

A white industrial robotic arm is shown in a factory setting, positioned over a metal workpiece on a conveyor belt. The background is blurred, showing other factory equipment and lights. The text 'THE FUTURE OF INDUSTRIAL AI' is overlaid in the top right corner.

THE FUTURE OF INDUSTRIAL AI

TREND REPORT SPRING 2026



CENTER FOR
DIGITAL TECHNOLOGY
AND MANAGEMENT



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A Project of the Center for Digital Technology and Management

The Center for Digital Technology and Management (CDTM) is a joint, interdisciplinary institution for education, research, and entrepreneurship of the Ludwig Maximilians-University (LMU) and the Technical University of Munich (TUM).

It offers the certificate program "Technology Management" for students from various backgrounds, which provides students with tools and knowledge at the intersection of business and digital technologies.

The entire trend report was written by CDTM students under the close guidance of research assistants.

Visit www.cdtm.com for more information.

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PREFACE OF THE PROJECT PARTNER

Benno Blumoser



Julius Knolle



Syrine Torjmene



Artificial Intelligence (AI) is reshaping the world, and industrial settings are no exception. Yet industrial AI represents something fundamentally different from the wave that has captured public imagination through large language models and generative tools. It is not simply about processing text or generating content. It is about bridging the real and the digital: making sense of noisy, unstructured data from machines, sensors, and physical processes that do not conform to the assumptions underlying today's most celebrated models. This is a far more complex challenge, and precisely because of that complexity, a far more consequential one.

The stakes extend well beyond productivity. Industrial AI carries significant promise for sustainability: optimizing energy consumption, reducing material waste, and enabling industries to produce more with less. At a time when the pressure to decarbonize and operate more efficiently has never been greater, embedding intelligence directly into physical processes may prove to be one of the most powerful levers available. The transformation ahead is not only economic but also environmental.

Siemens has long been shaped by a belief that technology, applied thoughtfully, can change industries for the better. This conviction is rooted in the role the company is proud to have played in the second industrial revolution. That same conviction drives our engagement with industrial AI today, and it is what brought us, for the second time following a successful collaboration on "Digital Companions" in 2018,

to partner with the Center for Digital Technology and Management (CDTM) on this seminar.

The Center for Digital Technology and Management brings together some of Munich's most talented students, combining technological depth, entrepreneurial thinking, and genuine sensitivity to the societal implications of innovation. Their outside perspective proved particularly valuable: their external view helped us see our own internal landscape more clearly, identifying potential we might otherwise have taken for granted. This is precisely what makes CDTM such a compelling thought partner for a company navigating transformation from within.

We already see many incremental innovations taking shape within Siemens: industrial co-pilots, AI-assisted process improvements, and intelligent quality control. The more profound opportunities, however, lie ahead, such as disruptive shifts that will redefine entire value chains and create new categories of industrial capability. It is these opportunities, alongside the technological, business, and societal thinking needed to pursue them responsibly, that this seminar set out to explore.

We would like to extend our sincere thanks to the students for their good humor, the precision of their questions, the thoroughness of their analysis, and their consistent commitment throughout. A particular thank you goes to Raunaq Jain, António Mateus, and Vera Eger, whose dedication brought the CDTM concept to a new level of

maturity and quality. Their contribution shaped the seminar in ways that will be felt well beyond these five weeks. We are also incredibly grateful to our colleagues from Advanta - Eddie, Tim, and Clemens - and from Digital Industries and Foundational Technologies - Anton and Michi - for their invaluable guidance and for consistently asking the right questions that helped us delve deeper. Furthermore, a special thank you to Volker, Ralf, and Alex from the Amberg factory and the Impulse center for providing us with hands-on insights into the fascinating reality of manufacturing. Your support and expertise were truly appreciated by everyone!

It was genuinely fun and deeply inspiring. Thank you for five weeks of curiosity, rigor, and imagination.

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PREFACE OF THE EDITORS



We shape our tools, and thereafter our tools shape us.

John Culpin ”

From the manufacturing floors that build our physical world to the intricate supply chains that sustain global commerce, our economies are increasingly driven by autonomous systems and intelligent machines. That is why industrial AI has become a defining frontier of our time, the capacity to merge human expertise with machine intelligence to reshape how we produce and operate. If we want this technological shift to foster sustainable growth, economic resilience, and human well-being, we must build AI systems that are reliable, transparent, and collaborative, augmented by design, rather than automated without oversight.

At CDTM, our mission is to connect, educate, and empower the innovators of tomorrow. We equip our students with the tools and mindset to become responsible leaders who actively shape their future environments rather than merely respond to change.

This Trend Report is the outcome of the Trend Seminar within our interdisciplinary Technology Management program. Over seven intensive weeks, 26 students from fields including Business, Psychology, Medicine, Mechatronics, Robotics, Biomechanical Engineering, Computer Science, and Engineering investigated the Future of industrial AI. Working in interdisciplinary teams, they conducted rigorous trend research, developed forward-looking scenarios, and translated their insights into actionable product and service ideas and concrete business concepts by combining domain expertise with fresh perspectives and an entrepreneurial mindset.

We would like to thank everyone who contributed to making this CDTM Trend Report possible. We are especially grateful to Siemens for its support of this seminar. Our special thanks go to Benno, Julius and Syrine for the collaboration, insightful discussions, and steady feedback throughout the project. We also extend our gratitude to our lecturers, whose expertise and commitment were instrumental to the success of this report.

We hope these insights equip industry leaders, practitioners, and policymakers alike to make timely, informed choices, as the integration of industrial AI will shape not only global innovation and competitiveness, but also the future of work and the quality of everyday life for all of us.

In addition, we very much thank all our lecturers, who shared their knowledge and largely contributed to this project's success:

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Last but not least, we would like to thank the CDTM students of the Spring 2026 class. They put great energy and enthusiasm into this project, which made it a pleasure for us to supervise the course and coach the individual teams. Special thanks to the Heads of the editing, layout, sources, marketing, and QA teams (Josefine, Jonas, Krrish, Paulina, and Lucy) for finalizing the report.
António Mateus and Raunaq Jain

METHODOLOGY

The objective of the Trend Seminar is to provide a methodological approach for diving into a specific subject or industry sector and contemplating its future trajectory. The seminar guides its participants through three phases of trend research: trend, exploration, and ideation. Following this approach, the seminar first analyzes current trends and developments using in-depth desk research, site visits, and interviews with leading experts to establish a shared industry understanding. Next, participants identify areas within the sector where problems and opportunities will likely arise. In the final seminar phase, the students generate future-proof business ideas for products and services, addressing the identified problems and opportunities.

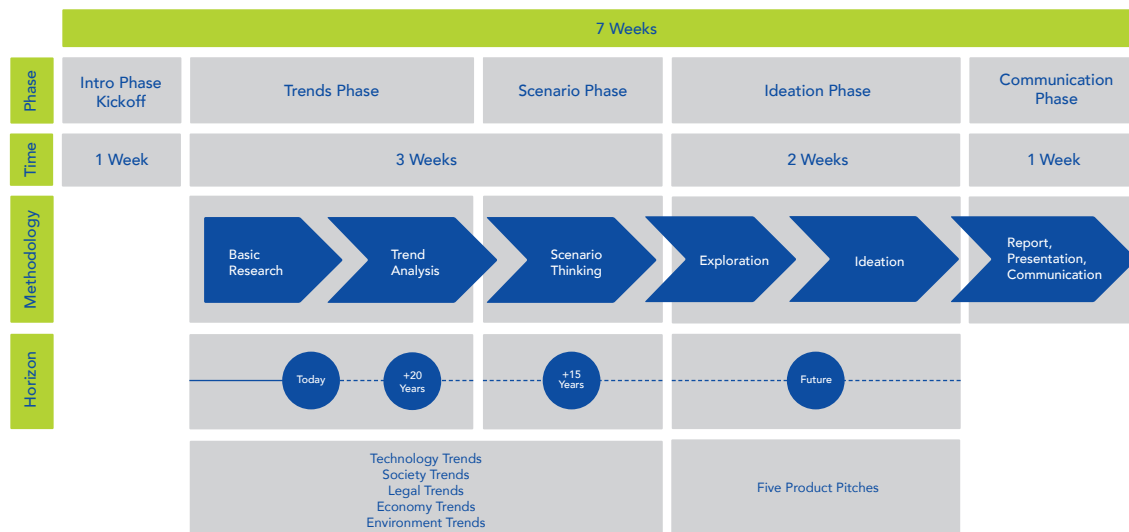
Up to twenty-six students, supervised by two doctoral candidates, pursue the Trend Seminar for seven weeks full-time during their semester break. The sector and framing for the seminar is provided by project partners from within the industry, who share their expertise and feedback, acting as sparring partners to the participants. In each phase, interdisciplinary subteams are formed with students from business, technology, and other disciplines. This interdisciplinarity allows for novel ways of thinking and the development of non-obvious ideas as well as leveraging the students' professional and personal growth throughout the course.

During the introduction week, the participants are prepared for the intense trend research ahead. First and foremost, the students are introduced to the specific industry the seminar is diving into. Project partners and industry experts present past and current industry developments from their individual stakeholder perspectives, engaging in open discussions with the students. Additionally, interactive sessions teach trend research methodologies and refine the participants' communication and teamwork skills.

Following the introduction, the **trends phase** of the seminar covers desk research, expert interviews, and expert lectures, enabling the participants to dive deep into the topic at hand. During the expert interviews, students are empowered to pose specific questions to challenge their initial assumptions on how the industry will develop. Beyond that, site visits at the project partners' facilities complement the students' body of research and allow for further verification of their hypotheses. The derived trends are extrapolated 20 years into the future, providing a long-term perspective, which is further refined through **scenario** workshops.

The first half of the **ideation phase** is about **exploring**. Future opportunities and problems are clustered into specific spaces based on the research done in the preceding phase. The students are reshuffled into new teams and explore these spaces by looking into existing startups and projects. Through interviews and discussions with industry experts, the teams validate their hypotheses to identify unmet needs and existing gaps in the industry landscape.

During the second half of the **ideation phase**, students brainstorm **business solutions** addressing the previously identified gaps. To facilitate the ideation process, the students are introduced to structured and unstructured ideation methods. This allows them to generate many ideas before consolidating them and building comprehensive business models. Finally, the research results and the business ideas are pitched to the project partners, industry stakeholders, and the general public.



LIST OF ABBREVIATIONS

AAS Asset Administration Shell	CMMS Computerized Maintenance Management System	ERP Enterprise Resource Planning	GPT General Pre-Trained Transformer	IoT Internet of Things	NDA Non-Disclosure Agreement
AI Artificial Intelligence	Cobots Collaborative Robots	ESG Environmental, Social, and Governance	HMLV High-Mix/Low-Volume	IP Intellectual Property	NIS2 Network and Information Security 2
API Application Programming Interface	CPS Cyber-Physical Systems	ESPR Ecodesign for Sustainable Products Regulation	HVAC Heating, Ventilation, and Air Conditioning	IPO Initial Public Offering	NIST National Institute of Standards and Technology
AR Augmented Reality	CRMA Critical Raw Materials Act	EU European Union	IAS International Accounting Standard	ISO International Organization for Standardization	OECD Organization for Economic Cooperation and Development
BPO Business Process Outsourcing	CSS Chemicals Strategy for Sustainability	FL Federated Learning	IASB International Accounting Standards Board	IT Information Technology	OEM Original Equipment
CAD Computer-Aided Design	DP Differential Privacy	FMOps Foundation Model Operations	IDC International Data Corporation	MaaS Manufacturing-as-a-Service	OT Operational Technology
CAGR Compound Annual Growth Rate	DPDP Digital Personal Data Protection	GDG Gross Domestic Product	IEC International Electrotechnical Commission	MES Manufacturing Execution System	PLC Programmable Logic Controller
CAPEX Capital Expenditure	DPP Digital Product Passport	GDPR General Data Protection Regulation	IFM Industrial Foundational Model	MiCA Markets in Crypto-Assets Regulation	PLM Product Lifecycle Management
CDTM Center for Digital Technology and Management	EaaS Equipment as a Service	GENIUS Guiding and Establishing National Innovation for U.S. Stablecoins	IFO Information und Forschung	ML Machine Learning	prEN Preliminary European Norm
CEAP Circular Economy Action Plan	EPD Environmental Product Declaration			MRO Maintenance, Repair, and Overhaul	R&D Research and Development

RMS

Reconfigurable Manufacturing System

RWA

Real-World Asset

SCADA

Supervisory Control and Data Acquisition

SI

System Integrator

SME

Small or Medium-sized Enterprise

SSbD

Safe and Sustainable by Design

TOPS

Tera Operations per Second

TRL

Technology Readiness Level

TSR

Total Shareholder Return

OPC UA

Open Platform Communications Unified Architecture

UNESCO

United Nations Educational, Scientific and Cultural Organization

US

United States

VLA

Vision-Language Action

WEF

World Economic Forum

WTO

World Trade Organization

WUE

Water Usage Effectiveness

ZB

Zettabyte

TRENDS

The following chapter lists current trends that have a strong influence on the development and long-term strategic orientation of the future of industrial AI. In accordance with the Trends Phase methodology, trends and related driving forces are structured into five areas: technological trends, societal trends, legal trends, economic trends, and environmental trends.

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TECHNOLOGICAL TRENDS

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Enabling Real-Time Inference

Advancing Maintenance Autonomy

Harmonizing Data Infrastructure

Extending Production-System Logic

Deploying Continuous Intelligence

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TECHNOLOGICAL TRENDS

Influencing the Future of Industrial AI

Industrial AI has moved beyond isolated point solutions, where individual algorithms handled single tasks such as defect detection or demand forecasting in disconnected deployments [1, 2]. It is becoming the operating logic of a new production paradigm where factories sense, reason, and adapt in real time [3]. The second- and third-order consequences of today's technological building blocks will compound over the next decades, creating new categories of competitive advantage where effects reinforce each other and binding constraints where critical challenges remain unsolved.

First-order effects are already visible. Edge processors move inference closer to the shop floor, reducing response time and enabling near-real-time local decisions that cloud-only architectures may struggle to support consistently [4]. Predictive maintenance replaces fixed schedules with data-driven foresight, improving downtime forecasting accuracy by up to 85%, reducing unplanned machine downtime by up to 50%, and extending machine life by 20% to 40% [5, 6]. Semantic data layers are starting to bridge the protocol fragmentation

that has kept operational technology (OT) isolated from the information technology (IT) systems where AI runs. Here, legacy assets without modern connectivity remain the dominant integration barrier in manufacturing environments [7, 8]. Physical AI is extending robotic capabilities beyond tightly scripted assembly settings into more adaptive, real-world, and high-mix low-volume (HMLV) industrial environments such as aerospace [9, 10]. Industrial foundation models offer broad cross-task adaptability, but deployment in tightly controlled industrial settings poses challenges related to generalization, trustworthiness, interpretability, and continual learning [11, 12].

The deeper story is what happens when these capabilities compound. When edge inference meets semantically harmonized data, it creates the precondition for closed-loop autonomy, where production lines self-regulate without human arbitration [4, 7]. When predictive maintenance matures through prescriptive into autonomous intervention, downtime stops being an event to recover from and becomes a residual that the system continuously minimizes [13]. When

physical AI makes automating HMLV work economically viable, the logic of mass production migrates into domains that have resisted systematization for decades, from aerospace to construction and medical devices [9, 10].

The same interconnectedness that enables these compounding gains, however, simultaneously widens the attack surface and raises the governance stakes, making data integrity, cybersecurity, and regulatory alignment structural prerequisites rather than secondary considerations. Industry 6.0 envisions cross-company AI ecosystems, federated learning across supply chains, and sustainability-driven manufacturing as converging outcomes of advanced connectivity and interoperability architectures [7]. Industrial foundation models demand an entirely new operational discipline, Foundation Model Operations (FMOPs), to manage data quality, detect drift, and maintain alignment across hundreds of specialist models running simultaneously [11, 14].

ENABLING REAL-TIME INFERENCE

Advancing Hardware Architectures to Meet Time-Sensitive Inference Demands

Processing data on factory-floor hardware rather than remote servers reduces latency and keeps proprietary production data on premises [4]. In collaborative robot-human environments, any delay between sensing and action directly reduces the safety margin [15]. Safety-critical processes, such as real-time collision avoidance of collaborating robots (cobots), therefore must meet certain response time thresholds [16]. Meeting these thresholds on-premises requires hardware that combines fast computation with high energy efficiency. Established semiconductor hardware increasingly struggles to satisfy this, which is driving development beyond conventional silicon [17]. Novel processor architectures exploit different physical mechanisms to achieve higher efficiency [18, 19]. Neuromorphic processors, inspired by the biological brain, deliver up to 100 times higher energy efficiency and 50 times higher speed than conventional processor architectures for inference tasks [18]. Photonic computing uses light instead of electrons to achieve inference at 29 femtojoules per operation and speeds more than 100 times faster than leading NVIDIA processors for generative AI workloads [19, 20].

Facts

- Because transmission of information cannot exceed the speed of light, centralized clouds face a physical minimum latency, making data proximity a strict constraint for latency-critical applications [21, 22].
- European Union (EU) data sovereignty regulations favor on-premises processing. General Data Protection Regulation (GDPR) carries fines up to 20M EUR or 4% of turnover, the Data Act mandates machine-readable access for switching between services, and the AI Act classifies safety-component AI as high-risk [23, 24, 25].

- Global robotics investments grew 230% between 2019 and 2024 and are projected to surpass 100B USD by 2030, accelerating demand for on-premises inference [26].

Key Drivers

- Industrial AI applications such as autonomous mobile robots and real-time quality control often operate under strict latency constraints for which on-premises compute is structurally well-suited [16].
- As human-robot collaboration scales globally [26], each new installation adds a latency-sensitive system to the factory floor, directly expanding demand for local compute infrastructure [15].
- Manufacturers deploying AI in safety-critical manufacturing steps face direct legal accountability under the AI Act and GDPR, creating structural pressure to retain data processing within controlled on-premises infrastructure [23].

Challenges

- Cybersecurity exposure is acute, with 52% of industrial companies having experienced cyber attacks involving operational technology or IoT devices. Yet only 40% offer regular cybersecurity training, and 60% rate their budget as inadequate [27].
- Legacy system integration remains difficult because more than 70% of North American factory machinery exceeds 20 years of age, and most equipment predates digital interfaces [28, 29].
- Distributing AI inference across factory-floor hardware expands the attack surface, making industrial systems more vulnerable to both physical and network-based threats [30].

Impact on Industrial AI

On-premises AI inference enables the millisecond-level response times that quality inspection, predictive maintenance, and real-time robot coordination require. Cloud architectures face a structural latency floor from data transmission distances [22], which on-premises compute eliminates by processing data at its source [4]. Furthermore, local inference reaches settings where cloud connectivity is structurally unavailable [4], such as offshore platforms, deep-sea operations, and mining. Novel hardware like neuromorphic and photonic processors achieve significant energy reductions at high computation speed [18, 19, 31].



ADVANCING MAINTENANCE AUTONOMY

Evolving Factory Maintenance from Preventive to Predictive to Prescriptive to Autonomous

Factories are increasingly progressing from preventive to predictive maintenance [32]. Preventive maintenance relies on fixed schedules, which often leads to unnecessary servicing or missed failures [33]. Predictive maintenance enhances this approach by utilizing sensor data, machine learning, and condition monitoring to forecast failures before they occur, thereby reducing downtime and optimizing spare parts planning [6, 32]. Prescriptive maintenance goes further by recommending specific actions, such as when to intervene and which component to replace, using digital twins and optimization models to evaluate trade-offs [13]. Autonomous maintenance represents the frontier, where AI systems not only detect and recommend but also execute maintenance decisions through robotics, self-calibrating machines, or closed-loop control systems [13]. Consequently, humans shift from operators to supervisors, focusing on system design and exception handling [13]. Driven by workforce constraints and the push for higher productivity, this evolution will fundamentally reshape factory operations [13].

Facts

- 74% of participating manufacturers view predictive maintenance as critical to future success, highlighting a clear shift toward data-driven tools that anticipate equipment failures [32].
- The global predictive maintenance market was valued at 14.29B USD in 2025 and is projected to reach 98.16B USD by 2033, growing at a compound annual growth rate of 27.9% [34].
- AI inference accounts for 80-90% of all AI computing energy, making energy-efficient on-premises computation a structural requirement for real-time maintenance applications [35].

Technological Trends

Key Drivers

- Predictive maintenance has achieved up to a 50% reduction in unplanned machine downtime, a 55% increase in maintenance staff productivity, a 20-40% extension in machine life, and up to a 40% decrease in maintenance costs [5, 6].
- Sensor networks and IoT connectivity generate continuous streams of data, enabling predictive and self-maintaining systems that proactively mitigate failures [2].
- Manufacturers increasingly face aging workforces and technician shortages, making automation attractive as it enables continuous operations even during labor disruptions or geopolitical supply shocks [32, 36].

Challenges

- Predictive maintenance relies on large volumes of high-quality labeled failure data, which are scarce in industrial settings because failures are rare and costly to observe, limiting model accuracy [37].
- 69% of surveyed facilities operate aging machinery that lacks modern sensors or connectivity, and retrofitting legacy equipment often requires custom hardware, which raises costs and limits scalability [32].
- As maintenance becomes more autonomous, practical tacit knowledge may erode among human operators, making recovery more difficult when rare failures exceed the AI system's trained response space [38].

Impact on Industrial AI

The shift from preventive to predictive, prescriptive, and ultimately autonomous maintenance marks a core trajectory of industrial AI maturity [6, 32]. AI systems now analyze real-time sensor data to predict failures, recommend optimal interventions, and increasingly execute maintenance autonomously [2, 37]. This transition reduces downtime, lowers lifecycle costs, and improves asset utilization while reshaping workforce roles toward supervision and system design [5, 32]. It also accelerates the adoption of digital twins, edge AI, and closed-loop control architectures [37, 39]. Maintenance autonomy ultimately becomes a gateway to self-optimizing factories, where AI continuously adapts operations for resilience and efficiency [13, 36].



HARMONIZING DATA INFRA-STRUCTURE

Unifying Data for AI Across the Shop Floor

Industrial AI requires interoperable and semantically coherent operational data [1, 40]. Today, this is largely unmet. Most production environments still rely on legacy machines using communication protocols for local control instead of semantically structured data exchange [1, 7, 40]. OT remains siloed from IT infrastructure without a data source connectivity layer [41, 42]. Even with modern, IoT-enabled machines, connectivity does not guarantee interoperability [42]. Vendors implement standards differently, producing data streams that are often syntactically compatible but semantically incompatible [43]. Yet modern edge platforms integrate semantic frameworks that define each data point, making heterogeneous assets usable [44]. Combined with multimodal inputs from vision and sensor systems [45], this enables a unified data layer across the shop floor. Without this harmonized data, each use case requires bespoke pipelines. With it, models generalize across assets and sites by using cross-process context for intelligent perception and decision-making [1, 46, 47]. Unlocked capabilities span from predictive maintenance and real-time process optimization to cross-organizational digital twins and closed-loop orchestration [48, 49, 50].

Facts

- Standardized and harmonized data enable interoperability. Interoperability has been shown to increase efficiency and innovation through seamless communication and data integrity across physical and digital domains [51].
- 70% of SMEs (Small and Medium Enterprises) manufacturing devices are legacy machines. Firms prioritize brown-field connectivity to unlock AI value via gateways and retrofiting [47, 52].
- The global data integration market is projected to grow from 19.21B USD in 2026 to 51.82B USD by 2035, at an 11.72% Compound Annual Growth Rate (CAGR) [53].

Key Drivers

- AI pilots in manufacturing are failing due to data fragmentation, creating organizational pressure for a harmonized data infrastructure [54].
- Internet of Things (IoT) sensor unit costs have fallen to 0.50 USD, from 1.30 USD in the early 2000s, and maturing edge platforms are lowering barriers to harmonization, making interoperability investments viable for SMEs as well as large manufacturers [46, 55].
- Open Platform Communications Unified Architecture (OPC UA) and the Asset Administration Shell (AAS) are establishing semantic vocabularies, while the EU Digital Product Passport (DPP) is making standardized data a necessity [48, 56]. Catena-X and Manufacturing-X make cross-company data sharing viable [49].

Challenges

- Ransomware against OT environments jumped 46% between Q4 2024 and Q1 2025 [57].
- IT and OT convergence, which enables data harmonization, simultaneously increases exposure to cyber attacks, with 65% of manufacturing executives ranking operational risk, including cybersecurity breaches as a top concern [54, 58].
- IT and OT teams operate under separate leadership with misaligned priorities, producing governance silos that must be resolved before semantic data standards can be adopted and scaled across the shop floor [41].

Impact on Industrial AI

The utility of industrial AI in heterogeneous environments depends on a unified representation-learning architecture that integrates domain-specific data to enable intelligent perception and decision-making [47]. Without semantically coherent, streamed OT data, AI models cannot generalize across assets, production lines, or supply chain partners [1, 46]. Harmonization at the asset level and at the ecosystem level unlocks the full AI spectrum ranging across the shop floor [48, 49, 59]. Long term, data interoperability could enable autonomous factory operations through closed-loop AI process orchestration [7, 51].

EXTENDING PRODUCTION-SYSTEM LOGIC

Expanding Structured Factory Workflows into Unstructured Domains Through Physical AI

Manufacturing is shifting from robots that follow fixed rules to machines that can sense and adapt [60]. For decades, industrial automation was confined to controlled environments where every robot movement was manually programmed for a specific setup [3, 61]. Physical AI is enabling the extension of these capabilities into domains considered too variable or specific to automate [9, 62]. In HMLV environments such as aerospace or defense, traditional automation fails because each variant requires its own programmed instructions, and the configuration cost exceeds the task's value [9, 63]. Physical AI promises to overcome this by enabling machines to learn tasks like autonomous sanding or complex assembly through reinforcement learning and simulation [9]. Instead of manually coding every movement for each variant, the system learns from data, converting the challenge from a configuration into a data problem [9, 61]. Today, the critical shift enabling physical AI is the move toward world models: foundation models that understand physics, reason about space and time, and improve through real-world interaction [64].

Facts

- By 2032, nearly 40% of aerospace production, one of the most complex HMLV industries, is expected to be lights-out, signaling that even the hardest-to-automate domains are now within reach [65].
- The global installed base of industrial robots reached 4.66M units in 2024, more than doubling over the past decade, with annual installations projected to surpass 700,000 units by 2028 [66].
- The global physical AI market is projected to grow from ~5B USD in 2025 to ~68B USD by 2034 at a ~33% CAGR, driven by surging demand for intelligent machines across manufacturing, logistics, and healthcare [67].

Technological Trends

Key Drivers

- With 98% of manufacturers reporting labor shortages [68] and 87% expecting these to worsen due to an aging workforce [69], HMLV sectors face compounding cost pressures from low automation rates [10, 70].
- Horizon Europe's robotics work program, Germany's Robotics Institute initiative, and sizable US autonomy and robotics budgets together direct hundreds of millions of public Research and Development (R&D) funding into industrial AI and robotics capabilities [71].
- Vision-Language-Action (VLA) foundation models are rapidly evolving as a promising path to unlock generalizable spatial reasoning capabilities [3, 72, 73].

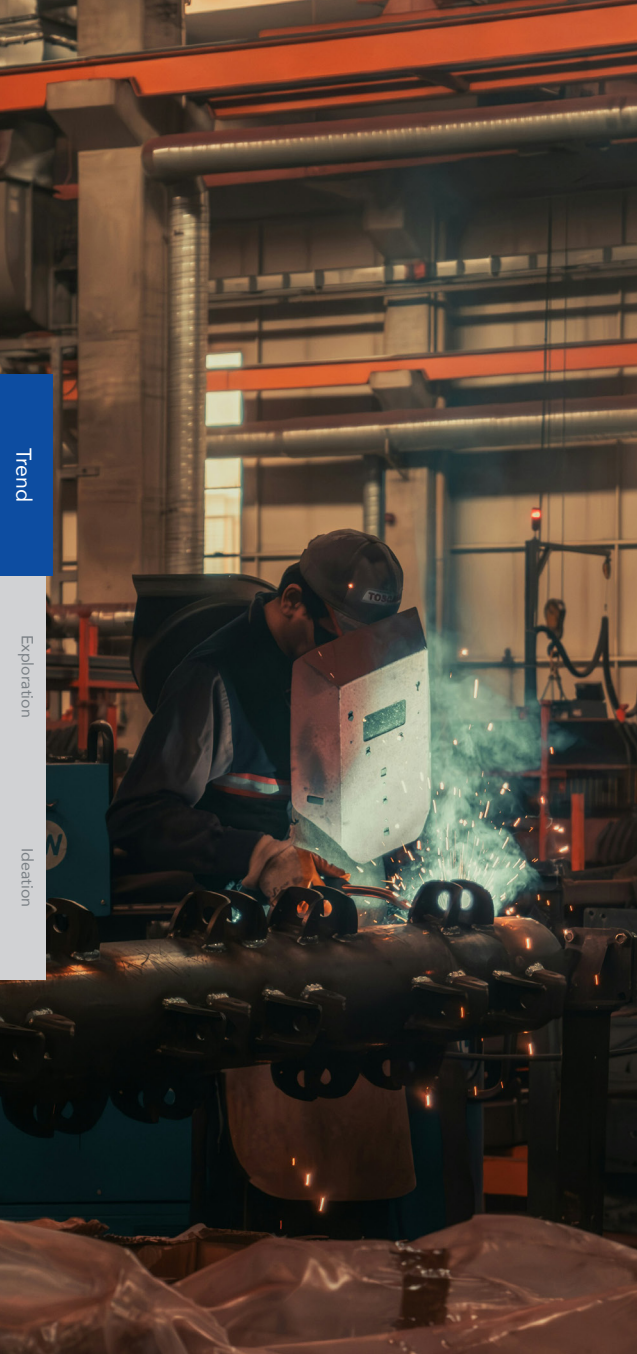
Challenges

- Access to proprietary operational data, robust digital infrastructure, and modernized control systems will be key bottlenecks, slowing adoption for late-digitizing manufacturers [74].
- Wider deployment raises concerns about workforce displacement, surveillance, military applications, and concentrated control of critical AI hardware and models [75].
- Humanoid and general-purpose robots remain niche and cost-inefficient versus specialized cells, with production-grade reliability still unproven, succeeding on only 15% of rare high-mix variants compared to 54% on common tasks [76, 77].

Impact on Industrial AI

Physical AI enables more scalable execution of traditionally custom work, extending automation into unstructured environments [9, 63]. As HMLV industries - aerospace, medtech, construction, and their Maintenance, Repair, and Overhaul (MRO) operations - adopt line-like orchestration, constraints shift from labor scarcity to the speed of deploying standardized production playbooks [10]. In parallel, capabilities become transferable across product configurations, spreading investment costs across product families [9, 63, 64]. This creates a new scale economy in complex industries, where cost curves decline with volume and advantage accrues to operators who industrialize expert workflows fastest [3, 10].





DEPLOYING CONTINUOUS INTELLIGENCE

Establishing Industrial Foundation Models as Operating Systems of the Factory Floor

Today, most industrial AI deployments are static, with task-specific models trained once and left running until they quietly lose accuracy as production conditions change [11, 12]. Industrial foundation models are set to change this. Within the next few years, a single unified AI system will process thousands of sensor streams and make real-time production decisions across an entire factory floor [78, 79]. In practice, this will not operate as a single monolithic model, but as a powerful base model at the top, with a fleet of smaller, fine-tuned, distilled variants deployed across individual production lines, as smaller models outperform models ten times their size on narrow, repetitive tasks [11, 12, 80]. Equipment ages, materials change, and conditions shift, gradually causing models to drift from the reality they were trained on [12]. If left unmanaged, data drift silently degrades accuracy until the model makes a costly decision [78, 79]. This is what makes an AI-embedded factory operating system a necessity, an autonomous layer that enforces quality standards, detects drift, and triggers re-distillation from the base model when needed [11, 12, 14].

Facts

- Industrial AI and IoT applications require 30 to 100 milliseconds of latency for real-time edge inference, necessitating techniques such as knowledge distillation to maintain accuracy under compute constraints [81].
- The global industrial AI market, valued at 9.5B USD in 2024, is projected to reach 54.5B USD by 2032, indicating strong investor confidence in the technology [82].
- 80% of manufacturers are currently using or planning to adopt generative AI, with incumbents such as Siemens and Microsoft already integrating foundation models into their industrial platforms [78].

Key Drivers

- Modern plants operate thousands of interconnected sensors, digital twins, and multi-stage processes whose volume and interdependency exceed what narrow models can handle, making the shift toward industrial foundation models necessary [12].
- Predictive maintenance and process optimization have already delivered measurable returns, giving manufacturers the confidence to invest further, with unified AI systems representing the logical next step [78, 79].
- Edge computing paired with knowledge distillation now enables low-latency inference with lower bandwidth consumption in industrial deployments, fulfilling infrastructure needs that were once a bottleneck [83].

Challenges

- In high-stakes industrial environments, AI hallucinations can trigger costly shutdowns or safety failures, making reliability verification a prerequisite for deployment in safety-critical production processes [11, 12].
- A universal industrial foundation model is highly unlikely given the variability in plant operations, equipment physics, and failure modes across industries, though domain-specific foundation models are feasible [12].
- Once deployed, industrial foundation models introduce a new operational burden in managing data quality, detecting drift, and maintaining model alignment, necessitating dedicated foundation model operations infrastructure [11, 14].

Impact on Industrial AI

Industrial foundation models shift factory operations from static, task-specific automations to a continuously learning intelligence layer, with a powerful base model and various fine-tuned, distilled versions running directly on production lines [11, 12, 80]. This architecture enables accuracy within latency and compute constraints while adapting to changing production conditions in real time [78, 79]. Even conservative adoption compounds over time, with fewer breakdowns, leaner designs, and more energy-efficient production systems [78, 79]. However, running a factory on this architecture requires continuous drift detection and model alignment, making dedicated AI operations infrastructure not optional but inevitable [11, 12, 14].

SOCIETAL TRENDS

INFLUENCING THE FUTURE OF INDUSTRIAL AI



Reconfiguring Trust Establishment
Evolving Toward Orchestrators
Encoding Tacit Human Knowledge into AI
Catalyzing Workforce Reskilling
Hollowing out Towns via Automation

Ali Batur Karakullukcu



Jonas Walcher



Lara Schupp



Marlene Böhm



Paulina Möhrle



SOCIETAL TRENDS

Influencing the Future of Industrial AI

As industrial AI matures technologically, its real-world impact will increasingly hinge on societal readiness. The impact ranges from trust between humans and autonomous systems, through a generational transition in the industrial workforce, to the race between technological change and skills adaptation.

Scaling AI in industrial environments depends on calibrated trust, which is no longer a soft cultural factor but a measurable system property that must be achieved on cognitive, emotional, and institutional levels [84]. However, this foundation is frequently undermined when surveillance tools meant to improve safety also create opacity, leading to worker dissatisfaction and performative productivity [85].

At the same time, the role of the industrial worker is shifting from manual execution to supervisory orchestration. As agentic AI systems, projected to grow at a 25% CAGR through 2030, begin to autonomously analyze data and adjust parameters, workers are transitioning into roles that resemble air-traffic control, intervening primarily in rare, com-

plex situations that make their work more strategic yet more demanding [86, 87]. Cobots growing at more than 30% per year, are accelerating this transition by placing autonomous systems directly along-side human operators on the factory floor [88].

A critical challenge in this transition is preserving the tacit knowledge embedded in experienced workers. With 13.4M people in Germany alone reaching retirement age within the next 15 years, and an estimated 1.9M manufacturing roles at risk of going unfilled by 2033, companies face the loss of decades of accumulated expertise [89, 90]. AI is being leveraged to digitize this tribal knowledge, shifting knowledge flows from senior-to-junior transmission toward system-mediated access [91].

Simultaneously, rapid technological change is widening the industrial skills divide. Employers expect 39% of workers' core skills to change by 2030, creating an urgent need for continuous reskilling [92]. Without large-scale intervention, the workforce risks fragmenting into highly skilled technical

specialists and routine workers displaced by automation, potentially pushing critical expertise toward platform-mediated or gig-based labor models [93, 94].

Lastly, the maturation of AI is decoupling production from local populations. As factories become capable of running with minimal human intervention, high-skill roles increasingly manage operations via remote networks. A 10 percentage point drop in manufacturing employment share is associated with roughly 9.5 fewer local amenities per 10,000 residents, illustrating the cascading community effects of this shift [95]. This geographic reorganization risks depriving legacy industrial communities of their economic anchors while concentrating growth in urban technological centers [96, 97]. This report examines five converging societal trends that will shape how industrial AI transforms not just production systems but the people and places that depend on them.

RECONFIGURING TRUST ESTABLISHMENT

Requiring System Reliability and the Careful Calibration of Human Reliance for Driving Trust

Safe Human-AI collaboration requires adaptive trust calibration to prevent operators from over-trusting or under-using autonomous systems [98]. Scaling AI needs workers' trust, but that foundation is undermined when worker surveillance and a lack of explainability create an environment of opacity [99]. The changes required to realize a symbiotic human-AI partnership can have a disruptive impact on the workforce within manufacturing companies [100]. Trust in AI differs significantly from trust in traditional automation due to the AI's ability to simulate human-like intelligence and autonomy [101]. Research indicates that trust in these systems is multi-dimensional and must be achieved at three levels [84]. Cognitive trust is grounded in the user's rational assessment of the system's competence, reliability, and predictability. Emotional trust arises from the affective bonds formed through anthropomorphic cues (such as human-like design) and responsive behaviors [102]. Lastly, institutional trust reflects an evaluative orientation toward AI as a regulated system by the granting of institutional status [84].

Facts

- Trust in AI can be increased by the perceived cognitive and emotional capacity of the systems and decreased by societal-level concerns [84].
- Explainability is one necessary foundation for human trust in AI, but true trust requires connecting ethical principles and technical requirements such as transparency [103].
- Fear of algorithmic flagging stifles dialogue [85], and AI monitoring can cause greater dissatisfaction and resistance than human supervision [104].
- 61% of United States (US) adults oppose tracking their movements, while about half reject AI-driven workforce decisions, such as layoffs [105].

Key Drivers

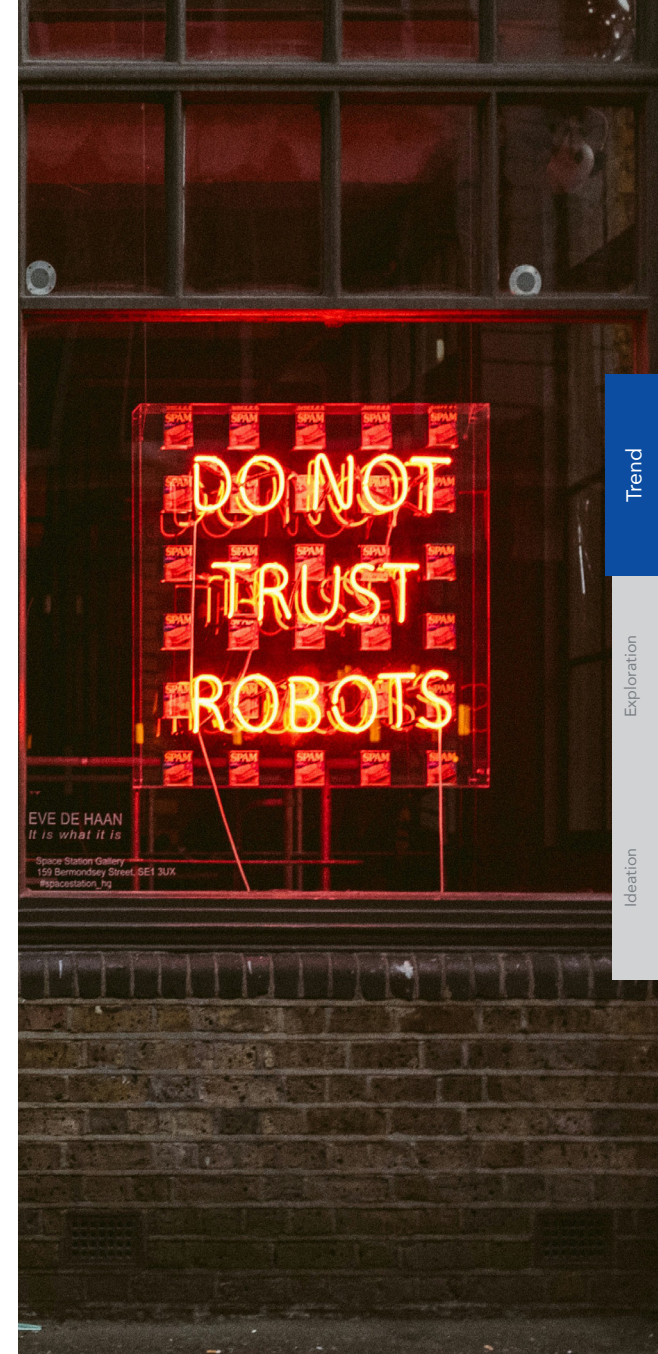
- In multi-agent industrial AI systems, trust must be established through a "trust by design" approach, embedding ethical principles such as transparency and accountability [106].
- Future workers in industrial sectors must not only possess high technological literacy but also a clear understanding of AI and data [92].
- As a response to privacy concerns, many corporations are deploying privacy-preserving AI techniques. This enables companies to claim they are protecting worker privacy while still exerting control [107].

Challenges

- Seeing an algorithm error disproportionately destroys trust compared to human error, even if the AI is more accurate. While explainability aims to bridge this gap, it often highlights flaws in logic, further increasing algorithm aversion [108, 109].
- When feeling threatened in their autonomy, workers tend to act with "performative productivity", as in appeasing the algorithm, which undermines genuine innovation [85].
- Trust suffers when algorithmic fallout occurs, which is when biased, automated systems ignore human commands or prioritize speed over fairness, causing severe personal harm and eroding industrial trust [110].

Impact on Industrial AI

In a high-trust scenario, autonomous systems are seamlessly embedded in work and social interactions, acting as trusted partners handling complexity while humans provide knowledge and judgment [111]. In a low-trust environment, the industry may stagnate. Resistance behaviors could undermine productivity gains, and the "privacy trap" will lead to a culture of fear and alienation [110]. Organizations that fail to build trust will find their AI projects stalling under operational stress and human resistance [99]. If AI monitoring is framed as a tool for developmental feedback, resistance is lower. This suggests transparency and worker control are the deciding factors in whether surveillance builds or destroys trust [99].



EVOLVING TOWARD ORCHESTRATORS

Shifting Industrial Workers to Supervisors of Autonomous Production Systems

Industrial production is entering a phase in which humans increasingly orchestrate autonomous machines and AI agents rather than directly operating them [112, 113]. Workers monitor processes, check decisions, and step in when problems occur [87, 112, 114]. This shift drives the “Irony of Automation”: as routine tasks disappear, human work shifts toward more complex matters such as managing exceptions, unforeseen circumstances, and the informal judgments that automated systems cannot replicate [87, 116]. Simultaneously, AI-driven manufacturing introduces new sources of error, including algorithmic bias, narrow optimization goals, and systems trained on historical data that cannot recognize novel situations, all of which require human oversight [116]. A comparable structure is already in place in software development, where engineers coordinate AI coding agents that generate and test code while humans focus on planning, debugging, and validation [117]. Similar transitions are seen in nuclear power plants and air traffic control, where automation turned operators into supervisors of complex socio-technical systems [112, 115]. As industrial AI spreads across production and logistics, workers increasingly rely on Augmented Reality (AR), wearables, and conversational human-machine interfaces instead of direct mechanical control [76, 92, 113].

Facts

- By 2030, automation will drive 82% of the projected 15-point drop in human work tasks, and only 19% from human-machine collaboration [92].
- The agentic AI market in manufacturing is expected to grow at ~25% CAGR through 2030 [86, 118].
- Cobots, designed to work alongside human workers, will grow at an average of 30% yearly until 2030, far faster than the overall industrial robotics market, which grows at about 6% annually [88].

Key Drivers

- AI agents that can plan, make decisions, and coordinate production are increasingly used in factories [113]. Agent-based industrial AI can analyze production data, adjust machine parameters, and optimize workflows autonomously.
- New technologies such as cobots, AR tools, and AI interfaces help workers supervise and interact with complex machines more effectively [113].
- Human workers increasingly act as trainers and validators of industrial AI, providing feedback when systems encounter new conditions, thereby continuously improving models [119].

Challenges

- Excessive automation may reduce workers’ awareness of what is happening in the system and skills, making it harder for workers to step in when systems fail [115].
- Many industrial skills are learned through hands-on work with machines, hence reduced manual interaction with machines may erode valuable craft knowledge [120].
- Coordinating humans and AI becomes complex because future factories may combine two models: the hierarchical approach of humans directing machines and the heterarchical model of humans and machines working as equal partners [114].

Impact on Industrial AI

Factories are moving toward architectures in which AI agents autonomously optimize production while humans supervise, review decisions, and intervene in edge cases [118, 121]. This requires balancing highly automated systems with the need for humans to understand and control them [122]. Also, it demands transparent decision-making, intuitive interfaces, and strong governance frameworks [76, 123, 124]. As workers increasingly supervise fleets of autonomous systems, cognitive ergonomics will become critical, shifting safety research from physical to cognitive workload and human-AI coordination [123]. Future factories may resemble remote control rooms, where workers oversee robots, digital twins, and AI planning systems.

ENCODING TACIT HUMAN KNOWLEDGE INTO AI

Integrating Vertical Knowledge on the Industrial Shop Floor

Industrial workers are increasingly becoming data generators and feedback providers for their algorithmic counterparts [125]. Currently, this is used for imitation learning, which does not meet the requirements for training complex industrial tasks, where performance depends on experience and situational judgment [119]. Industrial workers collect years of experience, shaped by training and context-dependent expertise [120]. When these knowledge holders leave, successors often face long ramp-up times to close skill gaps [126], during which errors and inefficiencies rise [126, 127]. Across manufacturing, generational change is a continuous process, with experienced employees retiring and taking vast accumulated knowledge with them [128]. Valuable knowledge is often implicit, embedded in experience and contextual understanding that is rarely transferred into static documents, leading to a lack of knowledge exchange [120, 129]. To address this, new approaches now ground AI in company-specific data and operator expertise, as general-purpose models underperform without business-specific context [130, 131].

Facts

- Within the next 15 years, nearly one-third of the workforce could retire [89], while 59% of manufacturing and retail workers aged 55 and older are expected to leave within the next five years [132].
- Deloitte and the Manufacturing Institute estimate that 1.9M manufacturing roles could go unfilled by 2033 [90].
- In industries with long product cycles, workforce headcount is planned years in advance. Shrinking proficiency disrupts assumptions about consistent productivity, forcing them to rehire retirees to relaunch legacy systems [127].

Key Drivers

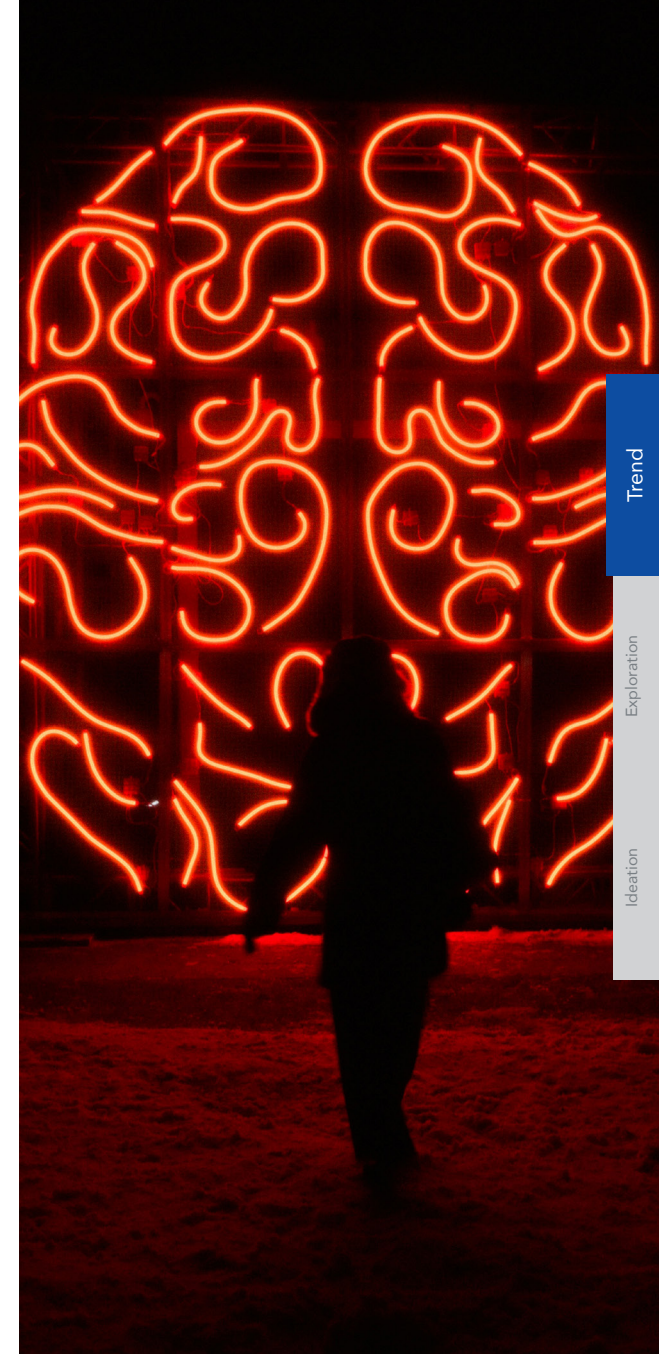
- Experienced workers are retiring faster than they can be replaced, leaving manufacturers with too few senior experts to onboard new hires and pass on know-how [127].
- Industrial operations are becoming even more complex through more specialization, larger systems, globalized R&D and production, as well as growing technology use. These are creating more coordination demands within companies and more dependencies across their wider industrial networks [133, 134].
- Captured knowledge becomes an organizational advantage when cross-functional visibility makes know-how usable beyond a single team or shift [135, 136].

Challenges

- Human input remains a weak point, as annotation and measurement bias in defect labeling or process-state tagging can directly undermine model performance [137, 138].
- Capturing experience at scale is difficult. Combining knowledge from emails, documents, or speech-to-text systems may help preserve know-how and improve efficiency, but it also raises clear concerns around surveillance and worker acceptance [139].
- At the same time, industrial knowledge is too heterogeneous for current machine learning alone, making hybrid systems necessary in which Machine Learning (ML), knowledge models, and human intelligence work together [129].

Impact on Industrial AI

Industrial AI depends on human data for training and refinement. Yet, as digitalization and automation improve efficiency, they also increase technical complexity [134, 141]. Rather than a one-time handover, knowledge transfer becomes a process of vertical integration and late shaping, leaving space for fine-tuning, adaptation, and the integration of human intelligence [129]. By translating tacit worker knowledge and capturing tribal knowledge, industrial AI digitizes parts of production that standard automation could not reach, while shifting knowledge flows from senior-to-junior transmission toward system-mediated access [140].



CATALYZING WORKFORCE RESKILLING

Risking Stable Jobs and Demanding Continuous Workforce Reskilling

Previous industrial revolutions mainly replaced manual tasks and led to gradual workforce reskilling [142]. The next wave of industrial innovation incorporates intelligence into cyber-physical systems (CPS), demanding rapid and continuous reskilling as well as human-AI collaboration capabilities [143]. Production roles are currently less exposed to displacement by AI than many knowledge-sector jobs [144], yet a large share of production activities is technically automatable [145]. As skill requirements rapidly evolve, the World Economic Forum (WEF) anticipates growing demand for AI, creative thinking, and cybersecurity expertise in manufacturing [92]. Workers can expect 39% of their skills to become outdated within the next decade, increasing pressure for companies to reskill workers while competing for scarce technical talent [92, 146]. Over time, these dynamics may widen differences between highly skilled technical specialists and routine production workers. Without large-scale reskilling and upskilling, this widening gap could fragment the industrial workforce, pushing technical tasks toward platform-mediated or gig-based labor models as firms seek flexible access to scarce expertise [94]. Such shifts could reduce employment stability and weaken traditional labor protections [147].

Facts

- AI usage in production roles is near zero, but it could reach 20%, indicating an increasing need for major skill transitions [144].
- Advanced manufacturers plan to upskill 29% of employees and reskill 15% into new roles within five years [92].
- Advanced skills drive vast productivity gains, with highly trained workers outperforming less-skilled peers by up to 50% even in basic tasks [127].
- The fastest-growing production roles demand higher technical proficiency [90].

Key Drivers

- Persistent labor and talent shortages are intensifying the skills divide, with many manufacturers struggling to recruit workers with the technical and digital capabilities required for AI-enabled production [90, 92].
- Rapid technological change, including robots and autonomous systems, is shortening the lifespan of workforce skills, with 39% of current skills expected to become outdated by 2030, increasing pressure for continuous upskilling and reskilling [92, 146].
- Even in roles where manual expertise remains essential, employers increasingly demand a combination of manual proficiency, technological literacy, and problem-solving capabilities [92].

Challenges

- Automation widens the gap between high-skilled technical specialists and routine workers, increasing labor-market polarization in manufacturing [90].
- Organizational readiness and training lag behind technology adoption. 71% of leaders believe their workforce is not ready to use AI, showing a readiness gap between investment and human capability [148].
- Delays in implementing AI slow adoption, as companies must rethink workflows, develop new skills, and make organizational changes to capture productivity benefits [149].

Impact on Industrial AI

Workforce capabilities and human capital are important complementary factors in enabling AI adoption in industry. As systems grow more complex, companies rely on workers who can deploy, operate, and continuously improve AI-driven production systems [149]. Without large-scale reskilling, many firms may struggle to move beyond pilot projects and scale AI across operations, limiting potential productivity gains. At the same time, scarce technical expertise may concentrate among specialized professionals or external providers, pushing companies to rely more on project-based or platform-mediated expertise to access critical AI capabilities [92, 94, 149].

HOLLOWING OUT TOWNS VIA AUTOMATION

Widening the Gap Between Factories and Their Surrounding Communities

For centuries, the model of industrial geography relied on physical proximity between factories and their workforces. The integration of AI in industrial settings suggests a restructuring of this dynamic. As these systems mature, operations are becoming increasingly capable of running on the physical floor with minimal human intervention. This change leads to a shift not only in the required skill sets, but also in their physical locations [96]. Highly automated facilities reduce the demand for localized manual labor and, in turn, create a need for people responsible for AI systems, such as data scientists and cybersecurity professionals [92]. These roles often manage operations via remote networks. Therefore, workers are increasingly becoming independent of the factory location. Consequently, this dynamic risks depriving legacy industrial communities of their historical economic anchors, while potentially redirecting wealth and population growth towards concentrated technological centers [150, 151, 152]. Structural economic transition for these regions will become necessary to adapt and avoid the massive civic collapse historically seen in the US “Rust Belt”, formerly industrialized states facing manufacturing decline [153, 154].

Facts

- A ten percentage-point drop in the manufacturing employment share is associated with roughly 9.5 fewer local amenities per 10,000 residents overall, with sizable declines across most service categories [95].
- Looking ahead, 44% of manufacturers plan to increase automation over the next five years to drive positive business outcomes [152].

Societal Trends

- Reflecting the shift toward a decentralized workforce, 63% of manufacturing organizations now have hybrid or remote working programs in place [155].
- Every new high-tech job creates 4.9 new jobs in the surrounding area, with three of those positions available for individuals without college degrees [156, 157].

Key Drivers

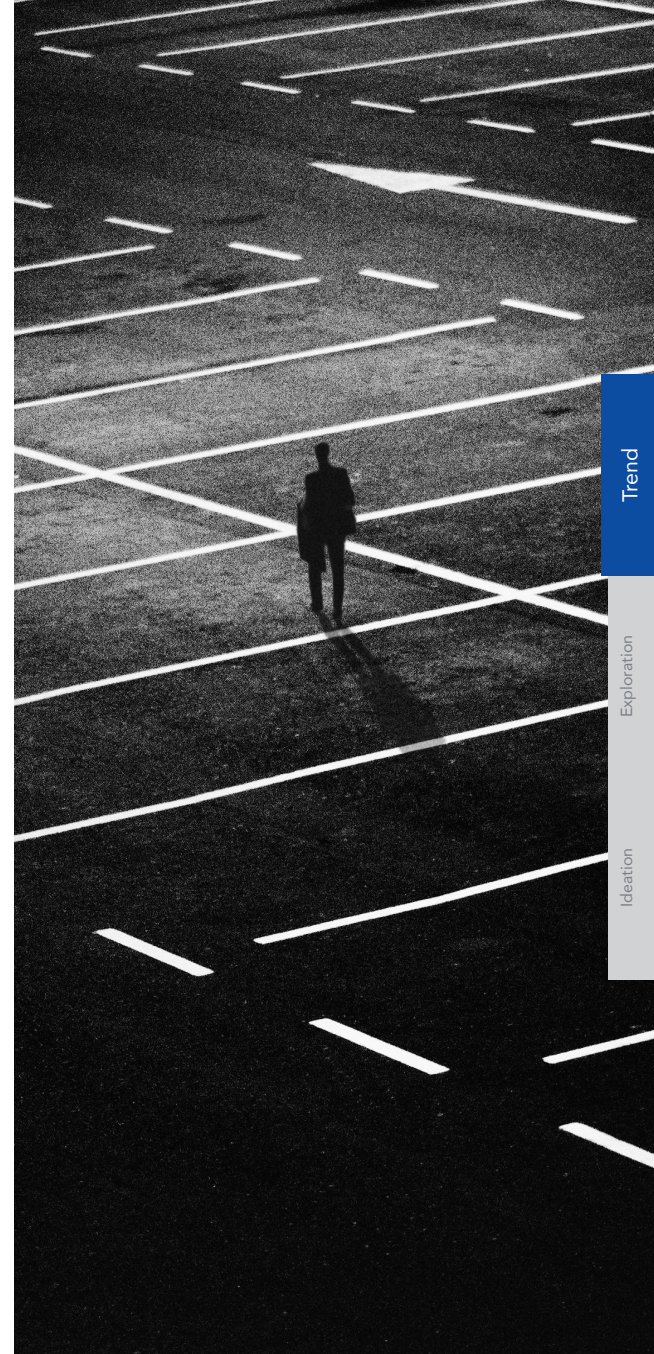
- AI-driven automation can boost productivity by 2-3x and achieve 99% defect reduction, encouraging businesses to adopt autonomous manufacturing systems [158].
- High-skill positions such as AI engineers and cybersecurity specialists are predominantly found in urban technology centers, which companies use to gain access to talent [159].
- COVID-19 demonstrated that knowledge-based industrial roles can be performed remotely at scale, accelerating organizational acceptance of decentralized workforce models [160].

Challenges

- Addressing the decline in taxpayers and residents in traditional industrial towns requires identifying new sources of income to sustain local infrastructure and services [161].
- Many conventional industrial firms will find it challenging to compete with the compensation and stock options offered by large software companies in order to attract top urban talent [162].
- When a city aligns itself with a company, like Stuttgart with Daimler, the factory gains a “social license” to operate. If the factory does not hire locally, this connection weakens, leading to potentially increased local backlash against environmental issues or complaints [163].

Impact on Industrial AI

While the integration of AI in industrial environments is still in its early stages, it has the potential to automate tasks on an unprecedented scale, leading to significant changes in the distribution of the industrial workforce across different regions. When a facility shifts toward autonomous operations, the resulting job losses can weaken the surrounding town's economy, reduce spending at local businesses, and contribute to population decline and lower civic engagement. This transition may also trigger political and labor resistance, depending on how quickly the local economy adapts [164, 165].





LEGAL TRENDS

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Closing the Assurance Gap
Rewriting the Rules of Work
Toward Geopolitical Data Blocs
Establishing the AI Compliance Playbook
Eroding Human Rights Enforcement



LEGAL TRENDS

Influencing the Future of Industrial AI

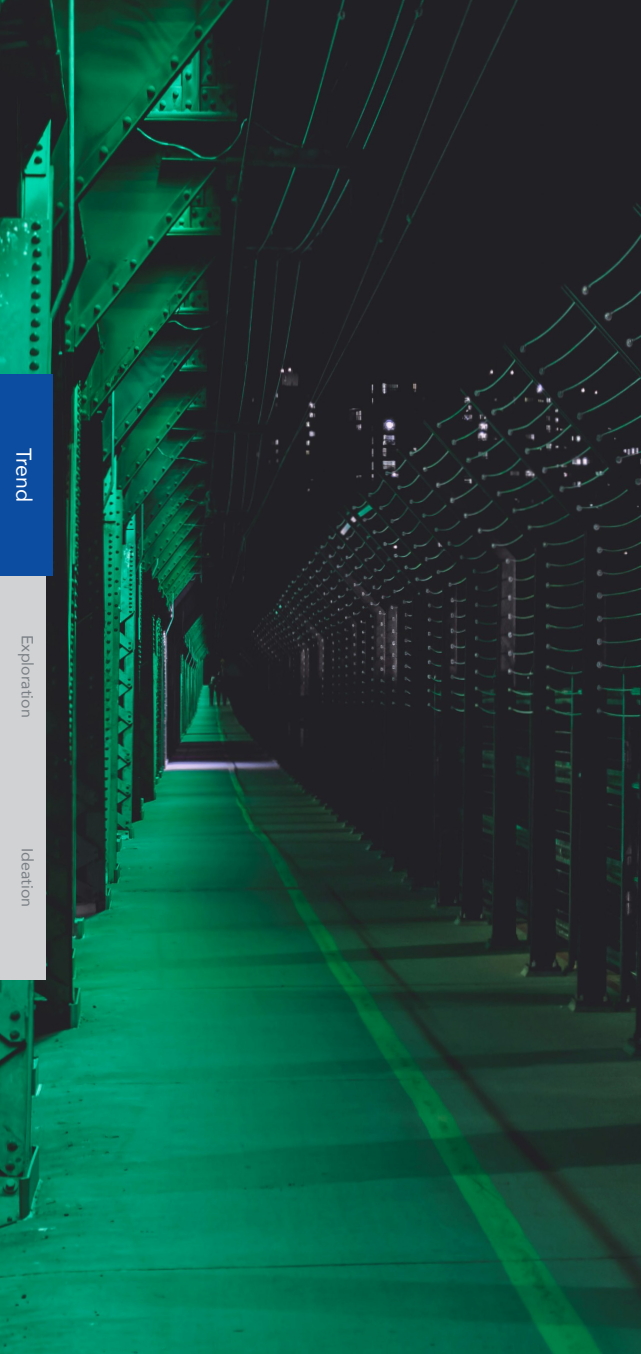
Across manufacturing, AI is increasingly involved in decisions that affect workers, consumers, and citizens, even though the legal frameworks surrounding those decisions were built for human actors, fixed systems, and clearer chains of responsibility [166]. As automation extends into cognitive and non-routine tasks, with the WEF projecting that the human share of work tasks will fall from 47% to 33% by 2030, legal systems face mounting pressure to address liability, accountability, and rights in contexts they were not designed for [92].

The core challenge is institutional. Legal frameworks depend on identifiable agents, stable artifacts, and bounded jurisdictions [166]. Industrial AI disrupts each of these assumptions. Self-adapting systems cannot be certified once and remain compliant, as their behavior continues to change after deployment [167]. Automated decisions in employment, safety, and welfare may have no clearly attributable human author [166]. Models trained across borders can simultaneously fall under multiple, conflicting data governance regimes [168, 169]. These are not edge cases but standard features of industrial AI operating at scale [166, 167]. Regulatory responses are accelerating but remain

incomplete. The EU AI Act introduces a risk-based framework covering high-risk industrial applications. Yet, key compliance pathways remain undefined, as harmonized technical standards have not yet been published, leaving providers without a clear path to compliance [170]. Meanwhile, data governance is fragmenting along geopolitical lines, with major blocs developing incompatible rules on where data can be stored, transferred, and used [168, 169]. In practice, this makes the legal geography of data a direct constraint on where industrial AI can be built and deployed. Beyond jurisdictional conflicts, human rights, largely designed for decisions attributable to identifiable human actors, are under strain as AI assumes consequential authority across industrial and social domains [166, 171]. Where taxation and welfare systems remain dependent on labor income, the automation of routine and low-skilled work in particular threatens to erode the fiscal base that funds the social protections displaced workers need most [92, 172].

The trends examined in this report are therefore not isolated compliance questions. They reflect a structural condition in which industrial AI is being deployed at a pace and scale

that existing legal architecture was not designed to absorb [166, 170]. Liability frameworks built for fixed products, human rights instruments built for identifiable agents, and welfare systems built on taxable labor are all being stress-tested simultaneously [166, 170, 171]. How governments and policymakers respond over the next fifteen years, whether through adaptive regulation, new accountability instruments, or coordinated governance across jurisdictions, will determine not only the legal conditions for industrial AI but the broader terms on which automation and democratic governance coexist [168, 169, 171].



CLOSING THE ASSURANCE GAP

Outpacing Certification Cycles to Secure Industrial AI

Industrial AI changes cybersecurity threats and defenses simultaneously. AI systems can find vulnerabilities, build adaptive attack strategies, and act at machine speed, making human-in-the-loop defense obsolete and demanding continuously learning AI defenders [173]. Legally, certification requires a fixed, verifiable artifact unsuitable for self-adapting systems [167]. Existing frameworks handle updates through delta certification and change control plans, assuming a human pre-defines permissible change boundaries [167, 174]. However, because a continuously self-adapting AI cannot pre-specify its behavioral envelope, its state shifts with each retraining cycle, so the certified artifact and deployed system are never the same [167, 174]. As AI-on-AI conflicts outpace certification cycles and quantum computing threatens hardware designed to last decades [175, 176], the industry must transition to a paradigm where continuous, real-time assurance replaces static, point-in-time compliance to keep autonomous systems secure [40, 167, 173, 174].

Facts

- Manufacturing is the most cyber-attacked sector globally, accounting for 27.7% of incidents in 2025 for the fifth consecutive year [177].
- Conventional safety case methods cannot certify continuously learning ML systems, as the certified artifact and deployed system diverge after each retraining cycle [167].
- National Institute of Standards and Technology (NIST) post-quantum cryptography standards signal that systems built on current encryption face a security architecture crisis within their operational lifespans [175].
- 65% of manufacturing executives rank operational risk, including cybersecurity breaches, as a top concern as IT and Operational Technology (OT) convergence expands the attack surface [40, 178].

Key Drivers

- Because offensive AI adapts in real time, the speed asymmetry between attackers and certifiable defenders is structurally unbridgeable, with defensive AI relying on pre-approved boundaries that simply cannot be defined against an AI-driven threat landscape [173, 174].
- IT and OT convergence in industrial environments expands the attack surface while increasing breach severity. A failure in one AI-enabled node can cascade across a production ecosystem, making continuous assurance an existential operational necessity [178].

Challenges

- The certification paradox for continuously self-adapting industrial AI has no legal resolution. Delta certification works for bounded, human-initiated changes but fails for systems that autonomously rewrite their behavioral parameters under adversarial pressure, leaving courts and vendors without an accountability construct [167, 173, 174].
- Compounding this certification paradox is the risk of geopolitical fragmentation, as multinational vendors may soon face incompatible compliance demands from the EU, US, and China with no international body mandated to resolve them [179].

Impact on Industrial AI

The certification gap will become one of the defining legal constraints on industrial AI over the next 20 years. Even once new assurance frameworks are legislated, corporations typically require multiple years to integrate new security architectures before certification can begin, meaning regulatory responses routinely arrive after threats have evolved [180, 181]. Vendors building self-adapting industrial AI continuously will face a compounding legal vacuum. Early movers who build continuous assurance architectures combining runtime monitoring, automated anomaly reporting, and post-quantum-ready encryption will gain a durable competitive advantage as these practices transition from best practice to mandatory market-access requirements [175].

REWRITING THE RULES OF WORK

Adapting Labor, Tax, and Redistribution Policies to AI-Driven Displacement

As AI and automation expand from routine manual work into cognitive tasks, the assumption that labor markets will continue to provide broad access to stable human work is beginning to erode [172, 182]. The WEF projects that the human share of work tasks will fall from 47% to 33% by 2030, with 82% of this decline driven by automation [92]. This penetration into cognitive work devalues accumulated human skills, compressing wage returns on prior education and training across entire occupational categories [92, 150, 182]. Fewer workers in taxable employment shrink the revenue base funding public pensions and unemployment insurance, while simultaneously increasing demand for social transfers to compensate the displaced [183]. This dual fiscal pressure, combined with the legal obligation of states to guarantee the right to work under Article 23 of the Universal Declaration of Human Rights [184] and national constitutions, such as Germany's Article 12 Basic Law [185], forces governments to reconsider their policy frameworks. Proposed responses range from AI taxes imposed on model providers to redistribute productivity gains to universal basic income transfers, to guarantee meaningful economic participation [172, 182, 186, 187].

Facts

- AI automation could affect 45% of manufacturing jobs in Europe, North America, and Asia in the next decade [188].
- 11% of workers are projected to be unable to upskill by 2030, facing structural exclusion, while a further 41% would need no retraining at all [92].
- Employment-linked taxes account for nearly half of total tax revenues of Organisation for Economic Co-operation and Development (OECD), funding public pensions, insurance, and healthcare across member states [183].

Key Drivers

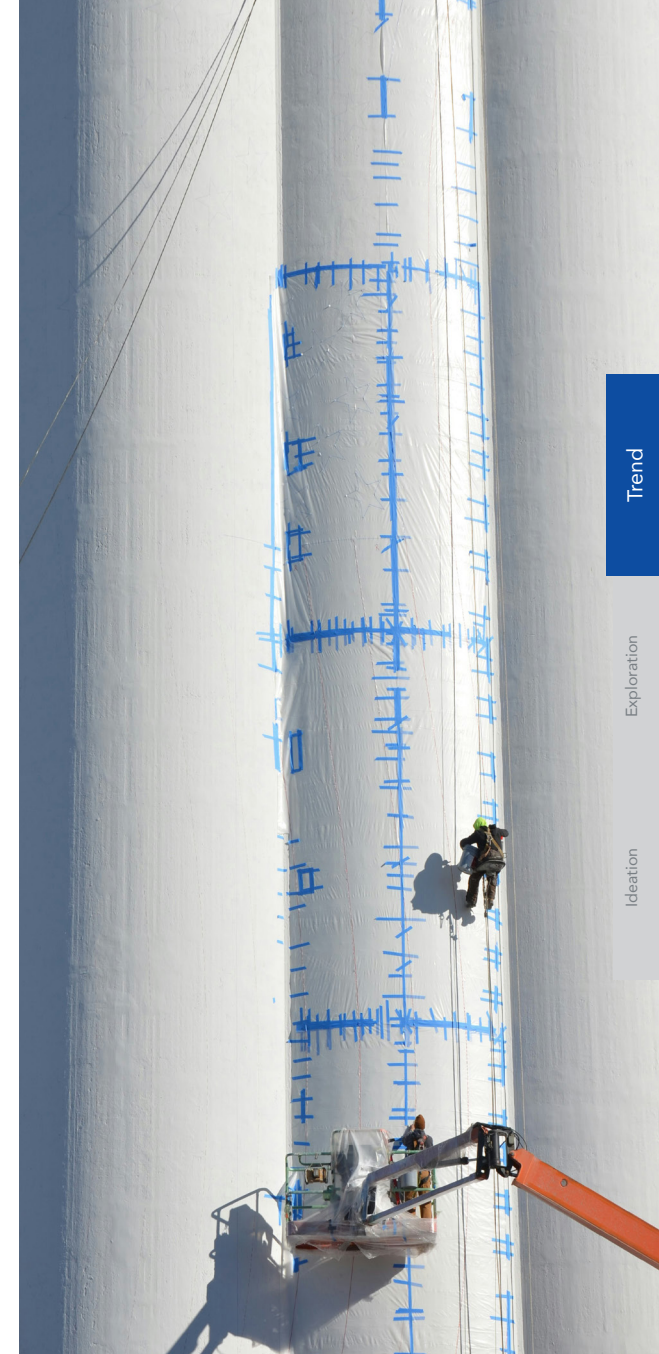
- Automation is extending into cognitive tasks previously considered replacement-resistant, while devaluing skills workers have already acquired, making displacement broader and harder to reverse through conventional reskilling [92, 150, 182].
- Productivity gains from AI concentrate on capital owners and highly skilled workers, while disproportionately affecting younger and lower-skilled workers, generating distributional imbalances with direct political pressure [172, 182].
- As unionization fell from 33.5% in 1954 to 10.1% in 2022 [189], collective bargaining capacity is declining, shifting responsibility for worker protection increasingly towards governments and regulators [190].

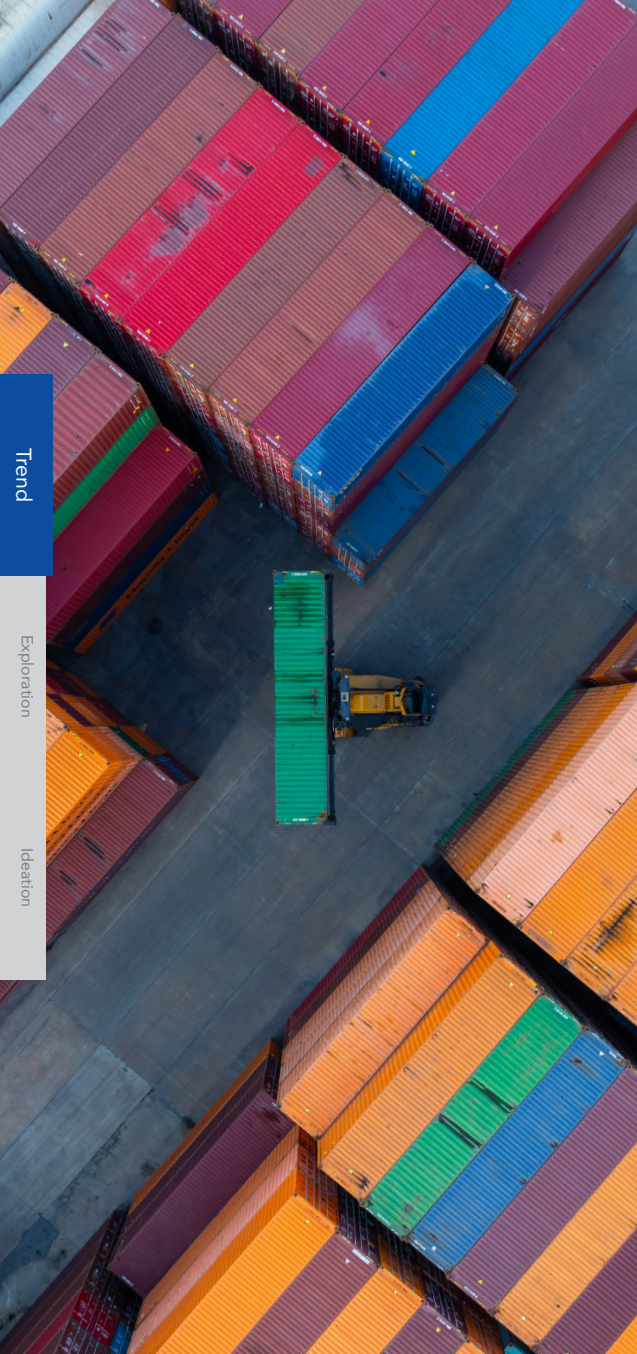
Challenges

- Designing automation levies is particularly challenging not only because there is no legal consensus on how to define a robot or AI system, but also because such policies require international coordination to prevent trade retaliation, double taxation, and competitive disadvantage for early-adopting jurisdictions [187].
- The net employment effects of AI remain sharply contested, as some studies predict substantial displacement while others anticipate net job growth through productivity gains, making it difficult to calibrate the scale of legislative response [92, 191].

Impact on Industrial AI

For industrial AI developers and adopters, this trend creates direct fiscal and political exposure. As governments face shrinking payroll tax revenues and rising demand for social transfers [183], they will scrutinize firms driving displacement [187]. Whether AI augments or replaces workers is not technologically predetermined but shaped by firm-level design choices, making workforce strategy a site of legal and political accountability [192]. Past automation shocks show adjustment burdens fall disproportionately on younger workers and industry-switchers, increasing the risk of mandatory contribution obligations [193]. Firms designing for human-AI complementarity will be better positioned to assume proactive duties to protect human employment as policy debates transition into binding law [172, 182].





TOWARD GEOPOLITICAL DATA BLOCS

Diverging Data Governance Regimes Will Fragment Industrial AI Supply Chains

Amid growing policy discourse about data sovereignty, industrial AI is increasingly shaped by the legal geography of data [168, 169]. Digital neo-protectionism is predicted to become a defining trade conflict of the 21st century [168] and the EU has positioned data governance as an instrument of strategic autonomy, seeking to reduce dependency on external actors through independent data spaces [169]. Globally, where third countries adopt EU rules nominally but implement them divergently, the resulting patchwork is harder to navigate for industrial AI developers than transparent differences would be [194, 195]. Within the EU itself, contradictory interpretations across member states create legal uncertainty that delays AI deployment and disadvantages smaller firms [196]. Existing trade frameworks introduce a further risk: should regulators classify pretrained models as data transfers, cross-border deployment of industrial AI could be curtailed by localization rules that existing policies were not designed to govern, accelerating fragmentation into incompatible data blocs [197, 198].

Facts

- The number of data localization measures worldwide more than doubled between 2017 and 2021, rising from 67 to 144 across 62 countries, with the most restrictive regimes in China, India, Russia, and Turkey [199].
- In 2024, the EU ran a digital services trade deficit of approximately 139B EUR with the US alone, concentrated in categories like cloud infrastructure, software, and platform licensing [200, 201].
- In 2025, liberalization occurred across insurance, financial services, and logistics, while restrictions on cross-border data flows continued to increase, particularly in Europe and the Asia-Pacific region [202].

Key Drivers

- Geopolitical tensions and supply chain disruptions have reframed data control as a matter of strategic security, accelerating the adoption of localization measures as instruments of digital industrial policy [168, 202].
- The EU Data Act mandates sharing of raw IoT data between manufacturers and users [203], but excludes inferred and derived data from these obligations [204], creating a legal vacuum that companies may fill through technical enclosure [205].
- EU's GDPR and India's Digital Personal Data Protection (DPDP) Act govern personal data but misalign on lawful processing bases, consent models, and automated decision-making rights, complicating compliance for cross-border industrial AI systems [206].

Challenges

- A 2025 OECD and World Trade Organization (WTO) analysis estimates that full fragmentation of cross-border data flows would reduce global GDP by 4.5% and exports by 8.5% [207].
- Over 80% of Europe's digital services and products are imported, and 92% of the EU's data is stored on US-based cloud servers [208].
- Despite data protection measures like federated learning, vulnerabilities such as gradient inversion attacks can lead to reconstruction of sensitive or proprietary training data, meaning industrial data can effectively leak across borders without any raw data being explicitly transferred [209].

Impact on Industrial AI

Regulatory fragmentation directly constrains the diversity of data, which industrial AI models require [210]. Foundation models for manufacturing, energy, and logistics depend on training data from multiple jurisdictions, but overlapping national regulations and conflicting export rules restrict cross-border access [169, 194, 211]. Where models are treated as compressed representations of their training data, localization mandates may extend not only to sensor inputs but to the model itself [197], while inferred and derived data remain outside existing access frameworks [204]. The resulting barriers concentrate advantage with platform operators that can absorb compliance costs across jurisdictions, while smaller industrial firms face disproportionate friction in training and deploying AI across borders [168, 205].

ESTABLISHING THE AI COMPLIANCE PLAYBOOK

Defining Industrial AI Compliance for Decades From Today's Standard-Setting

The EU AI Act classifies industrial AI systems covering robotics, autonomous machinery, and predictive maintenance as high-risk, requiring conformity assessments, human oversight, and audit documentation [170]. Under the revised Product Liability Directive, AI software is now explicitly a product under strict liability, shifting the legal burden to the provider [212]. Yet regulators demand transparency that developers resist to protect commercial interests, a paradox that no current standard resolves [213, 214]. No sector-specific rules define safe deployment of autonomous industrial systems, and the harmonized standards needed for a clear compliance pathway are delayed until late 2026 at the earliest [215]. Legislators delegate technical specifications to private standardization bodies where large technology firms already hold disproportionate influence [215, 216]. As industrial AI scales over the next 10-20 years, these voluntary standards will solidify into binding legal infrastructure, meaning firms shaping specifications now are defining liability for AI-caused harm before legislators catch up [216, 217].

Facts

- The EU AI Act requires conformity assessments for high-risk industrial AI, yet the harmonized standards needed to claim presumption of conformity are delayed until late 2026, leaving providers without a clear compliance pathway [170, 215].
- In late 2025, the Preliminary European Norm (prEN) 18286 standard entered public inquiry as the first draft AI Act standard, demonstrating that voluntary, industry-driven standards are already crystallizing today's compliance baseline [170, 215].

Legal Trends

- A Corporate Europe Observatory investigation found large technology firms leading standardization delegations without disclosing affiliations, raising concerns about industry capture of AI standard-setting [216].

Key Drivers

- AI deployment in safety-critical environments creates harm scenarios that voluntary ethics frameworks cannot address, making binding regulation unavoidable [217, 218].
- The opacity of AI systems creates a structural evidentiary barrier that fault-based tort law cannot resolve without reform, driving momentum to place primary liability on developers [219].
- The EU AI Act's extraterritorial reach creates global compliance obligations covering the entire system lifecycle, aligning with mandates emerging across major jurisdictions [217, 218].

Challenges

- The unresolved tension between legally mandated interpretability and commercially driven secrecy makes formal standardization indispensable [213, 214], since voluntary principles and guidelines alone cannot bridge the documented gap between high-level ethics and actual AI practice [103].
- SMEs face disproportionate market exclusion. Large firms allocate up to three times more of their AI budgets to compliance, enabling them to navigate costlier alternative pathways that smaller providers cannot afford [215, 220].

Impact on Industrial AI

Industrial AI companies that do not engage in standard-setting will be assessed against criteria written by large competitors. Systems once deployed as black boxes must now carry auditable documentation across their full lifecycle [170]. The absence of sector-specific industrial rules leaves the compliance baseline open for dominant standard-setters to define. As liability frameworks for AI-caused harm mature over the coming decades, the technical baseline being written today will determine the evidentiary standard against which industrial harm is judged, creating a durable structural advantage for early movers [215, 219].



ERODING HUMAN RIGHTS ENFORCEMENT

Erosion of Rights Enforcement once AI Replaces Human Agents

AI has shifted from experimental technology to critical national infrastructure, driven by geopolitical rivalry between the US, China, and the EU and formalized in instruments such as the EU AI Act and the Council of Europe's Framework Convention on AI [221, 222]. As critical infrastructure, it gets built into the decisions societies depend on most: healthcare, welfare, criminal sentencing, and hiring. What differs from earlier automation is that industrial AI displaces human judgment in high-stakes decisions previously resistant to algorithmic substitution [171, 223]. The EU AI Act now mandates human oversight as a binding design requirement for high-risk systems, yet the scope and enforceability of this obligation remain contested [224]. This displacement marks the point at which human rights law begins to erode. Its enforcement rests on three premises: a human agent made the decision, that agent can be held to account, and harm attaches to a person whose dignity gives rise to a legal claim [166, 225]. When industrial AI makes the decision, all three fail at once. Rights persist in law, while the mechanisms for claiming them cease to function [166, 223]. The more embedded industrial AI becomes, the more this failure will compound.

Facts

- The EU AI Act and the Council of Europe's Framework Convention on AI are the first binding instruments addressing AI's threat to rights, but do not resolve cases where no human decision-maker is present [221].
- A 2024 study documents AI's erosion at three levels: inability to seek accountability, unraveling of rights justifications, and degradation of human dignity as a legal concept [223].
- Algorithmic decisions on welfare cause process failures, as decision logic is opaque and non-contestable [171].

- UNESCO, whose Recommendation on AI Ethics applies to all 194 member states, identifies AI displacing human responsibility as a systemic risk [226].

Key Drivers

- Geopolitical competition incentivizes states and corporations to deploy autonomous systems in public services before accountability frameworks adapt [171, 221, 222].
- The fundamental mismatch between legacy legal frameworks designed for human actors and the autonomy of modern systems actively drives accountability failures when harm occurs across borders [166, 225].
- A structural lag in regulatory adaptation grants technology companies a first-mover advantage, allowing them to embed autonomous systems into critical infrastructure long before legal constraints are established [171].

Challenges

- Human rights law has historically demonstrated the capacity to evolve in response to new technological realities. Its combination of legal remedies, moral justification, and political practice may generate adaptive responses that partially offset the accountability erosion this trend describes. [171]
- The concurrent emergence of the EU AI Act, the Council of Europe Framework Convention, and the UNESCO recommendation signals active institutional resistance to unchecked human displacement, which could slow the trend before it becomes structurally irreversible [221, 226].

Impact on Industrial AI

For industrial AI operations, especially in high-stakes domains, explainability and human oversight will move from optional ethical features to mandatory architectural requirements [170]. This will differentiate the industry: regulated sectors such as healthcare, justice, and welfare will require fundamentally different governance architectures than consumer applications, concentrating development among actors able to absorb massive compliance costs [170, 221]. The accountability vacuum also creates conditions for a new legal category in which autonomous systems carry assigned liability, reshaping corporate liability frameworks across jurisdictions over the next two decades [166, 223]. builds ensures long-term capacity and resilience [325].





ECONOMIC TRENDS

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Scaling Asset Tokenization of Factories

Reshoring Production Through Automation

Servitizing the Factory

Leveraging Data as Key Assets

Forging AI Labour Markets

Ava Mack



Julian Limmer



Lucy Strüfing



Moritz Hawener



Simon Peter



ECONOMIC TRENDS

Influencing the Future of Industrial AI

Manufacturing is undergoing its most significant structural transformation since the introduction of mass production. In this revolution, intelligence, rather than mechanization, serves as a primary accelerator. As industrial AI increasingly extends beyond task automation, it is fundamentally re-forming the valuation of physical capital, the organization of production, and the foundations of competitive advantage.

This transformation changes how physical assets are valued. When machines generate continuous performance data, physical assets become measurable - and what can be measured precisely can be priced, traded, and financialized. Blockchain-based tokenization is beginning to transform factory equipment into tradable financial instruments. In a sector that has been encountering up to 15-30% illiquidity premiums in the past, this development may unlock much-needed liquidity [233, 234].

Servitization, defined as the shift from selling equipment to guaranteeing performance outcomes, repositions industrial firms as service providers. In this context, AI enables remote

performance guarantees, making these business models commercially feasible [235, 236]. Potential profit margins for service-oriented manufacturers already surpass those of traditional equipment sales by more than twofold [235].

Underlying both shifts is a more fundamental revaluation. Manufacturing value once resided in physical assets, machinery, inventory, and labor. Now it increasingly depends on data, software, and the ability to act on both in a meaningful timeframe [227]. Operational data captured by machine sensors and controllers was once a mere byproduct of production, but is now being reclassified as an intangible asset [228, 229, 230], with the industrial data management market projected to grow by 103% to 213B USD between 2025 and 2030 [231]. Simultaneously, regulatory developments such as the EU Data Act are dismantling proprietary data barriers and shifting competitive advantage from data ownership to analytical capability [232].

These shifts reshape revenue models. But geopolitical instability and physical AI are simultaneously reorganizing where

production takes place [237]. Distributed and modular manufacturing systems are on the rise as reshoring becomes economically feasible through optimization of resilience rather than scale alone [238].

Finally, the labor market itself is undergoing significant restructuring. As AI automates routine tasks, critical skills concentrate among more expensive and technically specialized workers, intensifying the stakes of labor transfer [239, 240, 241]. The training firm bears the cost of workforce development, while outside firms capture the value by recruiting workers they did not invest in [242].

The underlying logic uniting these developments is that factories are evolving into financial instruments [243]. The quality of a factory's data infrastructure will determine both operational performance and economic value [244]. Organizations that recognize this shift early and invest strategically may be positioned to amplify their competitive advantage across all dimensions of industrial competition.

SCALING ASSET TOKENIZATION OF FACTORIES

Unlocking Liquidity in Industrial Assets by Fractionalizing Physical Capital

The tokenization of factory assets transforms physical infrastructure into digitally liquid assets. By converting industrial equipment into blockchain-based tokens, manufacturers can access an emerging asset market, though most initiatives remain at the proof-of-concept stage [245]. Markets in Crypto-Assets Regulation (MiCA) establishes unified EU rules for crypto-assets, and while it does not yet cover security tokens tied to industrial equipment, it signals growing institutional acceptance of tokenized ownership [246]. Fractionalization enables improved price discovery and shared ownership of otherwise illiquid assets [234], and the EU DPP mandates traceability [247]. Yet digitally financeable assets require factories to be digitally measurable. The oracle problem means that manipulated sensor data can trigger unauthorized actions on the blockchain [248], while legacy IT gaps complicate the transfer of operational data to decentralized ledgers [249]. A fragmented regulatory patchwork adds cross-border compliance hurdles [246]. Despite this, the tokenized equipment-leasing market is set to grow at a 23.7% CAGR [250], signaling a future where industrial liquidity is as dynamic as the AI that monitors it.

Facts

- Under a conservative scenario, tokenized assets could reach 12.5T USD by 2033 (~45% CAGR), yet most Real World Asset (RWA) tokens still show thin trading and limited liquidity [9, 251].
- The EU DPP creates a mandatory digital layer for physical goods, establishing the traceability infrastructure that factory tokenization depends on [247].
- Illiquid private assets typically suffer a 15-30% valuation discount compared to publicly traded equivalents. Tokenization could reduce this discount by enabling fractional ownership and broader market access [234, 252].

Key Drivers

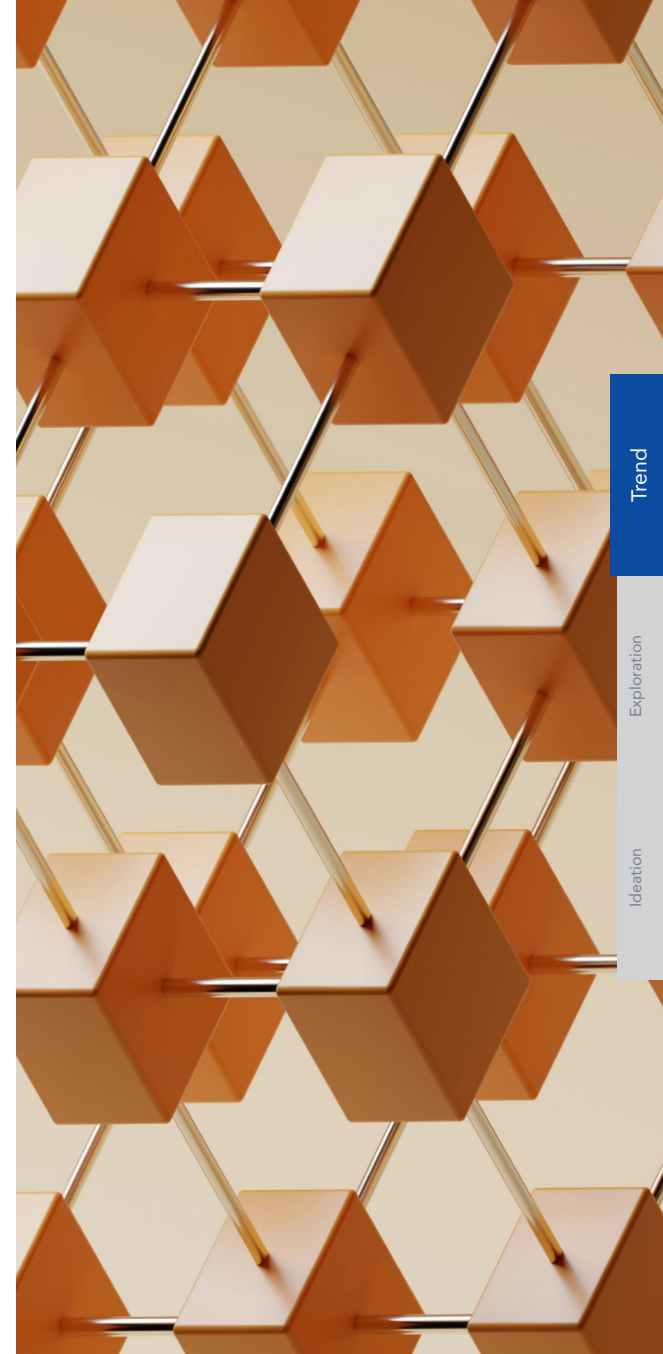
- Regulatory frameworks such as MiCA and the Guiding and Establishing National Innovation for U.S. Stablecoins (GENIUS) Act signal growing institutional legitimacy for tokenized assets, though sector-specific rules for industrial equipment remain undeveloped [246, 253].
- Fractionalization of assets that would normally be illiquid promotes trading and improved price discovery, and enables shared ownership of industrial resources [234].
- Blockchain enables data storage in an immutable, decentralized way suited for traceability in manufacturing processes, increasing trust throughout the supply chain [254].

Challenges

- Integrating distributed ledger technologies with legacy industrial infrastructure remains a significant challenge, as older systems were not designed for decentralized, real-time data exchange [249].
- Each jurisdiction defines and regulates tokenized assets differently, forcing companies to navigate separate compliance processes in every country, which slows global adoption [246].
- The connection between a physical factory and its digital twin introduces the oracle problem. If sensor data is manipulated, the blockchain records it as truth, which can trigger unauthorized actions such as auto-payoffs [248].

Impact on Industrial AI

As factories become tradable financial assets, their sensor networks and digital twins could provide data pipelines that feed on-chain valuation systems. In such a scenario, automated smart contracts would price tokens based on real-time operational performance [248, 252]. If performance data directly influences token pricing, manufacturers would face new financial incentives to invest in higher-quality data infrastructure. However, if sensor data is manipulated, the blockchain records it as truth [255], meaning data integrity becomes not just an operational concern but a financial one. Tokenization can further accelerate adoption by enabling fractional ownership, lowering the investment threshold and allowing faster settlement through programmable contracts [245].





RESHORING PRODUCTION THROUGH AUTOMATION

Driving Distributed, Resilient Manufacturing Systems by Geopolitics and AI

Geopolitical tensions and supply chain disruptions are encouraging governments and firms to relocate production capacity closer to domestic markets, increasingly framing industrial capacity as a matter of economic security [256]. At the same time, advances in AI and automation are raising productivity in knowledge-intensive roles and reducing reliance on labor-intensive processes, improving the relative cost position of high-wage economies [257]. These developments are changing how production capacity is organized and accessed. Manufacturing-as-a-Service (MaaS) enables firms to flexibly access and trade manufacturing capacity, allowing a more dynamic allocation of industrial resources across markets [258, 259]. In parallel, distributed microproduction facilities and decentralized additive manufacturing enable production closer to the point of consumption, reducing reliance on centralized inventory storage and shifting to on-demand manufacturing [260]. Together, these developments drive a transition toward distributed, digitally coordinated production systems, reducing the cost disadvantages of high-wage economies and enabling competitive reindustrialization closer to domestic markets [257, 261].

Facts

- Manufacturing is shifting to geographically dispersed production facilities, shortening lead times and reducing logistics dependencies across supply chains [262, 263].
- MaaS enables firms to flexibly trade production capacity, with over 45% of manufacturers having adopted it by 2024, and the market is projected to grow at a CAGR of 12.8% [258, 259].

- Widespread AI and automation adoption could add 0.5 to 3.4 percentage points annually to productivity growth, narrowing the unit-cost gap that has historically made high-wage economies uncompetitive in manufacturing [257].

Key Drivers

- Government industrial policy across the EU and US increasingly treats domestic manufacturing capacity as an instrument of economic security, with strong incentives for local production of strategic technologies [264, 265].
- Growing demand for customized products combined with shorter product lifecycles is making market and customer proximity a more important driver of distributed, automation-enabled production in high-wage economies [260].
- More than half of today's work activities could become technically automatable between 2030 and 2060, reducing dependence on location-specific talent pools and lowering barriers to geographic relocation of production [257].

Challenges

- Managing geographically dispersed production across multiple facilities increases operational complexity and coordination costs, creating organizational barriers that can partially offset the efficiency gains [266].
- High upfront capital expenditure for AI infrastructure, sensors, and system integration may limit adoption, particularly among SMEs [267, 268].
- In decentralized manufacturing environments, protecting IP across distributed production nodes poses a critical barrier to adoption, as digital design data must traverse multiple external facilities and partners [269].

Impact on Industrial AI

Distributed production systems are redefining the role of industrial AI, shifting value creation from centralized infrastructure to intelligence embedded at the plant level [270]. Realizing this shift at scale requires coordinated data sharing across production facilities, a governance gap that frameworks such as the EU Data Governance Act are beginning to address by establishing conditions for industrial data exchange between firms [271]. The long-term success of distributed systems will depend on bridging legacy infrastructure gaps between operational and information technology systems and overcoming high upfront capital expenditure [268, 272].

SERVITIZING THE FACTORY

Facilitating the Shift from Selling Equipment to Guaranteeing Industrial Outcomes

Industrial AI is facilitating a shift in how manufacturing capability is delivered, from equipment sales to continuous performance guarantees. Called servitization or Equipment as a Service (EaaS), the model allows vendors to keep asset ownership and instead charge buyers for outcomes such as throughput or efficiency [273]. Although servitization is not new, industrial AI makes it viable at scale. Historically, the lack of granular, real-time data made accurate assessments of asset performance difficult, making performance guarantees risky [236, 274]. Recent advancements, including continuous IoT monitoring and predictive analytics, make asset performance more transparent, reducing the information asymmetry that previously hindered outcome-based contracts [275]. AI further strengthens the model through service-to-design feedback loops, which continuously improve future equipment durability [236]. However, despite widespread recognition, most manufacturers remain in early-stage implementation, limited by organizational readiness and the potential costs of carrying assets on their balance sheets [273, 275].

Facts

- Research on 576 European manufacturing firms shows that the combination of servitization and AI-intensive strategies produces greater smart production gains than either alone [236, 274].
- 94% of manufacturing leaders report outcome-based models have impacted operations, but only 25% have fully implemented them, and just 21% have adopted predictive maintenance [275].
- Servitization turns large capital investments into operating costs, removing equipment from buyers' balance sheets and replacing one-time expenditure with predictable recurring payments [276].

Economic Trends

Key Drivers

- Industrial buyers increasingly demand outcomes, paying for guaranteed uptime or throughput rather than buying and maintaining industrial assets themselves [273].
- Eroding margins on equipment sales push manufacturers toward service-based revenue, with more predictable cash flows and deeper customer integration through extended contract cycles [235].
- AI enables predictive maintenance and remote monitoring, enabling vendors to accurately guarantee asset performance and price risk. This shifts both risk and reward from buyer to vendor [275].

Challenges

- Under servitization, vendors retain asset ownership and finance buyer usage over time. In a high-interest-rate environment, customers may prefer these models, but the financing costs can pressure vendor margins [273].
- Most manufacturers lack the needed digital infrastructure and billing systems. The service paradox literature finds that premature AI investment can hurt returns if integration bottlenecks are unresolved [273, 277].
- Defining and verifying contractual outcomes remains the key hurdle. IoT and AI analytics are closing this gap, but disputes remain, especially for factors outside the vendor's control [275].

Impact on Industrial AI

Servitization turns AI-based maintenance and monitoring capability into a core selling point [236, 274]. It raises the competitive floor for industrial AI adoption, as vendors without reliable performance monitoring cannot price risk or guarantee outcomes [235, 275]. Economically, vendors absorb both asset ownership and performance risk [273]. AI-driven outcome verification becomes the mechanism that determines pricing and profits [275]. This fundamentally reshapes industrial relationships, as the vendor's accumulated operational data becomes a competitive asset and switching costs grow with the vendor's operational knowledge [236].



Trend

Exploration

Ideation

LEVERAGING DATA AS KEY ASSETS

Shifting Toward Digitally Measurable Capital

The volume of data generated in industrial environments is growing exponentially, driven by IoT sensors, connected machines, and digital twin technologies, with manufacturing accounting for the largest share of deployments [278]. This data explosion transforms operational data from a byproduct of production into strategic assets, reshaping how industrial companies compete, are valued, and generate value [279]. The industrial data management market is projected to grow significantly by 2030, reflecting capital-allocation decisions already underway [231]. Data is undergoing an economic reclassification. High-quality data is now recognized as an intangible asset with measurable fundamental value [228, 229]. The Oxford Review of Finance notes that data raises asset pricing questions precisely because it is an asset that needs to be priced [228]. As capital markets develop valuation metrics derived from real-time factory performance, firms that credibly demonstrate data-driven operational excellence may command higher valuations and better financing terms. At the regulatory level, this logic is accelerated by the EU Data Act [280], pushing industrial data toward functioning as a signaling asset.

Facts

- In 2019, the International Data Corporation (IDC) projected that 41.6B connected IoT devices would generate approximately 79.4 ZB (Zetabytes) of data annually by 2025, with manufacturing among the largest sectors driving this growth [279].
- The industrial data management market was valued at 105.1B USD in 2025 and is projected to reach 213.2B USD by 2030 [231].
- The EU Data Act grants users of connected products, including industrial machinery, the right to access and share data generated through product use [280].

- Only 6% of companies qualify as AI high performers according to McKinsey, underscoring the gap between data-rich leaders and firms struggling to convert operational data into competitive advantage [281].

Key Drivers

- The growing relevance of non-financial indicators for intangibles-rich firms is pushing companies toward treating proprietary operational datasets as strategic assets [281].
- In 2024, the International Accounting Standards Board (IASB) launched a comprehensive review of IAS 38, specifically aimed at improving the recognition of tech-driven intangible assets such as data [283].
- The EU Data Act weakens proprietary industrial data moats by giving users of connected products the legal right to access and share data generated through their use [280]. Competitive advantage may shift toward building the strongest analytics layer on more widely accessible data.

Challenges

- Unlike traditional assets, data is non-rivalrous, meaning it can be used by multiple parties simultaneously, complicating established models of exclusive ownership and fair market value [228].
- Industrial data differs fundamentally from web data, with scarcer labels, more skewed distributions, and stricter privacy requirements. Its value depends on context, quality, and relevance rather than volume alone [278].
- Existing IP frameworks were not designed for data assets. Patents protect inventions and copyright protects creative expression, but raw industrial datasets qualify for neither, leaving firms without legal protection for their most valuable asset [284].

Impact on Industrial AI

Sensor data is typically noisy, sparse, and expensive to label, meaning investment in data infrastructure directly determines model quality [285]. Companies that treat data as a strategic asset will see their AI systems improve faster and compound their advantage over time [286]. The EU Data Act and the EU AI Act create a new governance layer that will determine which companies are permitted to deploy AI at what scale in industrial contexts [280]. Companies that generate data through their hardware and monetize intelligence through software will effectively control both sides of the industrial AI value chain.

FORGING AI LABOUR MARKETS

Turning Workforce Training into a High-Stakes Capital Investment with Scarce AI Talent

Workers with AI skills command a 56% wage premium over comparable roles, a figure that doubled in a single year [241]. Developing these specialists takes years of firm investment, but retaining them is increasingly difficult: Meta has offered individual researchers packages worth up to 300M USD, while OpenAI spent 1.5M USD per employee in stock compensation largely to prevent departures [287, 288]. When a trained specialist leaves, the firm that developed them receives nothing. In professional football, transfer fees address this: the hiring club pays a fee to the developing club, creating a financial incentive to invest in talent even when players move [289]. No equivalent exists in AI labor markets, and non-compete clauses, the traditional alternative, are increasingly being restricted under regulatory pressure [290]. A transfer fee for AI talent could fill this gap, compensating training firms without restricting worker mobility. The legal profession shows what this costs in practice: replacing a trained associate runs 200k USD to 500k USD, yet firms that hire laterally pay nothing to the firm that trained them [291]. In AI, where each specialist is more costly to develop and harder to replace, this dynamic is more acute.

Facts

- Demand for AI talent is growing against the broader trend: job postings requiring AI skills rose 7.5% year-on-year even as total job postings fell 11.3%, based on analysis of nearly one billion job ads across six continents [241].
- Meta has offered AI researchers packages worth up to 300M USD over four years. OpenAI's average stock compensation reached 1.5M USD per employee in 2025, 34 times the pre-IPO average of 18 other major tech companies over the past 25 years. [287, 288]

Economic Trends

- Across the OECD, large firms are over three times as likely to use AI as small firms (39% vs. 12%). Among SMEs using generative AI, fewer than 30% provide any AI-related training to employees. [292]

Key Drivers

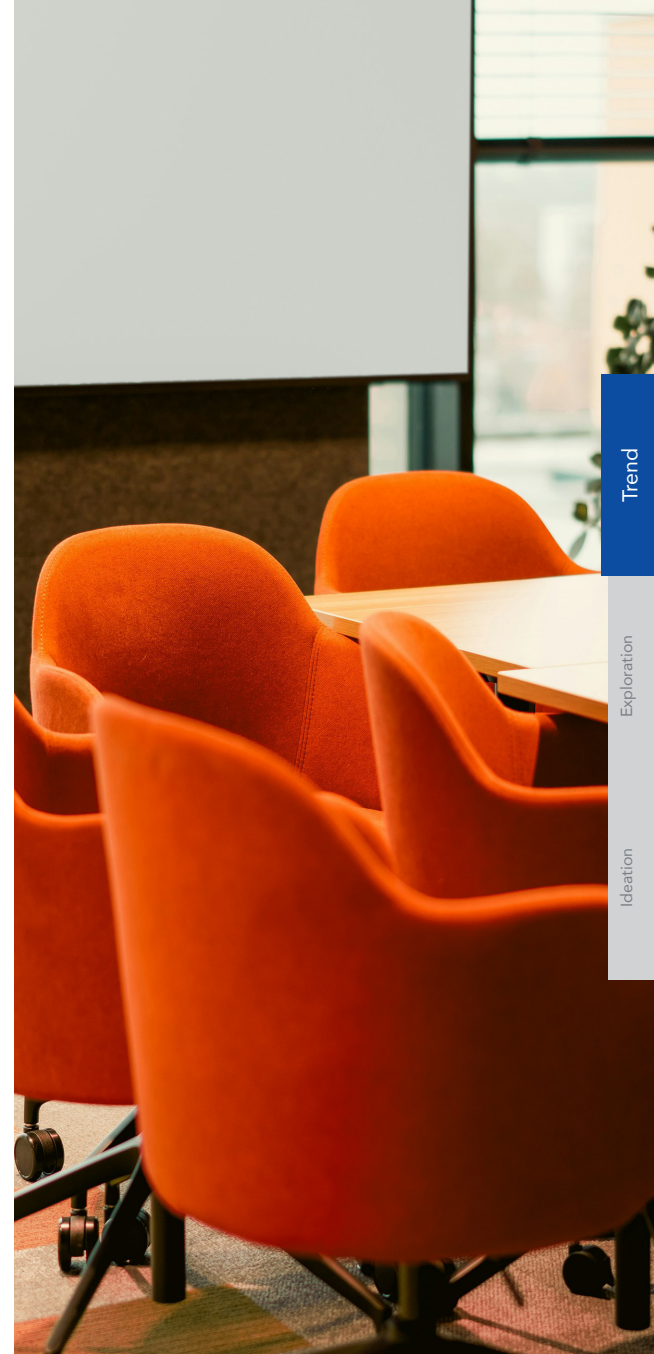
- The compensation gap between AI specialists and other workers is widening, making it increasingly profitable to recruit trained talent rather than develop it in-house. With individual signing bonuses reportedly reaching nine figures at leading firms, poaching is often cheaper than years of internal training, even at extreme prices. [287, 288]
- Regulatory changes are removing the few tools firms had to protect training investments. California and several other US states prohibit non-competes, and training repayment agreements face growing legal scrutiny, leaving firms with fewer ways to recoup development costs when workers leave. [290]

Challenges

- AI is automating many junior tasks that traditionally served as training grounds for future specialists. Employment for workers aged 22-25 in AI-exposed occupations has declined 13% since late 2022. [293]
- Firms often underinvest in employee training due to high turnover rates and the fear that trained employees may be recruited by competitors. Small companies, in particular, may struggle to invest in training because of limited resources. [282]

Impact on Industrial AI

Twice as many SMEs believe that generative AI increases skills' needs (20%) as say that it decreases them (9%) [292]. Despite this, small companies historically underinvest in digital training (e.g., only ~33% provide basic computer skills vs. 55% large firms), potentially due to resource constraints [282]. When it comes to AI-skilled workers, they also face recruitment challenges when competing with large corporations, risking talent shortages that hinder AI adoption [292]. If this trend persists, industrial AI expertise could concentrate on fewer, larger players. Indeed, the competitive advantage shifts from access to technology, which is increasingly commoditized, to the ability to develop and retain the people who can deploy it [292].





ENVIRONMENTAL TRENDS

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Concentrating Compute Near Water
Conserving Resources with Simulated Factories
Accelerating Materials Discovery
Establishing Public Recycling Hubs
Tracing Emissions Through Products



ENVIRONMENTAL TRENDS

Influencing the Future of Industrial AI

Environmental resilience is a fundamental requirement for establishing industrial AI [294]. As AI clusters become more central to industries, the underlying infrastructure demands resource dependability. Protecting these assets from climate-driven disruptions and ensuring a consistent supply of energy and resources are strategic prerequisites for industrial continuity. The fast expansion of AI has ambivalent consequences for the environment. Its growing physical footprint strains planetary boundaries, while its analytical capabilities offer tools to operate within them [295].

On the one hand, AI poses a high demand for resources such as energy, rare earth materials, and water, which are only increased by its exponential adoption in industry as it moves from occasional analytics to continuous, compute-intensive operations at a large scale [296]. For instance, executing AI-driven operations can consume up to ten times as much electricity as traditional computing and search tasks [297]. Many of these resource dependencies remain opaque, creating systemic vulnerabilities [296]. Without transitioning toward sustainable land use and circular material sourcing,

the hardware required for industrial intelligence risks hitting a physical growth ceiling [298].

On the other hand, AI serves as a catalyst for the global transition toward a circular economy. Circularity is a regenerative economic model designed to replace the linear “take-make-waste” approach and instead prioritizes sustainable resource production and consumption by reusing, recycling, or re-designing materials and products to maximize product lifecycles [299, 300]. Global implementation of circularity could reduce global emissions by 22.8B tons, providing the environmental stability necessary for long-term industrial operations [301].

Regulatory frameworks begin to embrace these practices, particularly in the EU. The EU Circular Economy Action Plan (CEAP), the EU Critical Raw Materials Act (CRMA), and the EU Ecodesign for Sustainable Products Regulation (ESPR) are transforming circularity from a series of isolated pilots into a standardized industrial process, paving the way for large-scale systemic shifts [247, 302, 303]. These mandates establish clear data protocols for industrial automation, thereby

lowering barriers to adoption and ultimately strengthening European resource sovereignty [304, 305]. A central mechanism introduced by these regulations is the DPP, a structured, machine-readable data container that tracks sustainability and lifecycle information across supply chains [304].

AI-driven solutions have the potential to optimize the entire industrial value chain and facilitate cross-value chain collaboration. Evidence from recent bibliometric and network analyses confirms that the field is rapidly expanding, with applications already moving beyond a select few pilot projects toward standardized, reproducible operational practices [306].

AI serves as a positive force in the transition toward a circular economy [307], however due to its resource consumption, the net effect on the environment is unclear. Still, the speed of adoption remains critical. To prevent infrastructure bottlenecks, the shift toward sustainable data center management must keep pace with the exponential growth of technology [308].

CONCENTRATING COMPUTE NEAR WATER

Drawing Data Centers to Large Water Sources for Natural Cooling

Growing demand for AI applications, like autonomous manufacturing and predictive maintenance [309, 310], has driven significant data center expansion [311, 312]. Yet many existing facilities sit in water-scarce regions, sited for reasons unrelated to water availability [311, 313]. As AI workloads grow more continuous and compute-dense, high-density servers present a growing cooling challenge [311]. To address these demands, new hyperscale facilities are increasingly located near oceans or rivers, where seawater or ambient cooling can reduce energy consumption [314, 315, 316]. Scandinavian projects, for example, use seawater cooling and feed waste heat into city district heating networks [317]. This geographic shift, while addressing cooling needs, introduces environmental consequences, particularly regarding the ecological impacts of chemical water treatment and thermal discharge [311, 313]. Water availability is increasingly recognized as an important factor in how and where industrial AI infrastructure can expand [318].

Facts

- Growing AI demand has accelerated data center expansion, with investment reaching approximately 500B USD in 2024 after nearly doubling since 2022 [311, 312].
- US-based AI server deployments alone are projected to consume 731-1,125M m³ of water annually by 2030, yet much of this capacity sits in water-stressed areas, highlighting the need for a geographic shift toward water-rich sites [311].
- Modern cooling strategies increasingly focus on heat reuse, in which waste heat from liquid-cooled systems is repurposed for district heating or industrial use [317].

Key Drivers

- Evaporative cooling leaves high concentrations of salts and conditioning chemicals in blowdown water, posing ecological risks. This factor drives interest in closed-loop or alternative cooling to reduce harmful discharges. [318]
- Freshwater scarcity in inland regions increasingly constrains data-center siting and motivates the exploration of alternative cooling strategies [319].
- Water-based cooling provides significant energy savings [320], with immersion cooling reducing power usage effectiveness by approximately 20% compared to forced air cooling [321]. This incentivizes locating data centers near large bodies of water or along the coast.

Challenges

- A major challenge is managing blowdown water, the concentrated waste removed from cooling towers. While conditioning chemicals are essential for operational longevity, they are often discharged back into local environments. This water contains high levels of dissolved solids and chemical residuals, including scale inhibitors, biocides, and corrosion products. If improperly managed, the discharge of this water can have an adverse impact on soil and groundwater, which are often sources of potable water. [318]
- Data-center water use can stress local resources, especially in dry regions, exacerbating competition with agriculture and communities [313, 320].

Impact on Industrial AI

The compute demands of industrial AI, including autonomous manufacturing and digital twins [50, 309], are contributing to a geographic shift in infrastructure toward regions with abundant water access. To manage the heat output of dense AI accelerators, some operators are exploring marine and coastal environments where seawater cooling, renewable energy availability, and lower land costs converge [314, 315, 316]. While this reduces energy consumption, discharging thermal plumes and chemically treated cooling water raises concerns about marine ecosystem impacts, including biofouling chemicals and temperature disturbances to benthic communities [322, 323]. Sustainable scaling of industrial AI may therefore require complementing carbon accounting with localized ecological assessments and stricter metrics such as Water Usage Effectiveness (WUE) [324].

CONSERVING RESOURCES WITH SIMULATED FACTORIES

Evolving Digital Twins into Live, Self-Optimizing Factory Operating Systems

Manufacturing efficiency improvements have historically centered on physical process changes and offline simulations [325, 326]. Without live digital twins, inefficiencies are often identified only after waste has occurred [327]. Even where firms use digital representations of factories, many systems described in literature have been lower-integration models or one-way digital shadows rather than fully operational digital twins used continuously during live operations [328]. Leading manufacturers are connecting digital twins to real-time operational data, turning them from static models into live replicas that continuously mirror and optimize performance [329, 330]. As simulations grow more accurate, they will expand from individual production cells to entire facilities and eventually link across supply chains to minimize resource consumption system-wide [331, 332]. At the same time, advances in automated 3D reconstruction are lowering the cost of building these virtual replicas [333]. The result is a shift from periodic physical trial-and-error toward continuous optimization that runs virtually first and physically second.

Facts

- Siemens and NVIDIA are developing a blueprint for next-generation AI factories, connecting digital twins, industrial software, and AI across the factory lifecycle [334].
- BMW built virtual replicas of more than 30 factories and achieved virtual start of production at its Debrecen plant more than two years before physical operations began, using simulation to resolve layout, logistics, and process decisions before any physical resource was committed [334, 335].

Environmental Trends

- NVIDIA's NuRec libraries enable streamlined 3D scene reconstruction from smartphone photos in minutes to hours, depending on scene complexity, reducing the time to digitize physical environments for simulation [336].

Key Drivers

- As simulations become more accurate, optimization shifts to the virtual world, reducing waste in the physical world and lowering costs, thereby increasing profits [337, 338].
- Carbon pricing and Scope 3 reporting obligations make waste increasingly costly, strengthening the case for simulation-first operations [339, 340].
- Smartphone-based 3D reconstruction and cloud processing are now reducing the cost of capturing factory geometry, lowering a major barrier to creating simulation-ready models [333].

Challenges

- Keeping a live digital twin synchronized with its physical counterpart remains difficult as machines wear off and conditions change, and is not yet fully solved [341].
- Full digital twin deployments require substantial manual modeling effort, domain expertise, and upfront system integration work, limiting accessibility for many mid-sized manufacturers [342, 343, 344].
- Operational digital twins depend on continuous data from sensors, control systems, and production tracking. Integrating these sources reliably is technically demanding, with poor data quality potentially compromising the entire simulation [342, 343].

Impact on Industrial AI

Large-scale factory simulation extends industrial AI from optimizing isolated processes to orchestrating entire production systems [329]. The progression moves from design-phase simulation to live operational twins that support real-time monitoring, prediction, and coordination of energy, production, and logistics within a facility [329, 330]. It may extend toward interconnected supply-chain simulations that provide end-to-end visibility and enable coordinated planning and control across networked operations [331, 332]. As simulation scope expands, facility-level simulation can reduce cross-system inefficiencies difficult to detect with point solutions, while supply-chain-level simulation may reduce overproduction, excess inventory, and logistics waste [337, 344].



ACCELERATING MATERIALS DISCOVERY

Shifting from Empirical Research to Decentralized Self-Driving Labs

The discovery of sustainable materials is critical for the transition towards sustainability. Historically, this process relied on trial-and-error laboratory experimentation [345], but materials science is shifting toward machine learning and generative models that rapidly predict new material compounds [345, 346]. By autonomously synthesizing and proposing structures, these technologies augment the traditional scientific method with data-driven design [347, 348]. As a result, the development cycles shorten, enabling identification of high-performance materials for next-generation industrial applications [346]. However, most industries face a bottleneck translating lab-scale breakthroughs into larger settings [349]. Formulations engineered in controlled labs frequently fail when exposed to operational complexities of asset-heavy factories [350]. This divide is being tackled with end-to-end digital pipelines encompassing discovery, prototyping, and scale-up [351]. Digital twin simulations can de-risk the lab-to-production transition before committing physical resources [351, 352].

Facts

- AI paired with cloud computing enables researchers to quickly navigate more than 32M candidates and predict around 0.5M potentially stable materials for clean energy applications, such as solid-state batteries, in less than 80 hours [345].
- Recent research shows that deep learning models can achieve ~20% higher accuracy than traditional ML approaches when screening compounds from natural resources, highlighting AI's potential to accelerate biomaterial discovery [347].
- Prototype platforms like Polybot use AI-driven robots to perform experiments without human intervention, linking local physical synthesis with remote compute facilities [353].

Key Drivers

- In chemical materials discovery, AI is expected to expand the search space and accelerate R&D throughput by up to 75%, while generative design, paired with in-silico evaluation, reduces physical resource demand [354].
- The EU Chemicals Strategy for Sustainability (CSS) and Safe and Sustainable by Design (SSbD) frameworks push industry to consider lifecycle-wide safety and environmental impact from the start, instead of retrospectively [355].
- Automated screening enables evaluation across environmental footprint and supply chain vulnerability, prioritizing non-scarce raw materials with lower ecotoxicity and greenhouse gas intensity [355].

Challenges

- Finding a promising material digitally does not guarantee it will scale [349, 350]. Despite advances in AI-driven discovery, examples of computationally designed materials which were put into production remain rare [345].
- Autonomous synthesis setups face physical and chemical constraints, limiting the range of replicable conditions. Simulations struggle to bridge this gap as data for modeling extreme conditions is scarce and fragmented [351].
- SSbD requires environmental assessment from production to end-of-life. The framework demands early sustainability assessment, but the necessary data only becomes available as Technology Readiness Levels (TRL) increase [355].

Impact on Industrial AI

AI-driven materials discovery drives a structural shift in industry, moving discovery out of centralized research settings and embedding it more closely with the operations of manufacturers [350, 351]. Because centralized computing infrastructure alone cannot capture the full complexity of factory-floor conditions [349, 350], the field is moving toward decentralized, self-driving laboratories [356, 357]. These platforms couple generative design with robotic synthesis so that new materials are tested and refined directly against production-relevant variables [346, 350, 351]. Research and manufacturing are merged into a closed loop, allowing industries to scale materials more efficiently and predictably [354, 355, 358].

ESTABLISHING PUBLIC RECYCLING HUBS

Leveraging AI to Automate Sorting and Recover Critical Materials at Scale

As demand for critical minerals grows, primary lithium and cobalt reserves risk depletion [359, 360]. AI enables large-scale recycling by automating sorting, classification, and process optimization beyond manual capability [361, 362]. However, AI-powered robotic sorting demands substantial upfront capital, and ROI remains variable, deterring private operators from full automation [363].

Publicly coordinated recycling hubs address this barrier by pooling infrastructure investment across multiple stakeholders, lowering per-facility capital exposure and enabling shared datasets AI sorting systems need to function at scale [299, 363]. The EU has moved in this direction through the CRMA and RESourceEU Action Plan, which establish domestic recycling targets for critical materials [364, 365]. By combining shared infrastructure with AI-driven sorting systems that outperform manual recovery rates [362, 366], public hubs produce high-purity output, building the case for sustained automation investment [363, 367].

Facts

- Global demand for lithium is projected to grow fivefold by 2040, with mine supply already expected to create a 40% shortfall by 2035, signaling an acute global supply gap [359].
- Scaled recycling of critical minerals could reduce new mining activity by up to 30% by 2040, while producing 80% fewer greenhouse gas emissions than primary extraction [359].
- Advanced deep learning models achieve up to 97.7% accuracy in identifying and classifying complex waste streams [366], while AI-powered robotic systems reach sorting speeds up to ten times those of manual workers [362].

Environmental Trends

Key Drivers

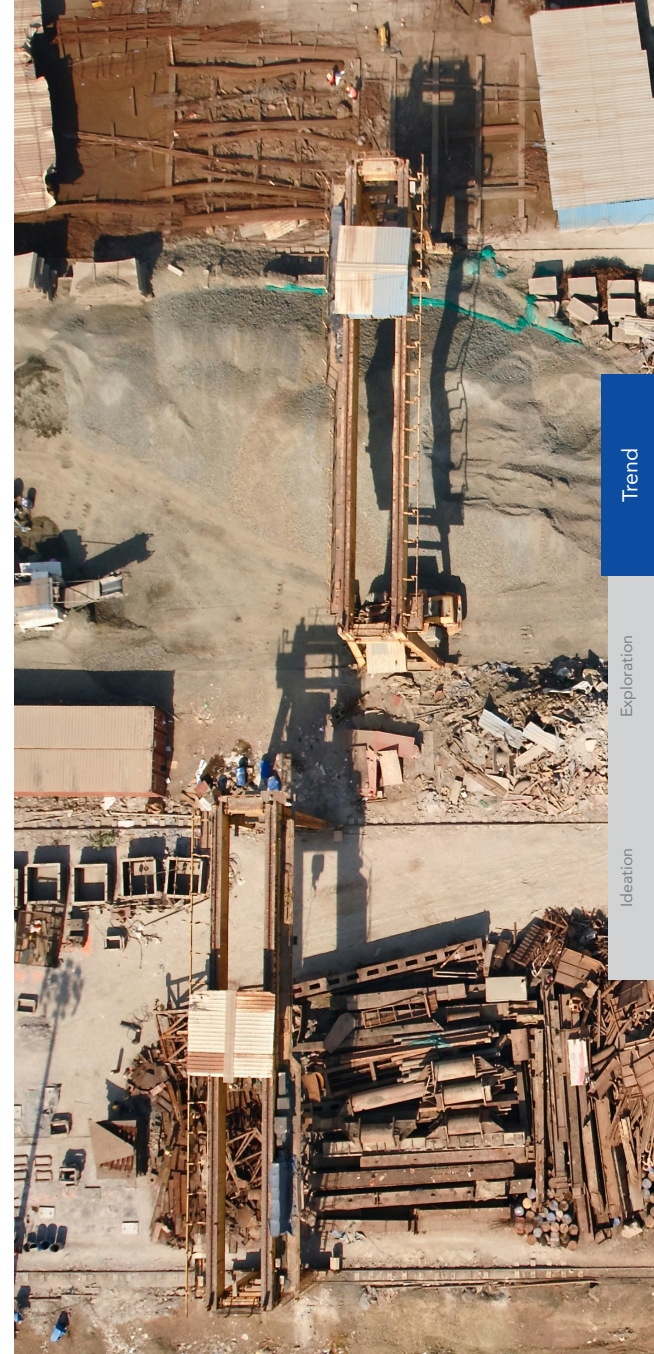
- Economic pressure from material scarcity and volatile commodity prices is making high-quality recycling financially attractive, pushing investment into scalable, automated solutions [359, 363].
- AI-driven sorting significantly improves recovery rates and material purity, directly enhancing the profitability of recycling operations compared to manual processes [362, 366].
- Policy frameworks such as the CRMA incentivize domestic recycling capacity, accelerate infrastructure development, and reduce dependence on primary resource imports [365].

Challenges

- Public investment in shared recycling infrastructure remains insufficient, with the EU facing an estimated financing shortfall of at least 29B EUR for the transition to a circular economy [368].
- Developing accurate AI sorting algorithms requires high-quality, task-specific training data, yet existing datasets in the waste management sector are often inadequate, requiring dedicated data collection efforts [369].
- Contamination and mixed material compositions in incoming waste streams reduce sorting accuracy and recovery rates, undermining the economic viability of automated facilities operating without controlled input streams [362, 363].

Impact on Industrial AI

Public recycling hubs extend industrial AI beyond factory settings into shared infrastructure serving multiple operators and waste streams simultaneously. This demands AI systems capable of handling highly heterogeneous material inputs, raising the bar for perception robustness and model generalization in real-world industrial conditions [369]. Aggregating sorting data across facilities can further improve model performance and enable scalable learning [370], but only under common data governance standards, a coordination role that neutral public infrastructure is structurally better placed to fulfill than competing private operators [371].



Trend

Exploration

Ideation



TRACING EMISSIONS THROUGH PRODUCTS

Linking Emissions Data Directly to Products through Digital Passports

Corporate climate accountability has focused on direct operations, but regulatory pressure now targets the entire value chain [372]. Exemplary of this expansion, Scope 3 emissions are indirect greenhouse gas outputs that span across a reporting network [373]. While much of Scope 3 is still estimated using industry averages or proxies [373, 374], incoming mandates require disclosure using best available data [375]. To escape these vague sector averages, industries are linking emissions data to individual items via persistent identifiers and digital passports, making Scope 3 measurable at the unit level [376, 377]. The EU Battery Regulation exemplifies this shift by mandating electronic records for battery life cycles [377]. Expanding this approach draws on four complementary layers: unique identity tags for products and facilities [376, 377], event-based tracking for manufacturing histories [378, 379], clear governance for footprint methodologies and access [376, 380], and application software to reconcile shared data consistently [374, 381].

Facts

- In a 2024 analysis by Boston Consulting Group and the Carbon Disclosure Project, reported supply chain Scope 3 emissions were on average 26 times larger than combined Scope 1 and 2 emissions [382].
- Approximately 98% of retail and wholesale greenhouse gas emissions fall under Scope 3, underlining the urgent need for direct product data tracking rather than relying on broad sector estimates [383].
- From February 18, 2027, certain batteries placed on the EU market must carry an electronic battery passport, linked via a QR code to a unique identifier [377].

Key Drivers

- EU regulations are establishing persistent identifiers, machine-readable passports, interoperability requirements, and access right structures for product data [376, 377].
- Across industrial sustainability, standards now cover complementary components of the technology stack, including carbon footprint methodologies, event-based visibility data, and interoperable asset representations [378, 379, 380].
- Research on DPPs and automated carbon data exchange suggests that lifecycle-linked data flows are strictly necessary to move beyond coarse approximations [374, 381, 384].

Challenges

- Persistent identifiers improve traceability [376, 377] but do not resolve methodological disputes around boundaries, allocation, and data quality on their own [373, 374].
- Suppliers may resist sharing process-level emissions data because it can reveal commercially sensitive information and raise privacy, governance, and data control concerns [374].
- Passport and interoperability approaches are still emerging and may evolve unevenly across sectors. Batteries are more concrete today than broader DPP implementations [376, 377, 384].

Impact on Industrial AI

For industrial AI, structured product data will improve the consistency of emissions inputs [374]. As data sharing matures, software can reconcile inputs and flag inconsistencies, supporting compliance despite ongoing methodological disputes [374, 381]. Ultimately, AI will reduce reliance on coarse approximations in Scope 3 tracking [381]. Beyond compliance, combining AI with DPPs enables a transparent circular economy [385]. With real-time visibility into component emissions and material histories, industries will shift from static reporting to dynamic carbon-adaptive decisions [381, 385]. AI systems can then automatically route end-of-life products to recycling, predict efficient sourcing, and decouple growth from new resource extraction [385].

EXPLORATION

In the upcoming chapter, the outcomes of the process for validating hypotheses and problem statements are explored. This phase primarily revolves around the discovery of white spaces and opportunity areas relevant for the future of industrial AI. By clustering the topic, findings are distilled into five key opportunity spaces, and the most critical problems and opportunities within the chosen domain are identified. The exploration phase places a priority on the testing and re-evaluation of hypotheses with expert insights, alongside an examination of the existing landscape to pinpoint selected players.

INDUSTRIAL DATA FLOWS46

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INSURANCE FRONTIER56

INDUSTRIAL DATA FLOWS

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Synthetic Data Generation

Privacy-Preserving Data Representation

High-Level Multimodal Data Fusion

Ava Mack 

Josefine Jacobs 

Lara Schupp 

Markus Meinert 

Sophia Schraml 

INDUSTRIAL DATA FLOWS

From Siloed Data to Unified Intelligence

Currently, manufacturing is undergoing a structural shift in which the competitive advantage of a factory is no longer determined solely by the machines on the factory floor, but by its ability to extract intelligence from the data those machines generate [386, 387]. Firms that build robust data-driven innovation capabilities demonstrate stronger performance, specifically under conditions of market turbulence, as the capacity to sense, integrate, and act on operational data becomes a decisive differentiator [386]. The WEF has identified advanced analytics and data infrastructure as the core enablers of next-generation manufacturing competitiveness [388]. Yet this is precisely where many companies face struggles [388]. Data generated across sensors, machines, and production processes holds substantial strategic value but only if it can be captured reliably, integrated across potentially heterogeneous sources, and shared without surrendering competitive control. These three interconnected challenges define the gap between the data manufacturing produces and the intelligence it deploys.

The first challenge is that labeled industrial data remains costly and time-consuming to collect at scale [389], specifically because real-world production environments offer limited

opportunity to observe rare failure modes. Synthetic data generation has emerged as a promising approach, providing a systematic framework for generating training datasets to support industrial AI development [390]. Without addressing this scarcity problem, models trained on insufficient or unrepresentative data will fail to generalize across the variability inherent to real manufacturing operations [389, 390].

The second challenge is data sovereignty. Even where companies hold rich proprietary datasets, sharing them risks exposing trade secrets and process knowledge. Federated learning, which enables collaborative model training without transferring raw data between parties, offers a promising architecture for industrial data collaboration [391]. However, it carries its own risks as gradient-level data reconstruction attacks have demonstrated that model updates are sufficient for attackers to reconstruct sensitive information even in the absence of direct data transfer [393]. Defending against these vulnerabilities remains a prerequisite for trustworthy industrial data ecosystems.

The third challenge is that industrial environments generate information across fundamentally incompatible modalities.

Time-series sensor readings, video streams, or operational records are rarely stored in consistent formats [391]. Multimodal fusion remains an open and underresearched problem in industrial automation [391]. Industry work on the topic confirms that integrating disparate sources requires principled methodological frameworks to handle noise, misalignment, and semantic inconsistency [392].

Together, data scarcity, integration complexity, and sovereignty constraints constitute the foundation of what it means to leverage industrial data as a strategic asset [386, 387, 388].

SYNTHETIC DATA GENERATION

Designing Real and Synthetic Data Streams as a Competitive Asset

Industrial AI systems require large volumes of high-quality, representative operational data, as model accuracy and reliability are determined by the quality, completeness, and relevance of the training data [390, 394]. In practice, data is scarce, expensive to label, and often misaligned with the model's needs [390]. Critical events such as equipment failures or abnormal operating regimes are the exception and rarely yield representative training datasets, leaving models dominated by normal operating conditions [395, 396].

Synthetic data generation directly addresses these structural constraints [390, 395]. Digital twins, physics-based simulations, and generative models can produce datasets covering rare faults and degradation trajectories without risking equipment or exposing sensitive information [394, 397]. In fact, object detection models trained solely on synthetic data can already outperform models trained on real images in multiple visual quality inspection scenarios [398]. Augmenting real data with synthetic data improves prediction accuracy, increases robustness, and enables safer pre-deployment testing in uptime-critical environments, creating a significant competitive advantage [398, 399]. However, effective governance remains essential as synthetic data must mirror real process constraints to avoid privacy, bias, and coverage risks [390, 400].

“

Simulation allows us to deliver solutions instantly - what used to take months of testing can now be done almost immediately.

”

Christoph Völker, Head of Industrial AI at iteratec [646]

Selected Players



MOSTLY AI



TONIC
THE FAKE DATA COMPANY



SIEMENS

Google



PRIVACY-PRESERVING DATA REPRESENTATION

Designing Industrial Data for Safe Federation Before the Protection Layer is Reached

Federated learning has emerged as a promising framework enabling competing industrial organisations to collaborate on AI model development without exchanging raw operational data [401, 402, 403]. Techniques like gradient inversion have demonstrated that the model updates exchanged in federated learning carry sufficient information to reconstruct the private data from which they were derived, even when secure aggregation is active across large client federations [404, 405, 406]. This vulnerability has been empirically extended to industrial time-series data, the dominant format in manufacturing and process industries [407]. Existing countermeasures, such as differential privacy, homomorphic encryption, and secure multi-party computation, address this issue at the protocol layer, yet each approach introduces utility costs that compound in operational industrial deployments [408].

A distinct opportunity emerges from where the structural problem originates. Industrial data is collected and processed for operational purposes, not for federation, and consequently encodes far more individual-sample information than any training objective demands [404, 409]. Sector-specific methods for transforming operational data into representations that retain model-relevant structure while reducing gradient reconstructability are largely absent across energy, manufacturing, and pharmaceutical industries [402, 407], leaving a significant and largely unaddressed gap in the field.

“

Industrial data is highly sensitive and often cannot be shared across organizations due to privacy and competitive constraints.

”

Eric Topham, Co-founder of OctaiPipe [647]

Selected Players



ETH zürich



SIEMENS





HIGH-LEVEL MULTIMODAL DATA FUSION

Integrating Multimodal Industrial Data Flows into Unified Frameworks

Modern industrial environments generate vast multimodal data, ranging from time-series sensor feeds and machine vision outputs to maintenance logs and expert knowledge [411]. Although Industry 4.0 has enabled the coexistence of these heterogeneous streams, cross-modal data fusion remains largely underexploited [412]. Traditional industrial systems process each data modality in isolation, producing fragmented workflows that preclude the discovery of cross-modal relationships [391]. Consequently, a significant share of data available to enterprises goes unleveraged, with fragmented modalities and incompatible formats among the primary barriers to value extraction [391].

The central opportunity is to build a production-ready harmonization layer as shared industrial infrastructure, integrating sensor streams, vision data, and unstructured domain knowledge to enable closed-loop AI process orchestration [413]. Manufacturers deploying integrated AI systems across production operations report productivity gains of two to three times alongside significant reductions in defects and energy consumption, underscoring the commercial imperative for a unified data infrastructure [414]. This unified middleware layer would unlock cross-modal pattern recognition, real-time decision support, and continuous process optimization within integrated manufacturing environments [413].

“

Industrial production generates vast amounts of data [...]. Analyzing this data holds enormous potential for companies, both in terms of efficiency and cost. However, [...] so far they can't use it. The problem: because the data exists in different formats, it cannot be processed uniformly.

”

Nathan Gruber, Co-founder and CEO of Manex AI [648]

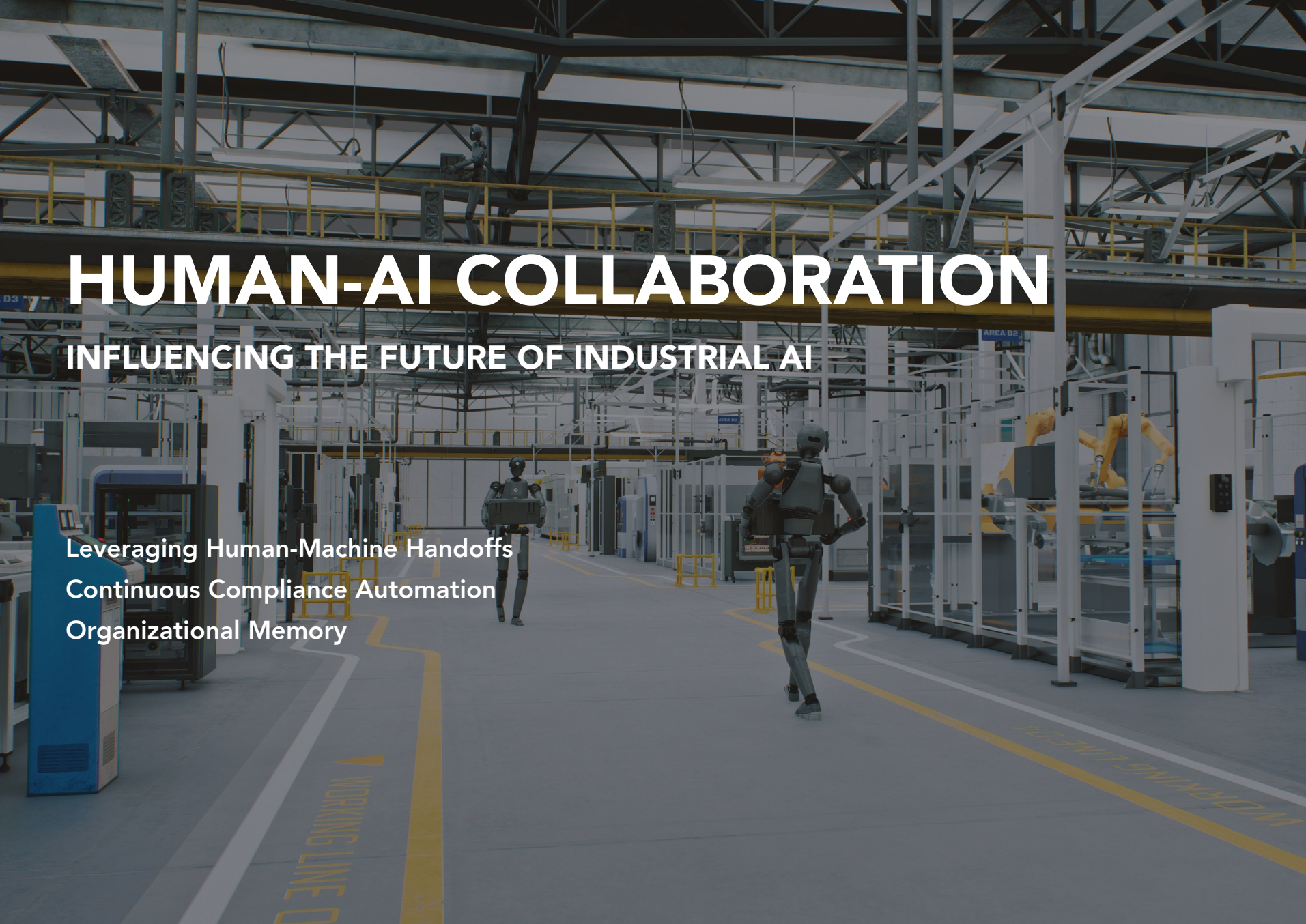
Selected Players



HUMAN-AI COLLABORATION

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Leveraging Human-Machine Handoffs
Continuous Compliance Automation
Organizational Memory



Alma Bonte



Jonas Walcher



Krrish Agarwalla



Niclas Fehr



Simon Peter



HUMAN-AI COLLABORATION

Bridging the Interaction Gap on the Industrial Shop Floor

Industrial AI once analyzed historical data to inform decisions, but now increasingly operates in real-time on the shop floor, adjusting processes, flagging anomalies, and advising workers as events unfold [415, 416]. This shifts intelligent systems from retrospective tools to direct operational participants, changing the demands on workers. Instead of performing clearly defined tasks, operators, engineers, and technicians must now collaborate with, supervise, and evaluate autonomous systems [417, 418]. As systems and workers share decision-making and oversight responsibilities, trust becomes a critical element of effective human-AI interaction [119, 418].

However, the infrastructure supporting this collaboration has not kept pace. Much of the hardware, interfaces, and organizational structures today were designed for settings where humans made decisions and machines executed [419]. Now, AI takes on intelligent tasks like fault diagnosis, intervention recommendations, and real-time process adaptation [415, 416]. The quality and smoothness of interaction between humans and intelligent machines is therefore becoming a central element of industrial productivity [420, 421]. This necessitates a connective layer that manages the bidirectional flow of information, governs control distribution, and main-

tains trust between workers and systems [119]. Addressing this gap offers three distinct opportunities.

First, the human-machine handoff needs improvement. When control shifts between a human and an AI system, maintaining situational awareness and enabling effective handovers is a central challenge [423, 424]. These transitions lack fluidity, mostly operating on a binary between full human control and full automation [167]. Designs focused on context-aware handoffs and graded responsibility sharing can therefore improve safety and efficiency [425].

Second, the intelligence of modern autonomous systems can smooth the compliance and certification process [426, 427]. As AI-enabled systems become more dynamic, maintaining conformity over their lifecycle grows demanding [427]. Continuous auditing approaches can automate parts of compliance assessment, monitoring, and reporting, reducing reliance on point-in-time audits [427]. If resulting documentation is audit-ready, reliability scales with system capability rather than against it [424].

Finally, organizational memory, much of which is tacit and

experiential, can be captured during operation and made accessible to humans and machines [422]. Currently, this knowledge risks being lost through turnover or retirement [421, 422]. Instead of relying solely on post-hoc documentation, tacit shop-floor knowledge can be systematically captured and externalized during operations, making it reusable across workers and systems [421, 422]. This turns individual expertise into a structured, searchable organizational asset.

LEVERAGING HUMAN-MACHINE HANDOFFS

Refining the Interaction Layer Between Humans and Intelligent Systems

As Industrial AI increasingly expands from analysis into operations, a new bottleneck emerges. In automated production lines, the transfer of control and context between systems and humans has become a source of friction [415, 416]. Most handoffs today are binary, meaning a system completes a task for human review or fails and returns control [416, 417]. Workers usually lack the context they need to make a good evaluation and must reconstruct the system's actions before they can act [417, 418]. When humans oversee AI systems, they may fail to detect inaccurate outputs, especially when oversight is difficult or signals are hard to interpret [417]. Reviews of human-AI collaboration show that automation bias can lead people to accept system recommendations too readily or intervene ineffectively [418].

This all-or-nothing division of roles could be replaced with systems that use fluid levels of autonomy, where independence is adjusted based on factors like risk [438]. Well-informed, timely human intervention can provide correction before full takeover is necessary [439]. Context can be delivered using cues that suit physical applications better than screens and chat interfaces [423]. Smooth handoffs can improve uptime, reduce maintenance effort, and increase automation adoption [438]. As automation increases in physical operations, transition quality may become important in determining how far automation can go. The interaction layer would thus become a core part of industrial AI system performance.

“

The interesting shift is not just better robots, but figuring out how humans and machines can interact better.

”

Zhenya Loginov, Partner at Accel [649]

Selected Players



COGNEX



KEYENCE



Honeywell



AVEVA



Trend

Exploration

Ideation

CONTINUOUS COMPLIANCE AUTOMATION

Expanding Compliance Regulations into Automated Shopfloor Infrastructure

With the integration of industrial AI into factory operations for reactor control and production line optimization, regulatory compliance has become a significant barrier to deployment [432, 433]. Today, compliance teams perform many manual tasks, such as logging decisions, reconstructing audit trails from fragmented systems, and cross-referencing regulatory frameworks [170]. These manual validation processes often take months to complete, while the underlying models they certify evolve continuously [434, 435]. Because industrial models adapt and retrain on live data, periodic manual compliance processes simply cannot keep pace [426, 435].

This creates a critical need for continuous compliance software embedded directly into industrial operations. Platforms that automatically audit safety boundaries in real time and generate regulator-ready documentation during live production are therefore needed. Such an automated compliance infrastructure would also shift the role of human auditors from manual documentation to oversight, clarification of roles, and ethical considerations [436]. For this shift to be effective, however, the outputs of such platforms must be sufficiently transparent for auditors to understand and evaluate the system's findings, not simply act on them [437].

“

By the time our manual certification processes are complete, the underlying technology has already moved on. We need compliance that operates at the speed of our production lines.

”

Robert Frittrang, Managing Director at BMW [650]

Selected Players



ORGANIZATIONAL MEMORY

Capturing Tacit Knowledge and Building the Missing Context Layer for Industrial AI

Manufacturing processes span a vast number of applications, tools, and tasks. The operational knowledge this entails is only partially captured in traditional written documentation, as much of it is tacitly held by experienced shop floor workers [419, 421]. Currently, established methodologies fail to systematically capture this human knowledge for industrial applications [119]. Accelerated by the silver tsunami, this expertise is increasingly at risk of being lost as the workforce that holds it approaches retirement: one quarter of the manufacturing workforce is over 55 years old [428], with 1.9M new roles projected to be unfilled in the US alone by 2033 [90]. As this expertise disappears, a knowledge gap emerges that data-driven models cannot fill, as they lack precisely the domain expertise held by retiring workers to validate outputs [419]. Worker acceptance and the cognitive burden of knowledge externalization remain open challenges [119, 421].

Connecting this captured human expertise with existing enterprise data creates a context layer that is currently absent in industrial organizations [419, 420, 429]. This layer could make organizational knowledge searchable, reusable, and scalable across teams, shifts, and sites. Expert judgment becomes accessible on demand, reducing dependence on individual availability and supporting knowledge transfer to younger workers [422, 430, 431].

“

We experience at least one outage per week lasting longer than a single shift, because the expert whose knowledge we need is simply not available.

”

Manufacturing Engineer at Siemens [651]

Selected Players



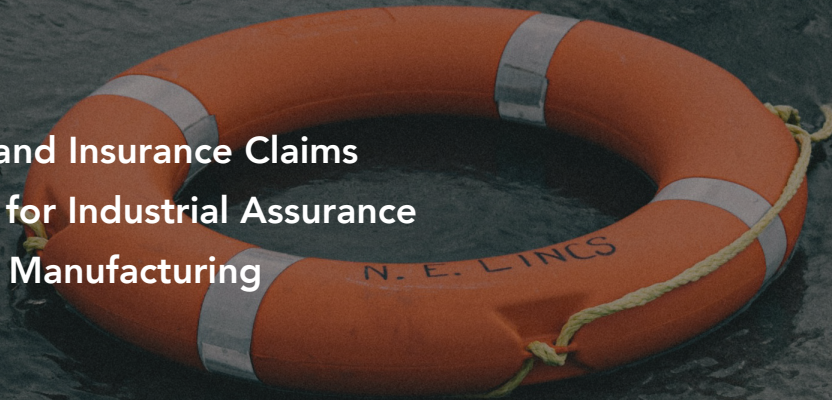
INSURANCE FRONTIER

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Bridging Machine Data and Insurance Claims

Digital Twin Simulations for Industrial Assurance

The AI Coverage Gap in Manufacturing



Marlene Böhm 

Noah Grohgan 

Dina Kurtalic 

Lucas Li 

Julian Limmer 

Uli Prantz 

INDUSTRIAL AI INSURANCE FRONTIER

Turning Industrial AI Risk into a Real-Time Insurance Opportunity

The convergence of industrial AI, cyber-physical systems, and operational data is changing not only how factories operate but also how risk is observed, assessed, and managed [440]. As production systems become more connected and autonomous, they create new forms of uncertainty that challenge traditional insurance logic [441, 442]. These include uncertainty about model behavior, failures under distributional shifts, and risks arising from interactions among models, machines, and physical environments [443, 444]. In industrial settings, such failures can create safety risks and complicate the attribution of responsibility when harm occurs [444, 445]. Traditional liability frameworks are often built around linear notions of causation, negligence, and fault, making them an imperfect fit for AI-driven systems whose behavior can be probabilistic, adaptive, and difficult to interpret [445].

At the same time, this transformation makes risk more observable. Connected assets, sensors, and digital infrastructures generate growing volumes of operational data that, in principle, can improve risk assessment, pricing, and

claims processes [446, 447, 448]. Yet, insurers often still face fragmented, incomplete, or difficult-to-use data environments, limiting the effectiveness with which this data can be incorporated into underwriting and claims decisions [448, 449]. These limitations leave a gap between the data-rich environments of modern industrial systems and the information insurers can reliably use in practice [447, 448, 449]. This mismatch defines an opportunity space at the intersection of insurance and industrial AI. Digital twins and connected risk models could support more forward-looking risk assessment and scenario analysis before losses occur [447].

More broadly, recent insurance literature points toward a shift in which technology supports not only retrospective compensation, but also more continuous forms of monitoring, risk reduction, and prevention [446, 448]. At the same time, AI-related failure modes may create coverage ambiguity because losses can be context-dependent, and assigning responsibility across software developers, equipment manufacturers, integrators, and plant operators can be difficult

[443, 445]. Better sensor data, remote monitoring, and more automated claims workflows also create the potential for faster and more accurate claims handling [448, 449, 450].

Taken together, these developments suggest that insurance in industrial AI may become more continuous, embedded, and operational. Rather than only absorbing losses after harm occurs, insurers and adjacent players may increasingly help measure, simulate, price, and prevent risk in near real-time [446, 447, 448]. Such a transition expands the opportunity beyond conventional policies toward AI-enabled underwriting, dynamic coverage models, digital assurance, and prevention tools built more directly into industrial operations [446, 447, 448, 450].

BRIDGING MACHINE DATA AND INSURANCE CLAIMS

Standardizing Machine-Generated Data for Faster, Fairer Coverage Decisions

Machine-generated operational data in industrial settings, capturing vibrations, thermal shifts, and maintenance events in real time, is increasing in volume [451]. Yet, insurance claim resolution remains largely dependent on manual processes [452]. When a machine failure occurs, the coverage decision rests on multiple factors: the cause of the failure, whether maintenance obligations were met, and whether the event qualifies as sudden and unforeseen under the applicable policy terms [451, 453]. Traditionally, loss adjusters respond by scheduling site visits, requesting documentation, and commissioning forensic engineers for ambiguous cases [451, 454].

A primary bottleneck in this process is not a lack of data but a lack of usable evidence. Manufacturers rarely possess the structured, reliable documentation that adjusters require for a decision [455]. Predictive maintenance platforms already collect much of the underlying information, and with appropriate interpretation and formatting, this data could answer the core questions an adjuster is concerned with [456, 457, 458, 459]. Yet, before it can serve as evidence, raw sensor output must be translated into coherent failure narratives, timestamped, and structured in an auditable format [460, 461].

This gap presents a concrete opportunity for a manufacturer-side middleware product that packages sensor and maintenance data into structured evidence aligned with insurer requirements, thus compressing the timeline from failure to claim resolution.

“

Data is a huge bottleneck for adoption in industrial AI. [...] Companies now are willing to share this data, as long as they get value out of it.

”

Thorben Rothe, Partner at IRIS Capital [652]

Selected Players



DIGITAL TWIN SIMULATIONS FOR INDUSTRIAL ASSURANCE

Advancing Insurance Risk Evaluation through Digital Twin Technology

Industrial insurers currently price risk using actuarial models built on aggregated historical data that cannot capture asset-specific behavior or real-time operating conditions [462]. Traditional certification methods face the same limitation, assessing systems at a fixed point in time rather than continuously throughout their operational lifecycle [463, 464].

Digital twins address both constraints by creating continuously updated virtual replicas of physical assets, enabling simulation of failure scenarios and behavioral testing under conditions that would be dangerous or impossible to reproduce physically [464]. They have already been demonstrated as evidence-generating tools for safety assurance in industrial environments, producing structured outputs that can support formal safety claims [464, 465]. Model fidelity is the critical constraint, as outputs are only as reliable as the underlying synchronization between the virtual model and its physical counterpart [466, 467].

These capabilities point toward an emerging assurance-as-a-service model, in which specialized firms generate verifiable simulation-based evidence of asset reliability for both certification and insurance underwriting purposes [465]. As industrial AI systems become more complex and harder to inspect through conventional means, digital twins represent a credible mechanism for closing the gap between how risk is currently assessed and how precisely it could be quantified.

“

Digital twins already represent real machines with over 85% accuracy and are used to test how they would behave under various scenarios.

”

Technical Presales Consultant at Siemens [653]

Selected Players

SIEMENS

GE VERNOVA

DASSAULT
SYSTEMES

Ansys

Swiss Re

Munich RE

AUGURY

zesty^{AI}

CESVIMAP

GEMINUM



Trend

Exploration

Ideation

THE AI COVERAGE GAP IN MANUFACTURING

Exposing the Coverage Gaps Left by AI-Driven Errors and Performance Shortfalls

Industrial AI creates two distinct uninsured exposures: liability for errors and financial risk when AI falls short of contractual thresholds [468, 469]. Policy language built around fault does not always align with AI losses, especially when harm arises without negligence. Insurance can partially address that gap by shifting attention from blame to compensation and risk allocation [469, 470].

Most industrial deployments operate under “silent AI” exposure, where general liability and errors-and-omissions policies neither explicitly include nor exclude AI-related losses [471]. Insurers partly use absolute exclusions to cover claims arising from alleged AI usage [472]. From August 2026, the EU AI Act requires conformity assessments for high-risk industrial AI, turning compliance into a prerequisite for lawful deployment and access to the EU market [170, 473]. Directive 2024/2853 extends strict liability to AI software by December 2026 [212]. Swiss Re identifies this as generating unaddressed exposures across liability lines [474].

The gap between expanding liability and absent coverage creates an opportunity. Parametric coverage, paying out on observable outcomes such as throughput drops or accuracy drift, sidesteps causation [470]. Munich Re’s aiSure backs warranties, letting providers offer guaranteed accuracy thresholds [469]. Whoever solves the underwriting problem first builds a claims history no rival can access [474].

“

AI is probabilistic. You can say the answer is 99.5% right, but you can never say it is 100% right. This ‘probabilistic’ nature is the price you pay for flexibility, but it creates a financial risk that traditional insurance wasn’t built for.

”

Peter Bärnreuther, AI Risk Expert at Munich RE [654]

Selected Players



A blue industrial robotic arm is the central focus, positioned in a factory environment. The arm is extended, and its joints are visible. In the background, there are various industrial structures, including conveyor belts and other machinery, all slightly out of focus. The lighting is bright, typical of a factory floor.

MACHINE-ORIENTED FACTORIES

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Distributed Factory Intelligence
Machine-Native and Vertical Infrastructure
Decoupling Workforce from the Factory Floor

Ali Batur Karakullukcu



Giulia Balzaretti



Lukas Plenk



Moritz Hawener



Sharayoo Jog



MACHINE-ORIENTED FACTORIES

Redefining Industrial Facilities for an Era of Automation at the Core

Manufacturers today are no longer deciding whether to automate, but how deeply to do so. The International Federation of Robotics recorded over 4.6M industrial robots in operational use globally in 2024, growing at 9% year-on-year, with annual installations forecast to reach 700,000 units by 2028 [66]. This is not simply more automation added to existing structures. The factory itself is being redesigned from the ground up, with machines at the center rather than the people operating them [66, 476].

How machine-focused a factory is falls along a spectrum. At one end, human-robot collaboration systems place machines and workers side by side, with automation handling precision and repetition while humans manage judgment and variation [477]. At the other end sit fully autonomous facilities, known as dark or lights-out factories, where no human workers are present, and production runs continuously without lighting, heating, or work shift changes [476]. In 2024, Xiaomi opened a facility in China spanning 81,000 square meters that runs with close to zero human presence, producing 10M smartphones a year through an AI-monitored system [478].

Fully autonomous factories remain the exception, but the di-

rection is clear. Competitive pressure, particularly from Asia, which accounted for 74% of all new robot deployments in 2024 compared to 16% in Europe, is accelerating the shift [66].

Three structural changes define how this transition unfolds in practice. First, it requires a new kind of intelligence on the factory floor. As machines multiply and interact, isolated automation systems become a bottleneck [479]. Multi-agent architectures allow machines to coordinate dynamically, share information, and make distributed decisions without central human oversight [479].

Second, the factory's physical space must follow. Fixed production lines designed for human workflows are being replaced by modular, reconfigurable systems that can be reorganized for new products without halting operations, delivering cost savings of up to 30% compared to traditional layouts [480].

Finally, as machines become the primary actors in production, the role and location of the workforce change entirely. As physical and manual skills in manufacturing decline at more

than twice the rate of the broader economy, the factory of the future will require a fundamentally different kind of workforce, one that is more technical, more distributed, and no longer defined by physical presence on the shop floor [481].

Together, these three spaces shape the machine-oriented factory, each representing a distinct space for innovation, investment, and structural reform.

DISTRIBUTED FACTORY INTELLIGENCE

Breaking Automation Silos with an Interoperable Intelligence Layer

Today's factory software stack remains constrained by vendor-specific integrations, monolithic Manufacturing Execution Systems (MES) and Supervisory Control and Data Acquisition (SCADA) logic, and brittle point-to-point automation that breaks when product mix, routing, or machine state changes [482]. That is why we are seeing a transition from isolated islands of equipment into a new paradigm that treats the factory as a distributed physical system [483]. Standards such as VDA 5050 are beginning to normalize fleet interoperability [484], and initiatives focused on adapters that enable legacy equipment to communicate with new management systems create new opportunities for management optimization [485].

Multi-agent systems offer a powerful way to orchestrate this network. Each asset operates autonomously, handling exceptions locally and avoiding the single points of failure, throughput ceilings, and compounding latency of centralized control [486, 487]. A single agent with full context recreates this bottleneck in software. Coordination can degrade sequential tasks as handoffs fragment context [488], yet multi-agents show emergent robustness absent in single-agent setups [487].

While large OEMs can build proprietary stacks, mid-size manufacturers are limited by integration budgets and heterogeneous equipment, facing disproportionate barriers including high integration costs, limited IT capacity, and incompatible legacy systems [489]. Only around 30% of manufacturers have scaled digital solutions beyond pilot [490], and the middleware market is set to grow from \$24.4B to \$40.2B by 2033 [491], signaling a large underserved vertical for cross-vendor coordination.

“

AI adoption remains below expectations because AI tools require integration with legacy systems that are sometimes decades old, difficult to understand, and more complex than modern, well integrated cloud-based architectures.

”

Silviu Apostu, Principal at Matterwave Ventures [655]

Selected Players



KINEXON



Honeywell





MACHINE-NATIVE AND VERTICAL INFRASTRUCTURE

Redesigning Industrial Facilities as Vertically Integrated, Autonomy-Ready Systems

The transition to autonomous manufacturing is driving a departure from human-centric facility design toward machine-native infrastructure. This involves two shifts: modularity and vertical stack integration.

Modular factories use Reconfigurable Manufacturing Systems (RMS) to redeploy production units as product cycles shorten [492, 493]. Automated modular construction can significantly improve assembly time and cost efficiency compared to traditional sequential approaches [494]. While greenfield sites can offer cost efficiency by reducing the need for human-centric infrastructure such as Heating, Ventilation, and Air Conditioning (HVAC) and ambient lighting [495], digital twin technologies are increasingly applied to optimize and modernize brownfield manufacturing facilities [496]. Building on this, autonomy-ready retrofit stacks represent a potential near-term opportunity to extend automation capabilities in existing facilities without requiring full greenfield investment.

The second shift is physically stacking these modular units into high-rise factory configurations. Conceptual work on vertical factory designs suggests that high-rise configurations can reduce facility footprint and enable high-density production on constrained urban plots [497]. Localized smart urban manufacturing could additionally provide a climate-resilient hedge against supply chain shocks [498], while waste heat from high-density machinery on lower levels can power temperature control for the entire stack or adjacent urban structures [499].

“

Factories will look different. It is not about replacing humans with humanoids but about smart workflows and maximized automation, where AI closes gaps.

”

Jana Petry, Investment Manager at UVC Partners [656]

Selected Players

SAMSUNG

amazon



RHENUS
LOGISTICS

BECKHOFF



RA Rockwell
Automation

BYD



DECOUPLING WORKFORCE FROM THE FACTORY FLOOR

Transitioning from Static Shifts to Remote Orchestration and On-Demand Dispatch

As machines take on more factory tasks, human labor is being redefined. The WEF estimates 39% of workers' core skills will change by 2030, driven by robotics and automation [92]. Robots increasingly handle routine and repetitive tasks, while humans remain essential for supervision, exception handling, and non-routine interventions [500]. Keeping mechanics on fixed shifts can limit workforce flexibility when labor demand varies over time, prompting manufacturers to explore more adaptive staffing approaches supported by digital tools and external labor pools [90].

Two emerging tracks address this challenge. First, remote orchestration allows technicians to use teleoperation systems to monitor and control robots across sites without being physically present [501, 502]. Over time, a skilled operator might orchestrate multiple facilities from one location. Second, on-demand maintenance dispatch uses more flexible staffing approaches that use digital platforms and external labor pools to fill work slots dynamically and respond to changing operational needs [90]. As machines become better at self-reporting their conditions, predictive systems absorb the diagnostic workload that once required constant human attention, enabling one operator to maintain more systems with less effort [503].

The opportunity lies in building platforms that connect predictive failure signals to system-agnostic operators and enable remote oversight across facilities [90, 92]. Once in place, manufacturers can shift from rigid staffing models toward a leaner, faster-to-deploy workforce.

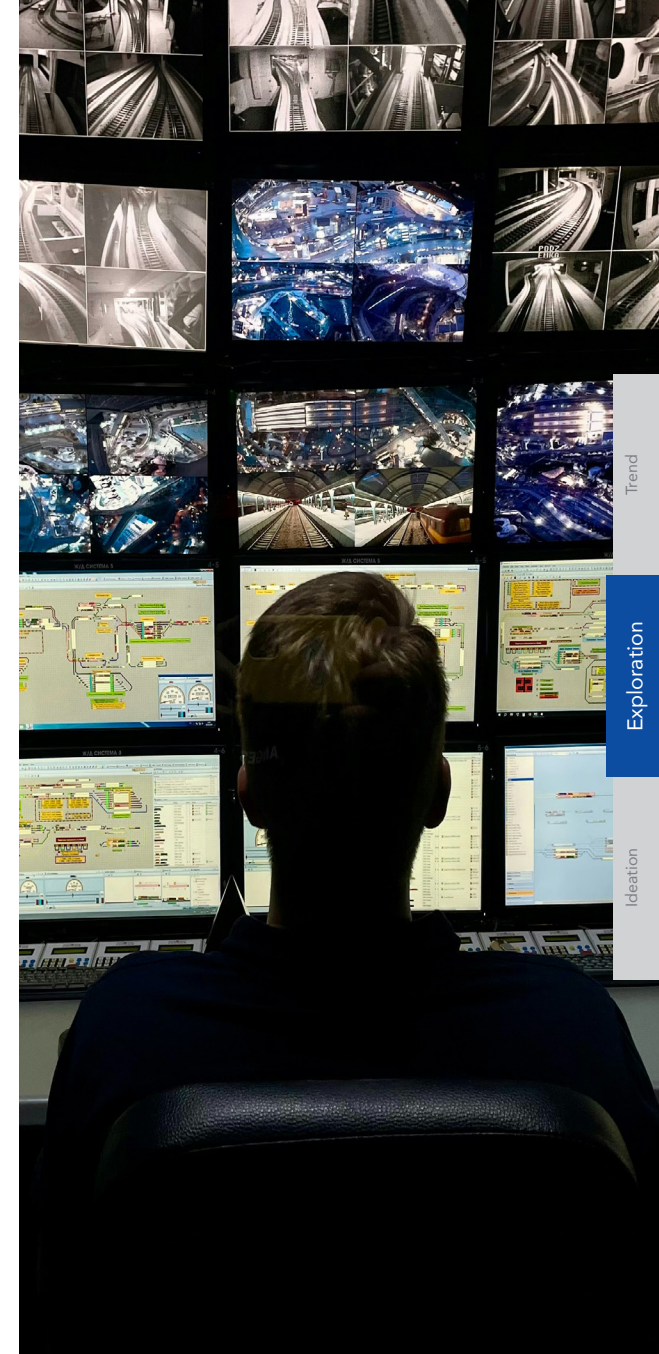
“

A worker will have to control many more machines in the future. We have a labor shortage and need the adaptability of workers to operate multiple systems.

”

Factory Manager at Siemens [657]

Selected Players



A large, complex industrial machine, likely a conveyor system or a large-scale crusher, is shown in operation. The machine is constructed from heavy metal beams and plates, with various components like rollers, pulleys, and structural supports visible. It is situated in a rugged, hilly environment, possibly a mining or construction site, with dry, brownish vegetation in the background. The machine's structure is intricate, with multiple levels and sections connected by long, angled beams. The overall scene conveys a sense of heavy industrial activity and scale.

RESOURCE LOOP

INFLUENCING THE FUTURE OF INDUSTRIAL AI

Closing the E-Waste Loop

Designing Lasting Machinery

Expanding the Scope of Digital Product Passports

Alessandro Sodano



Justus Beck



Lucy Strüfing



Max van Bentum



Paulina Möhrle



RESOURCE LOOP

Leveraging Digital Product Passports to Enable Closed-Loop Material Systems

The proliferation of AI-enabled industrial products is simultaneously intensifying demand for critical raw materials and creating conditions for more effective recovery within industrial systems. Increasingly, AI-enabled products are growing more complex, more reliant on rare earth elements, and increasingly difficult to process at end-of-life, outpacing the capacity of existing recycling infrastructure to extract value economically [504, 505]. Yet this is precisely where systemic action remains absent. Currently, materials that hold substantial strategic value are being lost at scale. Only if supply chains can be made traceable and recovery infrastructure intelligently orchestrated value can be retained. Three interconnected challenges define the gap between the materials industrial systems consume and those they recover.

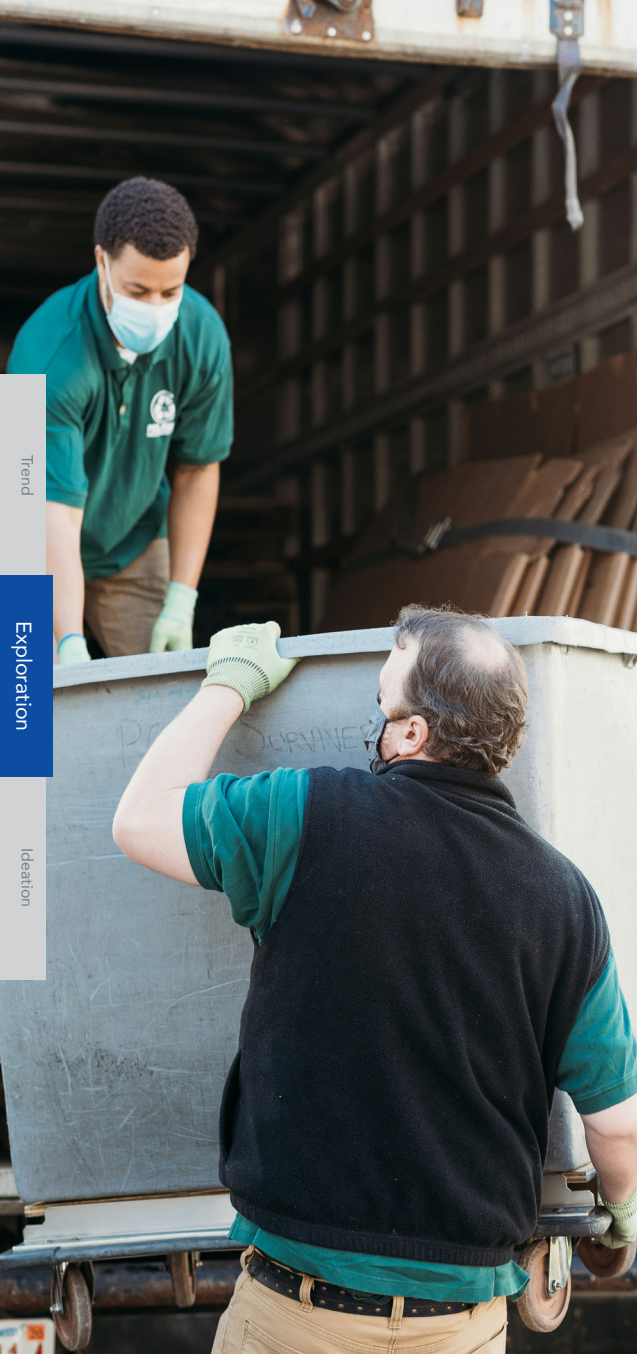
The first challenge is material recovery. Globally, only approximately 1% of rare earths are recovered from end-of-life products [506, 507], while the EU imports 95% of its rare earth supply and collects just 37.5% of its e-waste against a 65% target [508, 509]. Existing operators only recover what is

economically feasible, leaving the remainder lost or handled under uncontrolled conditions elsewhere [510, 511]. AI as an orchestration layer routing end-of-life material streams based on real-time composition data has foundational demonstrations in adjacent circular economy applications [299]. Without building this recovery infrastructure, the EU Critical Raw Materials Act's guideline of 25% domestic recycling of strategic materials by 2030 will remain structurally out of reach [512].

The second challenge is designing for longer, more sustainable lifecycles. Even where manufacturers hold detailed knowledge of their products' composition and performance characteristics, they historically lose control over assets after the point of sale, weakening incentives for lifecycle optimization [518, 519]. AI-powered predictive and prescriptive maintenance, outcome-based models such as EaaS, or AI-driven design for circularity embedded in Computer-aided design (CAD) workflows offer a path to realigning those incentives [5, 6, 236, 520, 521]. Modular de-

sign strategies could allow OEMs to capture aftermarket revenue at approximately twice the margin of equipment sales [522]

The third challenge is product data infrastructure. Industrial supply chains generate information across fundamentally incompatible systems so that composition records, environmental footprints, and lifecycle handling requirements are rarely captured in consistent or interoperable formats [513, 514]. The EU Ecodesign for Sustainable Products Regulation mandates DPPs as a direct response, requiring structured digital records of a product's composition, environmental impact, and lifecycle management, with non-compliance resulting in exclusion from the EU market [515]. Batteries face this requirement from 2027, with e.g., textiles or electronics following through 2030 [377, 516]. Firms implementing DPPs solely for compliance are missing the circular business models the underlying data infrastructure makes possible [517].



CLOSING THE E-WASTE LOOP

AI can Orchestrate Recycling Flows to Recover Critical Materials at Scale

Industrial AI is increasing the demand for critical raw materials while making their recovery more difficult [504]. The increasing use of rare earths and the complexity of materials is challenging for recycling due to the high cost of dismantlement, inefficient collection systems, and costly recovery methods [505].

Despite an established legal framework, the EU collects only 37.5% of its e-waste, well below the 65% target [509]. There is no primary production of rare earth elements in the EU [523], and globally, only 1% of rare earths are typically recycled from end-of-life products [506, 507]. Existing operators extract only what is easy to identify and economically worthwhile [510]. The rest is lost. What cannot be recovered economically is often processed in the Global South [511] under toxic, uncontrolled conditions [523].

The opportunity is the processing layer [299]. With AI as an orchestration layer, streams can be routed to the right process based on composition and market prices. Foundational concepts have already been demonstrated in adjacent circular economy applications [512]. Legally, the EU Critical Raw Materials Act requires 25% domestic recycling of strategic materials by 2030 [524]. However, no company has disrupted this layer at scale yet [299]. The collection infrastructure is operational, and the technology side is catching up. The opportunity lies in orchestrating the two.

“

Everything we extract from the earth has to become high-performance material, waste is no longer an option.

”

Christoph Völker, Head of Industrial AI at iteratec [646]

Selected Players

Cyclic
Materials

HYPRMAG
Magnet Recycling

ERI

NOVEON
MAGNETICS

greyparrot

TOMRA

Re
ELEMENT
TECHNOLOGIES

umicore

SOLVAY

PHOENIX
TAILINGS

DESIGNING LASTING MACHINERY

OEMs using AI to Build Assets with a Focus on Longevity

In one-off CapEx sales, which have historically been the standard industrial revenue model [518], OEMs lose control over assets after the point of sale, and therefore lack incentives to invest in lifecycle optimization [519]. Now, servitization models are shifting incentives toward longevity. AI-powered predictive and prescriptive maintenance can extend machine lifespans [5, 6]. Transparent AI systems act as an enabler via predictive maintenance and continuous visibility of condition and performance through to end-of-life [236].

To capture lifecycle value, OEMs must integrate AI-driven design techniques for circularity, such as formal disassembly information models embedded and modular designs [520, 521]. Beyond structural design, AI use in micro-labs on the factory floor also enables the discovery of high-performance materials specifically engineered for durability and easier recovery [525, 526].

Modular designs also create new business opportunities for OEMs by enabling ownership of second-hand markets through interchangeable modules and control over remanufacturing [527, 528]. Aftermarket income today can already offer double the Total Shareholder Return (TSR) of equipment sales [522]. In the coming years, repurposing and servitizing second-hand markets will be fundamental for OEMs to secure high-margin revenue. By offering parts and services to customers after the initial sale, companies can tap into a lucrative revenue stream with profit margins up to four times those of new units [529].

“

If everything becomes a service, OEMs effectively become risk selling companies.
That means they have a real incentive to make equipment last.

”

Employee at Siemens AI Lab [658]

Selected Players

SIEMENS

Protokol

madaster

AVERY DENNISON

IBM

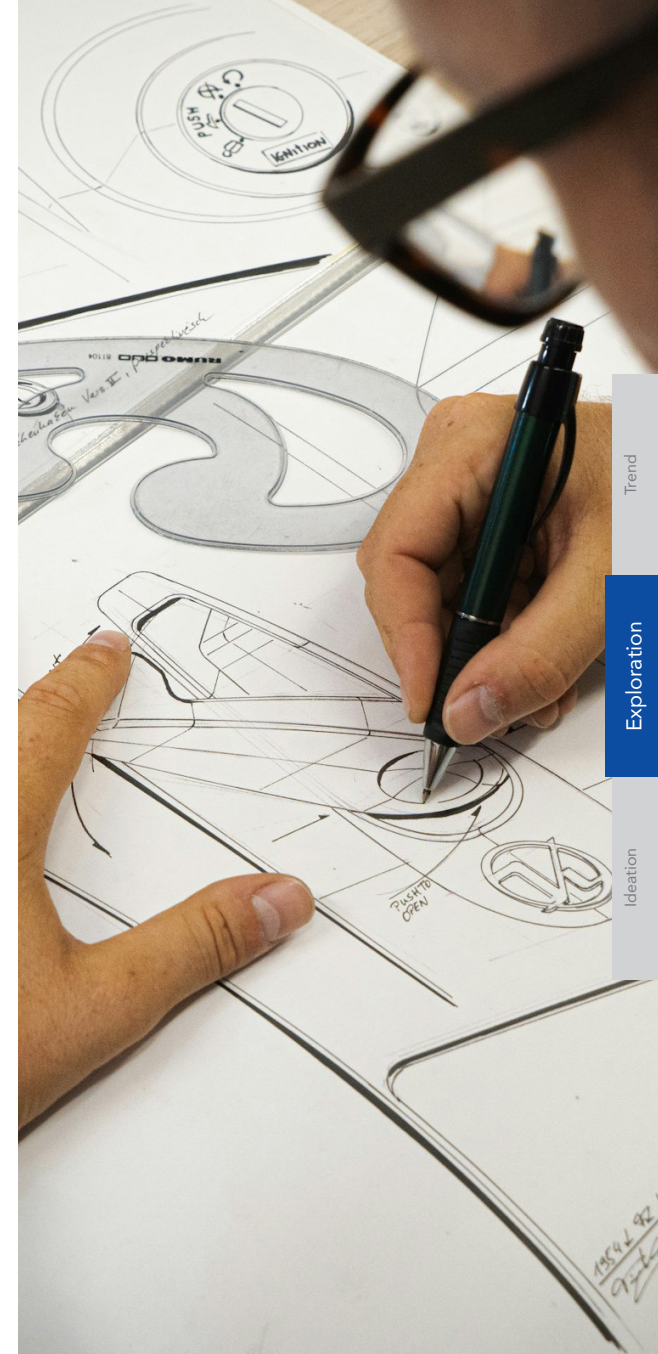
Munich RE

TextileGenesis
a LECTRA company

SPHERITY

CIRCULARISE

KEZZLER



Trend

Exploration

Ideation

EXPANDING THE SCOPE OF DIGITAL PRODUCT PASSPORTS

Building the Product Data Infrastructure for a Circular Economy

Product data across European supply chains is fragmented [530]. The EU's Ecodesign for Sustainable Products Regulation mandates DPPs: digital records of a product's composition, environmental footprint, and lifecycle management [515]. Non-compliance results in exclusion from the EU market [515]. Batteries are the first regulated category from February 2027, with textiles, steel, electronics, and furniture rolling out through 2030 [377, 516].

In practice, companies face significant gaps in data availability, data quality, and procedural realignment [513]. Required data often does not exist or is held by suppliers across dozens of countries, systems need integration, and new verification infrastructure must be built [514]. Early standards and pilots exist but remain immature relative to the scale required [531].

Most companies, particularly SMEs, are not yet aware of or preparing for these requirements [513]. Current tooling is limited, and companies that implement DPPs only for compliance reasons are at risk of missing the potential for new circular business models [517]. Solving these data availability, quality, and tooling challenges at scale would create the shared product data infrastructure that a functioning circular economy requires.

“

We go into a market where we can't sell hardware without the data.

”

Senior Researcher at Siemens [659]

Selected Players



IDEATION

The following chapter describes five novel ideas of great relevance for *The Future of Industrial AI*, especially in view of the previously identified trends. Each of the ideas is developed to solve a specific problem in the identified problem spaces.

ANNOTE.....	72	FLARE	84
OpsMemory.....	76	Complena.....	88
RiskFlow.OS.....	80		

Ava Mack



Josefine Jacobs



Lara Schupp



Markus Meinert



Sophia Schraml



ANNOTE

The Expert Pipeline for Industrial Training Data

ANNOTE is a domain-led data labeling platform designed to power the next generation of IFMs by transforming raw, open-source engineering assets into validated training sets. Currently, industrial AI is trapped in narrow operational silos. While large language models achieved broad generalization by pre-training on the full, messy diversity of human internet discourse, manufacturing AI often relies on narrow, task-specific industrial datasets and still faces generalization limits.

As a result, they suffer from severe domain shift, failing the moment operating conditions or defect types deviate from a specific plant's exact distribution [211, 532]. The underlying problem is structural: while there are vast open-source resources containing millions of 3D CAD models, process logs, and mechanical configurations available, they largely remain unlabeled and invisible to model builders. Consequently, AI teams spend up to 80% of their project time on basic data preparation, according to industry estimates [533]. Research confirms that data diversity and quality must be balanced jointly to maximize downstream generalization [534]. Using

a wide variety of pre-training data creates essential foundational knowledge that fine-tuning alone cannot provide [535]. Industrial models currently lack this broad pre-training layer.

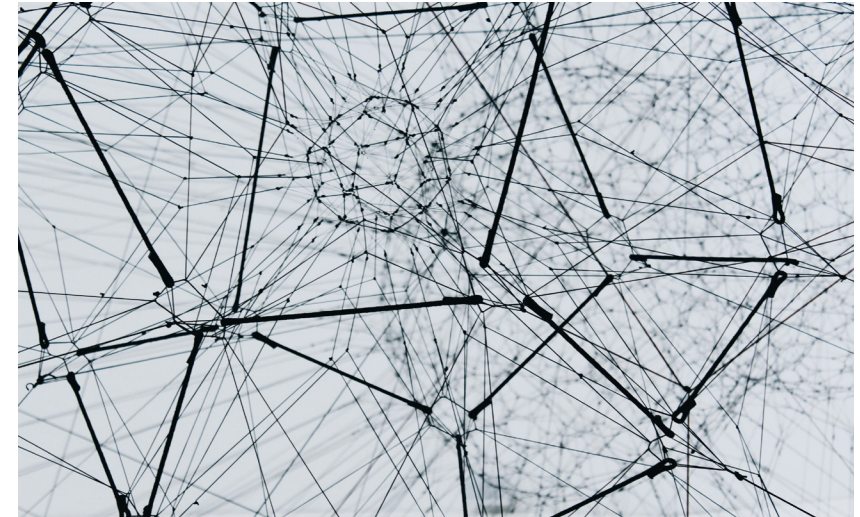
Recent evidence shows that high-quality human-in-the-loop annotation, including expert-level feedback, has become a critical component in training advanced AI systems at scale [536]. ANNOTE adapts this model for the industrial sector. Because active engineers are scarce, ANNOTE mobilizes an underutilized workforce of advanced engineering students and retired professionals.

This specialized talent possesses the precise foundational knowledge required to accurately categorize broad-spectrum open-source datasets. By exclusively utilizing public repositories, ANNOTE bypasses the risk of exposing corporate intellectual property and resolves the primary bottleneck to scaling industrial AI [211, 532]. ANNOTE's datasets are not highly classified, proprietary factory secrets. Instead, they are the structurally necessary breadth layer without which

pre-training remains narrow and generalization poor. By deploying a specialized workforce to label a fragmented open-source landscape, ANNOTE is building the diversity-rich pre-training infrastructure that the global industrial AI supply chain currently lacks [534, 535].

Problem

- Accurately labeled industrial data is critically scarce. Millions of raw datasets across open-source platforms remain entirely invisible to training pipelines, depriving IFMs of the diversity required for robust generalization [211, 532].
- Training on isolated and homogeneous datasets produces models prone to overfitting. These models fail to generalize across diverse manufacturing floors because single-firm silos lack the structural diversity that robust IFMs require [532].
- Validating industrial data requires specialized expertise that firms struggle to allocate efficiently. Gartner estimates that by 2026, organizations will abandon 60% of AI projects due to insufficiently prepared training data [537].
- Industrial datasets remain trapped in proprietary silos as firms fear sharing operational information could expose core competitive advantages [284].

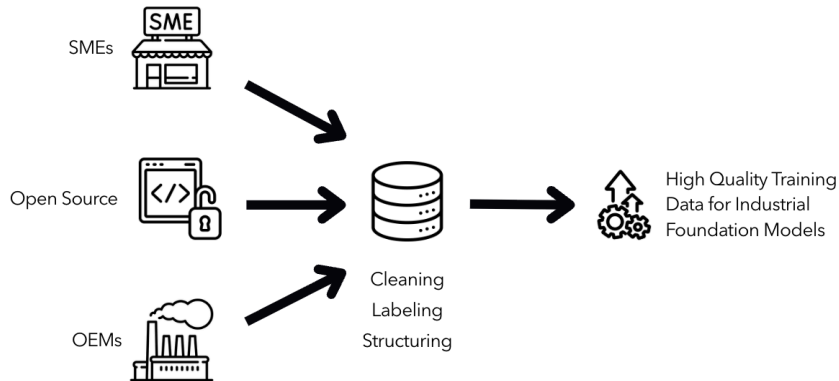


ANNOTE must transform fragmented public archives into diverse expert-labeled assets to fuel next-generation industrial foundation models.

Solution

- ANNOTE accelerates the development of IFMs by unlocking untapped open-source archives and combining specialized talent with robust quality assurance.
- The approach of multisource aggregation enhances overall model diversity, preventing overfitting and fostering resilient AI that uncovers insights beyond the limited scope of single-firm datasets.
- Furthermore, ANNOTE bridges the expertise gap through a curated pool of engineering students and retirees. This streamlines the validation of complex physics data, ensuring high-fidelity labels for OEMs without requiring them to allocate expensive internal talent to data preparation.
- By curating millions of files from platforms such as Thingiverse, GrabCAD, and the ABC Dataset, ANNOTE successfully bypasses IP restrictions and repurposes 3D models into high-quality training data.

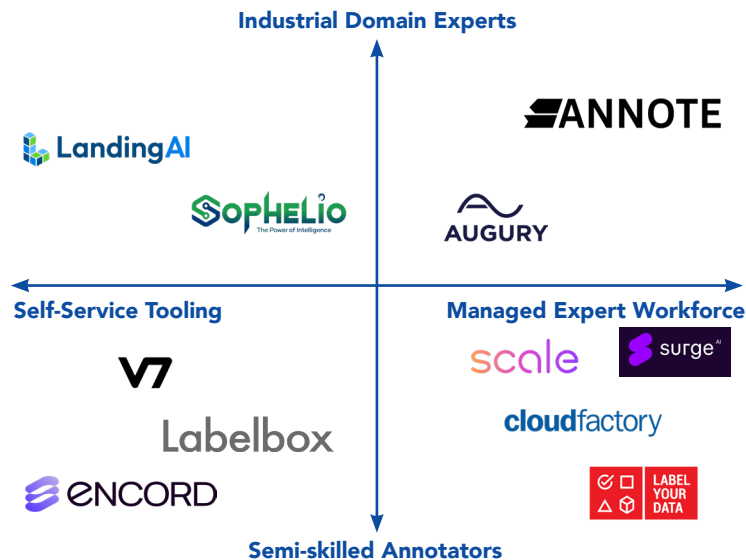
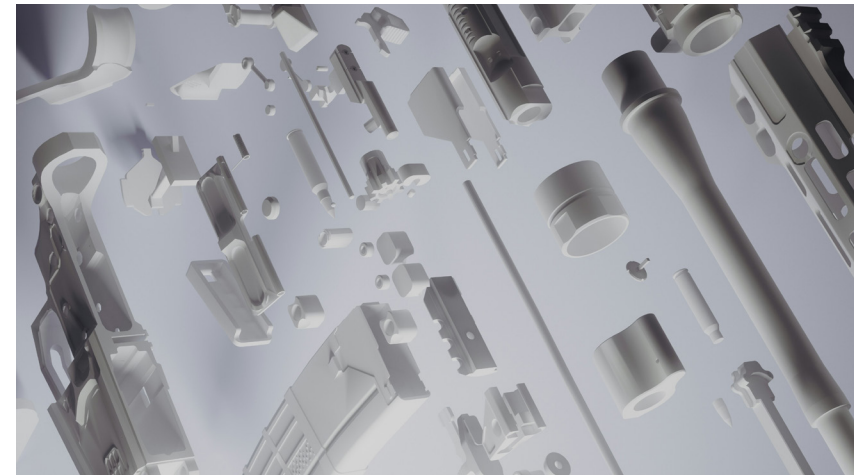
Through expert validation, ANNOTE transforms unusable raw data into high-performance training assets for industrial foundation models.



Market Drivers

- The market potential for data labeling is driven by a convergence of global regulatory mandates and structural shifts toward high-fidelity AI.
- The global data collection and labeling market is projected to reach 17.1B USD by 2030, reflecting a CAGR of 28.4% [538].
- As IFMs mature, AI teams spend approximately 80% of project effort on data preparation, making expert curation of telemetry and sensor streams the primary bottleneck rather than algorithm design [533].
- Market demand is catalyzed by the EU AI Act, which mandates that high-risk industrial AI systems utilize training and validation datasets that are relevant, representative, and free of errors [170].
- The EU Data Act supports this expansion by mandating machine data portability, unlocking vast silos of telemetry that require professional labeling to be converted into tradable AI-ready assets [280].

EU regulation is unlocking industrial data at unprecedented scale. ANNOTE converts the flood into AI-ready training assets.



Competition

- Specialized data annotation providers, such as Surge AI, have demonstrated the scalability of expert-driven labeling for training advanced AI systems [539]. However, they lack capabilities in the industrial sector.
- Leading data labeling providers, such as Scale AI, are increasingly expanding into foundation model infrastructure and large-scale AI system support [540].
- Generic data labeling Business Process Outsourcing (BPO) companies such as Cogito and Label Your Data offer low-cost, high-volume annotation but lack engineering domain expertise.
- Internal data science teams are the default approach, but many remain stuck in pilots because data preparation slows progress [541].
- Industrial data marketplace platforms such as Dawex and GAIA-X address the data distribution problem but solely transport raw, unlabeled datasets [542].

ANNOTE acts as a bridge in the market, connecting labelers who lack domain expertise with manufacturers who cannot label their data effectively.

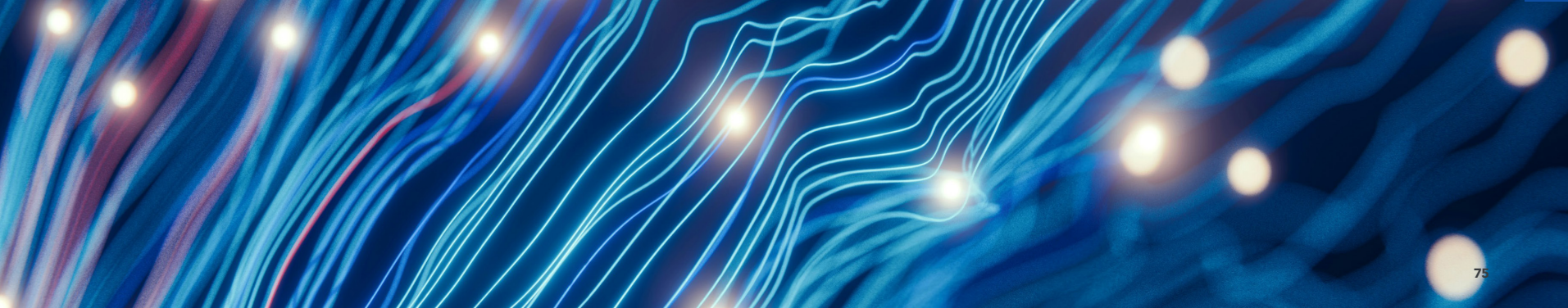
Assumption Tree



Trend

Exploration

Ideation





OpsMemory

Every Repair Builds Your Knowledge Base

OpsMemory is an AI-powered knowledge management platform built for industrial maintenance teams. It addresses one of manufacturing's most persistent challenges: the loss of tacit knowledge, the experience-based, often semiconscious expertise that workers accumulate over years but struggle to articulate [547, 548]. This knowledge spans a wide spectrum, from intuitive pattern recognition to the unspoken rules behind rapid diagnostic decisions [548, 549]. It is critical to process quality and continuity, yet it remains stored almost entirely inside workers' heads [421, 550]. With roughly a quarter of the industrial workforce set to retire by the end of the decade [551], the risk of this expertise walking out the door is acute [90]. The impact is especially severe in maintenance, where diagnosing equipment failures depends on experiential judgment [120]. A particularly critical moment of loss occurs at shift change, when technicians carry away insights about half-finished diagnostics that never reach any log [120]. Without a structured capture mechanism, the next crew starts without context, missing important cues. Unplanned downtime already costs the 500 largest manufactur-

ers an estimated 1.4T USD per year [552]. At the same time, technicians spend only 25-35% of their shifts on hands-on tasks, while the rest is consumed by planning, waiting, and navigating incomplete documentation [553].

OpsMemory tackles this through Deep Conversational Intelligence. Drawing on research on intelligent assistants that elicit tacit knowledge through systematic reflection [554], the platform's AI copilot does not merely provide fixes. It probes technicians about the reasoning behind their decisions, asking targeted follow-ups such as why a component was chosen or what ruled out an alternative cause. The copilot thereby encodes expert rationale into the knowledge base well beyond what surface-level documentation captures [550, 555]. Complementing this is an adaptive validation loop. The system presents technicians with assumptions derived from past repairs and asks them to confirm or correct them. Rather than requiring workers to articulate complex reasoning from scratch, this low-friction approach lets them validate the sys-

tem's understanding in seconds, increasing both the quality and volume of captured knowledge [556]. These mechanisms turn knowledge capture into a seamless byproduct of everyday work. In later versions, the copilot will also surface live sensor data for real-time diagnostics and capture additional modalities such as video to enrich the knowledge base.

OpsMemory begins with maintenance to build a robust knowledge layer, then expands into full factory operations to strengthen the institutional memory of every facility it serves.

Problem

- Most of what experienced workers know about diagnosing faults and managing edge cases has never been written down. It exists only as tacit knowledge, built over years through trial, error, and pattern recognition that no formal training replicates [547, 548].
- By the end of the decade, roughly 25% of the industrial workforce will have retired, taking expertise that no maintenance manual or standard operating procedure currently captures. The knowledge gap compounds with every departure [90, 551].
- The same loss plays out on a smaller scale at every shift handover: live context about on-going faults, unusual machine behavior, and partially completed diagnostics fail to transfer, forcing incoming crews to repeat work already done [120].
- Existing knowledge management tools demand structured input that shop-floor workers lack the time and incentive to provide [421].

Start capturing tacit expertise now, before decades of hard-won operational knowledge leave with the workforce.



Solution

- OpsMemory gives every technician an AI copilot that draws on manuals, sensor data, and proven fixes by colleagues, so the right answer is always one question away.
- During a repair, the copilot pulls live machine data, connects anomalies to known resolution steps in real time, and turns raw sensor readings into actionable guidance without the technician ever leaving the machine.
- Compliance reports and shift handover notes are auto-generated from the repair conversation itself, capturing context that manual logs routinely miss. The technician reviews and approves in seconds without writing a single line.
- Every completed repair feeds back into the knowledge base, credited to the technician who solved it. The system tracks whether each fix holds over time and automatically retires entries that no longer apply.

Let's turn every repair into institutional memory, so critical expertise stays with the organization, not just the individual.

Your conversational AI copilot that...

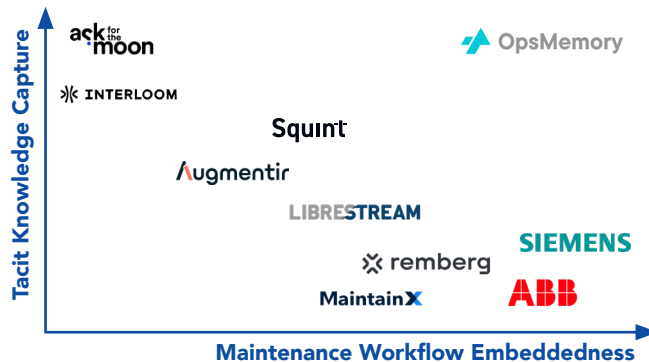


- 1 Talks through every **fix** based on **past repairs & manuals**
- 2 Surfaces **live sensor data** for real-time **insights**
- 3 Turns **conversations** into **reports** & shift handovers

Market Drivers

- A third of mechanical engineering firms in Germany cannot fill most of their skilled positions [557], and the Information und Forschung (IFO) Institute warns the structural outlook is worse: demographic aging and rapid technological change will keep tightening supply [558].
- At the same time, EU machinery regulations now require full lifecycle maintenance traceability, adding documentation requirements that pull technicians further from hands-on work [559].
- The financial stakes are high. Manufacturing turnover in production roles exceeds 30%, and replacing a single skilled worker costs 50-200% of their annual salary, making knowledge retention as much a financial necessity as an operational one [560, 561].
- The market is responding: the industrial copilot segment stands at roughly 4.5B USD today and is projected to exceed 48B USD by 2036, a broad bet that AI-assisted workflows can offset the shrinking workforce [562].

Evolving labor markets and a growing scarcity of skilled workers are pushing manufacturers to make the most of the expertise they already have.



Competition

- The competitive landscape splits along two axes: how deeply a tool captures tacit expertise, and how tightly it is embedded in the maintenance workflow itself.
- Established maintenance platforms from Siemens, ABB, MaintainX, and remberg sit deep inside the workflow but focus on structured task execution rather than extracting the reasoning behind a repair [563, 564, 565, 566].
- Connected-worker tools such as Augmentir and Librestream add guided instructions, remote expert access, and some tribal knowledge capture, but treat knowledge retention as a secondary output rather than the core product [567, 568].
- Dedicated knowledge-capture platforms like Ask for the Moon, Interloom, and Augmented Industries come closest to preserving tacit expertise, but they operate outside the maintenance workflow and depend on separate documentation effort [569, 570, 571].

Current tools solve parts of the problem. The missing piece: capturing tacit knowledge as a byproduct of work, not an extra task.

Assumption Tree

Tacit Knowledge Loss Is Accelerating

Germany alone will lose 12.9M workers to retirement by 2036 [572]. Globally, manufacturing must fill 3.8M jobs by 2033 [573]. Retiring workers take with them knowledge that is learned through daily experience and thus hard to document [574]. This knowledge drain is accelerating as retirements rise, companies lose tacit know-how faster than they can capture or transfer it.

Technicians Have No Time to Document

Technicians spend only 25-35 % of their shifts on actual maintenance, with the rest consumed by planning, waiting, and information search [553]. Traditional knowledge capture requires workers to document expertise on top of this workload. Without active enforcement, these efforts consistently fail [550].

Assistant Works in Hands-on Context

Controlled experiments show diagnostic support can reduce maintenance task time by 15% without increasing cognitive load [575]. Voice interfaces allow hands-free interaction when workers hold tools, wear gloves, or move across the floor. Headset devices address ambient noise, though cultural acceptance needs validation per site.

Sensors Add Context Without Input

Modern equipment generates continuous telemetry covering cycle times, temperatures, and pressures. Before-and-after sensor snapshots contextualize repairs without verbal explanation, addressing the insight that we can know more than we can tell [576]. Machine data may capture patterns workers apply unconsciously.

Technicians Will Share Knowledge if They Benefit

Tacit knowledge remains undocumented because sharing offers no personal return [550]. The only viable path is near-zero marginal effort from the worker, while offering them immediate value through faster diagnosis and automated reporting. Knowledge extracted as a side effect lets workers feel augmented rather than monitored.

Voice Plus Sensors Unlock Knowledge Capture

If voice AI is viable in maintenance settings and sensor data provides additional context, then tacit knowledge can be extracted from what the technician shares and what the equipment measures. Conversation supplies qualitative reasoning, while telemetry adds quantitative structure, together forming a robust foundation for the knowledge layer.

The Knowledge Base Compounds Over Time

If every repair interaction helps the worker and enriches the database, the knowledge asset grows as a byproduct of daily work. Fix-effectiveness tracking and later jobs can validate entries, flag contradictions, and retire stale knowledge. The result is a self-improving system whose value compounds.





RiskFlow.OS

Pricing Industrial Risk in Real Time

Industrial manufacturing is undergoing rapid datafication. Nearly half of manufacturers already use industrial IoT solutions, and 57% have adopted cloud computing [40]. The sensor infrastructure for real-time monitoring of operational risk is expanding rapidly [577]. Yet none of this intelligence systematically reaches the insurers who price that risk. Industrial property insurance still relies on retrospective methods such as historical loss tables, periodic inspections, and policyholder-reported data [448, 578].

This creates a structural information asymmetry: Insurers cannot observe true operational risk and apply conservative, category-level premiums, while operators generate rich evidence of reliability that no insurer ever sees [441, 579]. RiskFlow.OS closes this gap by connecting machine-floor sensor data to risk intelligence, serving manufacturers and the insurers who cover them.

The cost of this disconnect for manufacturers is severe. Over two-thirds of industrial businesses experience unplanned

downtime at least once per month, at a median cost of 125,000 USD per hour [565]. The data to predict and prevent these failures increasingly exists within factory systems, but it remains siloed, used at best for internal optimization and invisible to the insurance market [580]. RiskFlow.OS connects to existing factory sensors via standard protocols, applies AI models trained across a factory network to detect early failure signatures, and delivers actionable maintenance recommendations alongside automated compliance reporting.

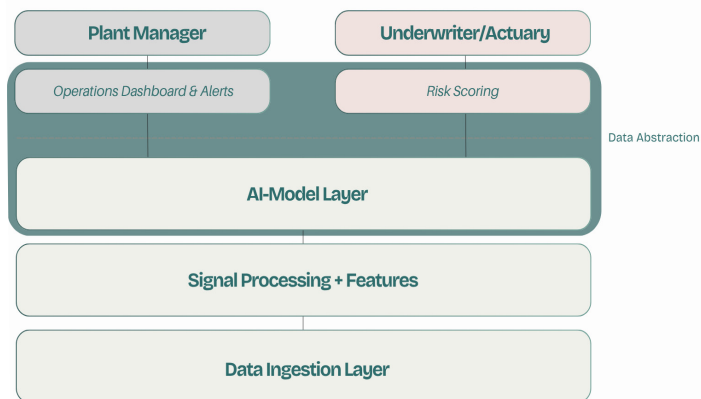
On the insurance side, AI is shifting the business model from loss compensation to prediction and prevention [578]. Integrating IoT sensor data enables dynamic premium adjustment and policyholder-specific underwriting [441]. RiskFlow.OS delivers a continuous, auditable risk score that enables data-driven pricing, improves portfolio loss ratios, and unlocks new customer segments. The platform allows insurers to differentiate more reliably between high- and low-risk operators, overcoming the adverse selection that made insuring for well-maintained SMEs unprofitable [579].

Every factory onboarded simultaneously sharpens manufacturers' predictive models and refines insurers' actuarial data, creating a compounding network effect that constitutes the platform's core structural moat.

Problem

- 92% of manufacturers consider smart manufacturing critical for competitiveness, and nearly half already deploy IoT solutions [40].
- For manufacturers, this valuable operational data stays trapped inside factory walls and is never translated into the insurance pricing that determines their premiums [580].
- For insurers AI introduces entirely new, hard-to-price risks that insurers are not yet equipped to handle, while standardized premiums fail to reflect actual operational risk, causing inefficiencies and customer losses [578, 581].
- The result is a persistent pricing gap: manufacturers with best-in-class AI safety systems pay the same costly premiums as those without, in part because insurers lack visibility into how machines are actually used, removing any financial incentive to invest in risk reduction.

This leaves space to turn data into a shared language between manufacturers and insurers, unlocking smarter operations and more accurate risk pricing.



Solution

- By interfacing with existing machine sensors, RiskFlow.OS avoids hardware changes. Signs of failure are detected and logged with timestamped, traceable resolution records [577].
- For manufacturers, these logs enable risk benchmarking against the factory network, highlighting where improvements reduce cost and insurance exposure [582].
- For insurers, each maintenance record serves as audit-ready underwriting evidence, enabling continuous risk assessment superior to annual inspections [583].
- Models train across the factory network using abstracted data, so each new participant improves prediction accuracy and sharpens risk scoring for the whole portfolio [584].
- When manufacturers ignore high-confidence alerts or maintain assets poorly, this signal is captured and acted upon at renewal [585].

RiskFlow.OS builds the trust layer that adds value for both insurers and manufacturers whilst remaining strict about data security risks.

Market Drivers

- The average large plant loses 253M USD/year to unplanned downtime, with per-hour costs doubling since 2019 [552].
- The EU Network and Information Systems 2 (NIS2) Directive, with fines up to 10M EUR or 2% of global turnover, creates a legal imperative for auditable risk management across operations and supply chains [586].
- Europe's 128.5B EUR property insurance market is an untapped lever for manufacturers who can supply certified, real-time data proving lower risk than industry benchmarks [587].
- Reinsurers have validated the data-for-risk model by linking IoT data to financial guarantees, confirming carrier interest in underwriting based on operational intelligence [588].

These converging pressures create a clear market imperative for a trusted data layer that turns operational risk into a strategic financial asset.

Integration Depth



Competition

- Munich Re acquired the IoT startup Relayr to build a sensor-to-insurance data layer, but wound down the venture in 2024. The product effectively made Munich Re a competitor of insurers, creating channel conflict and disincentivizing them from sharing their information on the platform. This proves the need for a neutral intermediary [589].
- Players like Augury are moving toward risk transfer, but rely on their own proprietary hardware for sensing and collection. This leads to onboarding friction, limits scalability, and creates vendor lock-in. This therefore represents a point solution [590].
- Scalable software tools, such as Siemens Senseye, are powerful but tied to a single OEM's ecosystem. This makes them a non-neutral player for manufacturers with diverse equipment, preventing them from becoming a universal trust layer [591].
- The fragmented landscape of expensive in-house teams and tailored projects from SIs like Deloitte represents the status quo. These solutions are slow, do not scale, and lack the independent certification required to gain the broader insurance market's trust [592].

The key differentiator of RiskFlow.OS is its independence, which positions it as the only neutral data intermediary.

Assumption Tree

Datafication of the Shop Floor

Modern industrial machines are increasingly equipped with sensors and connected systems (PLCs, SCADA), generating continuous streams of telemetric data such as vibration, temperature, and pressure [577]. This enables real-time condition monitoring, with data volumes set to grow as sensor costs fall and connectivity becomes standard [593].

Self-Selection Bias in Industrial Insurance

Insurance markets are characterized by asymmetric information, as insurers cannot observe a policyholder's true operational risk. This forces them into bundled, category-level coverage rather than tailored policies, which disproportionately attracts high-risk companies. Knowing this, insurers apply conservative premiums, systematically overcharging low-risk operators [441, 579].

Distrust of Insurers

Insurers inherently distrust unaudited, self-reported operational data from clients due to information asymmetry at the core of underwriting [448]. This forces reliance on broad industry benchmarks rather than actual risk-management practices, leading to conservative pricing that penalizes proactive operators [441].

Manufacturers' Willingness to Share

Nearly three-quarters of manufacturers are open to sharing data, but only if they retain sovereignty and control over its use [594]. The primary barrier is not technical but a fear of losing competitive advantage, requiring platforms that enable policy-based sharing without relinquishing data ownership [595].

Shared Data Platform as Trust Layer

Because operational data now exists at scale and insurers lack access to it, a shared data platform becomes economically rational for both sides. Such a platform must act as a neutral and independent intermediary that guarantees data integrity and sovereignty for all participants [595, 596].

Insurers Are Open to Adjusting Premiums

Insurers misprice risk by necessity, not choice. Where data resolves the information gap, insurers demonstrably shift to policyholder-specific pricing, directly reducing adverse selection and moral hazard [597]. Insurers actively seek data-driven underwriting to replace broad-category policies [448].

Mutual Gain Through Data Transparency

A neutral data intermediary resolves the information asymmetry that distorts industrial insurance markets [579]. Manufacturers gain data-driven leverage for fairer premiums. Insurers gain the precision to profitably serve well-maintained companies previously priced out by conservative benchmarks [595].

Trend

Exploration

Ideation

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FLARE

On-Demand Teleoperation Platform for Fault Recovery

Driven by AI, robotics, and industrial IoT, 60% of manufacturers are moving toward operating more than two fully lights-out processes, and the global dark factories market is expanding at 8.7% annually toward a 194B USD valuation [495, 598]. In this new setup, production runs with minimal human presence, and the operator's function has narrowed to resolving conditions where automation fails [599]. However, this operational shift is hindered by outdated models of human intervention that rely on fixed local maintenance shifts from the legacy manufacturing era [599].

This mismatch accelerates an ongoing skills gap. The US manufacturing industry alone faces up to 1.9M unfilled positions by 2033, as technical training cannot keep up with the complexity of modern industrial equipment [90]. This skills gap is driving both a productivity crisis and rising costs. Downtime recovery now averages 81 minutes per incident, 65% longer than five years ago, partly because plants lost many experienced technicians after the pandemic [552]. For a large facility, the annual cost of unplanned downtime averaged 253M USD in 2024 [552].

The pressure for change comes from both sides. The vast majority of plant managers prefer to pay for maintenance outcomes rather than fixed contracts [600], and 68% of manufacturing leaders identify flexible scheduling as one of the most impactful factors for frontline worker retention [601]. The problem is not a shortage of automation. It is a systemic failure to place the right expertise at the right fault at the right moment.

Medicine already dealt with this issue. Telesurgery enables robotic procedures performed across distances of over 5,000 km [602]. Industry is slowly adopting the same solution. Academic research and early deployments demonstrate that remote expert intervention is technically deliverable for industrial fault resolution [599, 603].

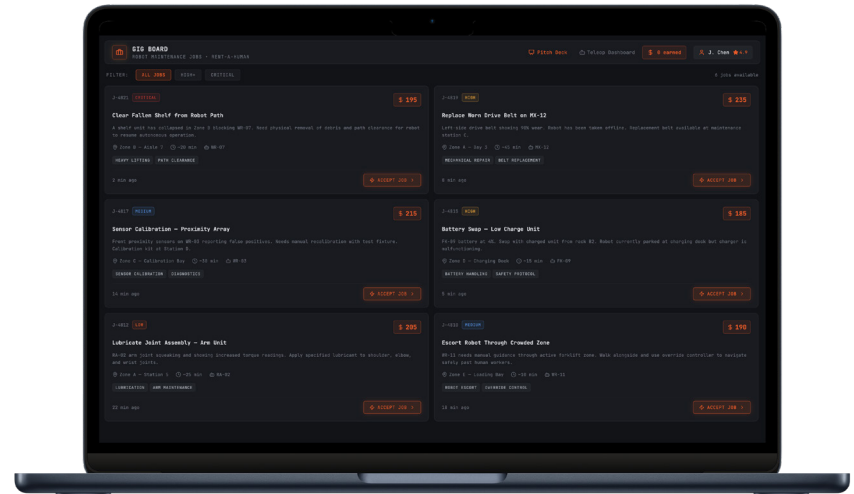
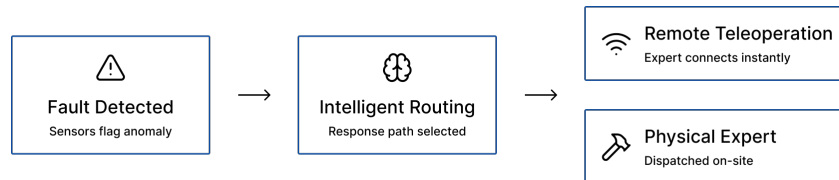
FLARE is a hybrid on-demand platform built on that promise. Fault events route automatically to a global pool of verified teleoperators and certified field technicians, matched in real time by fault type and machine-specific credentials. Factory IP is protected by isolated access lay-

ers that expose only what each operator needs to know to resolve the specific fault in front of them. On-site dispatches arrive provisioned with diagnostics, required tooling, and credentials, so resolution begins before the first tool is picked up. Because FLARE operates at the software interface layer common to OEM-standardized machines, expertise becomes a global rather than a local resource.

Problem

- Unplanned downtime costs the world's 500 largest manufacturers 1.4T USD annually, equivalent to 11% of their revenues, with automotive losses reaching 2.3M USD per idle hour, while recovery has surged to 81 minutes [552].
- The cognitive complexity of modern industrial equipment has far surpassed the capabilities of the generalist on-site workforce, leading to critical delays and high error rates during knowledge-dense maintenance [604].
- Despite advances in automation, research confirms that human judgment remains critical for resolving rare, unpredictable failures. Human judgment adds context, intuition, and accountability that AI systems alone cannot provide, making human-in-the-loop essential for both safety and efficiency [605].
- To provide this fallback, operators are bound to fixed local shifts to handle rare exceptions, a highly inefficient model where wrench time averages just 28%, leaving nearly three-quarters of capacity unutilized [553].

The factory floor does not need more full-time guards. It needs the right expert, at the right moment, from anywhere.



Solution

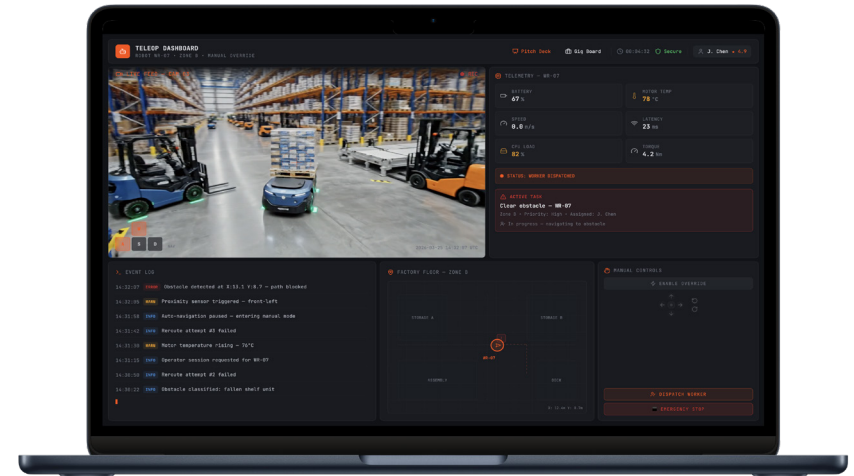
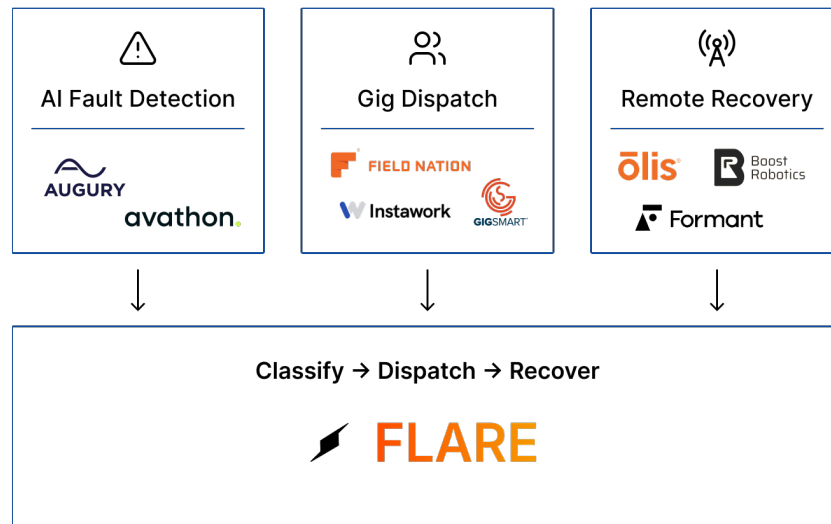
- FLARE is a hybrid on-demand maintenance platform that integrates with existing fault-detection systems to automate responses, requiring no new hardware or workflow changes.
- When a system encounters an edge case, FLARE instantly routes the issue to a global pool of certified teleoperators who resolve the fault remotely using isolated system logs and restricted camera feeds to protect the factory's IP.
- If physical intervention is required, the system automatically dispatches the nearest gig-technician whose technical certifications match the machine's complexity.
- To minimize on-site delays, these dispatched physical workers receive automated pre-arrival briefings containing the exact fault diagnosis, required tools, and facility access credentials.
- Every remote and physical resolution is recorded and integrated into the system, continuously improving dispatch speed and diagnostic accuracy, while also providing information to the OEMs.

When machines fail, FLARE sends the signal, activating an on-demand network of remote and local experts to fix faults and restore uptime.

Market Drivers

- Unplanned downtime is costly enough to force action, with Siemens estimating average annual losses of 253M USD per large plant [552].
- Operational labor shortages are creating severe industrial bottlenecks, with the 2024 European Employment Services (EURES) data ranking plant and machine operators as the second-highest deficit, behind craft trades, with 8.2 identified shortages per unique occupation in that category [606].
- Mixed-fleet operations are becoming more realistic as interoperability matures, and VDA 5050 Version 3.0.0 was published in March 2026 as the latest open cross-vendor standard for fleet-to-mobile-robot communication [607].
- Manufacturers face a critical need to balance EU AI Act human oversight requirements with the labor-saving ROI of their robotics [608].

FLARE enables robotic companies to sell uptime guarantees through a unified control and recovery platform.



Competition

- AI fault detection platforms, such as Augury and Avathon, provide sensor-driven diagnostics for manufacturing and automatically generate CMMS work orders for internal teams, but resolution depends on on-site staff availability. Remote expert advisory is offered, whereas external technician dispatch is not [609, 610, 611, 612].
- Remote recovery tools, such as Olis Robotics, enable browser-based robot monitoring, control, and error recovery, claiming up to 90% reduction in downtime through a partnership with Kawasaki [613, 614, 615]. However, the platform assumes a qualified engineer is already present and cannot dispatch one when physical intervention is required [613, 614].
- Gig-worker platforms, such as Field Nation, provide on-demand technicians but focus on IT and low-voltage work [616, 617]. While the platform covers some manufacturing tasks, it does not offer certified OT-level robot repair, and dispatch is human-initiated with no machine telemetry integration [616, 617].

FLARE is the only platform that automatically connects a fault signal to a certified technician, without a human in the loop.

Assumption Tree

Downtime Is Costly and Frequent

Two-thirds of industrial companies experience unplanned downtime at least once per month, at an average cost of 125,000 USD per hour [618]. This costs the world's 500 largest manufacturers 1.4T USD annually [552]. Neither retained staff nor OEM call-outs close the response gap fast enough to contain these losses.

Maintenance Models Are Flawed

Manufacturers must either keep specialists on standby at high cost or wait for OEM support, which is too slow and rigid for complex equipment [618]. Neither suits automated facilities that depend on near-continuous throughput. Increasing system complexity and the presence of mixed vendors widen the gap between fault and qualified intervention [503].

A Qualified Operator Pool Exists

A distributed workforce of credentialed industrial experts can be structured as a modular labor pool, available remotely or on-site, without permanent employment [645]. Expertise will shift from equipment-specific to system-agnostic. Structured certification, validation, and precise matching will matter more than generic gig marketplaces.

Teleoperated Maintenance is Possible

Adoption of 5G/6G in manufacturing plants will deliver ultra-low latency under 100 ms for teleoperation [603]. API standards (ROS 2, VDA 5050) will enable standardized robot control software through unified telemetry and control interfaces across heterogeneous fleets of machines [619]. Video streaming quality is sufficient for remote maintenance.

Factories Need On-Demand Maintenance

High downtime costs and inadequate response models create pressure on manufacturers. Retaining full-time specialists for every robot type and failure mode is economically unsustainable [618, 620], driving a shift towards outcome-based maintenance agreements [618]. An on-demand intervention model triggered upon fault addresses both gaps simultaneously.

Factories Will Trust External Dispatch

Manufacturers must satisfy two conditions: consent to share machine fault data with external service providers and accept externally dispatched operators to intervene on critical equipment. Contractual safeguards, including NDAs, zero-trust data access, certified vetting, and full session audit trails, are minimum conditions for adoption [621, 622, 623].

Need for Efficient Maintenance

Cross-manufacturer, resolution-agnostic dispatch creates value that neither OEMs nor gig platforms can replicate. OEMs cannot serve cross-brand fleets; gig platforms lack fault classification and robot-specific credentialing. The layer connecting fault detection to certified resolution, remote or physical, across any floor is needed and missing.





Complena

Continuous Compliance

Environmental regulations affecting manufacturers across the EU, from the ESPR and DPP to evolving sustainability reporting requirements, are not only growing in scope but shifting in unpredictable ways with limited clarity on what to report, as shown by the recent Omnibus package that significantly altered reporting obligations overnight [247, 624]. For SMEs, the challenge is not just today's compliance but also the uncertainty about what data they will need tomorrow. A survey of over 1,000 German firms found that two-thirds were either not aware of the DPP or did not consider it relevant, and only 4% had taken steps to prepare [513]. Collecting environmental product data manually is slow and expensive, while creating it from scratch where it does not exist is even harder, particularly for SMEs without dedicated compliance teams [625].

Complena's first target customer groups are machine builders and industrial SMEs, who buy components from large manufacturers such as Siemens. Unlike most suppliers, these large manufacturers already publish detailed product-level environmental data [626], including CO₂ emissions, water

usage, and material composition, but this information is scattered across unstructured public sources. Complena's customers need exactly this data to build their own product-level environmental profiles, but they currently do so by hand.

Complena solves this in two steps. First, AI automatically retrieves, reads, and structures product-level environmental data from public unstructured sources. Customers map which supplier components go into which of their own products. When a supplier updates their environmental data, the change automatically flows into every dependent product. Suppliers are then rated on how complete and available their environmental data is, creating a natural incentive to improve.

Not all suppliers have the needed environmental data yet [374]. Where data is missing, Complena flags this clearly so customers know exactly which suppliers have gaps. This is why Complena starts with SMEs who buy from large manufacturers like Siemens: much of the data already exists and is publicly available, giving customers a strong foundation from

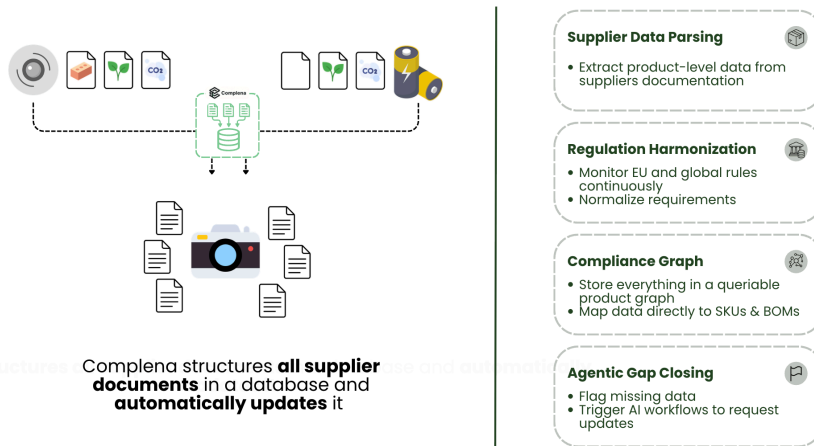
day one. For the remaining gaps, customers can request the missing information or consider alternatives with better data coverage.

The core value of Complena is simple: we turn unstructured public information and raw production data into a structured, living data layer that covers the entire supplier network. This removes the need for manual data collection and makes environmental data readiness not a one-time project but a continuous, automated process, so that when regulations change, shift, or expand, the data is already in place.

Problem

- EU regulations, such as the ESPR, are introducing mandatory product-level data requirements, starting with battery passports in 2027 and expanding to textiles, aluminum, and other categories through 2030, yet 81% of European companies lack the structured lifecycle data needed for compliance [247, 625].
- The regulatory landscape is unstable. The Omnibus package reduced CSRD reporting scope, while ESPR obligations continue to expand through new delegated acts. SMEs cannot plan around requirements that shift between policy cycles [624].
- A survey of over 1,000 German firms found that two-thirds were unaware of the DPP, and only 4% had taken steps to prepare [513].
- This data gap cannot be closed retroactively. Product-level environmental assessments require primary data collected during manufacturing [627]. SMEs that delay building structured data will risk facing compliance deadlines without the records to meet them.

SMEs are drowning in fragmented environmental product data as compliance requirements become increasingly complex.



Solution

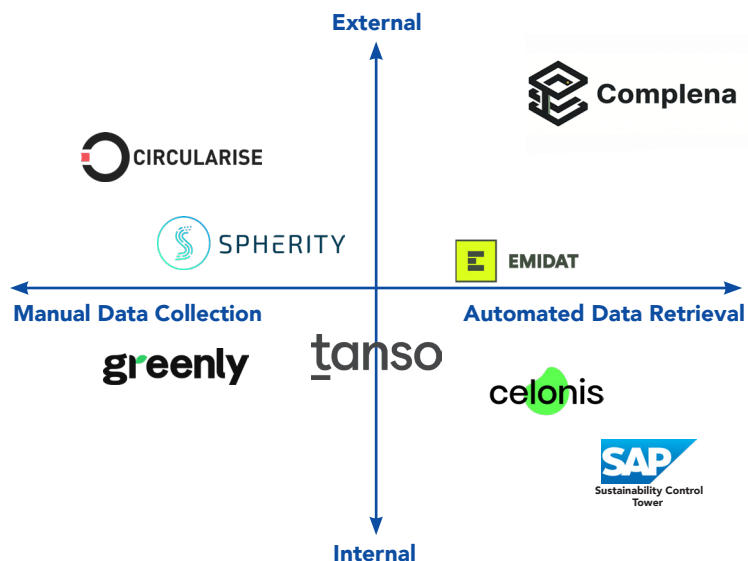
- Complena automatically retrieves and structures product-level environmental data from public sources such as EPDs, datasheets, and product pages without manual uploads or dedicated compliance staff [626].
- Customers map which supplier components go into which of their products. When a supplier updates their data, the change automatically flows into every dependent product record.
- Complena maps products to regulatory and buyer data requirements, flagging gaps before they become a compliance risk.
- The resulting data layer has dual value: internally, it shows where carbon footprint concentrates and where cost optimization is possible. Externally, it positions the SME as a data-ready supplier, as buyers increasingly tie ESG data to contract eligibility [628].
- As pre-verification frameworks mature, data collected through validated software carries regulatory weight, replacing per-document verification with streamlined annual audits [629].

Complena structures, maintains and keeps your product data complete, so every compliance or data request is answered rapidly.

Market Drivers

- Over 33M SMEs operate in the EU, more than 2M of which manufacture physical products subject to growing data requirements [630], yet most lack the staff and tools to manage compliance independently [625].
- The regulatory environment is not just expanding but unstable. The Omnibus package cut CSRD scope by roughly 90% while ESPR obligations advance, with DPP deadlines from 2027 for batteries through 2030 for further categories [624, 516]. This volatility makes one-off compliance projects wasteful.
- Large buyers already require structured data from suppliers for reporting and risk management, with responses increasingly tied to contract eligibility and preferred supplier status [631, 628].
- AI for document parsing, data extraction, and regulatory mapping has matured into a viable compliance tool for SMEs. The global regtech market is projected to grow from 24B USD in 2025 to over 112B USD by 2033, with the SME segment expanding fastest [632].

Regulatory volatility, buyer demands, and AI maturity are converging to make automated product data management viable and necessary.



Competition

- Emidat [633] and Tanso [634] focus on helping manufacturers calculate and report their own carbon footprints and EPDs, using internal data, emission factor databases, and manual supplier engagement. They require the company to already have or actively collect its input data.
- Spherity [635] and Circularise [636] provide DPP and traceability infrastructure, but depend on each supply chain participant actively submitting data through the platform. Where suppliers do not participate, the data gap remains.
- Celonis [637] optimizes internal processes using data from enterprise systems such as ERP, and is not designed to source external environmental product data or address regulatory compliance gaps across the supply chain.
- Complena starts where these tools stop: at the point where supplier data exists publicly but has not been collected. By automatically retrieving, structuring, and propagating this data, Complena closes the gap before manual input or supplier onboarding is required.

While other companies wait for supplier input, we retrieve existing data and turn it into continuous compliance at the product level.

Assumption Tree

Regulatory and Political Uncertainty

The compliance challenge was reshaped, rather than removed, by the Omnibus simplification of CSRD [638]. SMEs face a moving target, with ESPR, DPP, and ISO requirements still advancing, but scope constantly shifting [639]. This uncertainty makes one-off compliance projects and consultant engagements wasteful, because whatever is built today may not be compliant tomorrow.

Software Pre-verification

Regulatory frameworks are increasingly moving toward pre-certification of software tools used for compliance reporting and data structuring [640]. If a platform like Complena achieves pre-verified status, the data it collects and structures carries official weight. The customer's audit burden is removed, and the software turns from a data tool into a trusted compliance instrument.

Data from Large Suppliers

Large manufacturers already disclose product-level environmental information, such as CO2 footprints, material composition, EPDs, driven by their own regulatory obligations and market positioning [626]. This data is public, but scattered across PDFs, data-sheets, product pages, and press releases. It is practically inaccessible to downstream SMEs without significant manual effort.

Structuring Data

Modern AI can read and map product-level environmental data from unstructured public sources into structured, compliance-ready fields [641]. This makes disclosed but scattered supplier information useful for SMEs without dedicated research staff.

Automated Compliance

When regulations shift, manual compliance work has to be redone. Pre-verified software that continuously structures and updates data can adapt to changing requirements without having to start from scratch. This makes it the only approach that does not scale proportionally with regulatory complexity.

Oversight Beyond Compliance

Structuring data unlocks benefits independent of any regulation: identifying where carbon footprint concentrates across the supply chain, spotting cost-optimization opportunities by comparing materials and suppliers [642], and improving resilience to natural disasters [643]. Where transparency is valued by customers, this could support stronger pricing [644].

Monetary and Strategic Gains

SMEs that invest in automated compliance solve the reporting problem and gain a durable data infrastructure that reduces costs, supports pricing power, and absorbs future regulatory change without proportional effort. Compliance transforms from a recurring expense to a competitive advantage.



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SOURCES

- [1] Barua DA. Leveraging artificial intelligence for smart production management. Scientific Reports. 2025. Accessed March 1, 2026. <https://pmc.ncbi.nlm.nih.gov/articles/PMC12644757/>
- [2] Hector I, Panjanathan R. Predictive maintenance in Industry 4.0: a survey of planning models and machine learning techniques. PeerJ Computer Science. 2024;10:e2016. Accessed March 1, 2026. <https://pmc.ncbi.nlm.nih.gov/articles/PMC11157603/>
- [3] World Economic Forum. Physical AI: Powering the New Age of Industrial Operations. WEF; 2025. Accessed March 8, 2026. https://reports.weforum.org/docs/WEF_Physical_AI_Powering_the_New_Age_of_Industrial_Operations_2025.pdf
- [4] Shi W, Cao J, Zhang Q, Li Y, Xu L. Edge computing: vision and challenges. IEEE Internet of Things Journal. 2016;3(5):637-646. <https://doi.org/10.1109/JIOT.2016.2579198>
- [5] McKinsey and Company. Manufacturing analytics unleashes productivity and profitability. McKinsey and Company. Published August 14, 2017. Accessed March 1, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/manufacturing-analytics-unleashes-productivity-and-profitability>
- [6] Siemens. Readiness for Predictive Maintenance at Scale: 2023 Report. Siemens; 2023. Accessed March 1, 2026. https://assets.new.siemens.com/siemens/assets/api/uuid:8ee59c19-1c37-4516-a290-2844096f1cff/Readiness-Report-2023_original.pdf
- [7] Verma A, Prasad VK, Kumari A, et al. Industry 6.0: Vision, technical landscape, and opportunities. Alexandria Engineering Journal. 2025;130:139-174. doi:10.1016/j.aej.2025.08.040
- [8] Alqoud A, Schaefer D, Milisavljevic-Syed J. Industry 4.0: Challenges and Opportunities of Digitalisation Manufacturing Systems. In: 2022. doi:10.3233/ATDE220560
- [9] Thakur A, Kaipa K, Banerjee AG, et al. Physical AI for powering the next revolution in robotics. Journal of Computing and Information Science in Engineering. 2025;25(12). doi:10.1115/1.4070122.
- [10] McKinsey and Company. Improving productivity in low-volume, high-complexity manufacturing. McKinsey and Company. Published July 17, 2024. Accessed March 8, 2026. <https://www.mckinsey.com/industries/aerospace-and-defense/our-insights/improving-productivity-in-low-volume-high-complexity-manufacturing>
- [11] Ayyat M, Osman M, Nadeem T. Opportunities and challenges of foundation models in industrial manufacturing. IEEE Access. 2025;13:138745-138775. <https://doi.org/10.1109/ACCESS.2025.3589777>
- [12] Ren L, et al. Foundation models for the process industry: challenges and opportunities. Engineering. 2025;52:53-59. <https://doi.org/10.1016/j.eng.2025.03.023>
- [13] Azeta J, Omeche TT, Daniyan I, et al. Artificial intelligence and robotics in predictive maintenance: a comprehensive review. Frontiers in Mechanical Engineering. 2026;11:1722114. doi:10.3389/fmech.2025.1722114
- [14] Tantithamthavorn CK, Palomba F, Khomh F, Chua JJ. MLOps, LLMops, FMOps, and beyond. IEEE Software. 2025;42(1):26-32. <https://doi.org/10.1109/MS.2024.3477014>
- [15] Marvel JA, Norcross R. Implementing speed and separation monitoring in collaborative robot workcells. Robotics Comput Integr Manuf. 2017;44:144-155. doi:10.1016/j.rcim.2016.08.001.
- [16] Zhou Z, Chen X, Li E, Zeng L, Luo K, Zhang J. Edge intelligence: paving the last mile of artificial intelligence with edge computing. Proc IEEE. 2019;107(8):1738-1762. doi:10.1109/JPROC.2019.2918951.
- [17] Atwamy M, Pardo S, Serunjogi S, Rasras M. A review of emerging trends in photonic deep learning accelerators. Front Phys. 2024;12:1369099. doi:10.3389/fphy.2024.1369099.
- [18] Intel Corporation. Intel builds world's largest neuromorphic system to enable more sustainable AI. Intel Newsroom. Published 2024. Accessed March 1, 2026. <https://newsroom.intel.com/artificial-intelligence/intel-builds-worlds-largest-neuromorphic-system-to-enable-more-sustainable-ai>
- [19] Zhang S, Jiang X, Wu B, et al. Photonic edge intelligence chip for multi-modal sensing, inference and learning. Nat Commun. 2025;16(1):10136. doi:10.1038/s41467-025-65151-x
- [20] Chen Y, Sun X, Tan L, et al. All-optical synthesis chip for large-scale intelligent semantic vision generation. Science. 2025;390(6779):1259-1265. doi:10.1126/science.acv743
- [21] Ericsson. Realizing time-critical communication with 5G. Ericsson. Published October 2021. Accessed March 1, 2026. <https://www.ericsson.com/en/blog/2021/10/realizing-time-critical-communication-with-5g>
- [22] Rumble SM, Ongaro D, Stutsman R, Rosenblum M, Ousterhout JK. It is time for low latency. In: Proceedings of the 13th USENIX Workshop on Hot Topics in Operating Systems (HotOS XIII). USENIX Association; 2011. Accessed March 6, 2026. https://www.usenix.org/legacy/events/hotos11/tech/final_files/Rumble.pdf
- [23] European Commission. What if my company/organisation fails to comply with the data protection rules? Published March 31, 2026. Accessed March 31, 2026. https://commission.europa.eu/law/law-topic/data-protection/rules-business-and-organisations/enforcement-and-sanctions/sanctions/what-if-my-companyorganisation-fails-comply-data-protection-rules_en
- [24] European Commission. Data Act explained. Published March 31, 2023. Accessed March 31, 2026. <https://digital-strategy.ec.europa.eu/en/factpages/data-act-explained>
- [25] European Commission. Navigating the AI Act. Published March 31, 2026. Accessed March 31, 2026. <https://digital-strategy.ec.europa.eu/en/faqs/navigating-ai-act>
- [26] Ano Kuhanathan A, Latorre M, Dejean G. No Country for Old Robots: How Can Europe Leap Over the Robotics Tech Frontier? Allianz SE Economic Research; 2025. Accessed March 9, 2026. https://www.allianz.com/en/economic_research/insights/publications/specials/no-country-for-old-robots.html
- [27] OneKey. OT and IoT Cybersecurity Report 2024. OneKey; 2024. Accessed March 1, 2026. <https://www.onekey.com/resource/ot-iiot-cybersecurity-report-2024>
- [28] Caldwell L. Smart and vulnerable: you don't have to be. Forbes. Published July 16, 2025. Accessed March 1, 2026. <https://www.forbes.com/sites/liscaldwell/2025/07/16/smart-and-vulnerable-you-dont-have-to-be/>
- [29] Association for Advancing Automation. Legacy equipment and digital transformation. Published March 31, 2026. Accessed March 31, 2026. <https://www.automate.org/robotics/industry-insights/legacy-equipment-digital-transformation>
- [30] Malik J, Pastore F. An empirical study of vulnerabilities in edge frameworks to support security testing improvement. Empir Softw Eng. 2023;28(4):99. doi:10.1007/s10664-023-10330-x
- [31] Huang T, Huang W, Zhang B, Chen W, Pan X. Optimizing energy consumption in centralized and distributed cloud architectures with a comparative study to increase stability and efficiency. Energy Build. 2025;333:115454. doi:10.1016/j.enbuild.2025.115454
- [32] WTW Media. Plant Engineering 2025 State of Manufacturing Operations. WTW Media; 2025. Accessed March 1, 2026. <https://www.plantengineering.com/wp-content/uploads/sites/4/2025/04/Plant-Engineering-2025-State-of-Manufacturing-Operations.pdf>
- [33] Shin J, Jun H. On condition based maintenance policy. J Comput Des Eng. 2015;2(2):119-127. doi:10.1016/j.jcde.2014.12.006
- [34] Grand View Research. Predictive maintenance market analysis. Published March 30, 2026. Accessed March 30, 2026. <https://www.grandviewresearch.com/industry-analysis/predictive-maintenance-market>
- [35] O'Donnell J, Crownhart C. We did the math on AI's energy footprint. Here's the story you haven't heard. MIT Technol Rev. 2025;Vol:1-1. Published May 20. Accessed March 30, 2026. <https://www.technologyreview.com/2025/05/20/1116327/ai-energy-usage-climate-footprint-big-tech/>

- [36] Alicke K, Foster T, Trautwein V. Supply Chains: Still Vulnerable. McKinsey & Company; 2024. Accessed March 1, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/supply-chain-risk-survey-2024>
- [37] Abd Wahab NH, Hasikin K, Lai KW, et al. Systematic review of predictive maintenance and digital twin technologies challenges, opportunities, and best practices. *PeerJ Comput Sci.* 2024;10:e1943. doi:10.7717/peerj-cs.1943
- [38] Gouraud J, Delorme A, Berberian B. Autopilot, mind wandering, and the out of the loop performance problem. *Front Neurosci.* 2017;11:541. doi:10.3389/fnins.2017.00541
- [39] Heide KM, Denkena B, Winkler M. A bidirectional digital twin system for adaptive manufacturing. *J Manuf Mater Process.* 2025;9(12):400. doi:10.3390/jmmp9120400
- [40] Deloitte. 2025 smart manufacturing survey. Published March 31, 2026. Accessed March 31, 2026. <https://www.deloitte.com/us/en/insights/industry/manufacturing/2025-smart-manufacturing-survey.html>
- [41] Chang M, Koerber B, Soganci M. Converge IT and OT to turbocharge business operations' scaling power. McKinsey. Published June 28, 2022. Accessed March 31, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/converge-it-and-ot-to-turbocharge-business-operations-scaling-power>
- [42] Venanzi R, Di Modica G, Foschini L. Towards IT/OT integration in industry digitalization: a comprehensive survey. *J Netw Comput Appl.* 2026;245:104373. doi:10.1016/j.jnca.2025.104373
- [43] Kampker A, Heimes HH, Dorn B, Clever H, Ludwigs R, Li RY. Leveraging Industry 4.0 solutions for lithium-ion battery manufacturing: a gap analysis of OPC UA companion specifications. *Procedia CIRP.* 2024;126:853-858. doi:10.1016/j.procir.2024.08.273
- [44] Shin M, Jung J. An edge AI system framework based on the asset administration shell standard. *Systems.* 2026;14(2):205. doi:10.3390/systems14020205
- [45] Gartner Inc. Gartner hype cycle identifies top AI innovations for 2025. Gartner. Published August 5, 2025. Accessed March 30, 2026. <https://www.gartner.com/en/newsroom/press-releases/2025-08-05-gartner-hype-cycle-identifies-top-ai-innovations-2025>
- [46] McKinsey & Company. A manufacturer's guide to scaling Industrial IoT. McKinsey & Company. Published February 5, 2021. Accessed March 30, 2026. <https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/a-manufacturers-guide-to-generating-value-at-scale-with-industrial-iot>
- [47] Wang K, Dave P, Hanchate A, Sagapuram D, Natarajan G, Bukkapatnam STS. Implementing an open-source sensor data ingestion, fusion, and analysis capabilities for smart manufacturing. *Mfg Lett.* 2022;33(suppl):893-901. doi:10.1016/j.mfglet.2022.07.109
- [48] Gupta P, Hoffmann D, Ludemann-Ravit B, Luder A. Digital twin and data interoperability architectures for smart manufacturing. *IFAC-PapersOnLine.* 2025;58(1). doi:10.1016/j.ifacol.2025.08.040
- [49] Catena-X Automotive Network e.V., Information-Technology Promotion Agency, Japan. Catena-X and Ouranos ecosystem successfully demonstrate data space interoperability. Catena-X. Published March 31, 2025. Accessed March 30, 2026. <https://catena-x.net/news/catena-x-and-ouranos-ecosystem-successfully-demonstrate-data-space-interoperability/>
- [50] Nguyen P, Kim M, Nichols E, Yoon H. AI-driven digital twins for manufacturing: a review across hierarchical manufacturing system levels. *Sensors.* 2025;26(1):124. doi:10.3390/s26010124
- [51] Bousdekis A, Mentzas G. Enterprise integration and interoperability for big data-driven processes in the frame of Industry 4.0. *Front Big Data.* 2021;4:644651. doi:10.3389/fdata.2021.644651
- [52] Allied Market Research. Industrial multiprotocol gateway market size, share, and industry analysis, 2024-2032. Allied Market Research. Published 2024. Accessed March 30, 2026. <https://www.alliedmarketresearch.com/industrial-multiprotocol-gateway-market-A07055>
- [53] Precedence Research. Data integration market size, share, and trends 2024 to 2034. Precedence Research. Published March 30, 2026. Accessed March 30, 2026. <https://www.precedenceresearch.com/data-integration-market>
- [54] West Monroe. Manufacturing outlook 2026. West Monroe. Published 2026. Accessed March 1, 2026. <https://go.westmonroe.com/2026ManufacturingOutlook>
- [55] Rodseth R, Mayer M, Rothkugel J. IIoT at a tipping point: what needs to change for it to deliver real value and why we think now is the time. Activant Capital. Published August 2024. Accessed March 1, 2026. <https://activantcapital.com/research/iiot-at-a-tipping-point>
- [56] European Commission. EU's digital product passport: advancing transparency and sustainability. European Commission. Published September 27, 2024. Accessed March 30, 2026. <https://data.europa.eu/en/news-events/news/eus-digital-product-passport-advancing-transparency-and-sustainability>
- [57] Honeywell. Ransomware attacks targeting industrial operators surge 46 percent in one quarter. Honeywell report finds. Honeywell. Published June 2025. Accessed March 30, 2026. <https://www.honeywell.com/us/en/press/2025/06/ransomware-attacks-targeting-industrial-operators-surge-46-percent-in-one-quarter-honeywell-report-finds>
- [58] Deloitte. Manufacturing organizations get real about AI and data strategy. Deloitte Insights. Published October 14, 2020. Accessed March 30, 2026. <https://action.deloitte.com/insight/4246/manufacturing-orgs-get-real-about-ai-data-strategy>
- [59] Pribis R, Beno L, Drahos P. Asset administration shell design methodology using embedded OPC unified architecture server. *Electronics.* 2021;10(20):2520. doi:10.3390/electronics10202520
- [60] Shah R, Arockia Doss AA, Lakshmaiya N. Advancements in AI-enhanced collaborative robotics: towards safer, smarter, and human-centric industrial automation. *Results in Engineering.* 2025;27:105704. doi:10.1016/j.rineng.2025.105704
- [61] Wolf T, Willige A. What is physical AI -- and how is it changing manufacturing? World Economic Forum. September 9, 2025. Accessed March 8, 2026. <https://www.weforum.org/stories/2025/09/what-is-physical-ai-changing-manufacturing/>
- [62] Salehi V. Fundamentals of Physical AI. arXiv. November 12, 2025. Accessed March 8, 2026. <https://arxiv.org/abs/2511.0949>
- [63] Nambiar S, Wiberg A, Tarkian M. Automation of unstructured production environment by applying reinforcement learning. *Front Manuf Technol.* 2023;3:1154263. doi:10.3389/fmtec.2023.1154263.
- [64] Ding J, Zhang Y, Shang Y, et al. Understanding World or Predicting Future? A Comprehensive Survey of World Models. *ACM Computing Surveys.* 2025;58(3):Article 57. <https://doi.org/10.1145/3746449>
- [65] Tata Consultancy Services. Future-Ready Skies 2025: Survey Report. TCS; 2025. Accessed March 8, 2026. <https://www.tcs.com/content/dam/global-tcs/en/pdfs/what-we-do/industries/manufacturing/paris-air-show/future-ready-skies-survey-report.pdf>
- [66] International Federation of Robotics. Global robot demand in factories doubles over 10 years. Published September 25, 2025. Accessed March 31, 2026. <https://ifr-press-releases/news/global-robot-demand-in-factories-doubles-over-10-years>
- [67] Cervicorn Consulting. Physical AI Market Size to Hit USD 68.54 Billion by 2034. Published September 16, 2025. Accessed March 1, 2026. <https://www.cervicornconsulting.com/physical-ai-market>
- [68] Brewer M. From AI to Outcomes: How Manufacturers Are Transforming Service. IFS Blog. January 22, 2026. Accessed March 2, 2026. <https://blog.ifs.com/2026/01/from-ai-to-outcomes-how-manufacturers-are-transforming-service/>
- [69] Capgemini Research Institute. The resurgence of manufacturing: Reindustrialization strategies in Europe and the US – 2025. Published March 2025. Accessed March 2, 2026. <https://www.capgemini.com/wp-content/uploads/2025/03/Final-Web-Version-Report-Reindustrialization-Edition-2.pdf>
- [70] Buschle F, Moya-Quiruga Gomez R, Müller S, Sjödin E. Jump-starting digital transformations at low-volume, high-complexity manufacturers. Published September 4, 2018. Accessed March 8, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/operations-blog/jump-starting-digital-transformations-at-low-volume-high-complexity-manufacturers>
- [71] International Federation of Robotics. Robotics Research: How Asia, Europe and America Invest (World Robotics R&D Programs 2025). IFR; 2025. Accessed March 1, 2026. <https://ifr.org/news/robotics-research-government-programs-asia-europe-and-america-2025/>
- [72] Deloitte. How Robotics and Physical AI Are Reshaping Industries and Society. Deloitte Insights; November 4, 2025. Accessed March 1, 2026. <https://roboticsandautomationnews.com/2025/11/05/deloitte-report-says-physical-ai-era-has-begun-as-intelligent-robots-reshape-industries>
- [73] Stanford University. The 2025 AI Index report. Published March 31, 2026. Accessed March 31, 2026. https://hai.stanford.edu/assets/files/hai_ai_index_report_2025.pdf
- [74] Citi Global Insights. Embodied Intelligence: The Rise of Physical AI. 4 December 2025. Accessed March 1, 2026. <https://www.citigroup.com/global/insights/embodied-intelligence-the-rise-of-physical-ai>
- [75] SNS Insider. Physical AI Market Size, Share & Growth Report 2033. SNS Insider; 2025. Accessed March 2, 2026. <https://www.snsinsider.com/reports/physical-ai-market-9007>
- [76] Boston Consulting Group. Unlocking the Value of AI in Manufacturing (BCG Executive Perspectives). BCG; 2025. Accessed March 8, 2026. <https://www.bcg.com/assets/2025/executive-perspectives-unlocking-the-value-of-ai-in-manufacturing-30june.pdf>
- [77] Zhu J, Zhang J, Song J, Gao L, Shen HT. Beyond the Majority: Long-tail Imitation Learning for Robotic Manipulation. Published February 6, 2026. Accessed March 8, 2026. <https://arxiv.org/abs/2602.06512>

- [78] Gomez Y. AI in process manufacturing: from operational gains to strategic advantage. Microsoft. Published May 28, 2025. Accessed March 30, 2026. <https://www.microsoft.com/en-us/industry/blog/manufacturing-and-mobility/manufacturing/2025/05/28/ai-in-process-manufacturing-from-operational-gains-to-strategic-advantage/>
- [79] IBM. How foundation models can help make steel and cement production more sustainable. Published March 30, 2026. Accessed March 30, 2026. <https://www.ibm.com/think/topics/foundation-models-manufacturing>
- [80] Belcak P, Heinrich G, Diao S, Fu Y, Dong X, Muralidharan S, Lin YC, Molchanov P. Small language models are the future of agentic AI. arXiv. 2025;2506.02153. doi:10.48550/arXiv.2506.02153
- [81] Samson HH. Lightweight transformer architectures for edge devices in real-time applications. arXiv. 2026;2601.03290. doi:10.48550/arXiv.2601.03290
- [82] Congruence Market Insights. Industrial AI solutions market size, trends, share, growth, and opportunity forecast, 2025 – 2032. Published November 2025. Accessed March 2nd, 2026. <https://www.congruencemarketinsights.com/report/industrial-ai-solutions-market>
- [83] Wang Y, Yu Z, Wu J, Wang C, Zhou Q, Hu J. Adaptive knowledge distillation-based lightweight intelligent fault diagnosis framework in IoT edge computing. IEEE Internet of Things J. 2024;11(13):23156–23169. doi:10.1109/JIOT.2024.3387328
- [84] Jang M. Building trust in AI: the role of technical capacity, social risk, and corporate institutional accountability. Information. 2026;17(2):212. doi:10.3390/info17020212
- [85] Global Institute for Human Rights Research. Redefining productivity in the age of workplace surveillance. Human Rights Research. Published July 29, 2024. Accessed March 6, 2026. <https://www.humanrightresearch.org/post/redefining-productivity-in-the-age-of-workplace-surveillance>
- [86] Mordor Intelligence. Agentic AI in manufacturing and industrial automation market size & share analysis - growth trends & forecasts (2025 - 2030). Published March 31, 2026. Accessed March 31, 2026. <https://www.mordorintelligence.com/industry-reports/agentic-artificial-intelligence-in-manufacturing-and-industrial-automation-market>
- [87] Bainbridge L. Ironies of automation. *Automatica*. 1983;19(6):775–779. doi:10.1016/0005-1098(83)90046-8
- [88] Financial Times. Iran war prompts foreign central banks to sell US Treasuries. Published March 30, 2026. Accessed March 31, 2026. <https://www.ft.com/content/78c1d4e9-ad30-47f5-ab7b-390df5bc1f10>
- [89] Statistisches Bundesamt (Destatis). 13.4 Millionen Erwerbspersonen erreichen in den nächsten 15 Jahren das gesetzliche Rentenalter. Published September 3, 2025. Accessed March 9, 2026. https://www.destatis.de/DE/Presse/Pressemitteilungen/2025/08/PD25_N048_13.html
- [90] Coykendall J, Hardin K, Morehouse J, et al. Taking charge: Manufacturers support growth with active workforce strategies. Deloitte Insights. Published April 3, 2024. Accessed March 9, 2026. <https://www.deloitte.com/us/en/insights/industry/manufacturing/supporting-us-manufacturing-growth-amid-workforce-challenges.html>
- [91] Krause F, Paulheim H, Kiesling E, et al. Managing human-AI collaborations within Industry 5.0 scenarios via knowledge graphs: Key challenges and lessons learned. *Frontiers in Artificial Intelligence*. 2024;7:1247712. doi:10.3389/frai.2024.1247712
- [92] World Economic Forum. The Future of Jobs Report 2025. World Economic Forum; 2025. Accessed March 28, 2026. https://reports.weforum.org/docs/WEF_Future_of_Jobs_Report_2025.pdf
- [93] Acemoglu D, Restrepo P. Automation and polarization. National Bureau of Economic Research; 2022. doi:10.3386/w30528
- [94] Guo Q, Liu X, Li S. Manufacturing workers or platform gig workers? The impact of digital transformation in manufacturing and service sectors on job quality and labor allocation. *Journal of Digital Economy*. 2025;4:72–94. doi:10.1016/j.jdec.2025.06.003
- [95] Berland B, Tabellini M, Tricaud C. Left behind: The local effects of deindustrialization in France. Working paper, Harvard Business School; January 2026. Accessed March 3, 2026. https://www.hbs.edu/ris/Publication%20Files/012026_BerlandTabelliniTricaud_efab3ac2-c1f0-4348-83a7-6e8070ee9f32.pdf
- [96] Ajuzieogu UC. The economic geography of AI: spatial distribution of benefits and costs. ResearchGate. Published May 2025. Accessed March 28, 2026. <https://www.researchgate.net/publication/391430918>
- [97] Muro M, Liu S. The geography of AI: which cities will drive the artificial intelligence revolution? Brookings Institution; 2021. Accessed March 28, 2026. https://www.brookings.edu/wp-content/uploads/2021/08/Al-report_Full.pdf
- [98] Okamura K, Yamada S. Adaptive trust calibration for human-AI collaboration. *PLoS One*. 2020;15(2):e0229132. Published 2020 Feb 21. doi:10.1371/journal.pone.0229132
- [99] Pawar PS, Varghese BS. A study on the impact of AI monitoring tools on employee productivity in the IT sector. *TIJER*. 2025;12(8):a602–a606. Accessed March 31, 2026. <https://tijer.org/tijer/papers/TIJER2508070.pdf>
- [100] Wang X, Long L. The innovation paradox in human-AI symbiosis: ambidextrous effects of AI technology adoption on innovative behavior. *Front Artif Intell*. 2025;8:1635246. doi:10.3389/frai.2025.1635246
- [101] Glikson E, Woolley AW. Human trust in artificial intelligence: review of empirical research. *Acad Manag Ann*. 2020;14(2):627–660. doi:10.5465/annals.2018.0057
- [102] Shang R, Hsieh G, Shah C. Trusting your AI agent emotionally and cognitively: development and validation of a semantic differential scale for AI trust. In: Proceedings of the 2024 AAAI/ACM Conference on AI, Ethics, and Society. Association for Computing Machinery; 2024. <https://doi.org/10.48550/arXiv.2408.05354>
- [103] Diaz-Rodríguez N, Del Ser J, Coeckelbergh M, et al. Connecting the dots in trustworthy artificial intelligence: from AI principles, ethics, and key requirements to responsible AI systems and regulation. *Inf Fusion*. 2023;99:101896. doi:10.1016/j.inffus.2023.101896
- [104] Maurer R. AI surveillance in the workplace linked to employee resistance. *SHRM*. Published August 12, 2024. Accessed March 6, 2026. <https://www.shrm.org/topics-tools/news/employee-relations/ai-surveillance-in-the-workplace-linked-to-employee-resistance>
- [105] Rainie L, Anderson M, McClain C, Vogels EA, Gelles-Watnick R. Americans' views on use of AI to monitor and evaluate workers. Pew Research Center. Published April 20, 2023. Accessed March 30, 2026. <https://www.pewresearch.org/internet/2023/04/20/americans-views-on-use-of-ai-to-monitor-and-evaluate-workers/>
- [106] Mentzas G, Hribernik K, Stahre J, Romero D, Soldatos J. Editorial: human-centered artificial intelligence in industry 5.0. *Front Artif Intell*. 2024;7:1429186. doi:10.3389/frai.2024.1429186
- [107] Patel SN. Do privacy-preserving technologies harm workers? Prof. Seema N. Patel unpacks impacts of emerging AI tools. UC Law San Francisco. Published November 18, 2025. Accessed March 6, 2026. <https://www.uclawsf.edu/2025/11/18/do-privacy-preserving-technologies-harm-workers-prof-seema-n-patel-unpacks-impacts-of-emerging-ai-tools/>
- [108] Leichtmann B, Humer C, Hinterreiter A, Streit M, Mara M. Effects of explainable artificial intelligence on trust and human behavior in a high-risk decision task. *Comput Hum Behav*. 2023;139:107539. doi:10.1016/j.chb.2022.107539
- [109] Dietvorst BJ, Simmons JP, Massey C. Algorithm aversion: People erroneously avoid algorithms after seeing them err. *J Exp Psychol Gen*. 2015;144(1):114–126. doi:10.1037/xge0000033
- [110] Akter S, McCarthy G, Sajib S, et al. Algorithmic bias in data-driven innovation in the age of AI. *Int J Inf Manag*. 2021;60:102387. doi:10.1016/j.jinfomgt.2021.102387
- [111] World Economic Forum. AI strategic foresight: future thinking for the age of AI. World Economic Forum. Published December 20, 2025. Accessed March 6, 2026. <https://www.weforum.org/stories/2025/12/ai-strategic-foresight-future-thinking/>
- [112] Parasuraman R, Sheridan TB, Wickens CD. A model for types and levels of human interaction with automation. *IEEE Trans Syst Man Cybern A Syst Hum*. 2000;30(3):286–297. doi:10.1109/3468.844354
- [113] World Economic Forum. Frontier Technologies in Industrial Operations: The Rise of Artificial Intelligence Agents. January 2025. Accessed March 31, 2026. https://reports.weforum.org/docs/WEF_Frontier_Technologies_in_Industrial_Operations_2025.pdf
- [114] Cimini C, Pirola F, Pinto R, Cavalieri S. A human-in-the-loop manufacturing control architecture for the next generation of production systems. *J Manuf Syst*. 2020;54:258–271. doi:10.1016/j.jmsy.2020.01.002
- [115] Gerdes I, Jameel M, Hunger R, Christoffels L, Gürlük H. The automation evolves: concept for a highly automated controller working position. In: Proceedings of the 33rd Congress of the International Council of the Aeronautical Sciences (ICAS); September 4–9, 2022; Stockholm, Sweden. Accessed March 30, 2026. https://elib.dlr.de/190172/1/Paper_The%20automation%20evolves_Concept%20for%20a%20highly%20automated%20controller%20working%20position_Final2.0.pdf
- [116] Chen Y, et al. Systemic exceptions in manufacturing AI environments. arXiv. 2023. Accessed March 31, 2026. <https://arxiv.org/pdf/2308.02025>
- [117] Takerngsaksiri W, Pasuksmit J, Thongtanunam P, Tantithamthavorn C, Zhang R, Jiang F, Li J, Cook E, Chen K, Wu M. Human-in-the-loop software development agents. arXiv [Preprint]. 2024. Accessed March 31, 2026. <https://arxiv.org/abs/2411.12924>

- [118] Jautelat S, Niemann J, Barg J, et al. Empowering advanced industries with agentic AI. McKinsey & Company. September 8, 2025. Accessed March 31, 2026. <https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/empowering-advanced-industries-with-agentic-ai>
- [119] Chen H, Li S, Fan J, Duan A, Yang C, Navarro-Alarcón D, Zheng P. Human-in-the-loop robot learning for smart manufacturing: A human-centric perspective. *IEEE Transactions on Automation Science and Engineering*. 2025. Accessed March 31, 2026. https://ira.lib.polyu.edu.hk/bitstream/10397/115298/1/Chen_Human_Loop_Robot.pdf
- [120] Johnson T, Fletcher S, Baker W, Charles R. How and why we need to capture tacit knowledge in manufacturing: case studies of visual inspection. *Appl Ergon*. 2019;74:1-9. doi:10.1016/j.apergo.2018.07.016.
- [121] McKinsey Global Institute. Agents, Robots and Us: Skill partnerships in the age of AI. 2025. Accessed March 31, 2026. <https://www.mckinsey.com/mgi/our-research/agents-robots-and-us-skill-partnerships-in-the-age-of-ai>
- [122] Romero D, et al. Operator 4.0 interfaces and human-machine interaction. 2016. Accessed March 31, 2026. https://publications.lib.chalmers.se/records/fulltext/241372/local_241372.pdf
- [123] Fallaha M, Zeki Murat Cinar, Orhan Korhan, Qasim Zeeshan. Operator 4.0 and Cognitive Ergonomics. Lecture notes in management and industrial engineering. Published online January 1, 2020:217-228. doi:https://doi.org/10.1007/978-3-030-42416-9_20
- [124] Bastubbe Y, Jain D. Why should manufacturers embrace AI's next frontier – AI agents – now? *World Economic Forum*. Published January 22, 2025. Accessed March 30, 2026. <https://www.weforum.org/stories/2025/01/why-manufacturers-should-embrace-next-frontier-ai-agents/>
- [125] Ide E. Automation, AI, and the Intergenerational Transmission of Knowledge. *Social Science Research Network*. Preprint posted online July 22, 2025:5360803. doi:10.2139/ssrn.5360803
- [126] Schupp S. COVID-19, economic crises and digitalisation: How algorithmic management became an alternative to automation. *New Technol Work Employ*. 2023;38(2):311-329. doi:10.1111/ntwe.12246
- [127] Weddle B, Mellors N, Malinauskaitė A, Voelker A, Cassidy S. Investing in the manufacturing workforce to accelerate productivity. McKinsey & Company. July 2, 2025. Accessed March 31, 2026. <https://www.mckinsey.com/industries/aerospace-and-defense/our-insights/investing-in-the-manufacturing-workforce-to-accelerate-productivity>
- [128] Massingham PR. Measuring the impact of knowledge loss: a longitudinal study. *JKM*. 2018;22(4):721-758. doi:10.1108/JKM-08-2016-0338
- [129] Cui X, Huang Z, Adel N. Bias in, bias out: Annotation bias in multilingual large language models. *Proceedings of Interdisciplinary Workshop on Observations of Misunderstood, Misguided and Malicious Use of Language Models*. 2025;Varna, Bulgaria:1-16. doi:10.1000/xyz123
- [130] Katiraei N, et al. A roadmap for managing an ageing workforce in the manufacturing sector: an Italian case study. *HRB Open Res*. 2025. doi:10.12688/hrbopenres.13990.1
- [131] Kernan Freire S, Wang C, Foosherian M, Wellsandt S, Ruiz-Arenas S, Niforatos E. Knowledge sharing in manufacturing using LLM-powered tools: user study and model benchmarking. *Front Artif Intell*. 2024;7:1293084. doi:10.3389/frai.2024.1293084
- [132] Workplace Intelligence, Flip. Frontline generational skills gap study. Workplace Intelligence. Published March 17, 2025. Accessed March 31, 2026. <https://workplaceintelligence.com/frontline-generational-skills-gap-study/>
- [133] Sharma A, Kumar V, Borah SB, Adhikary A. Complexity in a multinational enterprise's global supply chain and its international business performance: A bane or a boon? *J Int Bus Stud*. 2022;53(5):850-878. doi:10.1057/s41267-021-00497-0
- [134] Herrera-Vidal G, Coronado-Hernández JR, Maheut J. Complexity management challenges in the industry 4.0 era: a systematic review in production systems. *Results Eng*. 2025;27:104553. doi:10.1016/j.rineng.2025.104553
- [135] Bryan L. L. Making a market in knowledge. *McKinsey Quarterly*. Published August 1, 2004. Accessed March 31, 2026. <https://www.mckinsey.com/capabilities/strategy-and-corporate-finance/our-insights/making-a-market-in-knowledge>
- [136] Micheal D. Knowledge Sharing Mechanisms and Their Impact on Cross-Functional Project Collaboration. *New York University*; April 7, 2022. https://www.researchgate.net/publication/400298569_Knowledge_Sharing_Mechanisms_and_Their_Impact_on_Cross-Functional_Project_Collaboration. Accessed March 31, 2026
- [137] Hop S. Transforming the industrial sector in a corporate world with increased complexity. Published January 29, 2025. Accessed March 9, 2026. <https://www.latzerassociatesgroup.com/blogs/transforming-the-industrial-sector-in-a-corporate-world-with-increased-complexity/>
- [138] Akhavan T, Cataldo A, Sadeghi E. Improving manufacturing applications of machine learning by understanding defect classification and the critical error threshold. *Int J Metacast*. 2022;16(2):1011-1023. doi:10.1007/s40962-021-00637-0
- [139] Kernan Freire S, He T, Wang CW, Niforatos E, Bozzon A. Factory operators' perspectives on cognitive assistants for knowledge sharing: challenges, risks, and impact on work. *arXiv [Preprint]*. Published online September 30, 2024. doi:10.48550/arXiv.2409.20192
- [140] Workerbase GmbH. AI in manufacturing knowledge management: How factory leaders preserve expertise and stay competitive. Published n.d. Accessed March 9, 2026. <https://workerbase.com/blog/ai-in-manufacturing-knowledge-management/>
- [141] Jöhnk J, Ollig P, Rövekamp P, Oesterle S. Managing the complexity of digital transformation—How multiple concurrent initiatives foster hybrid ambidexterity. *Electron Markets*. 2022;32(3):603-621. doi:10.1007/s12525-021-00510-2
- [142] Makrehchi M. Three lenses on the AI revolution: risk, transformation, continuity. *arXiv*. 2025;2510.12859. doi:10.48550/arXiv.2510.12859
- [143] Acemoglu D, Restrepo P. Automation and new tasks: how technology displaces and reinstates labor. *J Econ Perspect*. 2019;33(2):3-30. doi:10.1257/jep.33.2.3
- [144] Handa K, Tamkin A, McCain M, Huang S, Durmus E, Heck S, et al. Which economic tasks are performed with AI? Evidence from millions of Claude conversations. Preprint. *arXiv:2503.04761*. Published February 11, 2025. Accessed March 8, 2026. <https://arxiv.org/abs/2503.04761>
- [145] Chui M, George K, Manyika J, Miremadi M. Human + machine: a new era of automation in manufacturing. McKinsey & Company. Published September 7, 2017. Accessed March 29, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/human-plus-machine-a-new-era-of-automation-in-manufacturing>
- [146] World Economic Forum. Empowering Frontlines: Retaining, Training and Upskilling Industrial Workforce. *World Economic Forum*; 2025. Accessed March 8, 2026. https://reports.weforum.org/docs/WEF_Empowering_Frontlines_2025.pdf
- [147] OECD. Handbook on Measuring Digital Platform Employment and Work. OECD Publishing; 2023. Accessed March 29, 2026. https://www.oecd.org/en/publications/handbook-on-measuring-digital-platform-employment-and-work_0ddcac3b-en/full-report/component-4.html
- [148] Kyndryl. People Readiness Report 2025: Are Organizations Ready for AI? Kyndryl; 2025. Accessed March 29, 2026. <https://www.kyndryl.com/content/dam/kyndrylprogram/doc/en/2025/people-readiness-report.pdf>
- [149] Brynjolfsson E, Rock D, Syverson C. Artificial intelligence and the modern productivity paradox: a clash of expectations and statistics. *NBER Working Paper*. 2017;24001. doi:10.3386/w24001
- [150] Acemoglu D, Restrepo P. Robots and jobs: evidence from US labor markets. *J Polit Econ*. 2020;128(6):2188-2244. doi:10.1086/705716.
- [151] Rockwell Automation. 9th Annual State of Smart Manufacturing Report. Rockwell Automation; 2024. Accessed March 3, 2026. <https://static1.squarespace.com/static/6500be7b90b0f770653f355f/t/6795342daf06ad7acfd19e1c/1737831499334/Rockwell+Automation+-+2024+9th+Annual+State+of+Manufacturing+Report.pdf>
- [152] Rockwell Automation. State of Smart Manufacturing Report 2025. Rockwell Automation; 2025. Accessed March 3, 2026. <https://www.rockwellautomation.com/content/dam/rockwell-automation/documents/pdf/campaigns/state-of-smart-2025-cpg/INFO-BR029C-EN-P.pdf>
- [153] Hartley DA. Urban Decline in Rust-belt Cities. *EC (FRB Cleveland)*. Published online May 20, 2013:1-6. doi:10.26509/frbc-ec-201306
- [154] World Resources Institute. Germany: The Ruhr Region's Pivot from Coal Mining to a Hub of Green Industry and Expertise. Published April 1, 2021. Accessed March 10, 2026. <https://www.wri.org/snapshots/germany-ruhr-regions-pivot-coal-mining-hub-green-industry-and-expertise>
- [155] Accenture. Work in progress: The future of work depends on us. Published 2022. Accessed March 29, 2026. <https://www.accenture.com/content/dam/accenture/final/capabilities/strategy-and-consulting/talent-and-organization/document/Accenture-Work-In-Progress-How-The-Future-Of-Work-Depends-On-Us.pdf>
- [156] Aven R. The New Geography of Jobs. *Journal of Economic Geography*. 2014;14(1):224-225. doi:10.1093/jeg/lbt016
- [157] Moretti E. Local Multipliers. *American Economic Review*. 2010;100(2):373-377. doi:10.1257/aer.100.2.373

- [158] Bristol H, de Boer E, de Kroon D, Hou F, Shahani R, Torti F. How manufacturing's lighthouses are capturing the full value of AI. McKinsey & Company; April 2024. Accessed March 29, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/how-manufacturing-lighthouses-are-capturing-the-full-value-of-ai>
- [159] El-Komboz LA, Fackler T. Productivity Spillovers Among Knowledge Workers in Agglomerations: Evidence from Github. SSRN. Preprint posted online 2023. doi:10.2139/ssrn.4600283
- [160] Bartik AW, Cullen ZB, Glaeser EL, Luca M, Stanton CT. The rise of remote work: Evidence on productivity and preferences from firm and worker surveys. *J Econ Manag Strategy*. 2024;33(1):15-56. doi:10.1111/jems.12535
- [161] Schackmar J, Fleschurz R, Pallagst K. The Role of Substitute Industries for Revitalizing Shrinking Cities. *Sustainability*. 2021;13(16):9250. doi:10.3390/su13169250
- [162] Rietmann C. Digital pioneers in the periphery? Toward a typology of rural Hidden Champions in times of digitalization. *Journal of Small Business & Entrepreneurship*. 2024;36(2):281-301. doi:10.1080/08276331.2021.1979909
- [163] Feng D, Liu Y, Ge Y. Social License to Operate for NIMBY Infrastructures: The Mechanism of the Four Components of Procedural Justice. *Buildings*. 2024;14(8):2465. doi:10.3390/buildings14082465
- [164] Layne R. Where Do Workers Go When the Robots Arrive? | Working Knowledge. Harvard Business School. April 6, 2020. Accessed March 29, 2026. <https://www.library.hbs.edu/working-knowledge/where-do-workers-go-when-robots-arrive>
- [165] Muro M. Countering the geographical impacts of automation: Computers, AI, and place disparities. *Brookings*. February 14, 2019. Accessed March 29, 2026. <https://www.brookings.edu/articles/countering-the-geographical-impacts-of-automation-computers-ai-and-place-disparities/>
- [166] Teo SA. How artificial intelligence systems challenge the conceptual foundations of the human rights legal framework. *Nord J Hum Rights*. 2022;40(1):1-22. doi:10.1080/18918131.2022.2073078
- [167] Perez-Cerrolaza J, Abella J, Borg M, et al. Artificial intelligence for safety-critical systems in industrial and transportation domains: a survey. *ACM Comput Surv*. 2024;56(7):176. doi:10.1145/3626314
- [168] Panchenko V, Reznikova N, Bulatova O. Regulatory competition in the digital economy: new forms of protectionism. *Int Econ Policy*. 2020;(32-33):49-79. doi:10.33111/iep.2020.32_33.03_eng
- [169] Calderaro A, Blumfelde S. Artificial intelligence and EU security: the false promise of digital sovereignty. *Eur Secur*. 2022;31(3):415-434. doi:10.1080/09662839.2022.2101885
- [170] European Commission. Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Off J Eur Union. 2024. Accessed March 9, 2026. <https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai>
- [171] Bakiner O. The promises and challenges of addressing artificial intelligence with human rights. *Big Data Soc*. 2023;10(2). doi:10.1177/20539517231205476
- [172] Campa R. Human right to work and humanlike AI at work: technological unemployment as a legal and ethical issue. *Stud Iuridica Lublinensia*. 2025;34(2):375-394. doi:10.17951/sil.2025.34.2.375-394
- [173] Lohn A, Knack A, Burke A, Jackson K. Autonomous Cyber Defence: A Roadmap from Lab to Ops. Centre for Emerging Technology and Security (CETaS), The Alan Turing Institute, and Center for Security and Emerging Technology (CSET), Georgetown University; June 2023. Accessed March 7, 2026. https://cetas.turing.ac.uk/sites/default/files/2023-06/autonomous_cyber_defence_final_report.pdf
- [174] Gilbert S, Fenech M, Hirsch M, Upadhyay S, Biasucci A, Starlinger J. Algorithm change protocols in the regulation of adaptive machine learning-based medical devices. *J Med Internet Res*. 2021;23(10):e30545. doi:10.2196/30545
- [175] National Institute of Standards and Technology. Post-quantum cryptography. Published January 3, 2017. Accessed March 7, 2026. <https://www.nist.gov/pqcrypto>
- [176] McLaughlin S, Konstantinou C, Wang X, Davi L, Sadeghi A, Maniatakos M, et al. The cybersecurity landscape in industrial control systems. *Proc IEEE*. 2016;104(5):1039-1057. doi:10.1109/JPROC.2015.2512235
- [177] IBM Security. IBM X-Force Threat Intelligence Index 2026. IBM Think. Published February 25, 2026. Accessed March 7, 2026. <https://www.ibm.com/think/premium/threat-intelligence-report-executive-summary>
- [178] Kok A, Martinetti A, Braaksma J. The impact of integrating information technology with operational technology in physical assets: a literature review. *IEEE Access*. 2024;12:111832-111845. doi:10.1109/ACCESS.2024.3442443
- [179] Chun J, Schroeder de Witt C, Elkins K. Comparative global AI regulation: policy perspectives from the EU, China, and the US. *arXiv*. 2024;2410.21279. doi:10.48550/arXiv.2410.21279
- [180] Kianpour M, Raza S. More than malware: unmasking the hidden risk of cybersecurity regulations. *Int Cybersec Law Rev*. 2024;5:169-212. doi:10.1365/s43439-024-00111-7
- [181] Yousuf S, Lyon V. AI is raising the stakes in cybersecurity. Boston Consulting Group. Published December 18, 2025. Accessed March 31, 2026. <https://www.bcg.com/publications/2025/ai-raising-stakes-in-cybersecurity>
- [182] Tyson L, Zysman J. Automation, AI & Work. *Daedalus*. 2022;151(2):256-271. doi:10.1162/daed_a_01914
- [183] OECD. Revenue Statistics 2025. OECD Publishing; December 9, 2025. https://www.oecd.org/en/publications/2025/12/revenue-statistics-2025_07ca0a8e.html. Accessed March 9, 2026.
- [184] United Nations. Universal Declaration of Human Rights. Adopted December 10, 1948. <https://www.un.org/en/about-us/universal-declaration-of-human-rights>. Accessed March 3, 2026.
- [185] Federal Republic of Germany. Basic Law for the Federal Republic of Germany (Grundgesetz). May 23, 1949. https://www.gesetze-im-internet.de/english_gg/. Accessed March 3, 2026.
- [186] Herke B, Visek L. The attitudes of young citizens in higher education towards universal basic income in the context of automation. *Int J Soc Welf*. 2022;31(3):310-322. doi:10.1111/ijsw.12533
- [187] Merola R. Inclusive growth in the era of automation and AI: how can taxation help? *Front Artif Intell*. 2022;5:867832. doi:10.3389/frai.2022.867832
- [188] Hawksworth J, Berriman R, Goel S. Will robots really steal our jobs? An international analysis of the potential long term impact of automation. PwC; 2018. Accessed March 30, 2026. https://www.pwc.com/hu/hu/kiadvanyok/assets/pdf/impact_of_automation_on_jobs.pdf
- [189] Romero PD, Whittaker JM. A Brief Examination of Union Membership Data. Congressional Research Service; June 16, 2023. Report No. R47596. Accessed March 30, 2026. <https://www.congress.gov/crs-product/R47596>
- [190] Nissim G, Simon T. The future of labor unions in the age of automation and at the dawn of AI. *Technology in Society*. 2021;67:101732. doi:10.1016/j.techsoc.2021.101732
- [191] Frank MR, Autor D, Bessen JE, et al. Toward understanding the impact of artificial intelligence on labor. *Proc Natl Acad Sci USA*. 2019;116(14):6531-6539. doi:10.1073/pnas.1900949116
- [192] Tschang FT, Almirall E. Artificial intelligence as augmenting automation: implications for employment. *Acad Manag Perspect*. 2021;35(4):642-659. doi:10.5465/amp.2019.0062
- [193] Dauth W, Findeisen S, Südekum J, Wößner N. The adjustment of labor markets to robots. *J Eur Econ Assoc*. 2021;19(6):3104-3153. doi:10.1093/jeaa/jvab012
- [194] Almada M, Radu A. The Brussels Side-Effect: How the AI Act Can Reduce the Global Reach of EU Policy. *Ger Law J*. 2024;25(4):646-663. doi:10.1017/glj.2023.108
- [195] Hoch S, Mügge D. EU influence in global AI governance and its limits. *RegulAite Working Paper* 01/2025. University of Amsterdam; January 2025. Accessed March 31, 2026. <https://regulaite.eu/images/pdf/HochMugge2025.pdf>
- [196] Annal J. AI at Risk in the EU: It's Not Regulation, It's Implementation. *Eur J Risk Regul*. 2025;16:1168-1177. doi:10.1017/err.2025.19
- [197] Franceschelli G, Cevenini C, Musolesi M. Training Foundation Models as Data Compression: On Information, Model Weights and Copyright Law. *arXiv*. Preprint posted online March 12, 2025;arXiv:2407.13493. doi:10.48550/arXiv.2407.13493
- [198] Sekine T. EU's AI regulation and international economic law: the complex impact of the EU AI Act on global economic governance. *SSU Working Paper*. University of Tokyo; October 8, 2024. doi:10.2139/ssrn.4997043
- [199] Cory N, Dascoli L. How barriers to cross-border data flows are spreading globally, what they cost, and how to address them. Information Technology and Innovation Foundation; July 19, 2021. Accessed April 1, 2026. <https://www.tif.org/publications/2021/07/19/how-barriers-cross-border-data-flows-are-spreading-globally-what-they-cost/>
- [200] Eurostat. EU services exports reach record high in 2024. Eurostat News. Published December 17, 2025. Accessed April 1, 2026. <https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20251217-1>
- [201] Rutte M, Guinea O. Openness as Strength: The Win-Win in EU-US Digital Services Trade. European Centre for International Political Economy (ECIPE); March 2024. Accessed April 1, 2026. <https://ecipe.org/publications/openness-strength-eu-us-digital-services-trade/>
- [202] Organisation for Economic Co-operation and Development. OECD Services Trade Restrictiveness Index 2026: Policy Trends. OECD Publishing; 2026. doi:10.1787/db87d74e-en

- [203] Regulation (EU) 2023/2854 of the European Parliament and of the Council of 13 December 2023 on harmonised rules on fair access to and use of data (Data Act). Off J Eur Union. 2023;L2854:1-71. Accessed March 30, 2026. <http://data.europa.eu/eli/reg/2023/2854/oj>
- [204] Leistner M, Antoine L. IP Law and Policy for the Data Economy in the EU. *Economics*. 2023;17(1):20220043. doi:10.1515/econ-2022-0043
- [205] Eckardt M, Kerber W. Property rights theory, bundles of rights on IoT data, and the EU Data Act. *Eur J Law Econ*. 2024;57(1-2):113-143. doi:10.1007/s10657-023-09791-8
- [206] International Network of Privacy Law Professionals. How does India's new privacy law compare to GDPR? Published January 24, 2024. Accessed April 01, 2026. <https://inplp.com/latest-news/article/how-does-indias-new-privacy-law-compare-to-gdpr/>
- [207] Organisation for Economic Co-operation and Development; World Trade Organization. Economic Implications of Data Regulation: Balancing Openness and Trust. OECD Publishing; February 2025. doi:10.1787/aa285504-en
- [208] European Commission. A European Strategy for Data. COM(2020) 66 final. Published February 19, 2020. Accessed [date]. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52020DC0066>
- [209] Wainakh A, Zimmer E, Subedi S, et al. Federated learning attacks revisited: a critical discussion of gaps, assumptions, and evaluation setups. *Sensors*. 2022;23(1):31. doi:10.3390/s23010031.
- [210] Chakravorti B, Filipovic A, Bhaskar S. Regulating Cross-Border Data Flows: Harnessing Safe Data Sharing for Global and Inclusive Artificial Intelligence. United Nations University; 2023. Accessed April 1, 2026. <https://unu.edu/publication/regulating-cross-border-data-flows-harnessing-safe-data-sharing-global-and-inclusive>
- [211] Ren L, Wang H, Dong J, et al. Industrial Foundation Model. *IEEE Trans Cybern*. 2025;55(5):2286-2301. doi:10.1109/TCYB.2025.3527632
- [212] European Parliament and Council. Directive (EU) 2024/2853 on liability for defective products. Official Journal of the European Union. Published November 18, 2024. Accessed March 30, 2026. <https://eur-lex.europa.eu/eli/dir/2024/2853/oj/eng>
- [213] Judge B, Nitzberg M, Russell S. When code is not law: rethinking regulation for artificial intelligence. *Policy and Society*. 2024;44(1):85-97. doi:10.1093/polsoc/puae020
- [214] Buick A. Copyright and AI training data: transparency to the rescue? *Journal of Intellectual Property Law and Practice*. 2025;20(3):182-192. doi:10.1093/jiplp/jpae102
- [215] Leyden A. Standards and the EU AI Act: legitimacy, state of play, and future challenges. *Information and Communications Technology Law*. 2025. doi:10.1080/13600834.2025.2570966
- [216] Corporate Europe Observatory. Setting the Rules of Their Own Game: How Big Tech Is Shaping AI Standards. Published January 9, 2025. Accessed March 9, 2026. <https://corporateeurope.org/en/2025/01/setting-rules-their-own-game-how-big-tech-shaping-ai-standards>
- [217] Schuett J. Risk Management in the Artificial Intelligence Act. *European Journal of Risk Regulation*. 2024;15(2):367-385. doi:10.1017/err.2023.1
- [218] Hadfield GK, Clark J. Regulatory markets: the future of AI governance. *Jurimetrics*. 2026;65:195-240. doi:10.48550/arXiv.2304.04914
- [219] Buiten MC, de Streel A, Peitz M. The law and economics of AI liability. *Computer Law and Security Review*. 2023;48:105794. doi:10.1016/j.clsr.2023.105794
- [220] Perboli G, Simionato N, Pratali S. Navigating the AI regulatory landscape: Balancing innovation, ethics, and global governance. *Economics and Political Studies*. 2025;13(4):367-397. doi:10.1080/20954816.2025.2569584
- [221] Lasek-Markey M. Towards a human rights-based approach to ethical AI governance in Europe. *Philosophies*. 2024;9(6):181. doi:10.3390/philosophies9060181
- [222] Schmid S, Lambach D, Diehl C, Reuter C. Great power competition for global leadership in artificial intelligence (AI): reconstructing AI narratives of the United States, China, and the European Union. *Review of International Studies*. 2026. doi:10.1017/S0260210525000543
- [223] Teo SA. Artificial intelligence and its 'slow violence' to human rights. *AI Ethics*. Published online 2024. doi:10.1007/s43681-024-00547-x
- [224] Enqvist L. 'Human oversight' in the EU artificial intelligence act: what, when and by whom? *Law, Innovation and Technology*. 2023;15(2):508-535. doi:10.1080/17579961.2023.2245683
- [225] Chatham House. AI Governance and Human Rights: Why Human Rights? Chatham House; 2023. Accessed March 31, 2026. <https://www.chathamhouse.org/2023/01/ai-governance-and-human-rights/03-governing-ai-why-human-rights>
- [226] UNESCO. Recommendation on the Ethics of Artificial Intelligence. UNESCO; 2021. Accessed March 31, 2026. <https://www.unesco.org/en/artificial-intelligence/recommendation-ethics>
- [227] Crouzet N, Eberly JC, Eisefeldt AL, Papanikolaou D. The economics of intangible capital. *J Econ Perspect*. 2022;36(3):29-52. doi:10.1257/jep.36.3.29
- [228] Veldkamp L. Valuing Data as an Asset. *Review of Finance*. 2023;27(5):1545-1562. doi:10.1093/rof/rfac073
- [229] Valuing data assets can be key to unlocking board-level support for data modernization and transformation. Deloitte Insights. Accessed March 8, 2026. <https://www.deloitte.com/us/en/insights/topics/digital-transformation/valuing-data-assets.html>
- [230] OECD. Measuring data as an asset. OECD Econ Dep Work Pap. 2022. doi:10.1787/b840fb01-en.
- [231] Industrial Data Management Market Size, Share, Trends and Growth Drivers 2030. Markets and Markets; 2025. Accessed March 3, 2026. <https://www.marketsandmarkets.com/Market-Reports/industrial-data-management-market-150678178.html>
- [232] Strittmatter M, Meyer J, Meierhofer J, Vogt H, Kugler P, Dobler M. The EU Data Act: opportunities and research perspectives for data-driven companies. *Progress in IS*. 2025;Vol(Issue):21-33. doi:10.1007/978-3-031-86958-7_2
- [233] Damodaran A. Marketability and Value: Measuring the Illiquidity Discount. *SSRN Journal*. Published online 2005. doi:10.2139/ssrn.841484
- [234] Samaties P, Steger S, Maus S, Biesaga A. Tokenization of Real-World Assets. Unlocking a New Era of Ownership, Trading, and Investment. Roland Berger; 2023. Accessed March 3, 2026. <https://www.rolandberger.com/en/Insights/Publications/Tokenization-of-real-world-assets-unlocking-a-new-era-of-ownership-trading.html>
- [235] Deloitte. 2026 Manufacturing Industry Outlook. Deloitte Insights. Published November 2025. Accessed March 2, 2026. <https://www.deloitte.com/us/en/insights/industry/manufacturing-industrial-products/manufacturing-industry-outlook.html>
- [236] Bustinza OF, Molina LM, Vendrell-Herrero F, Opazo-Basaez M. AI-enabled smart manufacturing boosts ecosystem value capture. *International Journal of Production Economics*. 2024;277:109387. doi:10.1016/j.ijpe.2024.109411
- [237] World Economic Forum. How technological advances are strengthening supply chains. Published January 2024. Accessed March 2, 2026. <https://www.weforum.org/stories/2024/01/how-technological-advances-like-ai-are-strengthening-supply-chains/>
- [238] Hempel L, Conway M, Doheny M, Singhal S. Decoding disruption to reshape manufacturing footprints. McKinsey. Published January 8, 2026. Accessed March 31, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/decoding-disruption-to-reshape-manufacturing-footprints>
- [239] National Academies of Sciences, Engineering, and Medicine. Artificial Intelligence and the Future of Work. Washington, DC: The National Academies Press; 2025. doi:10.17226/27644
- [240] Babina T, Fedyk A, He AX, Hodson J. Firm investments in artificial intelligence technologies and changes in workforce composition. In: *Technology, Productivity, and Economic Growth*. National Bureau of Economic Research; 2023:75-117. <https://doi.org/10.3386/w31325>
- [241] PwC. The Fearless Future: 2025 Global AI Jobs Barometer. PwC; 2025. Accessed April 1, 2026. <https://www.pwc.com/gx/en/services/ai/ai-jobs-barometer.html>
- [242] Acemoglu D, Pischke J. Why do firms train? Theory and evidence. *Q J Econ*. 1998;113(1):79-119. doi:10.1162/003355398555531
- [243] Dong F, Doukas J. The role of intangible assets in shaping firm value. *Eur Financ Manag*. 2025;31(4):1325-1353. doi:10.1111/eufm.12547.
- [244] Xiong F, Xie M, Zhao L, Li C, Fan X. Recognition and evaluation of data as intangible assets. *SAGE Open*. 2022;12(2):1-12. doi:10.1177/21582440221094600.
- [245] Financial Stability Board. The financial stability implications of tokenisation. Published October 22, 2024. Accessed March 8, 2026. <https://www.fsb.org/uploads/P221024-2.pdf>
- [246] Mirdala R. Tokenization of real-world assets: Legal frameworks, market dynamics, and policy pathways for a decentralized financial future. *Journal of Applied Economic Sciences*. 2025;20(2):285-311. doi:10.57017/jaes.v20.2(88).09
- [247] European Parliament and Council. Regulation (EU) 2024/1781 establishing a framework for the setting of ecodesign requirements for sustainable products (ESPR). Official Journal of the European Union. 2024. Accessed March 3, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:3A32024R1781>
- [248] Weingartner T. Tokenization of physical assets and the impact of IoT and AI. EU Blockchain Observatory and Forum. 2019. Accessed March 3, 2026. https://blockchain-observatory.ec.europa.eu/document/download/23c89c26-725a-4121-be7b-75d41405f146_en

- [249] Proskurovskaya A, Birch K. Tokenization of everything? Exploring the limits of blockchain technologies in the governance of financial markets and assets. *Finance and Society*. Published December 9, 2025:1-21. doi:10.1017/fas.2025.10026
- [250] The Business Research Company. Tokenized Equipment-Leasing Market Report 2026. The Business Research Company; 2026. Accessed March 3, 2026. <https://www.researchandmarkets.com/reports/6190835/tokenized-equipment-leasing-market-report>
- [251] Mafrur R. Tokenize everything, but can you sell it? RWA liquidity challenges and the road ahead. arXiv. Preprint posted 2025. doi:10.48550/ARXIV.2508.11651
- [252] Officer MS. The price of corporate liquidity: Acquisition discounts for unlisted targets. *J Financ Econ*. 2007;83(3):571-598. doi:10.1016/j.jfineco.2006.01.004.
- [253] World Economic Forum. Stablecoin regulation: the genius act. Published July 2025. Accessed March 31, 2026. <https://www.weforum.org/stories/2025/07/stablecoin-regulation-genius-act/>
- [254] Nielsen CP, Da Silva ER, Yu F. Digital twins and blockchain: proof of concept. *Procedia CIRP*. 2020;93:251-255. doi:10.1016/j.procir.2020.04.104
- [255] Duley C, Gambacorta L, Garratt R, Koo Wilkens P. The oracle problem and the future of DeFi. Bank for International Settlements. Published September 7, 2023. Accessed March 8, 2026. <https://www.bis.org/publ/bisbull76.pdf>
- [256] Saenz H, Borchert A. Businesses accelerate reshoring and near-shoring amid heightened geopolitical uncertainties and rising costs. Bain & Company. Published November 13, 2024. Accessed March 1, 2026. <https://www.bain.com/about/media-center/press-releases/2024/businesses-accelerate-reshoring-and-near-shoring-amid-heightened-geopolitical-uncertainties-and-rising-costs-bain-company-finds/>
- [257] Chui M, Hazan E, Roberts R, et al. The economic potential of generative AI: The next productivity frontier. McKinsey & Company. Published June 14, 2023. Accessed March 31, 2026 <https://www.mckinsey.com/capabilities/tech-and-ai/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier>
- [258] Tao F, Zhang L, Liu Y, Cheng Y, Wang L, Xu X. Manufacturing Service Management in Cloud Manufacturing: Overview and Future Research Directions. *Journal of Manufacturing Science and Engineering*. 2015;137(4):040912. doi:10.1115/1.4030510
- [259] Intel Market Research. Manufacturing as a service (MaaS) market growth analysis, dynamics, key players and innovations, outlook and forecast 2026-2032. Published December 23, 2025. Accessed March 31, 2026. <https://www.intelmarketresearch.com/as-a-service-market-23560>
- [260] Rauch E, Matt DT, Dallasaga P, et al. Collaborative cloud manufacturing: design of business model innovations enabled by cyberphysical systems in distributed manufacturing systems. *Journal of Engineering*. 2016;2016:1308639. doi:10.1155/2016/1308639
- [261] Bagnon P, Chareyre M, Buvat J, et al. The Resurgence of Manufacturing: Reindustrialization Strategies in Europe and the US. Capgemini. Published March 2024. Accessed March 1, 2026. <https://www.capgemini.com/wp-content/uploads/2024/03/Final-Web-Version-Report-Reindustrialization.pdf>
- [262] Srai JS, Kumar M, Graham G, et al. Distributed manufacturing: scope, challenges and opportunities. *International Journal of Production Research*. 2016;54(23):6917-6935. doi:10.1080/00207543.2016.1192302
- [263] Erwin Rauch, T Acarkan, J Alonso, et al. AI as an Enabler for Long-Term Resilience in Manufacturing. Published October 21, 2021. Accessed March 31, 2026. <https://hdl.handle.net/10863/35831>
- [264] Draghi M. The Future of European Competitiveness. European Commission. Published September 2024. Accessed March 31, 2026. https://commission.europa.eu/topics/competitiveness/draghi-report_en
- [265] The White House. CHIPS and Science Act Will Lower Costs, Create Jobs, Strengthen Supply Chains, and Counter China. Published August 9, 2022. Accessed March 31, 2026. <https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2022/08/09/fact-sheet-chips-and-science-act-will-lower-costs-create-jobs-strengthen-supply-chains-and-counter-china/>
- [266] McIvor R, Bals L. A multi-theory framework for understanding the reshoring decision. *Int Bus Rev*. 2021;30(6):101827. doi:10.1016/j.ibusrev.2021.101827
- [267] IFS. What is Industrial AI? Published March 31, 2026. Accessed March 31, 2026. <https://www.ifs.com/de/glossary/what-is-industrial-ai>
- [268] Stekier M. 2025 top supply chain issues ranked. Plante Moran. Published February 14, 2025. Accessed March 8, 2026. <https://www.plantemoran.com/explore-our-thinking/insight/2023/03/top-supply-chain-issues-ranked>
- [269] Stackpole B. Securing Design IP in Distributed Manufacturing. *Digital Engineering* 24/7. Published April 22, 2024. Accessed March 8, 2026. <https://www.digitalengineering247.com/article/securing-design-ip-in-distributed-manufacturing>
- [270] Barbosa F, Blay K, Doheny M, et al. AI: The next frontier of performance in industrial processing plants. Accessed March 8, 2026. <https://www.mckinsey.com/industries/metals-and-mining/our-insights/ai-the-next-frontier-of-performance-in-industrial-processing-plants>
- [271] European Commission. European Chips Act | Shaping Europe's digital future. February 9, 2026. Accessed March 8, 2026. <https://digital-strategy.ec.europa.eu/en/policies/european-chips-act>
- [272] Kazmi SAA, Ghafoor MB, Akhtar MN, et al. Leveraging artificial intelligence for smart production management in industry 4.0. *Sci Rep*. 2025;15:8734. doi:10.1038/s41598-025-25413-6
- [273] Broring H, et al. OEM Servitization Strategies: Why Equipment as a Service Has Not Taken Off Yet. IoT Analytics. Published September 26, 2024. Accessed March 2, 2026. <https://iot-analytics.com/oem-servitization-strategies-equipment-as-a-service/>
- [274] Lafuente E, Vaillant Y, Persaud A. Digital service innovation for smarter production: servitized-AI progress towards smart products. *Technovation*. 2026;151:103466. doi:10.1016/j.technovation.2026.103466
- [275] IFS, Accenture. State of Service in Manufacturing 2025. IFS Blog. Published January 22, 2026. Accessed March 1, 2026. <https://blog.ifs.com/from-ai-to-outcomes-how-manufacturers-are-transforming-service/>
- [276] California Management Review. Equipment as a service in machine tool manufacturing: unlocking greater value for all. Published November 2025. Accessed March 29, 2026. <https://cmr.berkeley.edu/2025/11/equipment-as-a-service-in-machine-tool-manufacturing-unlocking-greater-value-for-all/>
- [277] Yan K, Pang X, Li Q, Tian G, Dong X. When does artificial intelligence innovation pay in servitization? A combined organizational learning and socio-technical systems perspective. *Journal of Innovation and Knowledge*. 2026;14:100960. doi:10.1016/j.jik.2026.100960
- [278] Smina N, Gahi Y, Gharib J. Data management in smart manufacturing supply chains: a systematic review of practices and applications (2020-2025). *Information*. 2025;17(1):19. doi:10.3390/info17010019
- [279] IDC. 41.6 billion connected IoT devices to generate 79 ZB of data by 2025. Published June 20, 2019. Accessed March 30, 2026. <https://www.cablinginstall.com/wireless-5g/article/14035174/idc-416-billion-connected-iot-devices-to-generate-79zb-of-data-by-2025>
- [280] European Parliament and Council. Regulation (EU) 2023/2854 on harmonised rules on fair access to and use of data (Data Act). Official Journal of the European Union. 2023. Accessed March 3, 2026. <https://eur-lex.europa.eu/eli/reg/2023/2854>
- [281] Singla A, Sukharevsky A, Hall B, Yee L, Chui M. The State of AI in 2025: Agents, Innovation, and Transformation. McKinsey and Company; 2025. Accessed March 3, 2026. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai>
- [282] Negoita M, Goger A. State-level policies to incentivize workplace learning: Impacts of California's incumbent worker training program. Washington, DC: Brookings Institution; July 2020. Accessed April 1, 2026. https://www.brookings.edu/wp-content/uploads/2020/07/Neigoita_Goger_final.pdf
- [283] IFRS Foundation. IASB launches comprehensive review of accounting for intangibles. Published April 23, 2024. Accessed March 3, 2026. <https://www.ifrs.org/news-and-events/news/2024/04/iasb-launches-comprehensive-review-accounting-for-intangibles/>
- [284] Fia T. Resisting IP overexpansion: the case of trade secret protection of non-personal data. *IIC International Review of Intellectual Property and Competition Law*. 2022;53(6):917-949. doi:10.1007/s40319-022-01204-8
- [285] Abdelzaher T, Hu Y, Kara D, et al. The bottlenecks of AI: challenges for embedded and real-time research in a data-centric age. *Real-Time Systems*. 2025;61(2):185-236. doi:10.1007/s11241-025-09452-w
- [286] Hramov AE, Pisarchik AN. Big data management and quality evaluation for the implementation of AI technologies in smart manufacturing. *Applied Sciences*. 2025;15(22):11905. doi:10.3390/app152211905
- [287] Fortune. Meta's \$100M signing bonuses for OpenAI staff are just the latest sign of extreme AI talent war. Published June 18, 2025. Accessed March 31, 2026. <https://fortune.com/2025/06/18/metass-100-million-signing-bonuses-openai-staff-extreme-ai-talent-war/>
- [288] Fortune / WSJ. OpenAI is paying workers \$1.5 million in stock-based compensation on average. Published February 18, 2026. Accessed March 31, 2026. <https://fortune.com/2026/02/18/openai-chatgpt-creator-record-million-dollar-equity-compensation-ai-tech-talent-war-career-retention-sam-altman-millionaire-staff/>

- [289] Hoey S, Peeters T, Principe F. The Transfer System in European Football: A Pro-Competitive No-Poaching Agreement? *International Journal of Industrial Organization*, 75, March 2021. Accessed March 31, 2026. <https://papers.tinbergen.nl/20034.pdf>
- [290] FTC. Non-Compete Clause Rule. Federal Register. Published May 7, 2024. Accessed March 31, 2026. <https://www.federalregister.gov/documents/2024/05/07/2024-09171/non-compete-clause-rule>
- [291] Rushing S. The cost of law firm associate turnover. *Lateral Link*. May 13, 2022. Accessed March 31, 2026. <https://laterallink.com/the-cost-of-law-firm-associate-turnover/>
- [292] OECD. AI Adoption by Small and Medium-Sized Enterprises. Published December 2025. Accessed March 31, 2026. https://www.oecd.org/en/publications/ai-adoption-by-small-and-medium-sized-enterprises_426399c1-en.html
- [293] Brynjolfsson E, Chandar B, Chen R. Canaries in the Coal Mine? Six Facts About the Recent Employment Effects of Artificial Intelligence. Stanford Digital Economy Lab. Published November 13, 2025. Accessed March 31, 2026. <https://digitaleconomy.stanford.edu/publications/canaries-in-the-coal-mine/>
- [294] IPCC. Technical summary. In: Portner HO, Roberts DC, Poloczanska ES, et al., eds. *Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press; 2022:37-118. doi:10.1017/9781009325844.002
- [295] Alnafrh I. The two tales of AI: a global assessment of the environmental impacts of artificial intelligence from a multidimensional policy perspective. *J Environ Manage*. 2025;392:126813. doi:10.1016/j.jenvman.2025.126813
- [296] Hlabisa S. The ecology of artificial intelligence: energy, water, materials, and land limits of digital systems. *Carbon Neutral Systems*. 2025;1:19. doi:10.1007/s44438-025-00018-8
- [297] International Energy Agency. *Electricity 2024: Analysis and Forecast to 2026*. International Energy Agency; 2024. Accessed March 31, 2026. <https://www.iea.org/reports/electricity-2024>
- [298] Consultancy.eu. The hidden cost of AI: new report warns over energy use and environmental impact. Consultancy.eu. Published February 11, 2026. Accessed March 30, 2026. <https://www.consultancy.eu/news/13183/the-hidden-cost-of-ai-new-report-warns-over-energy-use-and-environmental-impact>
- [299] Ellen MacArthur Foundation. *Artificial Intelligence and the Circular Economy: AI as a Tool to Accelerate the Transition*. Ellen MacArthur Foundation; 2019. Accessed March 30, 2026. <https://www.ellenmacarthurfoundation.org/artificial-intelligence-and-the-circular-economy>
- [300] Iacovidou E, Hahladakis JN, Purnell P. A systems thinking approach to understanding the challenges of achieving the circular economy. *Environ Sci Pollut Res*. 2021;28(19):24785-24806. doi:10.1007/s11356-020-11725-9
- [301] Circle Economy. *The Circularity Gap Report 2021*. Circle Economy; 2021. Accessed March 30, 2026. <https://www.circularity-gap.world/2021>
- [302] European Commission. A new Circular Economy Action Plan: for a cleaner and more competitive Europe. COM(2020) 98 final. Published March 11, 2020. Accessed March 30, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=COM:2020:98:FIN>
- [303] European Parliament, Council of the European Union. Regulation (EU) 2024/1252 establishing a framework for ensuring a secure and sustainable supply of critical raw materials (Critical Raw Materials Act). *Official Journal of the European Union*. 2024. Accessed March 30, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A02024R1252-20240503>
- [304] Chawla K, Chirvasuta T, Wolf MA, et al. Methodology for Defining Data Requirements for the Digital Product Passport Under the ESPR Framework. European Commission Joint Research Centre; 2025. Accessed March 30, 2026. <https://publications.jrc.ec.europa.eu/repository/handle/JRC145830>
- [305] Council of the European Union. Strategic autonomy: Council gives its final approval on the critical raw materials act. Published March 18, 2024. Accessed March 30, 2026. <https://www.consilium.europa.eu/en/press/press-releases/2024/03/18/strategic-autonomy-council-gives-its-final-approval-on-the-critical-raw-materials-act/>
- [306] Agarwal S, Schmid C. What is an AI-driven circular economy? *World Economic Forum*. Published January 8, 2026. Accessed March 30, 2026. <https://www.weforum.org/stories/2026/01/what-is-ai-driven-circular-economy/>
- [307] Stern N, Romani M, Pierfederici R, et al. Green and intelligent: the role of AI in the climate transition. *npj Clim Action*. 2025;4(1):56. doi:10.1038/s44168-025-00252-3
- [308] Cremona E, Czyzak P. Grids for Data Centres in Europe: Ambitious Grid Planning Can Win Europe's AI Race. *Ember*; 2025. Accessed March 30, 2026. <https://ember-energy.org/app/uploads/2025/06/Grids-for-data-centres-in-Europe.pdf>
- [309] Rahman MA, Shahriar MF, Iqbal K, Abushaiba AA. Enabling intelligent industrial automation: a review of machine learning applications with digital twin and edge AI integration. *Automation*. 2025;6(3):37. doi:10.3390/automation6030037.
- [310] Ran Y, Zhou X, Lin P, Wen Y, Deng R. A survey of predictive maintenance: systems, purposes and approaches. *IEEE Commun Surv Tutor*. 2019;21(3):2242-2272. doi:10.1109/COMST.2019.2898978.
- [311] Xiao T, Nerini FF, Matthews HD, Tavoni M, You F. Environmental impact and net-zero pathways for sustainable artificial intelligence servers in the USA. *Nat Sustain*. 2025;8(12):1541-1553. doi:10.1038/s41893-025-01681-y.
- [312] International Energy Agency. *Energy and AI*. Paris, France: International Energy Agency; 2025. Accessed March 8, 2026. <https://www.iea.org/reports/energy-and-ai>.
- [313] Siddik MAB, Shehabi A, Marston L. The environmental footprint of data centers in the United States. *Environ Res Lett*. 2021;16(6):064017. doi:10.1088/1748-9326/abfa1.
- [314] Google. *Hamina, Finland data center*. Google Data Centers. Accessed April 1, 2026. <https://www.google.com/about/datacenters/locations/hamina/>
- [315] Hale T. China is putting data centers in the ocean to keep them cool. *Scientific American*. July 16, 2025. Accessed April 1, 2026. <https://www.scientificamerican.com/article/china-powers-ai-boom-with-undersea-data-centers/>
- [316] Microsoft. *Project Natick*. Microsoft Research. Accessed April 1, 2026. <https://natick.research.microsoft.com/>
- [317] Yuan X, Liu J, Sun S, et al. Data center waste heat for district heating networks: a review. *Renew Sustain Energy Rev*. 2025;219:115863. doi:10.1016/j.rser.2025.115863.
- [318] Müller SI, Chapanova G, Diekow T, et al. Comparison of cooling tower blowdown and enhanced make up water treatment to minimize cooling water footprint. *J Environ Manage*. 2024;367:121949. doi:10.1016/j.jenvman.2024.121949.
- [319] Jiang F, Duan C, Chen B. Facility-level energy-driven water footprint and scarcity implications of Chinese data centers: a bottom-up analysis and scenario-based projection. *Appl Energy*. 2025;385:125528. doi:10.1016/j.apenergy.2025.125528.
- [320] Karimi L, Yacuel L, Johnson JD, et al. Water-energy tradeoffs in data centers: a case study in hot-arid climates. *Resour Conserv Recycl*. 2022;181:106194. doi:10.1016/j.resconrec.2022.106194.
- [321] Wang H, Yuan X, Zhang K, et al. Performance evaluation and optimization of data center servers using single-phase immersion cooling. *Int J Heat Mass Transf*. 2024;221:125057. doi:10.1016/j.ijheatmasstransfer.2023.125057.
- [322] Leng Q, Mohamat-Yusuff F, Mohamed KN, Zainordin NS, Hassan MZ. Impacts of thermal and cold discharge from power plants on marine benthos and its mitigation measures: a systematic review. *Front Mar Sci*. 2024;11:1465289. doi:10.3389/fmars.2024.1465289.
- [323] Zhou W, Yang Y, Han W, Song C, Meng Z, Zhang H, Han Q. Effects of thermal discharge on the structuring of macrobenthic biological traits around the Sanmen nuclear power plant in the East China Sea. *Mar Pollut Bull*. 2025;213:117705. doi:10.1016/j.marpolbul.2025.117705.
- [324] Lei N, Lu J, Shehabi A, Masanet E. The water use of data center workloads: a review and assessment of key determinants. *Resour Conserv Recycl*. 2025;219:108310. doi:10.1016/j.resconrec.2025.108310.
- [325] Thiede S, Bogdanski G, Herrmann C. A Systematic Method for Increasing the Energy and Resource Efficiency in Manufacturing Companies. *Procedia CIRP*. 2012;2:28-33. doi:10.1016/j.procir.2012.05.034
- [326] Herrmann C, Thiede S, Kara S, Hesselbach J. Energy oriented simulation of manufacturing systems – Concept and application. *CIRP Ann*. 2011;60(1):45-48. doi:10.1016/j.cirp.2011.03.127
- [327] Resman M, Heraković N, Debevec M. Integrating digital twin technology to achieve higher operational efficiency and sustainability in manufacturing systems. *Systems*. 2025;13(3):180. doi:10.3390/systems13030180
- [328] Kritzing W, Karner M, Traar G, Henjes J, Sih W. Digital Twin in manufacturing: A categorical literature review and classification. *IFAC-Pap*. 2018;51(11):1016-1022. doi:10.1016/j.ifacol.2018.08.474
- [329] Tao F, Zhang H, Liu A, Nee AYC. Digital Twin in Industry: State-of-the-Art. *IEEE Trans Ind Inform*. 2019;15(4):2405-2415. doi:10.1109/TII.2018.2873186
- [330] Lu Y, Liu C, Wang KIK, Huang H, Xu X. Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. *Robot Comput-Integr Manuf*. 2020;61:101837. doi:10.1016/j.rcim.2019.101837

- [331] Ivanov D, Dolgui A. A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Prod Plan Control*. 2021;32(9):775-788. doi:10.1080/09537287.2020.1768450
- [332] Park KT, Son YH, Noh SD. The architectural framework of a cyber physical logistics system for digital-twin-based supply chain control. *Int J Prod Res*. 2021;59(19):5721-5742. doi:10.1080/00207543.2020.1788738
- [333] Balakrishnan Selvakumaran S, Hall DM. From crowd to cloud: simplified automatic reconstruction of digital building assets for facility management. *J Facil Manag*. 2022;20(3):401-436. doi:10.1108/JFM-02-2021-0017
- [334] Siemens. Siemens and NVIDIA expand partnership to build industrial AI operating system. Published January 6, 2026. Accessed March 9, 2026. <https://press.siemens.com/global/en/pressrelease/siemens-and-nvidia-expand-partnership-build-industrial-ai-operating-system>
- [335] Martina Hatzel. BMW Group at NVIDIA GTC: Virtual production under way in future plant Debrecen. Published March 21, 2023. Accessed March 31, 2026. <https://www.press.bmwgroup.com/global/article/detail/T0411467EN/bmw-group-at-nvidia-gtc-virtual-production-under-way-in-future-plant-debrecen?language=en>
- [336] Han W, Deutsch I. Reconstruct a Scene in NVIDIA Isaac Sim Using Only a Smartphone. NVIDIA Technical Blog. Published October 23, 2025. Accessed March 9, 2026. <https://developer.nvidia.com/blog/reconstruct-a-scene-in-nvidia-isaac-sim-using-only-a-smartphone/>
- [337] Vatankhah Barenji A, Liu X, Guo H, Li Z. A digital twin-driven approach towards smart manufacturing: reduced energy consumption for a robotic cell. *Int J Comput Integr Manuf*. 2021;34(7-8):844-859. doi:10.1080/0951192X.2020.1775297
- [338] Zhao L, Fang Y, Lou P, Yan J, Xiao A. Cutting Parameter Optimization for Reducing Carbon Emissions Using Digital Twin. *Int J Precis Eng Manuf*. 2021;22(5):933-949. doi:10.1007/s12541-021-00486-1
- [339] European Commission. Chapter 2 - The EU Emission Trading System. Published March 31, 2026. Accessed March 31, 2026. https://climate.ec.europa.eu/eu-action/climate-strategies-targets/progress-climate-action/eu-climate-action-progress-report-2025/chapter-2-eu-emission-trading-system_en
- [340] European Commission. Corporate sustainability reporting. Published March 31, 2026. Accessed March 31, 2026. https://finance.ec.europa.eu/financial-markets/company-reporting-and-auditing/company-reporting/corporate-sustainability-reporting_en
- [341] Wei Y, Hu T, Zhou T, Ye Y, Luo W. Consistency retention method for CNC machine tool digital twin model. *J Manuf Syst*. 2021;58:313-322. doi:10.1016/j.jmsy.2020.06.002
- [342] Sharma A, Kosasih E, Zhang J, Brintrup A, Calinescu A. Digital Twins: State of the art theory and practice, challenges, and open research questions. *J Ind Inf Integr*. 2022;30:100383. doi:10.1016/j.jii.2022.100383
- [343] Fuller A, Fan Z, Day C, Barlow C. Digital Twin: Enabling Technologies, Challenges and Open Research. IEEE Access. 2020;8:108952-108971. doi:10.1109/ACCESS.2020.2998358
- [344] Ba L, Tangour F, El Abbassi I, Absi R. Analysis of Digital Twin Applications in Energy Efficiency: A Systematic Review. *Sustainability*. 2025;17(8):3560. doi:10.3390/su17083560
- [345] Chen C, Nguyen DT, Lee SJ, Baker NA, Karakoti AS, Lauw L, et al. Accelerating computational materials discovery with machine learning and cloud high-performance computing: from large-scale screening to experimental validation. *J Am Chem Soc*. 2024;146(29):20009-20018. doi:10.1021/jacs.4c03849
- [346] Xie E, Wang X, Siepmann JJ, Chen H, Snurr RQ. Generative AI for design of nanoporous materials: review and future prospects. *Digital Discov*. 2025;4(9):2336-2363. doi:10.1039/d5dd00221d
- [347] Wei D, Wang Z, Lin H, Yin XP, Wang Y. Research progress in artificial intelligence-assisted preparation of high-quality biomaterials. *ACS Omega*. 2026. doi:10.1021/acsomega.5c09392
- [348] Ozcan A, Coudert F, Rogge SMJ, Heydenrych G, Fan D, Sarikas AP, et al. Artificial intelligence paradigms for next-generation metal-organic framework research. *J Am Chem Soc*. 2025;147(27):23367-23380. doi:10.1021/jacs.5c08214
- [349] Alampara N, Schilling-Wilhelmi M, Jablonka KM. Lessons from the trenches on evaluating machine learning systems in materials science. *Comput Mater Sci*. 2025;259:114041. doi:10.1016/j.commatsci.2025.114041
- [350] Low AKY, Cheng JJW, Hippalgaonkar K, Ng LWT. Self-driving laboratories: translating materials science from laboratory to factory. *ACS Omega*. 2025;10(28):29902-29908. doi:10.1021/acsomega.5c02197
- [351] Hung L, Yager JA, Monteverde D, Baiocchi D, Kwon H, Sun S, Suram S. Autonomous laboratories for accelerated materials discovery: a community survey and practical insights. *Digital Discov*. 2024;3:1273-1295. doi:10.1039/D4DD00059E
- [352] Zhao T, Zeng Y. Digital twins for self-driving chemistry laboratories. *Nat Comput Sci*. 2026;6:15-16. doi:10.1038/s43588-025-00908-4
- [353] Vriza A, Chan H, Xu J. Self-driving laboratory for polymer electronics. *Chem Mater*. 2023;35(8):3046-3056. doi:10.1021/acs.chemmater.2c03593
- [354] Singla A, Sukharevsky A, Berteletti E, Yee L, Chui M. The next innovation revolution—powered by AI. McKinsey. Published June 20, 2025. Accessed March 30, 2026. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-next-innovation-revolution-powered-by-ai>
- [355] Abbate E, Garmendia Aguirre I, Bracalente G, et al. Safe and Sustainable by Design Chemicals and Materials: Methodological Guidance. EUR 31942 EN. Publications Office of the European Union; 2024. doi:10.2760/28450
- [356] Tobias AV, Wahab A. Autonomous 'self-driving' laboratories: a review of technology and policy implications. *R Soc Open Sci*. 2025;12(7):250646. doi:10.1098/rsos.250646
- [357] Tom G, Schmid SP, Baird SG, Cao Y, Darvish K, Hao H, Lo S, Pablo-García S, Rajanonsen EM, Skreta M, Yoshikawa N, Corapi S, Akkoc GD, Strieth-Kalthoff F, Seifrid M, Aspuru-Guzik A. Self-driving laboratories for chemistry and materials science. *Chem Rev*. 2024;124(16):9633-9732. doi:10.1021/acs.chemrev.4c00055
- [358] Hu J, Dong R, Feng Y, Hu M, Hu J. Foundation-model surrogates enable data-efficient active learning for materials discovery. Preprint. Posted March 13, 2026. arXiv:2603.12567
- [359] International Energy Agency. Global critical minerals outlook 2025. Published March 2023. Accessed March 31, 2026. <https://www.iea.org/reports/global-critical-minerals-outlook-2025>
- [360] Junne T, Wulff N, Breyer C, Naegler T. Critical materials in global low-carbon energy scenarios: The case for neodymium, dysprosium, lithium, and cobalt. *Energy*. 2020;211:118532. doi:10.1016/j.energy.2020.118532.
- [361] Cai C. How artificial intelligence can empower the robotic recycling industry: toward an adaptive, data-driven, and circular material recovery system. *Comput Artif Intell*. 2026;3(1):17-26. doi:10.70267/cai.26v3n1.1726.
- [362] Chertow M, Reck BK, Wrzesniewski A, Calli B. Outlook on the future role of robots and AI in material recovery facilities: Implications for US recycling and the workforce. *J Clean Prod*. 2024;470:143234. doi:10.1016/j.jclepro.2024.143234.
- [363] Rahman SMM, Reck BK. Techno-economic analysis of a material recovery facility employing robotic sorting technology. In: Nasr N, ed. *Technology Innovation for the Circular Economy*. 1st ed. Wiley; 2024:269-278. doi:10.1002/9781394214297.ch21.
- [364] Umweltpakt Bayern. ResourceEU: neuer EU-Aktionsplan für mehr Recycling und Rohstoffsicherheit. Accessed March 31, 2026. <https://www.umweltpakt.bayern.de/abfall/aktuelles/3963/resourceeu-neuer-eu-aktionsplan-mehr-recycling-rohstoffsicherheit>
- [365] European Parliament, Council of the European Union. Regulation (EU) 2024/1252 of 11 April 2024 establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending Regulations (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1724 and (EU) 2019/1020. *Official Journal of the European Union*. L, 2024/1252. May 3, 2024. Accessed March 31, 2026. <https://eur-lex.europa.eu/eli/reg/2024/1252/oj>
- [366] Bawankule R, Gaikwad V, Kulkarni I, Kulkarni S, Jadhav A, Ranjan N. Visual Detection of Waste using YOLOv8. In: 2023 International Conference on Sustainable Computing and Smart Systems (ICSCSS). IEEE; 2023:869-873. doi:10.1109/ICSCSS57650.2023.10169688
- [367] Lakhout A. Revolutionizing urban solid waste management with AI and IoT: A review of smart solutions for waste collection, sorting, and recycling. *Results Eng*. 2025;25:104018. doi:10.1016/j.rineng.2025.104018.
- [368] European Environment Agency. Circular economy financing and strategies. Published September 29, 2025. Accessed March 31, 2026. <https://www.eea.europa.eu/en/europe-environment-2025/thematic-briefings/circular-economy-and-other-enablers-of-transformative-change/circular-economy-financing-and-strategies>
- [369] Aberger J, Shami S, Häcker B, Pestana J, Khodier K, Sarc R. Prototype of AI-powered assistance system for digitalisation of manual waste sorting. *Waste Manag*. 2025;194:366-378. doi:10.1016/j.wasman.2025.01.027
- [370] Bemani A, Björnell N. Aggregation strategy on federated machine learning algorithm for collaborative predictive maintenance. *Sensors*. 2022;22(16):6252. doi:10.3390/s22166252
- [371] European Parliament, Council of the European Union. Regulation (EU) 2022/868 of 30 May 2022 on European data governance and amending Regulation (EU) 2018/1724 (Data Governance Act). *Official Journal of the European Union*. L 152, 3.6.2022:1-44. Accessed March 31, 2026. <https://eur-lex.europa.eu/eli/reg/2022/868/oj>
- [372] Klaußen L, Stoll C. Harmonizing corporate carbon footprints. *Nature Communications*. 2021;12(1):6149. doi:10.1038/s41467-021-26349-x

- [373] World Resources Institute, World Business Council for Sustainable Development. Corporate Value Chain (Scope 3) Accounting and Reporting Standard. Greenhouse Gas Protocol; 2011. Accessed March 30, 2026. https://ghgprotocol.org/sites/default/files/standards/Corporate-Value-Chain-Accounting-Reporting-Standard_041613_2.pdf
- [374] Stenzel A, Waichman I. Supply chain data sharing for scope 3 emissions. *npj Climate Action*. 2023;2:7. doi:10.1038/s44168-023-00032-x
- [375] European Commission. Regulation (EU) 2023/2772 supplementing Directive 2013/34/EU as regards sustainability reporting standards. Official Journal of the European Union. 2023. Accessed March 30, 2026. https://eur-lex.europa.eu/eli/reg_del/2023/2772/oj
- [376] European Parliament, Council of the European Union. Regulation (EU) 2024/1781 of 13 June 2024 establishing a framework for the setting of ecodesign requirements for sustainable products (Ecodesign for Sustainable Products Regulation). Official Journal of the European Union. L, 2024/1781. June 28, 2024. Accessed March 31, 2026. <http://data.europa.eu/eli/reg/2024/1781/oj>
- [377] European Parliament, Council of the European Union. Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 concerning batteries and waste batteries, amending Regulation (EU) 2019/1020 and Directive 2006/66/EC and repealing Directive 2006/66/EC. Official Journal of the European Union. 2023;L191:1-117. Accessed March 31, 2026. <http://data.europa.eu/eli/reg/2023/1542/oj>
- [378] GS1 AISBL. EPICS and CBV Implementation Guideline. Release 2.0. GS1 AISBL; 2023. Accessed April 1, 2026. <https://ref.gs1.org/standards/epics/>
- [379] Industrial Digital Twin Association e.V. Specification of the Asset Administration Shell Part 1: Metamodel. Version 3.1.2. IDTA-01001. Industrial Digital Twin Association e.V.; October 2025. doi:10.62628/IDTA.01001-3-1-2
- [380] International Organization for Standardization. ISO 14067:2018. Greenhouse gases—Carbon footprint of products—Requirements and guidelines for quantification. ISO; 2018. Accessed April 1, 2026. <https://www.iso.org/standard/71206.html>
- [381] Stroher T, Korner MF, Paetzold F, Strucker J. Bridging carbon data's organizational boundaries: toward automated data sharing in sustainable supply chains. *Electronic Markets*. 2025;35:33. doi:10.1007/s12525-025-00779-7
- [382] Boston Consulting Group, CDP. Scope 3 Upstream: Big Challenges, Simple Remedies. CDP; 2024. Accessed March 31, 2026. <https://www.eticanews.it/wp-content/uploads/2024/06/Scope-3-Upstream-Report.pdf>
- [383] EuroCommerce. Tackling the Hidden Carbon Footprint in European Retail and Wholesale Value Chains. EuroCommerce; 2024. Accessed March 31, 2026. <https://www.eurocommerce.eu/app/uploads/2024/06/eurocommerce-report-june-18-web.pdf>
- [384] Jensen SF, Kristensen JH, Adamsen S, Christensen A, Waehrens BV. Digital product passports for a circular economy: data needs for product life cycle decision making. *Sustainable Production and Consumption*. 2023;37:242-255. doi:10.1016/j.spc.2023.02.021
- [385] Psarommatīs F, May G. Digital Product Passport: A Pathway to Circularity and Sustainability in Modern Manufacturing. *Sustainability*. 2024;16(1):396. doi:10.3390/su16010396
- [386] Alghamdi Omar A, Agag G. Competitive advantage: A longitudinal analysis of the roles of data-driven innovation capabilities, marketing agility, and market turbulence. *Journal of Retailing and Consumer Services*. 2024;76:103547. doi:10.1016/j.jretconser.2023.103547
- [387] Maddala VSP. Data-Driven Manufacturing: Leveraging Analytics for Operational Excellence. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*. 2025;11(1):884-893. doi:10.32628/CSEIT2511291
- [388] The future of manufacturing is powered by data and analytics. Here's why. *World Economic Forum*. September 9, 2022. Accessed March 31, 2026. <https://www.weforum.org/stories/2022/09/manufacturing-data-advanced-analytics/>
- [389] Shafiee S. Synthetic data generation in manufacturing: a review of methods, domains, and emerging trends: 13th CIRP Global Web Conference. *Procedia CIRP*. 2026;139:440-445. doi:10.1016/j.procir.2025.08.199
- [390] Buggineni V, Chen C, Camelio J. Enhancing manufacturing operations with synthetic data: a systematic framework for data generation, accuracy, and utility. *Front Manuf Technol*. 2024;4. doi:10.3389/ftmtec.2024.1320166
- [391] Li X, Cheng Y, Møller C, Lee J. Data issues in industrial AI systems: A meta-review and research strategy. *Computers in Industry*. 2025;173:104361. doi:10.1016/j.compind.2025.104361
- [392] Evaluating gradient inversion attacks and defenses. In: *Federated Learning*. Academic Press; 2024:105-122. doi:10.1016/B978-0-44-319037-7.00014-4
- [393] Chaudhary V, Paudel P, Chaudhary V. Federated Learning: A Survey of Core Challenges, Current Methods, and Opportunities. Preprints. Preprint posted online January 5, 2026:2026010271. doi:10.20944/preprints202601.0271.v1
- [394] Gao RX, Wang L, Helu M, Teti R. Big data analytics for smart factories of the future. *CIRP Ann*. 2020;69(2):668-692. doi:10.1016/j.cirp.2020.05.002
- [395] Mikołajewska E, Mikołajewski D, Mikołajczyk T, Pączkowski T. Generative AI in AI-based digital twins for fault diagnosis for predictive maintenance in Industry 4.0/5.0. *Appl Sci*. 2025;15(6):3166. doi:10.3390/app15063166
- [396] Dzaferagic M, Marchetti N, Macaluso I. Fault detection and classification in Industrial IoT in case of missing sensor data. *IEEE Internet Things J*. 2022;9(11):8892-8900. doi:10.1109/JIOT.2021.3116785
- [397] Xiong J, Fink O, Zhou J, Ma Y. Controlled physics-informed data generation for deep learning-based remaining useful life prediction under unseen operation conditions. *Mech Syst Signal Process*. 2024;215:111352. doi:10.1016/j.ymssp.2024.111352
- [398] Huber C, Knoll D, Guthe M. Fully-synthetic training for visual quality inspection in automotive production. *Procedia CIRP*. 2025;134:777-782. doi:10.1016/j.procir.2025.02.205
- [399] NVIDIA. Synthetic data generation for physical AI. Accessed March 19, 2026. <https://www.nvidia.com/en-us/use-cases/synthetic-data-physical-ai>
- [400] Commission Nationale de l'Informatique et des Libertés (CNIL). AI system development: CNIL's recommendations to comply with GDPR. Published January 5, 2026. Accessed March 19, 2026. <https://www.cnil.fr/en/ai-system-development-cnils-recommendations-to-comply-gdpr>
- [401] Lycklama H, Burkhalter L, Viand A, Küchler N, Hithnawi A. RoFL: robustness of secure federated learning. *arXiv*. 2021;2107:03311. doi:10.48550/arXiv.2107.03311
- [402] Zhao JC, Sharma A, Elkordy AR, Ezzeldin YH, Avestimehr S, Bagchi S. LOKI: Large-scale data reconstruction attack against federated learning through model manipulation. *arXiv*. 2023;2303.12233. doi:10.48550/arXiv.2303.12233
- [403] McMahan HB, Moore E, Ramage D, Hampson S, Agüera y Arcas B. Communication-efficient learning of deep networks from decentralized data. *Proceedings of Machine Learning Research*. 2017;54:1273-1282. arXiv:1602.05629.
- [404] Zhu J, Yao R, Blaschko MB. Surrogate model extension (SME): A fast and accurate weight update attack on federated learning. *arXiv*. 2023;2306.00127. doi:10.48550/arXiv.2306.00127
- [405] Struppek L, Hintersdorf D, De Almeida Correia A, Adler A, Kersting K. Plug & play attacks: towards robust and flexible model inversion attacks. *arXiv*. 2022;2201.12179. doi:10.48550/arXiv.2201.12179
- [406] Geiping J, Bauermeister H, Dröge H, Moeller M. Inverting gradients — how easy is it to break privacy in federated learning? *Advances in Neural Information Processing Systems*. 2020;33:16937-16947. arXiv:2003.14053. doi:10.48550/arXiv.2003.14053
- [407] Sudars K, Namatevs I, Nikulins A, Ozols K. Privacy auditing of lithium-ion battery ageing model by recovering time-series data using gradient inversion attack in federated learning. *Appl Sci*. 2025;15(10):5704. doi:10.3390/app15105704
- [408] Gaikwad MA. Homomorphic encryption and secure multi-party computation: mathematical tools for privacy-preserving data analysis in the cloud. *Panam Math J*. 2024;33(2):75-88. doi:10.52783/pmj.v33.i2.876.
- [409] Nguyen NB, Chandrasegaran K, Abdollahzadeh M, Cheung NM. Label-only model inversion attacks via knowledge transfer. *arXiv*. 2023;2310.19342. doi:10.48550/arXiv.2310.19342
- [410] Daly K, Eichner H, Kairouz P, McMahan HB, Ramage D, Xu Z. Federated learning in practice: reflections and projections. *IEEE 6th International Conference on Trust, Privacy and Security in Intelligent Systems and Applications (TPS-ISA)*. 2024:148-156. arXiv:2410.08892. doi:10.48550/arXiv.2410.08892
- [411] Gaw N, Yousefi S, Gahroei MR. Multimodal data fusion for systems improvement: a review. *IJSE Transactions*. 2022;54(11):1098-1116. doi:10.1080/24725854.2021.1987593
- [412] Kolokas N, Vafeiadis T, Ioannidis D, Tzovaras D. A review of multisensor data fusion solutions in smart manufacturing: systems and trends. *Sensors*. 2022;22(5):1734. doi:10.3390/s22051734
- [413] Wang T, Zhang B, Jiang D, Li D. A multimodal large language model framework for intelligent perception and decision-making in smart manufacturing. *Sensors*. 2025;25(10):3072. doi:10.3390/s25103072
- [414] World Economic Forum. Global Lighthouse Network: Adopting AI at Speed and Scale. *World Economic Forum*; 2023. Accessed March 31, 2026. https://www3.weforum.org/docs/WEF_Global_Lighthouse_Network_Adopting_AI_at_Speed_and_Scale_2023.pdf

- [415] Siemens AG. Siemens introduces AI agents for industrial automation. Published May 2025. Accessed March 18, 2026. <https://press.siemens.com/global/en/pressrelease/siemens-introduces-ai-agents-industrial-automation>
- [416] Stracke L, Burggräf P, Sauer CR, Schütz M, Kaiser J. From human to machine: high-impact tasks for AI in production management – an expert study to reshape decision-making. *Prod Eng.* 2026;20(1):1-12. doi:10.1007/s11740-025-01416-0
- [417] Langer M, Baum K, Schlicker N. Effective human oversight of AI-based systems: a signal detection perspective on the detection of inaccurate and unfair outputs. *Minds Mach.* 2024;35(1):1-20. doi:10.1007/s11023-024-09701-0
- [418] Romeo G, Conti D. Exploring automation bias in human–AI collaboration: a review and implications for explainable AI. *AI Soc.* 2025;41(1):259-278. doi:10.1007/s00146-025-02422-7
- [419] Johnson M, Albizri A, Harfouche A, Fosso-Wamba S. Integrating human knowledge into artificial intelligence for complex and ill-structured problems: informed artificial intelligence. *Int J Inf Manag.* 2022;64:102479. doi:10.1016/j.jinfomgt.2022.102479
- [420] Deng C, Ji X, Rainey C, Zhang J, Lu W. Integrating machine learning with human knowledge. *iScience.* 2020;23(11):101656. doi:10.1016/j.isci.2020.101656
- [421] Hoerner L, Moryson R, Wehking KH, Röcker C. Using tacit expert knowledge to support shop-floor operators through a knowledge-based assistance system. *Comput Support Coop Work.* 2023;32:1019-1060. doi:10.1007/s10606-022-09445-4.
- [422] Jarrahi MH, Askay D, Eshraghi A, Smith P. Artificial intelligence and knowledge management: a partnership between human and AI. *Bu Horiz.* 2023;66(1):87-99. doi:10.1016/j.bushor.2022.03.002
- [423] Contreras CA, Rastegarpanah A, Chiou M, Stolkin R. A mini-review on mobile manipulators with variable autonomy. *Front Robot AI.* 2025;12:1540476. doi:10.3389/frobt.2025.1540476
- [424] Beer JM, Fisk AD, Rogers WA. Toward a framework for levels of robot autonomy in human-robot interaction. *J Hum Robot Interact.* 2014;3(2):74. doi:10.5898/JHRI.3.2.Beer
- [425] Sharkawy AN. Human-robot interaction: applications. *arXiv.* 2021;2102:00928. doi:10.48550/arXiv.2102.00928
- [426] Hinder F, Vaquet V, Hammer B. One or two things we know about concept drift - a survey on monitoring in evolving environments. Part A: detecting concept drift. *Front Artif Intell.* 2024;7:1330257. doi:10.3389/frai.2024.1330257
- [427] European Telecommunications Standards Institute. ETSI TS 104 008 V1.1.1 (2026-01): Continuous Auditing-Based Conformity Assessment for AI-enabled systems. Sophia Antipolis, France: ETSI; 2026. Available from: ETSI. Accessed on 31 March 2026. https://www.etsi.org/deliver/etsi_ts/104000_104099/104008/01.01.01_60/ts_104008v010101p.pdf
- [428] US Bureau of Labor Statistics. Employed people by detailed industry and age. Published January 22, 2021. Accessed April 1, 2026. <https://www.bls.gov/cps/cpsaat18b.htm>
- [429] Miller T, Durlik I, Łobodzińska A, Dorobczyński L, Jasionowski R. AI in context: harnessing domain knowledge for smarter machine learning. *Appl Sci.* 2024;14(24):11612. doi:10.3390/app142411612
- [430] Sonnenschein B. Knowledge management with AI: how artificial intelligence ensures knowledge transfer in SMEs. *Data Unplugged.* Published December 18, 2025. Accessed March 9, 2026. <https://www.data-unplugged.de/en/blog/knowledge-management-ai-knowledge-transfer-sme>
- [431] Kling N, Haugk S, Gebauer H. Towards a data-driven organisation: Making data a strategic knowledge asset in SMEs. *J Knowl Econ.* 2025;16:18424-18442. doi:10.1007/s13132-025-02631-x
- [432] Vakkuri A, Kemell K, Kultanen J, Abrahamsson P. The current state of industrial practice in artificial intelligence ethics. *IEEE Softw.* 2020;37(4):50-57. doi:10.1109/MS.2020.2985621
- [433] Schoeffer J, Machl T, Sperk L, et al. Requirement engineering for safety-critical machine learning systems. *Softw Qual J.* 2023;31:1-35. doi:10.1007/s11219-022-09590-0
- [434] Paleyes A, Urma RG, Lawrence ND. Challenges in deploying machine learning: a survey of case studies. *ACM Comput Surv.* 2022;55(6):1-29. doi:10.1145/3533378
- [435] Nahar N, Zhou S, Lewis G, Kästner C. A meta-summary of challenges in building machine learning systems. *Empir Softw Eng.* 2023;28(6):134. doi:10.1007/s10664-023-10344-9
- [436] Mökander J, Floridi L. Ethics-based auditing of automated decision-making systems: nature, scope, and limitations. *Sci Eng Ethics.* 2021;27(4):44. doi:10.1007/s11948-021-00319-4
- [437] Barredo Arrieta A, Díaz-Rodríguez N, Del Ser J, et al. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. *Inf Fusion.* 2020;58:82-115. doi:10.1016/j.inffus.2019.12.012
- [438] Adamides G, Christou G, Katsanos C, Xenos M, Hadzilacos T. Variable Autonomy through Responsible Robotics: Design Guidelines and Research Agenda. *ACM Transactions on Human-Robot Interaction.* 2024;13(1):1–41. doi:10.1145/3636432
- [439] Nie Q, Shen Y, Ma Y, et al. Probing augmented intelligent human-robot collaborative assembly methods toward Industry 5.0. *Electronics.* 2025;14(15):3125. <https://doi.org/10.3390/electronics14153125>
- [440] Srivastava R, Prashar A, Iyer S, Gotise P. Insurance in the Industry 4.0 environment: a literature review, synthesis, and research agenda. *Aust J Manag.* 2022;49(2):290-312. doi:10.1177/03128962221132458
- [441] Eling M, Lehmann M. The impact of digitalization on the insurance value chain and the insurability of risks. *Geneva Pap Risk Insur.* 2018;43(3):359-396. doi:10.1057/s41288-017-0073-0
- [442] Kayan H, Nunes M, Rana O, Burnap P, Perera C. Cybersecurity of industrial cyber-physical systems: a review. *ACM Comput Surv.* 2022;54(11):1-35. doi:10.1145/3510410
- [443] Amodei D, Olah C, Steinhardt J, Christiano P, Schulman J, Mané D. Concrete problems in AI safety. *arXiv.org.* Published 21. Juni 2016. Accessed 31 March 2026. <https://arxiv.org/abs/1606.06565>
- [444] Varshney KR. Engineering safety in machine learning. *arXiv.org.* Published January 16, 2016. Accessed 31 March 2026. <https://arxiv.org/abs/1601.04126>
- [445] Abbott R. The Reasonable Robot: Artificial Intelligence and the Law. Cambridge University Press eBooks. Published online 15. Juni 2020. doi:10.1017/9781108631761
- [446] Swiss Re. Insurance 3.0: Reimagining insurance with technology. Published September 5, 2023. Accessed March 31, 2026. <https://www.swissre.com/risk-knowledge/risk-perspectives-blog/reimagining-insurance-with-technology.html>
- [447] Spindler C, Hoehener J, de Wolf M, Tymoshenko O, editors. Data Logistics and AI in Insurance Risk Management. International Data Spaces Association; 2020. Accessed 31 March 2026. https://www.academia.edu/95230346/Data_Logistics_and_AI_in_Insurance_Risk_Management
- [448] OECD. Leveraging Technology in Insurance to Enhance Risk Assessment and Policyholder Risk Reduction. OECD; December 13, 2023. <https://doi.org/10.1787/2f5c18ac-en>
- [449] Nurse JR, Axon L, Erola A, Agrafiotis I, Goldsmith M, Creese S. The data that drives cyber insurance: a study into the underwriting and claims processes. *CyberSA.* 2020;1-8. doi:10.1109/cybersa49311.2020.9139703.
- [450] Krishnakanthan K, McElhaney D, Milinkovich N, Pradhan A. How top tech trends will transform insurance. McKinsey & Company. Published September 30, 2021. Accessed March 31, 2026. <https://www.mckinsey.com/industries/financial-services/our-insights/how-top-tech-trends-will-transform-insurance>
- [451] Ernst & Young Global Limited. Five leading questions to support your claims automation journey. EY Norway. Accessed March 31, 2026. https://www.ey.com/en_no/insights/consulting/five-leading-questions-to-support-your-claims-automation-journey
- [452] Pech M, Vrchota J, Bednář J. Predictive maintenance and intelligent sensors in smart factory. *Sensors (Basel).* 2021;21(4):1470. doi:10.3390/s21041470
- [453] Ucar A, Karakose M, Kırımca N. Artificial intelligence for predictive maintenance applications: key components, trustworthiness, and future trends. *Appl Sci.* 2024;14(2):898. doi:10.3390/app14020898
- [454] Swiss Re. Engineering insurance and reinsurance: an introduction. Swiss Re; 2011. Accessed March 19, 2026. https://www.swissre.com/dam/jcr:3af81051-50db-4ea7-9e07-c0398a9145f9/pub_engineering_insurance_and_reinsurance_en.pdf
- [455] Paczolt M. Using predictive analytics and AI in insurance claims. Milliman. Published January 25, 2023. Accessed March 19, 2026. <https://www.milliman.com/en/insight/your-data-is-better-than-you-think-using-ai-for-insurance-claims>
- [456] Brüggemann P, Catlin T, Chinczewski J, Lorenz JT, Prymaka S. Claims in the digital age: how insurers can get started. McKinsey & Company. Published April 4, 2018. Accessed March 19, 2026. <https://www.mckinsey.com/industries/financial-services/our-insights/claims-in-the-digital-age#/>
- [457] Noon RK. Introduction to forensic engineering. Boca Raton, FL: CRC Press; 2020. Accessed March 19, 2026. https://books.google.de/books?id=HC_wDwAAQBAJ
- [458] Hashemian HM, Bean WC. State-of-the-art predictive maintenance techniques. *IEEE Trans Instrum Meas.* 2011;60(10):3480-3492. doi:10.1109/TIM.2009.2036347
- [459] O'Donncha F, Zhou N, Martinez N, Rayfield JT, Heath FF III, Langbridge A, Vaculin R. Evidence-driven reasoning for industrial maintenance using heterogeneous data. *arXiv.* Published March 9, 2026. Accessed March 19, 2026. <https://arxiv.org/abs/2603.08171>

- [460] Siemens. Senseye Predictive Maintenance: Scalable & sustainable asset intelligence. Accessed March 18, 2026. https://assets.new.siemens.com/siemens/assets/api/uuid:37142e74-d43b-42cf-b284-970e6264a0be/Senseye-Predictive-Maintenance_original.pdf
- [461] Rockwell Automation. FactoryTalk Analytics GuardianAI. Accessed March 18, 2026. <https://www.rockwellautomation.com/en-us/products/software/factorytalk/maintenancesuite/factorytalk-analytics-guardianai.html>
- [462] Finger D, Albrecher H, Wilhelmy L. On the cost of risk misspecification in insurance pricing. *Jpn J Stat Data Sci*. 2024;7:1111-1153. doi:10.1007/s42081-024-00256-z
- [463] Grieves M. Digital twin certified: Employing virtual testing of digital twins in manufacturing to ensure quality products. *Machines*. 2023;11(8):808. doi:10.3390/machines11080808
- [464] Douthwaite JA, Lesage B, Gleirscher M, et al. A modular digital twinning framework for safety assurance of collaborative robotics. *Front Robot AI*. 2021;8:758099. doi:10.3389/frobot.2021.758099
- [465] Ansari F, Nixdorf S, Sihn W. Insurability of cyber physical production systems: How does digital twin improve predictability of failure risk? *IFAC-PapersOnLine*. 2020;53(3):295-300. doi:10.1016/j.ifacol.2020.11.063
- [466] Muñoz P. Measuring the fidelity of digital twin systems. In: *Proceedings of the ACM/IEEE 25th International Conference on Model Driven Engineering Languages and Systems*. 2022:182-188. doi:10.1145/3550356.3558516
- [467] Balta EC, Pease M, Moyné J, Barton K, Tilbury DM. Digital twin-based cyber-attack detection framework for cyber-physical manufacturing systems. *IEEE Trans Autom Sci Eng*. 2024;21(2):1695-1712. doi:10.1109/TASE.2023.3243147
- [468] Buiten MC. Product liability for defective AI. *Eur J Law Econ*. 2024;57(1):239-273. <https://doi.org/10.1007/s10657-024-09794-z>
- [469] Munich Re. aiSure: More AI opportunity, less AI risk. Munich Re; 2025. Accessed 31 March 2026. <https://www.munichre.com/en/solutions/for-industry-clients/insure-ai.html>
- [470] Lior A. Insuring AI: The role of insurance in artificial intelligence regulation. *Harv J Law Technol*. 2022;35(2). Accessed 31 March 2026. <https://jolt.law.harvard.edu/assets/articlePDFs/v35/2.-Lior-Insuring-AI.pdf>
- [471] Kennedys Law. Silent AI cover: the unforeseen risks for insurers. Kennedys; 2025. Accessed 31 March 2026. <https://www.kennedyslaw.com/en/thought-leadership/article/2025/silent-ai-cover-the-unforeseen-risks-for-insurers/>
- [472] Hulton Andrews Kurth LLP. The continued proliferation of AI exclusions. *Natl Law Rev*. 2025. Accessed 31 March 2026. <https://natlawreview.com/article/continued-proliferation-ai-exclusions>
- [473] Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). *Off J Eur Union*. 2024. Accessed March 30, 2026. <https://eur-lex.europa.eu/eli/reg/2024/1689/oj/eng>
- [474] Swiss Re Institute. Sigma Insights 01/2026: AI adoption is reshaping the risk landscape. Swiss Re; 2026. Accessed 31 March 2026. <https://www.swissre.com/institute/research/sigma-research/sigma-insights-01-2026-ai-adoption-is-reshaping-the-risk-landscape.html>
- [475] Mosaic Insurance. Mosaic partners with Munich Re's aiSure™ to provide pioneering coverage for AI vendors. Published February 26, 2026. Accessed March 31, 2026. <https://www.mosaicinsurance.com/resources/press-releases/~/-mosaic-partners-with-munich-re-ai-sure-to-provide-pioneering-coverage-for-ai-vendors/>
- [476] Wang R, Tong Y, Zhuang C. Lights-out factories: review and prospect. *Proc IMechE Part B J Eng Manuf*. 2026. doi:10.1177/09544054241305826
- [477] International Federation of Robotics. How robots work alongside humans: collaborative robots. IFR. Published December 4, 2024. Accessed March 17, 2026. <https://ifr.org/ifr-press-releases/news/how-robots-work-alongside-humans>
- [478] Lam B. No lights, no workers: AI-powered dark factories are reshaping China's manufacturing. *VnExpress International*. Published July 31, 2025. Accessed March 17, 2026. <https://e.vnexpress.net/news/tech/tech-news/no-lights-no-workers-ai-powered-dark-factories-are-reshaping-china-s-manufacturing-4921224.html>
- [479] Piccialli, F., Chiaro, D., et al. AgentAI: A comprehensive survey on autonomous agents in distributed AI for Industry 4.0. *Expert Systems with Applications*. Published June 2, 2025. doi:10.1016/j.eswa.2025.128404
- [480] Imsetif J, Nezamoddini N, Aqlan F. Job shop planning and scheduling of reconfigurable manufacturing systems. *Operations Management Research*. 2025;18:891-912. doi:10.1007/s12063-025-00551-2
- [481] Bughin J, Hazan E, Lund S, et al. Skill shift: Automation and the future of the workforce. McKinsey Global Institute. Published May 23, 2018. Accessed March 17, 2026. <https://www.mckinsey.com/featured-insights/future-of-work/skill-shift-automation-and-the-future-of-the-workforce>
- [482] Shojaeinasab A, Charter T, Jalayer M, et al. Intelligent manufacturing execution systems: a systematic review. *Journal of Manufacturing Systems*. 2022;62:503-522. doi:10.1016/j.jmsy.2022.01.004
- [483] Piperigkos N, Gkillas A, Arvanitis G, et al. Distributed intelligence in industrial and automotive cyber-physical systems: a review. *Frontiers in Robotics and AI*. 2024;11:1430740. doi:10.3389/frobot.2024.1430740
- [484] Verband der Automobilindustrie (VDA). Interface for the communication between automated guided vehicles (AGV) and a master control (VDA 5050). Version 2.1.0. January 2025. Published by VDA; 2025. Accessed 31 March 2026. https://www.vda.de/dam/jcr:f0c9c019-1506-4dee-998a-e92723fbf025/EN-VDA5050-V2_0_0.pdf
- [485] Givchchi O, Landsdorf K, Simoens P, Colombo AW. Interoperability for industrial cyber-physical systems: an approach for legacy systems. *IEEE Trans Ind Informatics*. 2017;13(6):3370-3378. doi:10.1109/TII.2017.2740434
- [486] Luo X, Pan C, Liu Z, Wang L, Pang S, He L. A novel multi-agent reinforcement learning framework for robust exception handling of manufacturing service collaboration based on asymmetric information. *Journal of Manufacturing Systems*. 2025;79:364-382. doi:10.1016/j.jmsy.2025.01.016
- [487] Boccella AR, Centobelli P, Cerchione R, Murino T, Riedel R. Evaluating centralized and heterarchical control of smart manufacturing systems in the era of Industry 4.0. *Applied Sciences*. 2020;10(3):755. doi:10.3390/app10030755
- [488] Kim Y, Gu K, Park C, et al. Towards a science of scaling agent systems. Preprint. arXiv:2512.08296. Revised December 17, 2025. doi:10.48550/arXiv.2512.08296
- [489] Modrak V, Soltysova Z. Barriers for Smart Manufacturing Implementation in SMEs: A Comprehensive Exploration and Practical Insights. *Applied Sciences*. 2025;15(19):10552. doi:10.3390/app151910552
- [490] McKinsey & Company. How digital manufacturing can escape pilot purgatory. McKinsey & Company. Published 2018. Accessed April 1, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/how-digital-manufacturing-can-escape-pilot-purgatory>
- [491] Newstrail. Integration and orchestration middleware market report. 2026. Accessed April 1, 2026. <https://www.newstrail.com/integration-orchestration-middleware-market-to-hit-40-2b-by-2033-at-7-4-cagr-growth/>
- [492] Bortolini M, Galizia FG, Mora C. Reconfigurable manufacturing systems: literature review and research trend. *Journal of Manufacturing Systems*. 2018;49:93-106. doi:10.1016/j.jmsy.2018.09.005
- [493] Kim DY, Park JW, Baek S, et al. A modular factory testbed for the rapid reconfiguration of manufacturing systems. *Journal of Intelligent Manufacturing*. 2020;31(3):661-680. doi:10.1007/s10845-019-01471-2
- [494] Ouda E, Haggag M. Automation in modular construction manufacturing: a comparative analysis of assembly processes. *Sustainability*. 2024;16(21):9238. doi:10.3390/su16219238
- [495] Pasha A. Lights-Out Manufacturing: Revolutionizing the Factory Floor with Automation. Bosch Software and Digital Solutions; 2024. Accessed April 1, 2026. Available from: https://bosch-sds.com/wp-content/uploads/2024/09/Lights-Out-Manufacturing_-Revolutionizing-the-Factory-Floor-with-Automation.pdf
- [496] Capgemini Research Institute; Everst Group. Making Brownfield Factories Smarter and Greener: A Business Case for Digital Manufacturing in Brownfield Factories. Paris (FR): Capgemini; 2024 Apr. Accessed March 31, 2026. <https://www.capgemini.com/fr-fr/wp-content/uploads/sites/6/2024/11/Making-Brownfield-Factories-Smarter-and-Greener.pdf>
- [497] Frey H, Laa B, Haselsteiner E, Madner V, Grob LM, Schwaigerlehner K. The vertical urban factory concept and sustainable transport: prototypes for European cities. *Journal of Road and Traffic Engineering*. 2020;66(1):1 to 8. doi:10.31075/PIS.66.01.01
- [498] Amjad MS, Diaz-Elsayed N. Smart and sustainable urban manufacturing for a circular economy. *Environment, Development and Sustainability*. 2024;26(12):31789-31815. doi:10.1007/s10668-024-04671-w
- [499] Angstmann M, Meyer K, Gartner S. Exploring the potential of urban manufacturer's waste heat for the residential heating transition in Germany. *IAT Discussion Papers*. 2025;03/2025. doi:10.53190/dp/202503

- [500] Uthai T, You H, Wang M, et al. Opportunities, challenges and roadmap for humanoid robots in construction. *Scientific Reports*. 2025; doi:10.1038/s41598-025-30252-6
- [501] Wan K, Li C, Lo FS, Zheng P. A virtual reality-based immersive teleoperation system for remote human-robot collaborative manufacturing. *Manufacturing Letters*. 2024;41:43-50. doi:10.1016/j.mfglet.2024.09.008
- [502] Kim S, Hernandez I, Nussbaum MA, Lim S. Teleoperator-robot-human interaction in manufacturing. *IIE Transactions on Occupational Ergonomics and Human Factors*. 2024;12(1-2):28-40. doi:10.1080/24725838.2024.2310301
- [503] Mallioris P, Aivazidou E, Bechtsis D. Predictive maintenance in Industry 4.0: a systematic multi-sector mapping. *CIRP Journal of Manufacturing Science and Technology*. 2024;50:80-103. doi:10.1016/j.cirpj.2024.02.003
- [504] Leal Filho W, Kötter R, Özyay PG, Abubakar IR, Eustachio JHPP, Matandirotya NR. Understanding rare earth elements as critical raw materials. *Sustainability*. 2023;15(3):1919. doi:10.3390/su15031919
- [505] Fujita Y, McCall SK, Ginosar D. Recycling rare earths: perspectives and recent advances. *MRS Bull.* 2022;47(3):283-288. doi:10.1557/s43577-022-00301-w
- [506] Danouche M, Bounaga A, Oulkhir A, Boulif R, Zeroual Y, Benhida R, Lyamlouli K. Advances in bio/chemical approaches for sustainable recycling and recovery of rare earth elements from secondary resources. *Sci Total Environ*. 2023;168811. doi:10.1016/j.scitotenv.2023.168811
- [507] Perrin MA, Duthell P, Wörle M, Mougél V. Recovery of europium from E-waste using redox active tetrathiotungstate ligands. *Nat Commun*. 2024;15:4577. doi:10.1038/s41467-024-48923-3
- [508] Eurostat. International trade in critical raw materials. Eurostat Statistics Explained. Published June 2025. Accessed March 17, 2026. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International_trade_in_critical_raw_materials
- [509] Eurostat. Waste statistics - electrical and electronic equipment. Eurostat Statistics Explained. Published October 2025. Accessed March 19, 2026. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Waste_statistics_-_electrical_and_electronic_equipment
- [510] Bielowicz B. Waste as a source of critical raw materials: a new approach in the context of energy transition. *Energies*. 2025;18(8):2101. doi:10.3390/en18082101
- [511] European Commission, Directorate-General for International Partnerships. E-waste management in Ghana: from grave to cradle. European Commission International Partnerships. Published 2018. Accessed March 17, 2026. https://www.international-partnerships.ec.europa.eu/policies/programming/projects/e-waste-management-ghana-grave-cradle_en
- [512] European Parliament and Council of the European Union. Regulation (EU) 2024/1252 of the European Parliament and of the Council of 11 April 2024 establishing a framework for ensuring a secure and sustainable supply of critical raw materials. *Official Journal of the European Union*. Published May 3, 2024. Accessed April 1, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1252>
- [513] Büchel J, Neligan A. Digital Product Passport: Finding the Right Balance Between Transparency for Circularity and Added Red Tape. *Intereconomics*. 2025;60(3):160-164. doi:10.2478/ie-2025-0031
- [514] Zhang Z, Gu J, Li R, Lian W, Ma C, Tian J. Bridging digital and green transitions: A literature review of digital product passport systems. *Renew Sustain Energy Rev*. 2026;228:116600. doi:10.1016/j.rser.2025.116600
- [515] Regulation (EU) 2024/1781 of the European Parliament and of the Council of 13 June 2024 Establishing a Framework for the Setting of Ecodesign Requirements for Sustainable Products. 2024. Accessed March 3, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32024R1781&qid=1719580391746>
- [516] Communication from the Commission: Ecodesign for Sustainable Products and Energy Labelling Working Plan 2025-2030. 2025. Accessed March 18, 2026. <https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:52025DC0187>
- [517] Zhang A, Seuring S. Digital product passport for sustainable and circular supply chain management: a structured review of use cases. *Int J Logist Res Appl*. 2024;27(12):2513-2540. doi:10.1080/13675567.2024.2374256
- [518] Hannover Messe. Enabling the EaaS Model: Insurance and Financing Strategies. Hannover Messe. 2021. Accessed March 18, 2026. https://www.hannovermesse.de/apollo/hannover_messe_2021/obs/Binary/A1086204/EN%20-%20Enabling%20the%20EaaS%20Model-Insurance%20and%20Financing%20Strategies%20LR.pdf
- [519] Vogt Duberg J, Sakao T. How can manufacturers identify the conditions for financially viable product-as-a-service? *Front Manuf Technol*. 2024;4:1498189. doi:10.3389/fmtec.2024.1498189
- [520] Sundin E, Elo K, Lee HM. Design for automatic end-of-life processes. *Assembly Automation*. 2012;32(4):389-398.
- [521] Hilton B. Design for Remanufacturing. REMADE Institute / US Department of Energy; 2021. doi:10.2172/1876418
- [522] McKinsey and Company. Why aftermarket and service are vital to OEMs and how to excel. McKinsey and Company. Accessed March 18, 2026. <https://www.mckinsey.com/~media/mckinsey/industries/advanced%20electronics/our%20insights/why%20aftermarket%20and%20service%20are%20vital%20to%20oems%20and%20how%20to%20excel/why-aftermarket-and-service-are-vital-to-oems-and-how-to-excel-vf.pdf>
- [523] Gauß R, Burkhardt C, Carencotte F, et al. Rare Earth Magnets and Motors Cluster of the European Raw Materials Alliance; 2021. Accessed March 31, 2026. https://www.eit.europa.eu/sites/default/files/2021_09-24_ree_cluster_report2.pdf
- [524] Awere E, Obeng PA, Bonoli A. E-waste recycling and public exposure to organic compounds in developing countries: a review of recycling practices and toxicity levels in Ghana. *Environ Technol Rev*. 2020;9(1):1-19. doi:10.1080/21622515.2020.1714749
- [525] Yadav MD, Nair AR, Parmar DR. From bench to bulk: navigating the scale-up challenge in chemical manufacturing. *Chem Ind Dig*. 2025. Accessed March 18, 2026. <https://chemindigest.com/chemical-industry-digest-october-2025-issue/>
- [526] Nematov D, Raufov I, Murodzoda S, Ashurov A, Sattorzoda S. The bright future of materials science with AI: self-driving laboratories and closed-loop discovery. *J Mod Nanotechnol*. 2025;5:2. doi:10.53964/jmn.2025002
- [527] Arnold M, Palomäki K, Le Blévenec K, Koop C, Geerken T. Contribution of remanufacturing to circular economy. Eionet Report ETC/WMGE. 2021. Accessed March 18, 2026. <https://www.eionet.europa.eu/etcs/etc-wmge/products/etc-wmge-reports/contribution-of-remanufacturing-to-circular-economy/@download/file>
- [528] Boorsma R, Sobek DK II, Bakker C, Balkenende R. Incorporating design for remanufacturing in the early design stage: a case study of a car door module. *Res Eng Des*. 2021;32(6):609-628. doi:10.1007/s00163-021-00362-0
- [529] Ambadipudi A, Brotschi A, Forsgren M, Kervazo F, Lavandier H, Xing J. Industrial aftermarket services: growing the core. McKinsey. Published July 27, 2017. Accessed April 01, 2026. <https://www.mckinsey.com/industries/industrials/our-insights/industrial-aftermarket-services-growing-the-core>
- [530] Gieß A, Möller F. Exploring the value ecosystem of digital product passports. *J Ind Ecol*. 2025;29(2):561-573. doi:10.1111/jiec.13621
- [531] Lopes C, Barata J. Digital Product Passport: A Review and Research Agenda. *Procedia Comput Sci*. 2024;246:981-990. doi:10.1016/j.procs.2024.09.517
- [532] Zhang H, Semuji SD, Wang Z, et al. Large scale foundation models for intelligent manufacturing applications: a survey. *J Intell Manuf*. 2026;37:119-170. doi:10.1007/s10845-024-02536-7
- [533] Cognilytica. AI Data Engineering Lifecycle Checklist. Cognilytica Research; 2020. Accessed March 26, 2026. <https://www.cloudera.com/content/dam/www/marketing/resources/whitepapers/ai-data-lifecycle-checklist-cloudera-whitepaper.pdf>
- [534] Zhang C, Cao Y, Gu J, et al. Harnessing diversity for important data selection in pretraining large language models. *arXiv*. 2024;2409.16986. Accessed March 26, 2026. <https://arxiv.org/abs/2409.16986>
- [535] Nvidia Research. Front-loading reasoning: the synergy between pretraining and post-training data. Technical report. 2025. Accessed March 26, 2026. https://research.nvidia.com/labs/adlr/files/Front_Loading_Reasoning_The_Synergy_between_Pretraining_and_Post_Training_Data.pdf
- [536] Ouyang L, Wu J, Jiang X, et al. Training language models to follow instructions with human feedback. *Adv Neural Inf Process Syst*. 2022;35:27730-27744.
- [537] Edjlali R. Lack of AI-ready data puts AI projects at risk. Gartner Newsroom. Published February 26, 2025. Accessed March 26, 2026. <https://www.gartner.com/en/newsroom/press-releases/2025-02-26-lack-of-ai-ready-data-puts-ai-projects-at-risk>
- [538] Grand View Research. Data Collection and Labeling Market Size, Share and Trends Analysis Report. Grand View Research; 2024. Accessed March 31, 2026. <https://www.grandviewresearch.com/industry-analysis/data-collection-labeling-market>
- [539] Goel S. Surge AI CEO says he worries that companies are optimizing for AI slop. *Business Insider*. Published December 2025. Accessed March 31, 2026. <https://www.businessinsider.com/surgeai-ceo-edwin-chen-companies-optimizing-ai-slop-benchmark-gaming-2025-12>

- [540] Mescal D. From Data Labeling to Foundation Models: The Rise of Scale AI. Accessed April 1, 2026. <https://momen.app/blogs/scale-ai-from-data-labeling-to-foundation-models-rise/>.
- [541] McKinsey and Company. The State of AI in Early 2024. McKinsey and Company; 2024. Accessed March 31, 2026. <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai-in-early-2024-gen-ai-adoption-spikes-and-traces-of-value-appear>
- [542] Grand View Research. Data Marketplace Platform Market Size Report. Grand View Research; 2024. Accessed March 31, 2026. <https://www.grandviewresearch.com/industry-analysis/data-marketplace-market-report>
- [543] Li W, Li T. Comparison of deep learning models for predictive maintenance in industrial manufacturing systems using sensor data. *Sci Rep*. 2025;15(1):23545. doi:10.1038/s41598-025-08515-z
- [544] Amaliah N, Tjahjono B, Palade V. Human-in-the-loop XAI for predictive maintenance: a systematic review. *Electronics*. 2025;14(17):3384. doi:10.3390/electronics14173384
- [545] Roh Y, Heo G, Whang SE. A survey on data collection for machine learning: a big data–AI integration perspective. *IEEE Trans Knowl Data Eng*. 2021;33(4):1328–1347. doi:10.1109/TKDE.2019.2946162
- [546] Han K, Rezapour R, Nakamura K, et al. An expert-in-the-loop method for domain-specific document categorization based on small training data. *J Assoc Inf Sci Technol*. 2023;74(6):669–684. doi:10.1002/asi.24714
- [547] Nonaka I, Takeuchi H. The Knowledge Company. Oxford University Press; 1995. Accessed 31 March, 2026. <https://global.oup.com/academic/product/the-knowledge-creating-company-9780195092691>
- [548] Leonard D, Sensiper S. The role of tacit knowledge in group innovation. *Calif Manage Rev*. 1998;40(3):112–132.
- [549] Eraut M. Non-formal learning and tacit knowledge in professional work. *Br J Educ Psychol*. 2000;70(1):113–136. doi:10.1348/000709900158001
- [550] Fenoglio E, Kazim E, Latapie H, Koshiyama A. Tacit knowledge elicitation process for Industry 4.0. *Discov Artif Intell*. 2022;2:6. doi:10.1007/s44163-022-00020-w
- [551] The Manufacturing Institute. The aging of the manufacturing workforce. National Association of Manufacturers. Published February 2020. Accessed March 9, 2026. <https://nam.org/new-report-dives-into-retaining-the-aging-manufacturing-workforce-5579/>
- [552] Senseye. The True Cost of Downtime 2024. Siemens; 2024. Accessed 31 March 2026. https://assets.new.siemens.com/siemens/assets/api/uuid:1b43afb5-2d07-47f7-9eb7-893fe7d0bc59/TCOD-2024_original.pdf
- [553] Rahman M. Strategies for improving maintenance efficiency and reliability through wrench time optimization. *J Ind Intell*. 2024;2(3):172–188. doi:10.56578/jii020304
- [554] Kernan Freire S, Wang C, Ruiz-Arenas S, Niforatos E. Tacit knowledge elicitation for shop-floor workers with an intelligent assistant. In: Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23). ACM; 2023. doi:10.1145/3544549.3585755
- [555] Lin X, Wu D. AI technology adoption, knowledge sharing, and manufacturing firms' innovation performance: the moderating effect of absorptive capacity. *IEEE Trans Eng Manag*. 2025;72:2137–2152.
- [556] Stürzebecher P, Bayrhammer E, Brauckmann N. From tacit to explicit: using live documentation and feedback loops to facilitate knowledge transfer. In: Proceedings of the 26th European Conference on Knowledge Management. 2025. <https://doi.org/10.34190/eckm.26.2.3839>
- [557] VDMA. Labor shortage costs German mechanical engineering a lot of sales. All About Industries. Published May 25, 2024. Accessed March 29, 2026. <https://www.all-about-industries.com/labor-shortage-costs-german-mechanical-engineering-a-lot-of-sales-a-53671af2ded6dd20768466b4bc6f4ae/>
- [558] ifo Institute. Shortage of skilled workers decreasing in Germany. Published February 18, 2026. Accessed March 29, 2026. <https://www.ifo.de/en/press-release/2026-02-18/shortage-skilled-workers-decreasing-germany>
- [559] European Parliament and Council of the European Union. Regulation (EU) 2023/1230 on Machinery. Published June 29, 2023. Applies from January 20, 2027. Accessed 31 March, 2026. <https://osha.europa.eu/en/legislation/directive/regulation-20231230eu-machinery>
- [560] Bureau of Labor Statistics. Job Openings and Labor Turnover Survey: manufacturing. US Department of Labor; 2025. Accessed March 29, 2026. <https://www.bls.gov/iag/tgs/iag31-33.htm>
- [561] Society for Human Resource Management. Turnover cost calculation spreadsheet. SHRM; 2022. Accessed March 29, 2026. <https://www.shrm.org/topics-tools/tools/forms/turnover-cost-calculation-spreadsheet>
- [562] Future Market Insights. Industrial Copilot Market Size, Share and Forecast to 2036. FMI; 2026. Accessed March 9, 2026. <https://www.futuremarketinsights.com/reports/industrial-copilot-market>
- [563] Siemens AG. Siemens expands Industrial Copilot with new generative AI-powered maintenance offering. Published 2024. Accessed 31 March, 2026. <https://press.siemens.com/global/en/pressrelease/siemens-expands-industrial-copilot-new-generative-ai-powered-maintenance-offering>
- [564] remberg GmbH. About us. Accessed March 2026. <https://www.remberg.de/en/about-us/>
- [565] ABB. Value of Reliability. Sapio Research; 2023. Accessed 31 March, 2026. <https://new.abb.com/news/detail/107660/abb-survey-reveals-unplanned-downtime-costs-125000-per-hour>
- [566] MaintainX. Maintenance management platform. Accessed March 2026. <https://www.getmaintainx.com>
- [567] Augmentir. AI-powered connected worker platform. Accessed March 2026. <https://www.augmentir.com>
- [568] Librestream. Remote expert support platform. Accessed March 2026. <https://librestream.co>
- [569] Ask for the Moon. Knowledge capture platform. Accessed March 2026. <https://www.askforthemoon.com>
- [570] Interloom. Expertise transfer platform. Accessed March 2026. <https://www.interloom.io>
- [571] Augmented Industries. Industrial knowledge platform. Accessed March 2026. <https://www.augmented-industries.com>
- [572] Federal Statistical Office (Destatis). 12.9 Million Economically Active People Will Reach Statutory Retirement Age in the Next 15 Years. Press release No. 330 of August 4, 2022. Destatis; 2022. Accessed March 8, 2026. https://www.destatis.de/EN/Press/2022/08/PE22_330_13.html
- [573] Wellener P, Hardin K, Kaji S, et al. Creating pathways for tomorrow's workforce today: beyond reskilling in manufacturing. Deloitte Insights. Published May 4, 2021. Accessed March 2026. https://www2.deloitte.com/content/dam/insights/articles/7048_DL_ER-I-Beyond-reskilling-in-manufacturing/DL_ER-I-Beyond-reskilling-in-manufacturing.pdf
- [574] Kwok A. Corporate Tacit Knowledge, LLMs, and AI. Industry–Science. Published May 25, 2025. Accessed March 8, 2026. <https://industry-science.com/en/articles/corporate-tacit-knowledge-llm-ai>
- [575] Shin H, Rothrock L, Prabhu V. Evaluating technicians' workload and performance in diagnosis for corrective maintenance. *Sensors*. 2024;24(6):1943. doi:10.3390/s24061943
- [576] Polanyi M. The Tacit Dimension. University of Chicago Press; 1966. Accessed 31 March 2026. <https://press.uchicago.edu/ucp/books/book/chicago/T/bo6035368.html>
- [577] Zhong RY, Xu X, Klotz E, Newman ST. Intelligent manufacturing in the context of Industry 4.0: a review. *Engineering*. 2017;3(5):616–630. <https://doi.org/10.1016/j.ENG.2017.05.015>
- [578] Eling M, Nuesse D, Staubli J. The impact of artificial intelligence along the insurance value chain and on the insurability of risks. *Geneva Pap Risk Insur*. 2022;47(2):205–241. doi:10.1057/s41288-020-00201-7
- [579] Akerlof GA. The market for “lemons”: quality uncertainty and the market mechanism. In: *Uncertainty in Economics*. Academic Press; 1978:235–251. <https://doi.org/10.1016/B978-0-12-214850-7.50022-X>
- [580] MaintainX. 25 maintenance stats, trends, and insights for 2026. Published 2025. Accessed March 26, 2026. <https://www.getmaintainx.com/blog/maintenance-stats-trends-and-insights>
- [581] Browne Jacobson. AI regulation in insurance: risk-based pricing and fairness. Published April 2025. Accessed March 29, 2026. <https://www.brownejacobson.com/insights/the-word-april-2025/ai-regulation-price-risk>
- [582] Horváthová J, Mokrišová M, Vrábliková M. Benchmarking — a way of finding risk factors in business performance. *J Risk Financial Manag*. 2021;14(5):221. doi:10.3390/jrfm14050221
- [583] McKinsey & Company. The future of AI in the insurance industry. Published July 15, 2025. Accessed March 25, 2026. <https://www.mckinsey.com/industries/financial-services/our-insights/the-future-of-ai-in-the-insurance-industry>
- [584] Blier-Wong C, Cossette H, Lamontagne L, Marceau E. Machine learning in P&C insurance: a review for pricing and reserving. *Risks*. 2021;9(1):4. doi:10.3390/risks9010004
- [585] Magdum R, Shinde M, Rudrawar H, Wajire P, Hiray S, Jakhete S. Decentralized predictive maintenance framework for dynamic vehicle insurance premiums. Paper presented at: 2025 Global International Conference on New Opportunities in Technology (GINOTECH); May 9–11, 2025; Pune, India. doi:10.1109/GINOTECH63460.2025.11076756
- [586] European Commission. The NIS2 Directive. Accessed March 25, 2026. <https://digital-strategy.ec.europa.eu/en/policies/nis2-directive>

- [587] Statista. Property Insurance — Europe. Accessed March 25, 2026. <https://www.statista.com/outlook/fmo/insurances/non-life-insurances/property-insurance/europe>
- [588] Munich Re. Pay-per-part: TRUMPF and Munich Re plan new business model for the manufacturing industry. Published October 14, 2020. Accessed March 25, 2026. <https://www.munichre.com/en/company/media-relations/media-information-and-corporate-news/media-information/2020/2020-10-14-pay-per-part.html>
- [589] Heck M. Munich Re wickelt einstiges Vorzeige-Start-up Relay ab. Handelsblatt. Published January 29, 2024. Accessed March 25, 2026. <https://www.handelsblatt.com/finanzen/versicherungen-munich-re-wickelt-einstiges-vorzeige-start-up-relay-ab-01/100134751.html>
- [590] Augury. Machine Health & Performance Platform. Accessed March 25, 2026. <https://www.augury.com/platform/>
- [591] Siemens. Siemens acquires Senseye and expands portfolio for predictive maintenance and asset intelligence. Published June 29, 2022. Accessed March 25, 2026. <https://press.siemens.com/global/en/pressrelease/siemens-acquires-senseye-and-expands-portfolio-predictive-maintenance-and-asset>
- [592] Deloitte. The renewal of core systems for insurance. Accessed March 25, 2026. <https://www2.deloitte.com/us/en/insights/industry/financial-services/core-systems-modernization-for-insurance-companies.html>
- [593] Mourtzis D, Angelopoulos J, Panopoulos N. A literature review of the challenges and opportunities of the transition from Industry 4.0 to Society 5.0. *Energies*. 2022;15(17):6276. <https://doi.org/10.3390/en15176276>
- [594] Küpper D, Okur A, Betti F, Bezamat F, Fendri M, Fernandez B. How manufacturers can unlock value from data sharing. BCG Global. Published January 8, 2021. Accessed 31 March 2026. <https://www.bcg.com/publications/2020/manufacturers-unlock-value-from-data-sharing>
- [595] Otto B, Jarke M. Designing a multi-sided data platform: findings from the International Data Spaces case. *Electron Markets*. 2019;29(4):561-580. <https://doi.org/10.1007/s12525-019-00362-x>
- [596] Taeuscher K, Laudien SM. Understanding platform business models: a mixed methods study of marketplaces. *Eur Manag J*. 2018;36(3):319-329. <https://doi.org/10.1177/0008125617736323>
- [597] Verbelen R, Antonio K, Claeskens G. Unravelling the predictive power of telematics data in car insurance pricing. *J R Stat Soc Ser C Appl Stat*. 2018;67(5):1275-1304. doi:10.1111/rssc.12283
- [598] Grand View Research. Dark Factories Market Size, Share and Trends Analysis Report by Technology Type, by End-use Industry, by Region, and Segment Forecasts, 2025–2030. Grand View Research; 2024. Accessed on 31 March 2026. <https://www.grandviewresearch.com/industry-analysis/dark-factories-market-report>
- [599] Ojer M, Valdés S, García A, Oregui X, Gastesi I, Lin X, Mendizabal-Arrieta I, Sanchez JR, Lazkano E. Operator as a service: a new concept for remote supervision of automated manufacturing lines. *IEEE Access*. 2025;13:93661-93671. <https://doi.org/10.1109/ACCESS.2025.3574415>
- [600] ABB. Value of Reliability: ABB Survey Report 2023. Industry's Perspective on Maintenance and Reliability. ABB; 2023. Accessed on 31 March 2026. <https://search.abb.com/library/Download>
- [601] PwC. Manufacturing talent strategy. Published March 30, 2023. Accessed April 01, 2026. <https://www.pwc.com/us/en/industries/industrial-products/library/manufacturing-talent-strategy.html>
- [602] Lozano-Zahonero S, Simó-Reigadas FJ, Poves-Alvarez R, et al. Insights from telesurgery expert conference on recent clinical experience and current status of remote surgery. *J Robot Surg*. 2024;18(1):240. <https://doi.org/10.1007/s11701-024-01984-w>
- [603] Arendt C, Böcker S, Schippers H, et al. Towards Future Industrial Connectivity: Evaluation of Private 5G and Wi-Fi Networks in Professional Industrial Environments. In: 2025 IEEE 21st International Conference on Factory Communication Systems (WFCS). IEEE; 2025:1-8. doi:10.1109/WFCS63373.2025.11077629
- [604] Raposo, G., Araújo, N., Parente, M., Lopes, A. M., Santos, A., Pereira, F., Leite, S., & Ramos Silva, A. (2025). Personalizing industrial maintenance operation using the model of hierarchical complexity. *Journal of Manufacturing and Materials Processing*, 9(4), 132. <https://doi.org/10.3390/jmmp9040132>
- [605] Ramzan F, Reforgiato Recupero D. A literature review on enhancing predictive maintenance in smart manufacturing industries: fostering human-technology collaboration and overcoming data scarcity limitations with advanced AI models. *Oper Res Forum*. 2025;6(4):1-20. doi:10.1007/s43069-025-00584-0.
- [606] European Labor Authority. Report on Labor Shortages and Surpluses: 2024. Publications Office; 2025. doi:10.2883/7472379
- [607] Verband der Automobilindustrie (VDA). Interface for the Communication between Mobile Robots and a Fleet Control: VDA 5050. Version 3.0.0. Verband der Automobilindustrie e.V.; March 2026. Accessed March 25, 2026. <https://www.vda.de/dam/jcr:09f03b91-13e2-4db3-bf30-4f221710071b/VDA5050-V3.0.0-2025-03.pdf?mode=view>
- [608] European Data Protection Supervisor. AI Act Regulation (EU) 2024/1689: Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 Laying down Harmonised Rules on Artificial Intelligence and Amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) (Text with EEA Relevance). Publications Office; 2025. doi:10.2804/4225375
- [609] Augury. Machine Health Solutions. Augury. Accessed March 25, 2026. <https://www.augury.com/machine-health-solutions/>
- [610] Avathon. Avathon launches the first system-level Industrial AI Platform. Avathon. Published October 17, 2024. Accessed on 31 March 2026. <https://avathon.com/press-release/avathon-launches-the-first-system-level-industrial-ai-platform/>
- [611] Augury. Enhance Operations with Interoperability as a Service. Augury. Accessed March 25, 2026. <https://www.augury.com/solutions/interoperability-as-a-service/>
- [612] Augury. AI Detection and Response Prevent Catastrophe. Augury. Published April 28, 2023. Accessed on 31 March 2026. <https://www.augury.com/blog/customers-partners/rapid-ai-detection-and-response-prevent-catastrophe-at-wood-products-plant/>
- [613] Olis Robotics. About Olis Robotics. Olis Robotics. Accessed March 25, 2026. <https://olisrobotics.com/about>
- [614] Olis Robotics. How Robot Integrators Benefit From Remote Control for Industrial Robots. Olis Robotics. Published October 25, 2022. Accessed on 31 March 2026. <https://olisrobotics.com/blog/remote-control-for-industrial-robots-benefits-integrators>
- [615] Ryden F, Marcovecchio P. Olis Robotics and Kawasaki partner to offer remote troubleshooting. The Robot Report. Published February 23, 2024. Accessed on 31 March 2026. <https://www.therobotreport.com/olis-robotics-and-kawasaki-partner-to-offer-remote-troubleshooting/>
- [616] Field Nation. Industries: Manufacturing. Field Nation. Accessed March 25, 2026. <https://fieldnation.com/manufacturing>
- [617] Field Nation. A guide to becoming a technician on Field Nation. Field Nation. Accessed March 25, 2026. <https://fieldnation.com/skills/field-nation-technician>
- [618] ABB. Value of Reliability: ABB Survey Report 2023 - Industry's Perspective on Maintenance and Reliability. ABB; 2023. Accessed March 26, 2026. https://library.e.abb.com/public/45afcf54780c489095517e653422d157/ABB_Survey%20Report%202023_1920x1080_20231010_JL_final_edits.pdf
- [619] Szilágyi Z, Hajdu K, Széll K, Galambos P. Novel Middleware Framework for Integrating Extended Reality into Robotic Manufacturing Processes. *JMMP*. 2026;10(2):46. doi:10.3390/jmmp10020046
- [620] MaintainX. The State of Industrial Maintenance 2024. MaintainX; 2024. Accessed March 26, 2026. <https://software.getmaintainx.com/hubfs/State%20of%20Industrial%20Maintenance%202024/2024%20State%20of%20Industrial%20Maintenance%20Report.pdf>
- [621] Azad MA, Abdullah S, Arshad J, Lallie H, Ahmed YH. Verify and trust: A multidimensional survey of zero-trust security in the age of IoT. *Internet of Things*. 2024;27:101227. doi:10.1016/j.iot.2024.101227
- [622] Pochmara J, Świetlicka A. Cybersecurity of Industrial Systems—A 2023 Report. *Electronics*. 2024;13(7):1191. doi:10.3390/electronics13071191
- [623] Takepoint Research. The State of Industrial Secure Remote Access: TPR Survey Report. Cyolo; 2023. Accessed March 26, 2026. <https://info.cyolo.io/hubfs/Analyst%20Reports/TPR%20Survey%20Report%20-%20Industrial%20Secure%20Remote%20Access.pdf>
- [624] European Commission. Omnibus package: proposal to simplify sustainability reporting and other obligations. Published April 1, 2025. Accessed March 26, 2026. https://finance.ec.europa.eu/news/omnibus-package-2025-04-01_en
- [625] KPMG. European Digital Product Passport Readiness Survey. Published February 2026. Accessed March 26, 2026. <https://kpmg.com/xx/en/our-insights/esg/european-digital-product-passport-readiness-survey.html>
- [626] Siemens AG. Siemens sets new pace for fast and transparent environmental product declarations. Press release. Published 2025. Accessed March 26, 2026. <https://press.siemens.com/global/en/pressrelease/siemens-sets-new-pace-fast-and-transparent-environmental-product-declarations>
- [627] European Commission Joint Research Centre. International Reference Life Cycle Data System (ILCD) Handbook: General Guide for Life Cycle Assessment - Detailed Guidance. EUR 24708 EN. Publications Office of the European Union; 2010. doi:10.2788/38479

- [628] Gillai B, Lee H, Kapica-Harward A, Lalchand G, McClintock D. Sustainable Procurement Barometer 2021. Stanford Graduate School of Business. Published 2021. Accessed March 26, 2026. <https://www.gsb.stanford.edu/faculty-research/publications/sustainable-procurement-barometer-2021>
- [629] EPD International. Pre-verified tools. Accessed March 26, 2026. <https://www.environdec.com/services/pre-verified-tools>
- [630] Eurostat. Enterprises by detailed NACE Rev. 2 activity and special aggregates. Published 2025. doi:10.2908/SBS_OVV_ACT
- [631] EFRAG. Voluntary Sustainability Reporting Standard for Non-listed SMEs (VSME). Published January 2024. Accessed March 26, 2026. <https://www.efrag.org/sites/default/files/sites/webpublishing/SiteAssets/VSMET20Standard.pdf>
- [632] Grand View Research. Regulatory Technology (RegTech) Market Size, Share and Trends Analysis Report. Published 2025. Accessed March 26, 2026. <https://www.grandviewresearch.com/industry-analysis/regulatory-technology-market>
- [633] Emidat GmbH. Emidat: climate-native product management. Accessed April 1, 2026. <https://www.emidat.com/>
- [634] Tanso Technologies GmbH. Carbon management software for businesses. Accessed April 1, 2026. <https://www.tanso.de/en/product/co2-management>
- [635] Spherity GmbH. Digital Product Passport (DPP) software. Accessed April 1, 2026. <https://www.spherity.com/digital-product-passport>
- [636] Circularise BV. Product traceability platform for supply chain compliance. Accessed April 1, 2026. <https://www.circularise.com/>
- [637] Celonis SE. Process mining and execution management. Accessed April 1, 2026. <https://www.celonis.com/>
- [638] European Council. Council and Parliament strike a deal to simplify sustainability reporting and due diligence requirements and boost EU competitiveness. Published December 09, 2025. Accessed April 01, 2026. <https://www.consilium.europa.eu/en/press/press-releases/2025/12/09/council-and-parliament-strike-a-deal-to-simplify-sustainability-reporting-and-due-diligence-requirements-and-boost-eu-competitiveness/>
- [639] White & Case. Simplified, not abandoned: EU corporate sustainability after the Omnibus I package. Published March 30, 2026. Accessed April 01, 2026. <https://www.whitecase.com/insight-alert/simplified-not-abandoned-eu-corporate-sustainability-after-omnibus-i-package>
- [640] Hogan Lovells. Digital Product Passports in the EU — comprehensive expansion under the Ecodesign for Sustainable Products Regulation and what can be learnt from the Battery Passport pilot. Published 2025. Accessed March 31, 2026. <https://www.hoganlovells.com/en/publications/digital-product-passports-in-the-eu-comprehensive-expansion>
- [641] CarbonBright. Leveraging AI for environmental product declarations (EPDs). Published March 15, 2023. Accessed April 01, 2026. <https://www.carbonbright.co/insight/leveraging-ai-for-environmental-product-declarations-epds>
- [642] Hannon E, Bengtsson J, Forsgren M, Lahaie P, Fredershausen A-C, Buna M, Huemer Y. Add innovation and performance by subtracting carbon and cost. McKinsey. Published May 02, 2025. Accessed April 01, 2026. <https://www.mckinsey.com/capabilities/operations/our-insights/add-innovation-and-performance-by-subtracting-carbon-and-cost>
- [643] Business Continuity Institute. BCI supply chain resilience report 2024. Published April 01, 2026. Accessed April 01, 2026. <https://www.thebci.org/resource/bci-supply-chain-resilience-report-2024.html>
- [644] Arora A, Freundt T, Gregg B, Hajro N, Meder C, Schumacher K. How playing offense on sustainability can power e-commerce performance. McKinsey. Published March 26, 2024. Accessed April 01, 2026. <https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/how-playing-offense-on-sustainability-can-power-e-commerce-performance>
- [645] Hussain-Khan S, Reuben S, Meyer-Weitz A. Exploring the work perceptions and experiences of gig workers globally: a scoping review. Admin Sci. 2026;16(2):98. doi:10.3390/admsci16020098.
- [646] C. Völker, Head of Industrial AI, iteratec (expert interview, March 2026)
- [647] E. Topham, co-founder of OctaiPipe (expert interview, March 2026)
- [648] N. Gruber, co-founder and CEO, Manex AI (in-class expert session, March 2026)
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THE FUTURE OF INDUSTRIAL AI

The physical world is the next frontier of AI. From the assembly lines that build our cars to the machines that manufacture the components of modern life, industry has always been the place where human expertise meets physical reality. While digital technology has long played a supporting role in this world, AI is now entering it from within, embedding itself into the machinery, the workflows, and the decisions that keep it running. This is a categorical shift, and its implications for factories, workers, and entire industrial ecosystems are only beginning to unfold.

The entry of AI into the physical world is not simply an upgrade to existing systems. Industry operates on principles of reliability, precision, and expertise accumulated over generations. Introducing AI into this environment raises questions that cannot be answered by technology alone.

How do we trust autonomous systems with processes where failure carries real physical consequences? What happens to the tacit knowledge embedded in the workforce when AI performs tasks that once required years of experience? And who bears responsibility when an AI-driven decision goes wrong on the shop floor?

Beyond the factory, the transformation reaches into societal, economic, legal, and environmental dimensions. Legal frameworks struggle to assign liability in systems where decisions emerge from models rather than people. The energy demands of running AI at industrial scale can clash with the industry's sustainability goals. Across a landscape dominated by SMEs, the gap between those who can adopt industrial AI and those who cannot threatens to reshape competitive dynamics across entire value chains.

This report explores how AI is reshaping industry and what this transformation demands from decision-makers in the space. It begins with an analysis of the technological, societal, economic, legal, and environmental trends shaping industrial AI and redefining the factory of the future. Building on this foundation, the exploration section identifies five opportunity spaces, and the ideation section transforms these into five tangible business concepts. Together, the three parts point out the direction for AI moving into the physical world, establishing a clear path for how this connection will dictate the future of the industrial sector.



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