining triggers, documentation, and accountability that extends well beyond the deployment phase. The AI Strategy 2030's commitment to responsible AI use practices addresses the governance dimension, but the operational infrastructure for lifecycle management is a separate requirement.

Organisational change and workflow redesign

The report addresses skills and ecosystem access but does not provide a change-management playbook. In practice, AI uptake depends on incentives, role redesign, operator trust calibration (including the staged deployment sequences documented in the medtech cases), and the integration of AI outputs into real decision rights within existing organisational structures. In healthcare, this translates into the 'clinical leadership' capacity that the evidence identifies as the least developed enabling condition for AI uptake: training medical professionals to utilise AI meaningfully, not merely deploying the technology alongside them.

Interoperability and standards as implementation requirements

The analysis highlights interoperability as a recurring constraint, particularly in medtech (PACS integration), manufacturing (supply chain data exchange), and energy (grid telemetry protocols). The report does not define minimum technical standards, APIs, reference architectures, or compliance test suites. Without these, scaling tends to fragment into non-interoperable vendor-specific deployments that limit the value of the data they generate.

Market-shaping for vendor presence

The synthesis identifies vendor-mediated adoption as the dominant pathway and notes that it depends on market presence. The policy levers that create vendor presence, anchor procurements, reference deployments, risk-sharing arrangements, localisation support, and predictable demand signals, are outside this report's scope but are a necessary complement to the access mechanisms it documents.

Public trust, transparency, and accountability in sensitive domains

The EU AI Act and sector-specific regulations appear in this report primarily as compliance frameworks. The legitimacy dimensions, explainability in deployment contexts, contestability of automated decisions, and mechanisms for accountability when systems fail, are important for scaling AI in health, energy, and public infrastructure, and will shape public acceptance in ways that technical compliance alone does not address.

These considerations do not alter the enabling-condition logic presented in this chapter, but they affect how quickly that logic can be translated into bankable programmes, credible partnerships, and sustained operations. They should be treated as a complementary implementation agenda alongside the sector-specific pathways set out in Chapter 2.

Appendix

APPENDIX
Diagnostic indicators by sector

The following indicators, drawn from the adoption pathways analysis in Chapter 2, provide a monitoring framework for tracking AI adoption readiness and progress across the seven sectors covered in this report.

Agritech

- Rural connectivity investment is reaching farming regions, including areas affected by the conflict.
- An agricultural testing facility with commercial SME access mandates is being established or accessed through EU network participation.
- EU agritech vendors are engaging the Ukrainian market through distributors or partnership programmes.
- The WINWIN national agricultural data platform is progressing in a form interoperable with the EU Common Agricultural Data Space.

Textiles

- The depth of EU supply chain integration among Ukrainian textile enterprises, as EU-integrated producers have the compliance-driven adoption incentive that is the primary driver in European cases.
- Whether pilot support programmes under the GDT Textile roadmap require vendors to be physically present during deployment, since programmes that fund remote rollouts are likely to produce stalled implementations.
- Whether the Twin Transition Roadmap's targets of 150 enterprises and 50+ pilot projects are being implemented with the bounded, ROI-first pilot structure that European evidence associates with successful operational transition.
- Whether EDIH network access for Ukrainian textile enterprises is being developed with sector-specific demonstration equipment.

Wood processing

- State Forest Agency operational capacity is being restored with data processing and response protocols incorporated, not only physical infrastructure.
- EU technology partners active in forest monitoring AI are engaging the Ukrainian market or participating in Ukrainian forestry partnerships.
- Reconstruction investment frameworks for wood processing facilities include requirements or incentives for digital integration at the design stage.
- EDIH network access for Ukrainian wood processing enterprises is being developed with relevant demonstration capability.

Medtech

- Ukrainian clinical AI companies have established multi-site clinical research partnerships with EU-recognised hospitals, as these partnerships generate the validation data CE marking requires.
- Hospital network infrastructure investment includes PACS interoperability standards, which is the gating condition for the most common EU imaging AI deployment pathway.
- Ukrainian medtech firms have initiated CE marking processes, since certification progress indicates the regulatory credibility pathway is being actively pursued.
- Clinical outcome measurement is built into Ukrainian AI deployments from the outset, enabling the evidence base that both EU regulatory pathways and procurement decisions require.

Automotive

- Ukraine's AUV and defence technology companies are establishing formalised EU partnership frameworks that could serve as the basis for ecosystem-based adoption, including the three strategic international agreements WINWIN targets.
- Regulatory sandbox provisions for autonomous systems are being developed in alignment with EU safety standards and UNECE WP.29 requirements.
- Reconstruction investment in industrial sites includes digital-first design mandates, creating the foundation for digital twin adoption in new or converted facilities.
- UNECE WP.29 regulatory alignment is progressing, which would indicate that the certification pathway for AI-equipped vehicles is being opened.

Semiconductors

- EDIH network access for Ukrainian firms is being formalised, as this is the gating condition for consortium-based fab AI adoption.
- Chips Act engagement that WINWIN targets is producing co-investment projects, not only memoranda, indicating that the partnership frameworks needed for scaling are being activated.
- The National Centre for Microelectronics that WINWIN envisions includes testing and validation functions equivalent to the EDIH testbed model, rather than being designed primarily as a research facility.
- Innovation cluster development is creating the ecosystem density that multi-partner AI consortia require in fabrication applications.

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