THE 2026 WORLD MANUFACTURING REPORT

NAVIGATING THE FUTURE OF MANUFACTURING: TRENDS COMPASS & TECHNOLOGY RADARS



WORLD MANUFACTURING FOUNDATION

The 2026 World Manufacturing Report
Navigating the Future of Manufacturing: Trends Compass & Technology Radars

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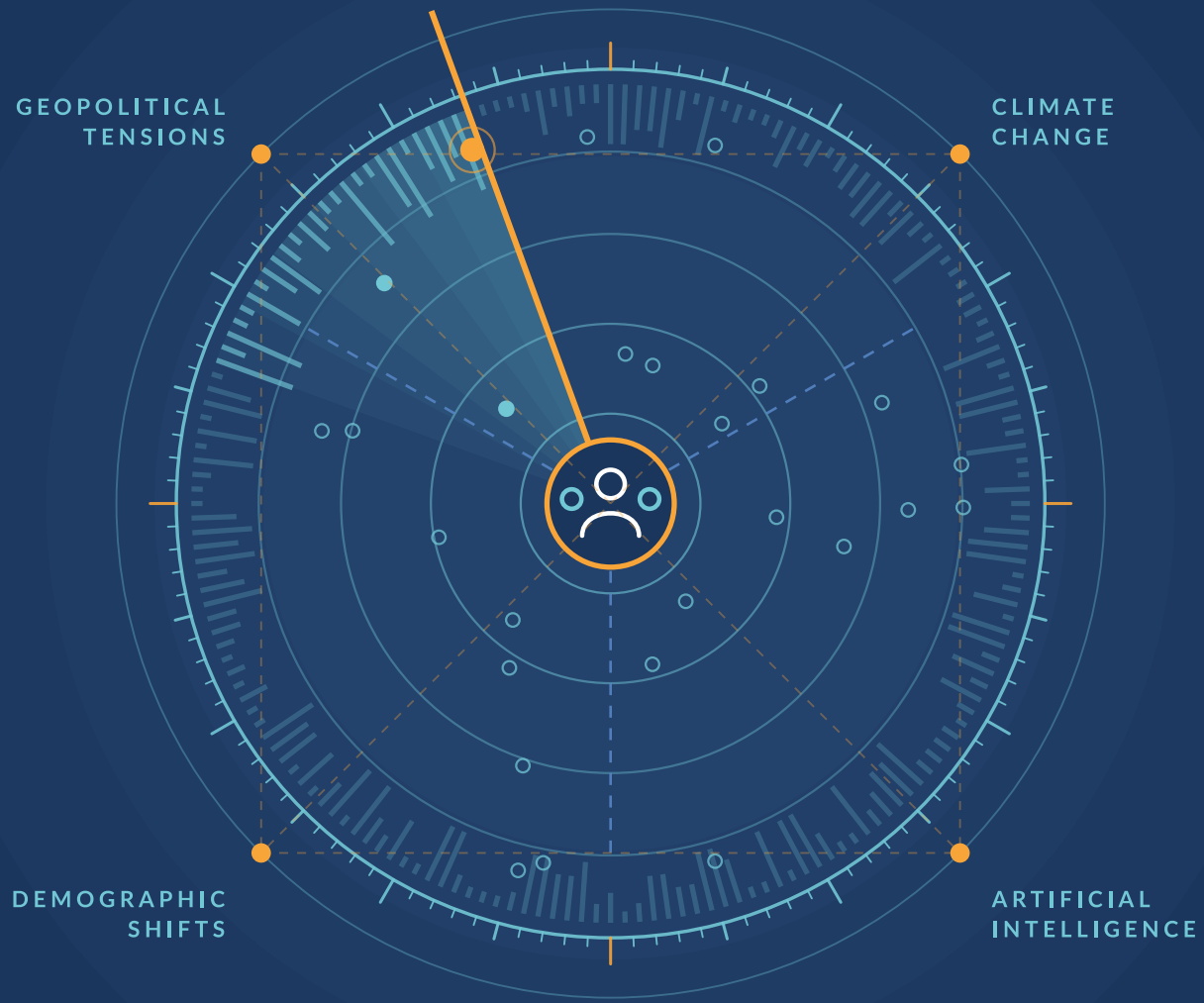
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WORLD MANUFACTURING FOUNDATION

FOREWORD

Instruments to read change continuously and to decide where **to act first.**

2026 WORLD MANUFACTURING REPORT



Foreword

Dear Readers,

With the mission of spreading industrial culture worldwide, the World Manufacturing Foundation (WMF) organises several international activities every year. The World Manufacturing Forum is its flagship event. It brings together industry, academia, policymakers, and institutions from around the world to exchange their views and share their visions on the future of manufacturing, its challenges and its opportunities for positive change.

As part of the World Manufacturing Forum, the World Manufacturing Report has been published and presented every year since 2018. The Editorial Board, composed of a selected group of experts, prepares the Report, which is enriched by the feedback and suggestions of the International Advisory Board. The topic of the World Manufacturing Report is aligned with the one selected for the Forum. The past editions are worth recalling. The first World Manufacturing Report: Recommendations for the Future of Manufacturing, published in 2018, presented our vision for the future of manufacturing. The 2019 Report: Skills for the Future of Manufacturing analysed the skills gap in the sector. The 2020 Report: Manufacturing in the Age of Artificial Intelligence provided insights on the trustworthy adoption of artificial intelligence. The 2021 Report: Digitally Enabled Circular Manufacturing highlighted the potential of digital technologies for the circular transition. The 2022 Report: Redesigning Supply Chains in the New Era of Manufacturing analysed the global megatrends and their implications for supply chains. The 2023 Report: New Business Models for the Manufacturing of the Future described the business models that manufacturers can adopt to remain competitive. The 2024 Report: New Perspectives for the Future of Manufacturing: Outlook 2030 identified the tipping points that will shape the sector towards 2030. Last year, the 2025 Report: Key Enabling Technologies for the Future of Manufacturing - Roadmaps & Platforms proposed two strategic roadmaps and a set of technology platforms to support the systemic digital transition of the sector.

This year's edition, *Navigating the Future of Manufacturing: Trends Compass & Technology Radars*, takes a further step. In a context where geopolitical tensions, climate change, demographic shifts and the rapid rise of artificial intelligence interact with one another, manufacturers can no longer rely on a single forecast of the future. They need instruments to read change continuously and to decide where to act first. The Report therefore offers two such instruments. Trends Compasses map the forces making supply chains and manufacturing systems more resilient, sustainable and human-centric. Technology Radars assess the readiness, strategic impact and time to mainstream adoption of five families of technologies: enterprise wearables and human-centred technologies, industrial data analytics, digital twins and extended reality, agentic and cognitive artificial intelligence, and physical AI and humanoid robotics. As tradition dictates, the Report concludes with 10 Key Recommendations on how to use these instruments within companies and institutions, supported by industrial case studies.

The World Manufacturing Foundation, through the World Manufacturing Report, commits to producing high-quality and non-partisan content on relevant themes and issues in manufacturing. We hope that this whitepaper will help policymakers, industrial leaders, academia and society at large to look beyond the urgency of daily operations, to anticipate change rather than react to it and to keep people at the centre of the technological transformation of our factories.

We thank the 2026 World Manufacturing Report Editorial Team and the International Advisory Board for their valuable contribution.

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2026

NAVIGATING THE FUTURE OF MANUFACTURING

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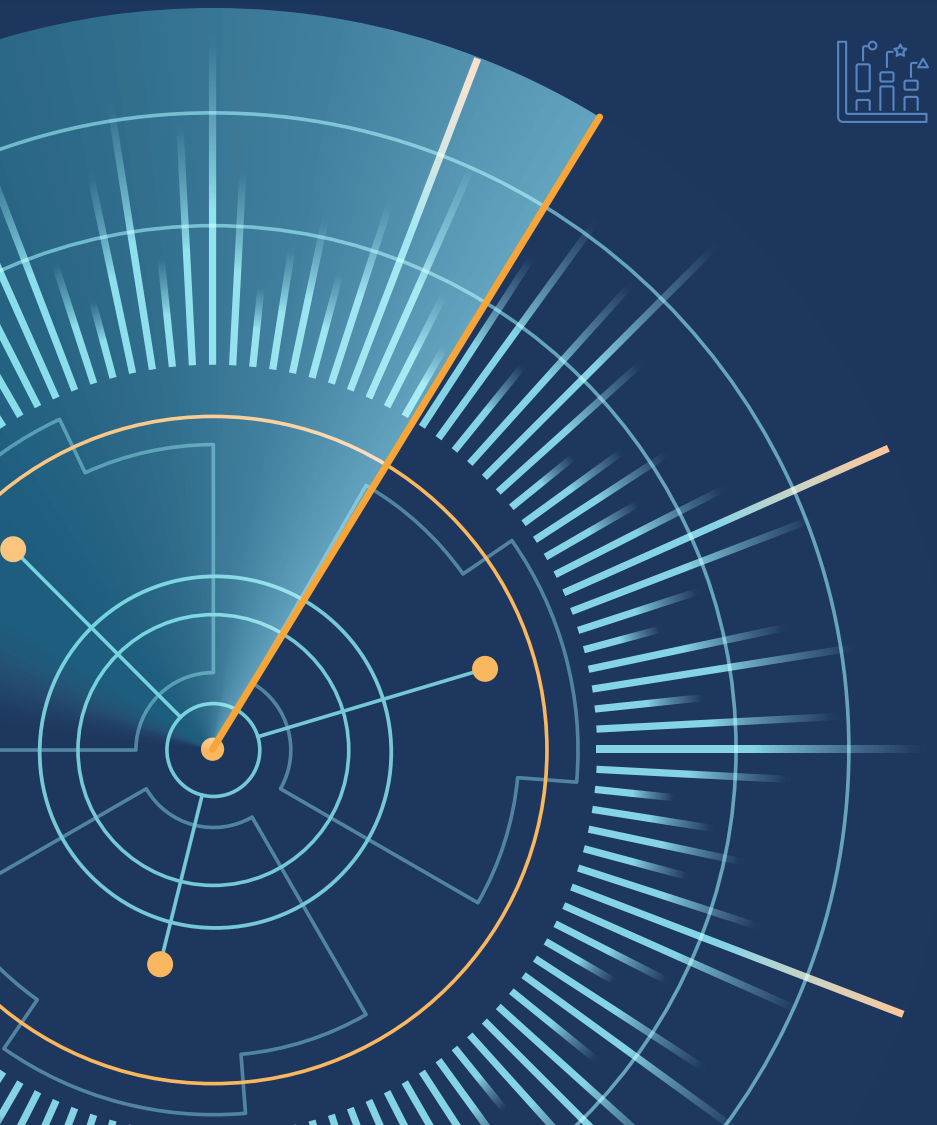
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THE 2026 WORLD MANUFACTURING REPORT

EXECUTIVE SUMMARY



Executive Summary

The 2026 World Manufacturing Report - ***Navigating the Future of Manufacturing: Trends Compass & Technology Radars***, provides manufacturers and policymakers with two strategic instruments to detect, assess and act upon the forces and technologies that will shape the sector in the coming years.

Disruption has become more frequent, more varied and more consequential. Geopolitical conflicts, trade restrictions and the concentration of critical inputs are reshaping supply networks. Climate change is affecting the physical assets and routes on which production depends. Demographic change and persistent skills gaps are making human capability harder to secure, while artificial intelligence and humanoids are redistributing tasks and decision rights across the factory. In this context, the *Report* argues that resilience, sustainability and human-centricity can no longer be treated as responses to failure or as discretionary objectives. They must become design properties of supply chains and manufacturing systems, considered before networks, plants and technologies are fixed.

The first instrument, the Trends Compass, maps the geopolitical, economic, social, technological, legal, and environmental forces behind three trends and assesses their impact on people, processes and technology, first across supply chains and then within manufacturing systems. Resilient supply chains and manufacturing systems require manufacturers to know where their critical dependencies lie, including below the first tier, and to build changeability into plant and product design. Sustainable supply chains and manufacturing systems address the environmental transition of the sector. Human-centric supply chains and manufacturing systems make capability, wellbeing, agency and inclusion explicit requirements, alongside cost, quality and delivery. Each trend closes with a call for action for manufacturers, policymakers, industry associations, and research and education institutions.

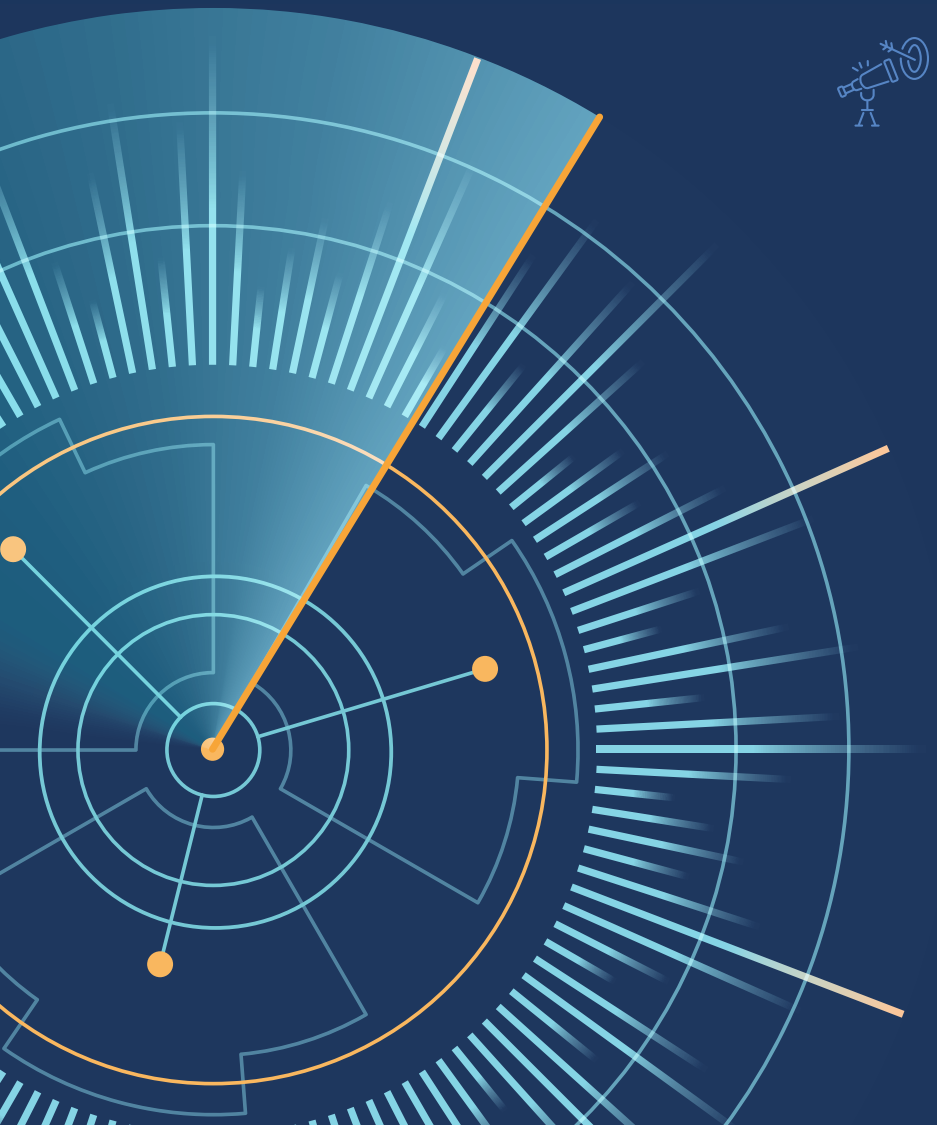
The second instrument, the Technology Radar, positions the five most relevant technology categories of five technology families according to their strategic impact, industrial technology readiness, current adoption stage and expected time to mainstream adoption. The radars cover enterprise wearable devices and human-centred technologies, from passive to hybrid exoskeletons; industrial data analytics, from trusted data spaces to circular value intelligence; digital twins, extended reality and industrial metaverses; agentic and cognitive artificial intelligence, from industrial assistants to autonomous operations agents; and physical AI and humanoid robotics, from AI-powered collaborative robots to humanoids for logistics and manufacturing. A common finding emerges: technology readiness does not automatically translate into industrial adoption. The main barriers increasingly lie at the interfaces between technology, data, organisations and people, and in the governance needed to deploy them with trust. The radars therefore suggest a staged pathway: scale the technologies that already generate value, pilot and validate the emerging ones, and build the data foundations, standards and skills that all of them require.

Finally, the Report proposes 10 Key Recommendations. The first five guide the use of a Trends Compass: systematically scan the environment, engage diverse stakeholders in interpreting trends, prioritise them according to relevance, impact and business strategy, translate them into actionable strategic initiatives, and review the compass regularly. The other five guide the use of a Technology Radar: continuously monitor emerging technologies, categorise them by manufacturing value and adoption readiness, validate them through experimentation and pilots, foster cross-functional technology governance, and update the radar regularly. Industrial case studies from companies, research projects and organisations illustrate how these instruments are being applied in practice.

01

CHAPTER 1

NAVIGATING THE FUTURE OF MANUFACTURING



Navigating the Future of Manufacturing

Manufacturing has always evolved in response to change. What distinguishes the present is the growing interconnection of geopolitical tensions, climate change, technological acceleration, demographic shifts, resource constraints, and regulatory developments. Navigating this environment requires more than predicting individual developments: it requires understanding the forces shaping manufacturing and identifying the technologies that can help industry respond.

The first half of the 2020s has challenged the idea that crises can be treated as isolated events followed by a return to stability. The concept of polycrisis captures the interaction of multiple global risks whose combined effects can exceed the sum of their individual impacts[1]. The related concept of permacrisis emphasises the persistence of instability over time[2]. Together, they describe an environment in which uncertainty is becoming a structural feature of strategic decision-making.

Therefore, for manufacturing, the challenge is no longer simply to identify the "next big trend" or "next disruptive technology", but to distinguish meaningful change from noise, understand interactions among different forces and decide where to act, what to monitor and when to invest. This is fundamentally a challenge of strategic foresight. Corporate foresight provides structured approaches for exploring external change and integrating future-oriented knowledge into strategic decision-making[3], while research shows that organisations better prepared for future change can achieve superior long-term performance[4].

The 2026 World Manufacturing Report adopts two complementary instruments: the Trends Compass and the Technology Radar.

1.1 Trends Compass: Understanding Where Manufacturing Is Heading

Trend analysis, environmental scanning, and horizon scanning are established foresight practices for identifying emerging developments, weak signals and drivers of change, and for assessing their potential implications[3,5,6,7]. Rather than predicting a single future, they help decision-makers organise uncertainty and identify developments that deserve strategic attention. Contemporary foresight also increasingly examines the interconnections and systemic effects among trends rather than treating them independently[6,7].

Building on this literature and practice, the WMF's Trends Compass applies an impact-oriented scanning approach to manufacturing. It considers developments across six dimensions: geopolitical, economic, societal, technological, legal, and environmental, and interprets how they may affect the future configuration of supply chains and manufacturing systems. The purpose is not to compile an exhaustive catalogue of megatrends, but to identify developments that can materially influence manufacturing and translate them into strategically meaningful areas of attention.

The metaphor of the compass is intentional: a compass does not predict the destination or prescribe a single route; it provides orientation. Accordingly, the WMF's Trends Compass (Figure 1.1) organises the forces of change around three interconnected manufacturing priorities: resilient, sustainable, and human-centric supply chains and manufacturing systems. Chapter 2 explores how global forces translate into implications for the people, processes, and technologies through which industrial systems are designed and operated.

The result is not a static list of megatrends, but an interpretative framework connecting developments in the external environment with their implications for manufacturing.

The Trends Compass addresses the first fundamental navigation question:

What changes in the world should manufacturing organisations be preparing for?

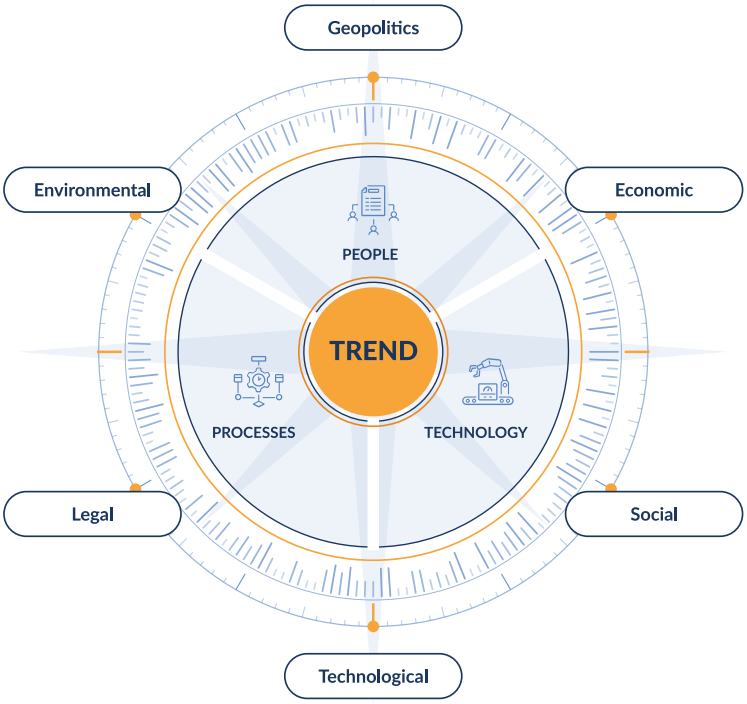


Figure 1.1. WMF's Trends Compass

1.2 Technology Radar - Understanding How Manufacturing Can Respond

Identifying relevant trends is only part of the challenge. Organisations must also understand which technologies can enable them to respond, when those technologies may become industrially relevant, and where attention and investment should be directed. Technology radars emerged within technology intelligence as visual tools for scouting, assessing, and communicating technological opportunities and threats. Research and practice use them to compare technologies according to dimensions such as relevance, maturity, impact and development stage, and emphasise their role as periodically updated decision-support instruments rather than one-off forecasts[8,9,10,11]. Manufacturing-specific applications have similarly combined maturity with enterprise value and deployment risk to support technology strategy[9]. Complementary approaches such as Gartner's Hype Cycle examine the evolution of technological maturity and adoption over time, supporting decisions on whether to move early or wait for further maturation[12].

Building on these approaches, the WMF's Technology Radar (Figure 1.2) synthesises recurring elements of technology foresight: technological maturity, strategic or business impact, diffusion/adoption, and expected evolution, into a multidimensional framework tailored to manufacturing. It deliberately separates dimensions that can evolve at different speeds: a technology may be technically ready but only weakly diffused across industry, while an emerging technology may already warrant strategic attention because of its potential impact. Each technology category is assessed along four dimensions:

- Industrial Technology Readiness: the degree to which the technology is technically mature and ready for implementation in industrial environments.
- Strategic Impact: its expected contribution to manufacturing competitiveness and value creation.
- Industrial Adoption Stage: the extent to which the technology is currently diffused across industry.

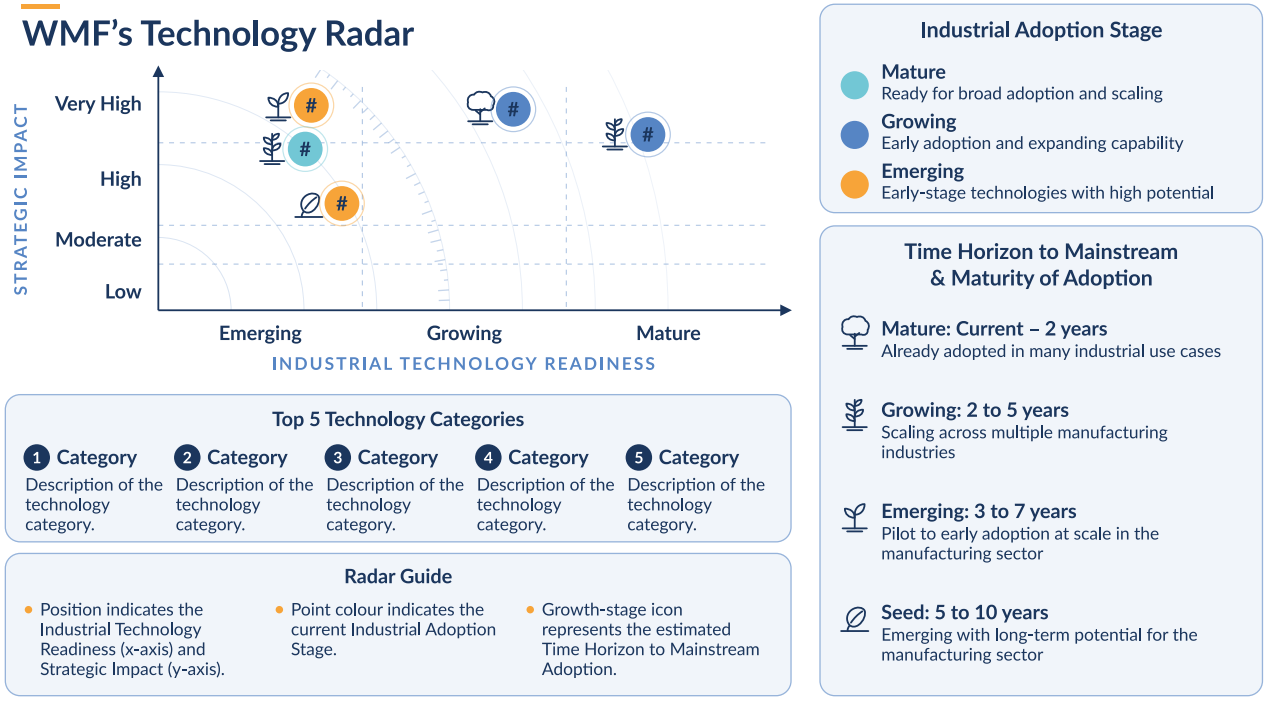


Figure 1.2. WMF's Technology Radar

- Time Horizon to Mainstream Adoption: the expected period before broad industrial adoption.

Combining readiness, impact, adoption, and time horizon provides a richer perspective than technological maturity alone. Therefore, the Technology Radar is not an absolute ranking, but a structured snapshot intended to support discussion and prioritisation as technologies and industrial experience evolve. Chapter 3 applies the framework to five domains: Enterprise Wearable Devices & Human-Centred Technologies; Industrial Data Analytics; Digital Twins, Extended Reality & Industrial Metaverses; Agentic & Cognitive Artificial Intelligence; and Physical AI & Humanoid Robotics.

Therefore, the Technology Radar addresses the second fundamental navigation question:

Which technologies should manufacturing organisations monitor, prepare for and adopt in response to the changes ahead?

1.3 Navigating with a Compass and a Radar: Connecting Trends and Technologies

The central methodological proposition of the 2026 WM Report is that trends and technologies should not be analysed in isolation. Trends reveal why manufacturing systems need to change, while technologies indicate ways in which that change can be enabled. The relationship is neither linear nor one-to-one: a manufacturing priority is rarely addressed by a single technological domain, and the same technology can contribute to several priorities.

Table 1.1 provides an indicative cross-reading of the three manufacturing priorities explored through the Trends Compass and the five technology domains analysed through the Technology Radars. The mapping highlights the relative strength and directness of these relationships and should be interpreted as a qualitative synthesis of Chapters 2 and 3, not as an additional technology-ranking exercise.

Table 1.1. How WMF technology domains contribute to resilient, sustainable, and human-centric manufacturing

Technology Radar Domain	Resilience	Sustainability	Human-centricity	Main rationale
Enterprise Wearable Devices & Human-Centred Technologies	○	○	●●●	Worker safety, ergonomics, workforce capability, augmentation
Industrial Data Analytics	●●●	●●●	●	Prediction, trusted data sharing, lifecycle intelligence, circular value intelligence
Digital Twins, XR & Industrial Metaverses	●●●	●●	●●●	Simulation, anticipation, remote collaboration, training, lifecycle optimisation
Agentic & Cognitive AI	●●●	●●	●●	Decision support, autonomous response, knowledge augmentation, optimisation
Physical AI & Humanoid Robotics	●●	●	●●●	Labour scarcity, flexible automation, safety, human-robot collaboration

●●● strong/direct contribution ●● relevant contribution ● enabling/secondary contribution ○ limited/indirect

The cross-reading highlights the systemic nature of manufacturing transformation. Industrial Data Analytics (IDA), Digital Twins, and Artificial Intelligence operate as cross-cutting enablers across several priorities, while Enterprise Wearable Devices are more strongly associated with worker safety, ergonomics, and augmentation, and Physical AI combines flexible automation with workforce and human-robot collaboration challenges.

Most importantly, the mapping reveals an intermediate layer between trends and technologies: the manufacturing capabilities required to respond to change. Trends and external pressures explain why manufacturing needs to change; their implications indicate what manufacturing systems need to be able to do; and technologies provide alternative means through which these capabilities can be enabled. Therefore, technologies should be interpreted as a portfolio for responding to multiple, interconnected pressures rather than as isolated responses to individual trends.

The 2026 WM Report adopts this combined approach to navigate rather than predict the future of manufacturing. Chapter 2 uses the Trends Compass to explore the forces shaping resilient, sustainable and human-centric manufacturing; Chapter 3 uses the Technology Radars to assess the maturity, strategic impact, adoption and expected evolution of selected technology domains. Together, they turn a complex and uncertain environment into orientation, priorities and informed action.

TRENDS COMPASS

A compass does not predict the destination or prescribe a single route; **it provides orientation.**

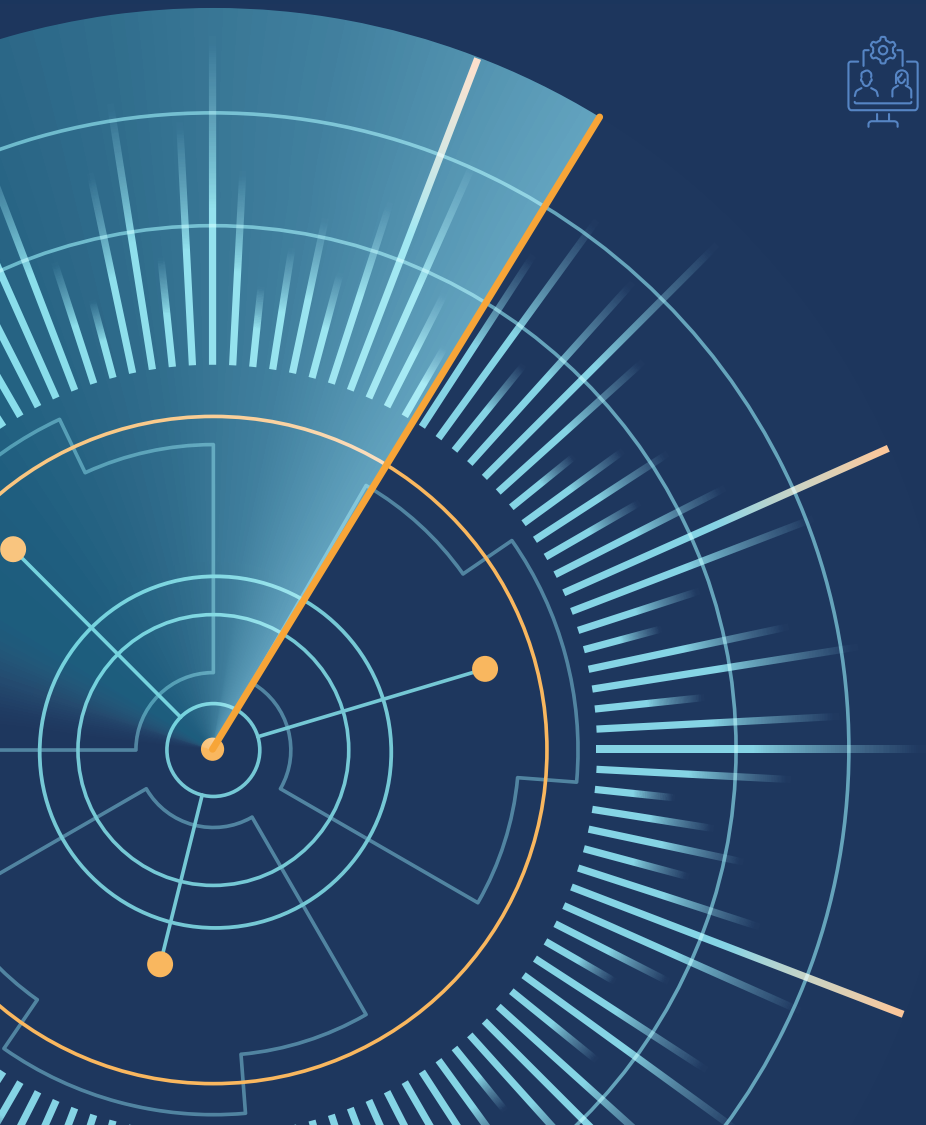
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02

CHAPTER 2

TRENDS ON THE HORIZON SHAPING THE FUTURE OF MANUFACTURING



Trends on the Horizon Shaping the Future of Manufacturing

2.1 Resilient Supply Chains and Manufacturing Systems Trends

"Resilience is becoming a design property of industrial systems rather than a response to failure".

Resilience describes the ability of supply chains and manufacturing systems to anticipate disruption, adapt their configuration and recover within acceptable time and cost[1]. Resilience treats variability, uncertainty and discontinuity as conditions the system must be built to withstand. Continuity of supply therefore becomes an explicit requirement alongside cost, quality, delivery and sustainability.

This shift reaches beyond contingency planning and insurance. A supply chain may survive a severe shock through unused capacity or the improvisation of experienced staff without having been designed to withstand it. Resilience requires those outcomes to be produced deliberately and proactively through decisions about network structure, sourcing, buffers, product architecture, automation, data and skills[2]. It therefore connects choices that have traditionally been separated across procurement, operations, engineering, information technology and risk functions, and it links the design of supply chains to the design of the plants that operate within them.

The significance of this shift is increasing because disruption has become more frequent, more varied and more consequential. Geopolitical conflicts are interrupting supply chains and reshaping trade rules and access to critical inputs; specialisation has concentrated capability in a small number of suppliers, sites and transport corridors; climate change is affecting the physical assets and routes on which production depends; and digitalisation has created new dependencies that can halt physical operations[3]. Firms increasingly face compound events in which several of these pressures interact, so resilience cannot be managed as a set of independent risks[4].

Section 2.1.1 examines the geopolitical, economic, social, technological, legal and environmental forces creating the need for greater resilience. Sections 2.1.2 and 2.1.3 then consider how those pressures affect people, processes and technology, first across supply chains and then within manufacturing systems. Section 2.1.4 translates these findings into priorities for manufacturers, policymakers and other stakeholders.

2.1.1 Global Trends Calling for Resilience

Manufacturers must be able to keep producing and delivering while the conditions around them change for the worse. Disruptions once absorbed through expediting, safety stock or local substitution increasingly reappear as lost output, contractual penalties, loss of market position or even failing supply chains. This makes exposure to disruption a design parameter that needs to be understood before networks, plants and technologies are fixed.

Geopolitical Trends

Trade policy and international conflicts have become a source of operational risks in recent years. Tariffs, export controls, sanctions, or military conflicts challenge established sourcing arrangements within short planning horizons. Concentration compounds this exposure. Extraction and, more acutely, the processing of several critical minerals required for electrification and electronics remain concentrated in a small number of countries, so that local policy decisions can affect input availability worldwide[5]. Physical corridors show a similar pattern: diversions away from the Red Sea and constraints on Panama Canal transits have demonstrated how a small number of maritime chokepoints can lengthen lead times and raise freight costs across unrelated sectors[6]. Sourcing and routing decisions therefore need to be assessed for political and corridor exposure, not only for cost and lead time.

Economic Trends

The economic case for resilience rests on the cost of interruption. Analysis of global value chains suggests that companies can expect disruptions lasting a month or longer with sufficient regularity that losses accumulated over a decade represent a material share of a year's earnings[7]. Exposure is frequently misidentified because it is assessed by expenditure. Suppliers representing low spend can carry

long recovery times when they hold unique tooling, qualifications or process knowledge, so conventional spend-based risk assessment understates where the network is actually fragile[8].

Resilience measures carry their own cost: Higher financing costs increase the burden of inventory and capacity buffers, while volatility in freight and energy prices changes the economics of network configuration. Disruption also propagates: an interruption at one node degrades performance across tiers and time well beyond the directly affected relationship[9]. Investment in resilience is therefore most effective where propagation risk is greatest, rather than distributed evenly across the supply base. A substantial proportion of disruptions originate below the first tier, where visibility and leverage are weakest[10].

Social Trends

Employers identify skills gaps as the most significant barrier to transformation, with roles in analytics, engineering and operations among those most affected[11]. Experienced planners, buyers, maintenance technicians and process engineers hold the tacit knowledge on which improvised recovery relies, and this knowledge is rarely captured in formal procedures. Workforce ageing and turnover therefore erode recovery capability in ways that do not appear in conventional risk assessments.

Social conditions across the supply chain matter as much as those within the focal firm. Industrial action at ports and in logistics has shown how labour relations at a small number of nodes can interrupt flows for entire sectors, while expectations of transparency on labour and environmental conditions increasingly affect which suppliers can be used. At the same time, industrial development strategies in emerging economies are creating new productive capacity and new sources of supply, changing where resilient networks can realistically be built[12]. Supplier workforce stability consequently becomes part of supply continuity rather than a separate social consideration.

Technological Trends

Digital capability is improving the ability to anticipate and evaluate disruption. Supply chain digital twins and simulation allow alternative network configurations, inventory positions and recovery sequences to be tested against disruption scenarios before commitments are made[3]. Combined with multi-tier mapping and automated monitoring of disruption signals, these tools shorten the interval between an event occurring and a decision being taken.

Likewise, new technologies create new failure modes. Insufficient cybersecurity affecting information and operational technology has halted production and distribution for extended periods, and supply chain compromise and ransomware remain among the most consequential threats reported for industrial organisations[13]. As cyber-physical production systems increase dependence on networks, software and externally hosted services, the availability of digital infrastructure becomes a precondition for physical output. Resilience therefore now includes the resilience of the digital layer itself, including the ability to operate in a degraded mode when it is unavailable.

Legal Trends

Regulation is converting several elements of resilience into explicit obligations. The European Union Critical Raw Materials Act establishes benchmarks for extraction, processing and recycling capacity, designates strategic raw materials and requires large companies using them to carry out risk assessments of their supply chains, including stress testing and monitoring[14]. The Corporate Sustainability Due Diligence Directive requires in-scope companies to identify, prevent and address adverse human rights and environmental impacts across their supply chains, which in practice requires knowledge of suppliers beyond the first tier[15].

Obligations are also extending to digital and sectoral resilience. The Network and Information Security (NIS) 2 Directive extends cybersecurity risk-management and supply chain security requirements to manufacturing and related sectors, with governance and incident-reporting duties attaching to management bodies[16], while the Cyber Resilience Act places security requirements on products with digital elements placed on the EU market[17]. Sector-specific instruments such as the European Chips Act illustrate a further development, combining capacity-building with monitoring and crisis-response mechanisms for strategically important supply chains[18]. These requirements increasingly determine what evidence manufacturers must be able to produce about their own networks.

Environmental Trends

Climate change is affecting the physical basis of production. Assessments confirm that the frequency and intensity of heat extremes, heavy precipitation and drought

have increased, with further increases projected under all considered scenarios[19], and successive years of record global temperatures have been accompanied by disruption to inland waterways, ports and industrial water supply. Flooding at supplier sites, heat constraints on plant operation and water stress affecting water-intensive processes are becoming recurring rather than exceptional operating conditions.

Environmental pressure is also reshaping network structure. Recycling, remanufacturing and greater material efficiency reduce dependence on primary extraction and on the jurisdictions where it is concentrated[7], and secondary material capacity is being encouraged through regulation. These routes introduce their own variability, since recovered materials and returned products arrive in uncertain quantities and conditions. The energy transition simultaneously increases demand for constrained materials. Environmental change is therefore both a source of disruption and a driver of the new network and process configurations through which resilience must be achieved.

Taken together, these trends change the strategic role of resilience. Access to inputs, continuity of operations, market access and the ability to adapt production increasingly depend on decisions taken when supply chains and manufacturing systems are designed. Figure 2.1 summarises how the main external pressures translate into resilience requirements.

These pressures rarely act in isolation. Geopolitical measures change where production can be located, which alters exposure to climate hazards and labour markets; digitalisation improves visibility while adding cyber dependence; regulation raises expectations for evidence about tiers of supply that most firms cannot yet see. Resilience therefore has to be assessed at system level, examining how a specific configuration performs under combinations of stress rather than how it responds to each risk considered separately.

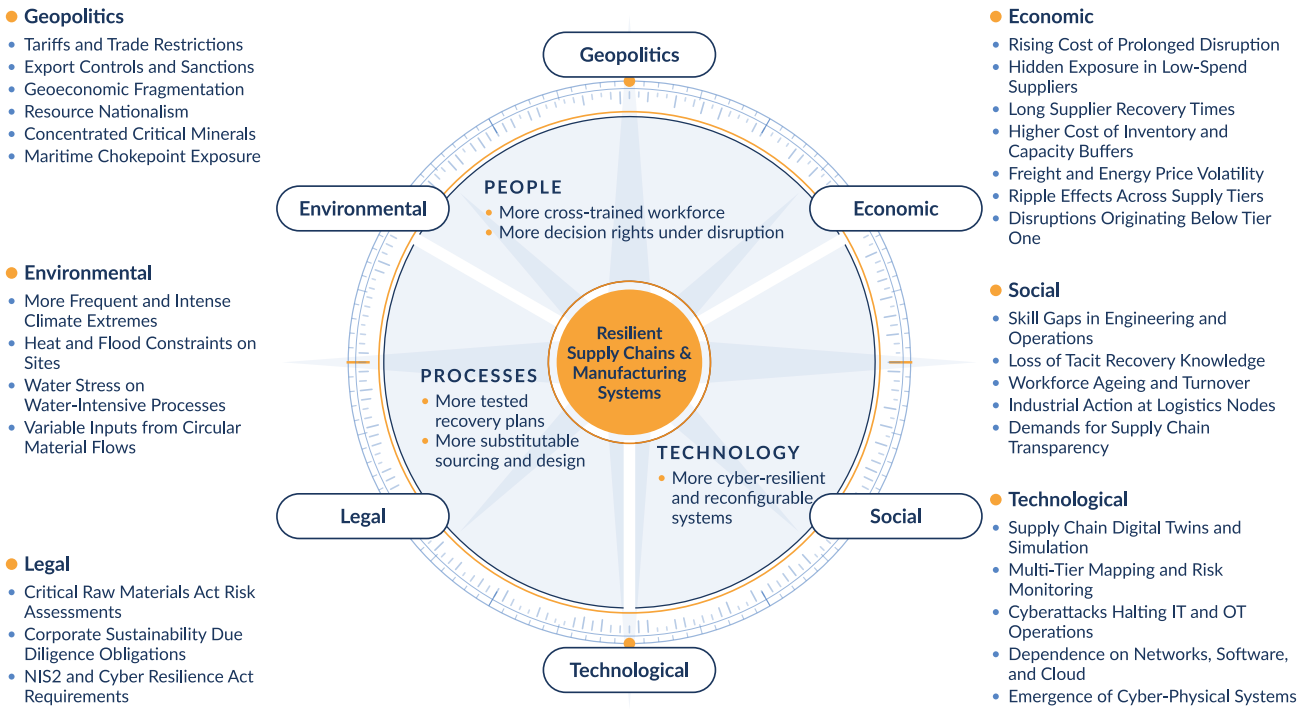


Figure 2.1. WMF's Trends Compass for Resilient Supply Chains and Manufacturing Systems

2.1.2 Trends Impacting Supply Chains (Re-)Design

Resilient supply chain design expands the unit of analysis from the focal firm to the network, and from average performance to performance under stress. The design question is how quickly the network can detect, absorb and recover from disruption at acceptable cost, alongside established requirements for service and efficiency.

Impact on People

Planners, buyers, logistics coordinators and plant managers make consequential decisions under incomplete information and time pressure, drawing on supplier relationships and experience that formal procedures do not contain. Continuity plans rarely anticipate the specific event. What determines outcomes is who is able to decide, how quickly, and with what authority. Pre-assigned decision rights, cross-functional response teams and rehearsed escalation routes therefore contribute more to recovery speed than documentation alone.

Capability also sits outside the organisation. Visibility of sub-tier exposure depends on supplier relationships that make disclosure possible, since sub-tier information is commercially sensitive and rarely obtainable through contractual demand alone. Firms with greater visibility, closer supplier relationships and more flexible operations have been found to recover more effectively from disruption, indicating that resilience is built through capability rather than through analysis alone[20]. Internal capacity remains a constraint: risk analytics, scenario planning and continuity management are frequently added to existing roles without corresponding time or authority, which limits what improved information can achieve.

Impact on Processes

Resilience is increasingly embedded in planning processes rather than handled as a separate risk activity. Scenario-based sales and operations planning, risk-adjusted sourcing decisions and periodic network stress testing bring disruption into decisions. Stress testing is particularly effective at identifying configurations in which the time required to recover a node exceeds the time the network can survive without it.

Sourcing and inventory processes are being restructured accordingly. Parts are increasingly segmented by criticality and recovery time rather than by expenditure; dual qualification is planned for the components that most constrain output, and decoupling points and postponement are positioned so that variety is created late and commitments remain reversible for longer. Design should balance the capabilities a network holds against the vulnerabilities it faces rather than maximizing capability in isolation[21]. Viability perspectives consider whether a network can sustain and evolve through severe and prolonged disruption, not only whether it can return to a previous operating point.

Impact on Technology

Technology is changing what supply chain design can evaluate. Control-tower architectures, multi-tier mapping and automated monitoring bring disruption signals into a common operating picture, while digital twins allow configurations to be tested against disruption scenarios before commitment. The practical constraint is data: sub-tier information is often incomplete, inconsistently structured or out of date, so the value of these systems depends on interoperability, data standards and sustained supplier engagement.

The digital layer must itself be designed for resilience. Cybersecurity risk management, supplier security requirements and incident reporting now carry legal relevance for many manufacturers. Planning, execution and logistics platforms need segmentation, tested recovery procedures and defined degraded modes so that operations can continue when systems are unavailable. Technology adds resilience only where processes and decision authority exist to act on what it reveals. Visibility without the ability to reallocate supply, capacity or transport changes the quality of reporting rather than the outcome of a disruption.

Table 2.1 summarises these impacts and resulting design responses for resilient supply chains.

Table 2.1. Design responses for resilient supply chains

Response	Focus	Resilience gains	Trade-offs
1. **Multi-sourcing**	Qualified alternative suppliers	• No single point of failure • Supply held in shocks	• Cost to qualify • Less volume leverage
2. **Regional footprint**	Sourcing closer to demand	• Shorter, simpler flows • Less chokepoint risk	• Higher unit cost • Thin local supply
3. **Buffers**	Stock and surge capacity	• Absorbs short shocks • Buys time to decide	• Capital tied up • Can mask weak design
4. **Sub-tier visibility**	Mapping of deeper tiers	• Reveals hidden risk • Faster detection	• Limited disclosure • Effort to keep current
5. **Supplier co-planning**	Joint continuity plans	• Faster joint response • Keeps suppliers viable	• Needs trust and time • Hard to scale
6. **Logistics options**	Alternative modes and routes	• Flow held if nodes close • Lower crisis cost	• High freight rates • Scarce spare capacity

2.1.3 Trends Impacting Manufacturing Systems (Re-)Design

Manufacturing system design determines whether a plant can change what it produces, in what quantity and with which inputs, and how quickly it can restart after interruption. System architectures have progressively moved from dedicated lines optimised for stable high-volume production towards flexible and reconfigurable configurations in which capacity and functionality can be adjusted as requirements change[22]. Changeability is increasingly treated as a designed property of the manufacturing system, addressed through modularity, scalability and the ability to integrate and redeploy equipment.

Impact on People

Whether a plant can redeploy people between lines and processes when demand shifts or an alternative material is substituted depends on how broadly the workforce has been trained and on how work is organized. Cross-training carries a cost in productive time and is frequently deferred under output pressure, which means that flexibility has to be planned as capacity rather than assumed to exist. Operators and maintenance personnel also perform the diagnosis, adjustment and recovery on which restart times depend, and their knowledge of equipment behaviour under non-standard conditions is rarely documented.

The relationship between people and automated systems shapes how this capability develops. As automation absorbs routine execution, the remaining human contribution concentrates in exception handling, diagnosis and recovery, which are precisely the activities that determine performance during disruption. Sustaining that contribution requires deliberate provision for learning time, supervised practice and the retention of operational knowledge as equipment and products change, alongside interfaces and decision rights that allow people to intervene effectively when automated responses are insufficient.

Impact on Processes

Process and product decisions taken well before disruption determine how much substitution is possible when it occurs. Part commonality, modular product architecture and the deliberate avoidance of single-source or single-specification components decide whether an alternative input can be used at all, while qualification and certification requirements determine how long substitution takes. Because requalification of materials, components or processes is lengthy, design for substitutability is more consequential for resilience than procurement flexibility exercised after an event.

Plant-level processes are being adjusted in the same direction. Reduced changeover times, buffer placement at deliberately chosen decoupling points and standardized restart procedures shorten the interval between interruption and resumed output. Maintenance regimes influence how much unplanned downtime coincides with external disruption, and simulation allows recovery sequences and capacity reallocation to be validated before they are needed rather than improvised during an event.

Impact on Technology

Technology choices determine how much of this flexibility is realizable in practice. Flexible automation, additive manufacturing for spare parts and tooling, and digital twins for simulation all reduce the time required to change what a plant produces. Their contribution depends on integration: equipment that cannot exchange information with planning and quality systems, or that requires extensive revalidation when reconfigured, limits the flexibility it was intended to provide. Interoperability and the ability to retrofit existing assets are therefore central, since most plants will operate mixed generations of equipment for many years.

Operational technology security has become inseparable from manufacturing system design. Converged information and operational technology environments expand the routes through which production can be interrupted, and industrial security practice accordingly emphasizes segmentation, defined security levels and secure integration of components as design requirements. Capacity to implement these measures is unevenly distributed: smaller manufacturers frequently lack the specialist resources that digital and security maturity assume, which makes external support and simplified implementation routes important if resilience is to extend across the supply base rather than remaining concentrated in large firms.

Across these developments, manufacturing system resilience depends on treating flexibility, workforce capability and digital dependence as connected design variables. Performance under stress will be determined by whether the surrounding system can be reconfigured, operated in degraded conditions and restored by the people available to run it, rather than by individual systems.

Table 2.2 summarises manufacturing system capabilities in

response to trends and impacts described above.

Table 2.2. Manufacturing system capabilities supporting resilience

Capability	Focus	Resilience gains	Challenges
1. **Modular lines**	Modular, scalable layouts	• Fast mix and volume change • Assets reused	• More design work • Integration effort
2. **Flexible automation**	Redeployable robots and cells	• Absorbs volume swings • Serves many products	• Capital cost • Safety re-approval
3. **Digital twins**	Simulation and stress tests	• Tests disruption cases • Shorter ramp-up	• Model upkeep • Specialist skills
4. **Predictive upkeep**	Condition-based asset care	• Fewer sudden stoppages • Better spares planning	• Sensing investment • Alerts without action
5. **Additive tooling**	On-demand parts and tools	• Bridges spare-part gaps • Shorter tooling lead time	• Approval burden • Material and volume limits
6. **Spread capacity**	Multi-site production	• Volume moved between sites • Less single-site risk	• Process alignment • Repeat qualification

2.1.4 Call for Action

Resilience needs to progress further to be a fundamental part of decisions through which supply chains and manufacturing systems are designed. Exposure, recovery time and the ability to reconfigure should be explicit criteria in network design, sourcing, product architecture and capital investment, assessed before configurations become costly to reverse. This requires manufacturers to know where their critical dependencies actually lie, including below the first tier, and to compare the time required to recover each dependency against the time the business can operate without it. Where that comparison cannot be made, the practical priority is to establish the information and relationships that would make it possible rather than to add generalized buffers.

For manufacturers, this points to a small number of durable commitments. Exposure and recovery capability should be governed with high priority. Changeability should be built into plant and product design. Qualification of alternative sources and materials should be maintained as a standing activity. Finally, cyber resilience should be treated as a condition of production rather than as an information technology matter. Workforce flexibility requires cross-training, retained operational knowledge and clear decision rights.

Policymakers and industry associations can help to enhance sub-tier transparency, common data standards, shared stress-testing methods and coordinated approaches to strategic material and component stocks. Regulatory requirements relating to raw materials, due diligence and cybersecurity will achieve more where they are aligned with one another and supported by practical implementation guidance, particularly for small and medium-sized manufacturers whose limited specialist capacity otherwise becomes a network-level vulnerability[23]. Skills provision extends this further, since capability for resilient operations needs to reach beyond leading firms to suppliers and to workers moving between employers.

Research and education institutions have a complementary role in improving the evidence on which these decisions rest. Better measures of recovery time, substitution capability and network exposure, together with realistic evaluation of resilience investments, would allow firms to allocate resources on evidence rather than on recent experience. Engineering and management education should correspondingly treat network structure, changeability and degraded-mode operation as design choices with measurable operational consequences.

For management, resilience must influence decisions before networks and manufacturing systems are final, and it must remain visible in governance once operations are stable. Resilience becomes operational when it changes specifications, sourcing decisions, plant design and the way performance is measured, rather than when it is documented in plans that are consulted only after disruption has occurred.

2.2 Sustainable Supply Chains and Manufacturing Systems Trends

"Supply chains and manufacturing systems achieve sustainability when they balance economic, societal, and environmental gains while ensuring that materials and data flow effectively across organisations and operations, thereby enabling longer product lifecycles, greater resource efficiency, and circular material flows".

Supply chains and manufacturing systems are under simultaneous pressure to reduce virgin resource use, prevent waste and emissions, retain the value of products and materials, and remain economically viable. The decreasing natural resources, increasing emissions, climate change and biodiversity loss push linear supply chains and manufacturing to transform towards sustainable, circular, resource-efficient and low-carbon manufacturing.

Sustainability of supply chains and manufacturing systems relies on the three pillars: economic sustainability means creating business value from resources, environmental sustainability means reducing ecological impacts, for example through resource efficiency and circulation, and social sustainability means improving employee and societal well-being through safer, more resilient, and clean industrial systems[1,2].

One solution for sustainability issues in manufacturing is to transition towards sustainable, circular manufacturing by redesigning products, processes and supply chains around three complementary strategies: narrowing resource flows through efficiency, extending product and component lifetimes, and closing loops through reuse, remanufacturing and recycling. Such circular manufacturing can be supported by data on materials, products, transactions and operations, and digital technologies that enable collecting, connecting, verifying and analysing data, modelling alternatives, guiding physical manufacturing processes and matching actors from the circular supply and value chain through, for example, platforms[2,3,4].

However, technology adoption alone does not create sustainable supply chains and circular manufacturing systems. Achieving such a transformation requires a broader systems perspective and multidisciplinary management capable of integrating manufacturing and digital technologies with circular economy principles, sustainability objectives, and business and supply chain considerations. The development of sustainable circular manufacturing systems depends on how circular manufacturing approaches and digital technologies are combined, which economic, environmental, and societal objectives are prioritised, and whether companies, supply-chain partners, and public stakeholders, such as policymakers and regulators, can align and coordinate their actions to enable resource circulation and sustainable value creation across industries, markets, and society[5,6,7].

Section 2.2.1 reviews the external trends accelerating sustainable and circular manufacturing. Sections 2.2.2 and 2.2.3 translate these developments into supply-chain and manufacturing-system redesign priorities. Section 2.2.4 provides a call for action for manufacturing managers, value-chain developers and policymakers.

2.2.1 Global Trends Calling for Sustainability

Geopolitical Trends

Geopolitical volatility is changing how manufacturers assess access to materials, technologies, data infrastructures and markets. Circular strategies can reduce dependence on virgin and geographically concentrated resources by keeping components and materials in productive use. At the same time, circular operations increasingly depend on globally distributed digital services, cloud infrastructures, data standards and equipment. Strategic autonomy and technological sovereignty therefore become relevant alongside resource security: firms need to understand where product data are stored, who controls critical software and platforms, and whether recovery and reprocessing can continue when cross-border data or material flows are disrupted. All these contribute to the sustainability of supply chains and manufacturing systems by ensuring economic, environmental and social sustainability[7,8].

Economic Trends

Sustainable value chains and manufacturing systems are moving from isolated environmental-oriented improvements towards operational and business-model-oriented improvements. As the business feasibility of the chains and systems is key, digitalisation has been suggested as one answer[2].

Digital technologies can improve resource productivity, equipment life, recovery yields and coordination, but implementation commonly requires substantial investment in infrastructure, integration, cybersecurity, training and process redesign. The business feasibility therefore depends on whether data and digital tools create measurable

economic value for all involved actors in the chain and the system[2,9].

Social Trends

Social trends are increasingly reshaping sustainable supply chains and manufacturing systems.

Growing consumer awareness and societal concern over sustainability, resource scarcity, and climate change are increasing demand for more circular and transparent production and consumption systems[8].

Beyond market demand, manufacturing companies face growing pressure from customers, investors, employees, regulators, and civil society organisations to demonstrate responsible resource use and sustainability performance. Furthermore, industry norms across many sectors are increasingly evolving to incorporate sustainability and circularity considerations[7,8,9].

These evolving social norms, institutional drivers and stakeholder expectations are encouraging firms and supply-chain partners to adopt more sustainable and circular manufacturing approaches[8].

Technological Trends

Digital technologies can play a key role in advancing sustainable circular supply chains and manufacturing systems. This development is often referred to as the twin transition, emphasising that sustainability and digitalisation progress together and mutually reinforce one another[5,10,11].

Sensors, RFID and QR codes capture product and process data. IoT and cloud technologies integrate and store it. Blockchain can verify transactions and provenance. Big-data analytics, artificial intelligence, machine learning and machine vision support prediction, inspection and optimisation. Digital twins, simulation, virtual and augmented reality, digital product passports and cyber-physical systems make alternatives visible and testable. Automation, robotics and additive manufacturing translate information into physical operations, while digital platforms connect actors, resources and services for more circular operations[3,4,9].

The critical requirement is therefore functional integration of data to enable sustainable material flows across the supply chain and manufacturing systems. Data capture without integration remains isolated; analytics without access to physical processing cannot close loops; platforms without sufficient participation and reliable data fail to match supply and demand. Manufacturers need interoperable portfolios of technologies that maintain continuity from information generation to decision-making and action[3,9].

Legal Trends

Sustainable supply chains and manufacturing systems are strongly driven by policies, regulation and institutional development[8].

Policy and regulatory initiatives increasingly shape the transition towards sustainable supply chains and manufacturing systems. Some particular initiatives in the EU are the European Green Deal and the Circular Economy Action Plan as overarching frameworks that steer industrial development towards improved resource efficiency, circular product design, waste and emissions reduction, and more systematic environmental monitoring.

Some other policy drivers are the EU Industrial Strategy, the SME Strategy for a Sustainable and Digital Europe, and the InvestEU Programme, which support the green and digital transformation through industrial renewal, capability development, financing, investment support, and public-private collaboration. Together, these initiatives institutionalise and legitimise the twin transition, encouraging manufacturers to redesign products and production processes, invest in digital and circular capabilities, and adopt business models based on product longevity, reuse, remanufacturing, recycling, and value recovery.

Regulation also directly influences how data, artificial intelligence, machinery, and interorganisational collaboration can be utilised across sustainable supply chains and manufacturing systems. Relevant instruments include the EU Artificial Intelligence Act, machinery-related directives, the General Data Protection Regulation (GDPR), broader data and AI legislation, and corporate responsibility requirements as important conditions for digitalised circular manufacturing.

These regulations affect how manufacturers deploy AI in areas such as inspection, predictive maintenance, sorting, production optimisation, and recovery operations, as well as how companies collect, process, verify, and share product and lifecycle data across organisational boundaries. For sustainable supply chains, the central managerial challenge is therefore not merely regulatory compliance, but developing interoperable data-governance practices, accountability structures, standards, and incentives that

enable data and materials to flow securely across companies[6,7].

Policy frameworks can further accelerate this development through taxation, investment support, standardisation, and harmonisation, but misalignment or regulatory uncertainty may also restrict data sharing, investment, collaboration, and the scaling of circular manufacturing solutions[8].

Many sustainability goals and requirements are encouraging lifecycle data infrastructures and digital product passports, but they also create questions about commercial confidentiality, intellectual property, authentication, access rights and administrative burden. Global manufacturers must design data governance so that different actors receive the information they need without exposing sensitive information unnecessarily.

Environmental Trends

Resource scarcity, climate change, biodiversity loss and waste accumulation intensify the need to retain material value across sustainable supply chains and manufacturing systems[9].

Intensified material usage and digitalisation can support more durable design, predictive maintenance, reuse, remanufacturing, recycling and optimised resource flows. However, the digital layer has its own footprint. Sensors, networks, cloud services, AI, blockchain and automation consume energy and hardware, and rapid technology renewal can increase electronic waste. This has only recently been recognised as an emerging issue[10].

Sustainable digitalised supply chain operations and manufacturing therefore require lifecycle assessment of both the operation and its enabling infrastructure. The relevant question is not whether an initiative is sustainable, but whether its total system effect reduces virgin resource use, energy consumption, waste and emissions while maintaining viable and socially responsible operations[12]. Figure 2.2 summarises how the main external pressures translate into sustainability requirements.

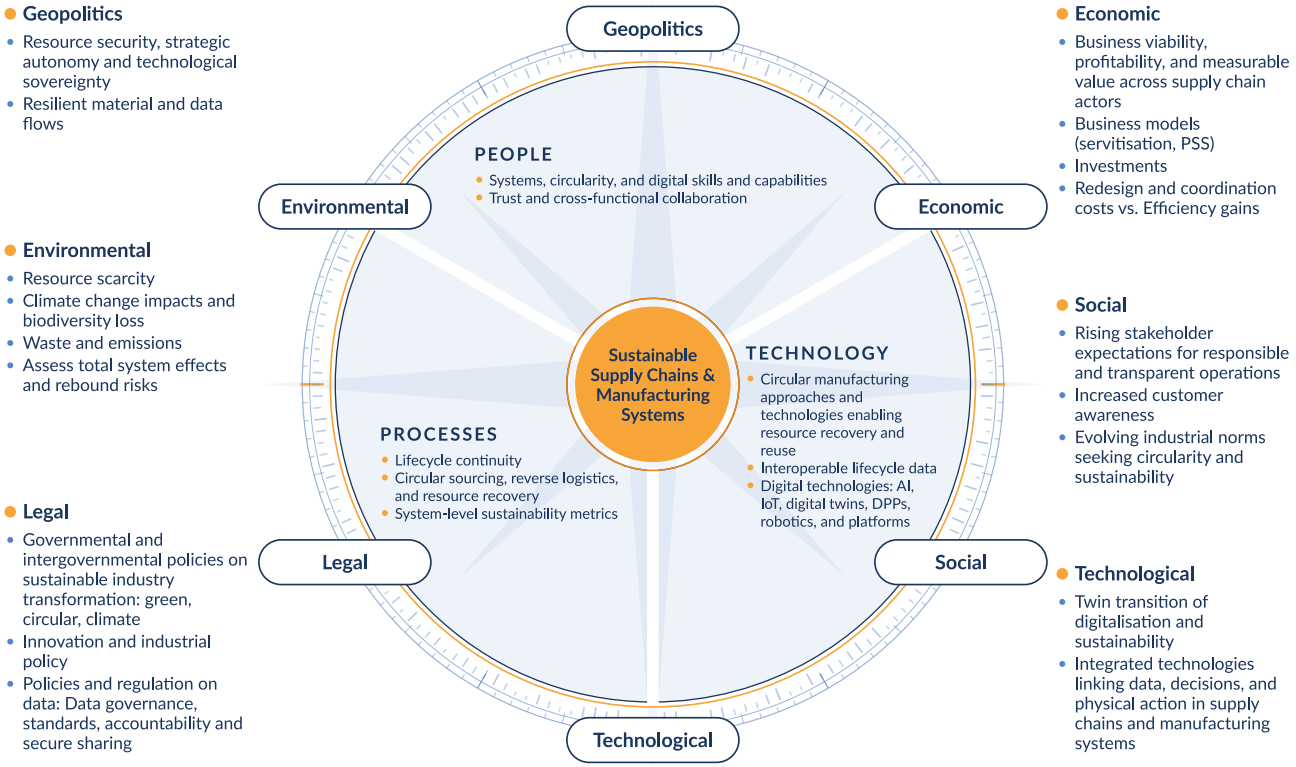


Figure 2.2. WMF's Trends Compass for Sustainable Supply Chains and Manufacturing Systems

2.2.2 Trends Impacting Supply Chains (Re-)Design

Sustainable, circular-oriented supply chains extend the design challenge and challenge companies and chains to reconsider how they operate and create their economic value and profit. They need to engage in recovering products, components and materials; preserving information across ownership changes; and coordinating material flows, data flows and related decisions among manufacturers, suppliers, users, logistics providers, repairers, remanufacturers and recyclers[7,13].

Impact on People

Work and needed capabilities change: The need for system-level knowledge and skills emerges. Supply-chain roles increasingly combine operational, commercial, sustainability and data responsibilities. Buyers and planners need to assess not only price, quality and delivery but also product history, recovery options, data availability and downstream value retention. Engineers and sustainability specialists must work with logistics, IT, legal and business-model teams. External partners need sufficient capability and motivation to engage and maintain accurate product and material data throughout the lifecycle[6,9,11].

Trust remains indispensable. Firms may hesitate to share process, composition or condition data that could reveal costs, designs or competitive capabilities. Clear access rules, reciprocity, cybersecurity practices and value-sharing arrangements are therefore prerequisites for useful transparency[9,13].

Industry associations and neutral ecosystem orchestrators can help establish shared language, governance and training[7,13].

Impact on Processes

Supply-chain processes must be redesigned around lifecycle continuity. Circular sourcing should define specifications for reused, remanufactured and recycled inputs. Product architecture and contracts should anticipate take-back, inspection, sorting, repair and reprocessing[1,13].

Reverse logistics must connect uncertain return volumes and conditions to production planning. Decisions about reuse, repair, remanufacture or recycling require consistent information on product identity, composition, use, condition and residual value[3,9].

Performance management must combine economic viability with environmental and social outcomes. Metrics should cover recovery yield, retained value, virgin-material displacement, absolute resource and energy use, emissions, worker safety and skills. Otherwise, local optimisation can shift burdens to another actor, lifecycle stage or region[12].

Impact on Technology

Supply chains need interoperable data infrastructures rather than disconnected pilots. Product identifiers and sensors establish visibility; IoT and cloud solutions connect lifecycle data; verification tools support trust; analytics guide routing and recovery choices; passports and digital twins provide shared representations; and platforms match recovered resources with users and service providers[3,4,9].

Technology portfolios must also remain accessible to smaller partners. Excessive complexity, expensive integration or demanding reporting can exclude SMEs and create gaps precisely where critical data and recovery capability reside. Scalable interfaces, common standards and shared services can reduce this risk[6,9].

2.2.3 Trends Impacting Manufacturing Systems (Re-)Design

Sustainable, circular manufacturing systems must handle greater variability than linear systems. Returned material and products differ in age, condition, configuration and contamination; recycled and dismantled inputs may vary in composition; and recovery routes depend on residual value and available capacity. System design must therefore connect flexible physical operations with timely, trustworthy data and human decision-making[9].

Impact on People

Operators, maintenance specialists and engineers need skills for diagnosing variable products and materials, interpreting digital models and working safely with automated systems. Human expertise is especially important when historical data are incomplete or unusual conditions fall outside model assumptions. Training and skills development should combine conventional manufacturing operations knowledge with sustainability and circular approach knowledge, environmental impact assessment, digital literacy, problem-solving and system-level understanding[11].

Work design should preserve meaningful human oversight. Clear intervention rights, explainable decision support, safe human-robot collaboration and transparent employee-data practices help prevent overreliance on automation. Firms should also plan how productivity gains affect roles, staffing and competence development of the workforce[7].

Impact on Processes

When manufacturing systems shift towards sustainable and circular operations, manufacturing processes need to extend and cover multiple connected stages, ranging from circular design to resource-efficient production, maintenance and repair, and later end-of-use recovery and reprocessing of materials, products and components. Design decisions should support disassembly, repairability, reuse and material identification. Due to circular strategies, new processual operations emerge. For example, inspection of back-flowing materials and products, and sorting determine feasible recovery routes for materials and products, while remanufacturing and recycling return value to production[9].

Continuity between such stages, ensuring sustainable circular operations in the system, is essential. Data generated during design and use must remain usable during recovery, and inspection results must inform production planning[3,9].

Impact on Technology

Multiple digital technologies can contribute to manufacturing systems' sustainability-seeking efforts. Machine vision and AI can assess condition and classify returned products. Digital twins and simulation can compare recovery scenarios. Robotics can support disassembly and sorting. Additive manufacturing can produce repair parts or use recovered feedstock. IoT and cloud services can connect equipment and lifecycle data, while passports provide structured product information throughout the product lifecycle[4,8,11].

Environmental and operational safeguards must be built into technology evaluation and implementation. Automation can increase energy demand; blockchain and cloud infrastructures have computational footprints; additive manufacturing may have scale and material limitations; and analytics can optimise the wrong objective. Decision models should therefore include absolute resource, energy, emissions and social criteria alongside throughput, quality and cost[12].

Table 2.3 summarises the key design and managerial responses required when supply chains and manufacturing systems transition towards sustainability and circularity. Together, these responses illustrate how the transformation extends beyond technological change to encompass processes, business models, workforce capabilities, and system-level coordination.

Table 2.3. Design responses for sustainable supply chains

Focus	Sustainability gains	Trade-offs
1. Design for resource circulation and efficiency		
Shift from linear throughput to reuse, repair, remanufacturing and recycling across product lifecycles.	• Reduced virgin-material use • Lower waste and emissions • Higher resource productivity	• More complex operations • Variable quality and availability of returned materials and products
2. Extend product and asset lifetimes		
Enable durability, maintenance, repair, upgrades and lifecycle services	• Lower resource consumption • Reduced environmental impact • Increased value retention	• Reduced sales of new products • Need for service and maintenance capabilities
3. Integrate lifecycle data and digital technologies		
Connect product, material and process data through interoperable digital infrastructures	• Better visibility and decision-making • Improved traceability and resource optimisation	• High investment and integration costs • Cybersecurity and data-governance challenges
4. Redesign supply-chain and manufacturing processes		
Align sourcing, production, reverse logistics, recovery and reprocessing activities	• Greater recovery yields • Reduced material losses • Improved system efficiency	• Increased operational complexity • Need for new coordination and performance systems
5. Develop sustainable, circular, data-enabled business models		
Move from product sales towards lifecycle services, resource recovery, servitisation and platform-based value creation	• New revenue streams • Greater resilience and value retention • Incentives for resource circulation	• Value capture challenges, need to understand multifaceted value • Revenue and incentive redistribution across actors
6. Strengthen workforce capabilities and collaboration for sustainability and circularity		
Develop systems thinking, circularity, sustainability and digital skills across organisations and ecosystems	• Improved implementation capability • Better cross-functional collaboration • Stronger adaptive capacity	• Training and transition costs • Capability gaps and change resistance
7. Adopt system-level governance and coordination		
Align circularity, digitalisation and sustainability objectives across actors and the industry	• Simultaneous economic, environmental and social value creation • Greater resilience and scalability	• Governance complexity • Potentially conflicting stakeholder objectives or sustainability goals and rebound risks

2.2.4 Call for Action

Manufacturers should treat sustainable circular supply chains and manufacturing systems as an extensive system transformation where objectives and operation modes drastically change to cover economic, environmental and societal aspects.

Managers should adopt a systems perspective when developing sustainable supply chains and manufacturing systems. Rather than focusing solely on individual technologies or isolated sustainability initiatives, they should align circular manufacturing approaches, digital technologies, business objectives, and sustainability goals across organisational boundaries. Success depends on effective collaboration, data sharing, and coordination among supply-chain partners and other stakeholders to enable resource circulation, create business value, and achieve environmental and societal benefits simultaneously.

Supply-chain and industry actors should establish shared data models, interfaces, quality criteria and cost- and value-sharing mechanisms. Collaborative actions within the chain and the system should enable design, production, use, recovery and reprocessing of materials and products. Discontinuities in material and data flows should become visible before scaling. Special attention is needed to ensure that smaller partners can participate in such development initiatives without disproportionate technology or reporting burdens.

Policymakers and public bodies should align circularity, climate, digital, industrial and workforce policies. Effective steering can combine harmonised interoperability and environmental standards, support for shared infrastructures and competence development, incentives for recovery and lifetime extension, and safeguards for cybersecurity, privacy, employment and fair access. Regulation should reward measurable system-level outcomes rather than reporting activity alone.

Most crucial is to understand that sustainable supply chains and manufacturing systems are achieved only when resource-efficient designs, circular and sustainable operations throughout lifecycle stages and involved supply chain and manufacturing system actors are connected, when economic, environmental and social objectives are included in optimisation, and when efficiency gains do not translate into more material and energy use.

Efficiency gains may also create rebounds. Lower processing costs, faster production or cheaper circular products can stimulate additional production and demand, partly offsetting reductions in resource and energy use. The managerial task is therefore to redesign the system so that data, operations around material flows, business models and chain coordination consistently support sustainability and circular decisions and circular physical action.

2.3 Human-Centric Supply Chains and Manufacturing Systems Trends

"Human-centricity changes what manufacturing is designed to achieve and how industrial decisions are made".

Human-centricity makes human capability, wellbeing, safety, agency, inclusion and fair labour conditions explicit requirements of supply networks and manufacturing systems, alongside established objectives such as cost, quality and delivery. This shifts people from being treated primarily as labour inputs to being recognised as a source of capability whose availability, skills and willingness to participate increasingly determine whether industrial strategies can be executed. On the market-facing side, the same principle extends to whether products respond to individual needs through accessibility, adaptability and personalisation.

This shift reaches beyond individual technologies or workplace initiatives. A production system may deliver good jobs or useful products under favourable local management without having been designed to do so. Human-centricity requires these outcomes to be considered when decisions are made about locations, suppliers, automation, work organisation, skills, data and equipment. It therefore links strategic choices that have traditionally been separated across operations, human resources, procurement and technology functions.

The significance of this shift is increasing because the external environment is making human capability harder to secure and more consequential to lose. Demographic change is altering workforce availability and physical capability; technological change is redistributing tasks and decision rights; regulation is placing stronger requirements on labour conditions, workplace technologies and accessibility; and climate change is changing the physical conditions under which industrial work can be performed. At the same time, production geography is being reconsidered under geopolitical pressure, exposing firms to new combinations of labour availability, skills and working conditions. Human-centricity is therefore becoming a practical condition for maintaining productive capacity and legitimacy rather than a discretionary social objective.

Section 2.3.1 examines the geopolitical, economic, social, technological, legal and environmental forces creating the need for more human-centric production. Sections 2.3.2 and 2.3.3 then consider how those pressures affect people, processes and technology, first across supply networks and then within manufacturing systems. Section 2.3.4 translates these findings into priorities for manufacturers, policymakers and other stakeholders.

2.3.1 Global Trends Calling for Human-Centricity

Manufacturers must be able to attract, develop, protect and retain the people on whom their production systems depend. Human consequences that were once absorbed through recruitment, local management or supplier substitution increasingly reappear as capacity shortages, failed technology adoption, market exclusion and legal exposure. This makes workforce conditions and human capability design parameters that need to be considered before networks, plants and technologies are fixed.

Geopolitical Trends

The reconfiguration of production geography is also a reconfiguration of labour. Government interventions in labour markets, including localisation requirements and restrictions on migration and visas, now directly affect manufacturers' ability to staff operations. Senior people executives already place such interventions among the geopolitical developments with the most immediate workforce consequences[1]. Location decisions themselves are influenced by labour regulation and skills availability. OECD evidence shows that firms have offshored partly in response to labour-protection and collective-bargaining requirements, while lack of qualified workers at home is also a significant driver of relocation[2].

Efforts to bring production closer to end markets do not automatically rebuild domestic employment. Reshoring remains limited and is frequently planned together with automation, reducing the number of jobs created and changing the capabilities those jobs require[2]. At the same time, diversification of supply can improve continuity without improving labour conditions. In critical-mineral supply chains, countries supplying similar materials can differ dramatically in informal employment and social-security coverage, with the greatest vulnerabilities often concentrated in lower tiers and artisanal operations[3]. Production geography must therefore be assessed as a human-capability and labour-conditions decision as well as a cost and security decision.

Economic Trends

The economic case for human-centricity is strengthening as labour scarcity collides with the legacy of efficiency-led transformation. Digitalisation has raised productivity, yet research also identifies weaker social outcomes at firm and network level and a shift in employment towards higher-paid occupations at the expense of many lower-skilled and middle-wage roles[4]. These changes leave manufacturers more dependent on scarce capabilities while increasing the importance of how technology affects job quality, security and progression.

Working conditions can consequently become a direct constraint on industrial capacity. Garment manufacturing provides a clear example: low pay, insecure employment, limited training and concerns over exploitative labour practices have discouraged younger entrants and complicated efforts to rebuild production in higher-cost locations[5]. More broadly, poor labour conditions can remain economically embedded because exploitation itself generates significant returns, including within industrial activity[6]. Human-centric investment therefore has to be understood in economic terms as well as social ones. Evidence that operator-centred predictive maintenance can achieve an attractive payback illustrates that productivity and human oversight can reinforce one another when both are considered in the investment case[7].

Social Trends

Manufacturing systems are increasingly out of step with the workforce available to operate them. Ageing populations and longer working lives make assumptions about physical load, work pace and workstation design more consequential[8]. At the same time, human-centric manufacturing has often given more attention to ergonomics and technology use than to management practices and worker voice[9]. As labour becomes harder to secure, system design must accommodate workforce variation and give workers meaningful influence over changes that affect their tasks and responsibilities.

Technological Trends

Automation is changing the role of people in production rather than removing the human dimension from manufacturing. Successive industrial transitions have enabled factories to produce more with fewer workers, and current trajectories continue that pattern[10]. The remaining human contribution is therefore shifting towards activities such as judgement, exception handling, learning and the setting and oversight of system objectives. As this shift continues, human-centricity becomes less about keeping people physically involved in every production task and more about ensuring that automated systems are designed around appropriate human oversight, judgement, responsibility and control.

AI, collaborative robotics and digital twins intensify this challenge because their adoption creates new demands for reskilling, governance and organisational readiness, particularly for smaller manufacturers with limited specialist capacity[11]. Technology can change both the skills required and the terms under which those skills are exercised. Its value will increasingly depend on whether manufacturers can develop the capabilities needed to use it effectively while retaining appropriate human authority over consequential decisions.

Legal Trends

Regulation is turning several elements of human-centricity into explicit design obligations. Under the EU Artificial Intelligence Act, employers deploying certain high-risk AI systems in the workplace must inform affected workers and their representatives and assign human oversight to people with the competence, training and authority required to perform that role[12]. Human oversight therefore has organisational consequences: it affects staffing, training and decision rights before the system enters operation.

Legal exposure is also extending through supply chains and towards the end user. Regulation (EU) 2024/3015 prohibits products made with forced labour from being placed on the EU market, irrespective of sector or origin, making labour conditions beyond the immediate firm relevant to market access[13]. On the customer side, the European Accessibility Act places obligations on manufacturers to design products in accordance with applicable accessibility requirements and to document conformity[14].

Environmental Trends

Climate change is altering the physical conditions under which industrial work is performed. The International Labour Organization (ILO) estimates that around 2.4 billion workers are likely to face excessive heat at work, with consequences for injury, mortality and healthy working life[15]. For manufacturers, heat exposure increasingly affects work patterns, facility design and sustained workforce performance.

Circular production can also increase reliance on skilled human labour. Inspection, disassembly, repair and testing involve uncertain product conditions and variable task sequences, making operator skills and health increasingly relevant to system performance[16]. Circularity therefore strengthens the case for production systems that can sustain safe, skilled and adaptable human work.

Taken together, these pressures change the strategic role of human-centricity. Workforce availability, capability, working conditions and human oversight increasingly affect whether manufacturers can locate production, adopt technology, maintain market access and sustain productive capacity. Table 2.4 summarises how the main external pressures translate into human-centric design requirements. Figure 2.3 summarises how the main external pressures translate into human-centric requirements.

Table 2.4. External pressures making human-centricity strategically necessary

External pressure	What is changing	Human-centric significance for manufacturing
Geopolitical	Production locations, migration regimes and supply relationships are being reconsidered.	Location and sourcing decisions increasingly depend on labour availability, skills and working conditions as well as cost and security.
Economic	Labour scarcity is increasing while digitalisation changes the composition and quality of work.	Poor working conditions can constrain capacity, while investment in human capability can support productivity and technology adoption.
Social	Workforces are ageing and becoming more varied in physical capability and expectations.	Production systems need to accommodate workforce variation and give workers greater influence over changes affecting their work.
Technological	Automation is redistributing tasks towards judgement, exception handling and system oversight.	Human capability increasingly centres on skills, responsibility and appropriate authority over consequential decisions.
Legal	Regulation is extending requirements relating to workplace AI, labour conditions and accessibility.	Human oversight, labour conditions and inclusive product design are becoming matters of compliance and market access.
Environmental	Heat exposure is affecting working conditions while circular production creates more variable tasks.	Manufacturing systems must sustain safe human performance and adaptable skilled work under changing operating conditions.

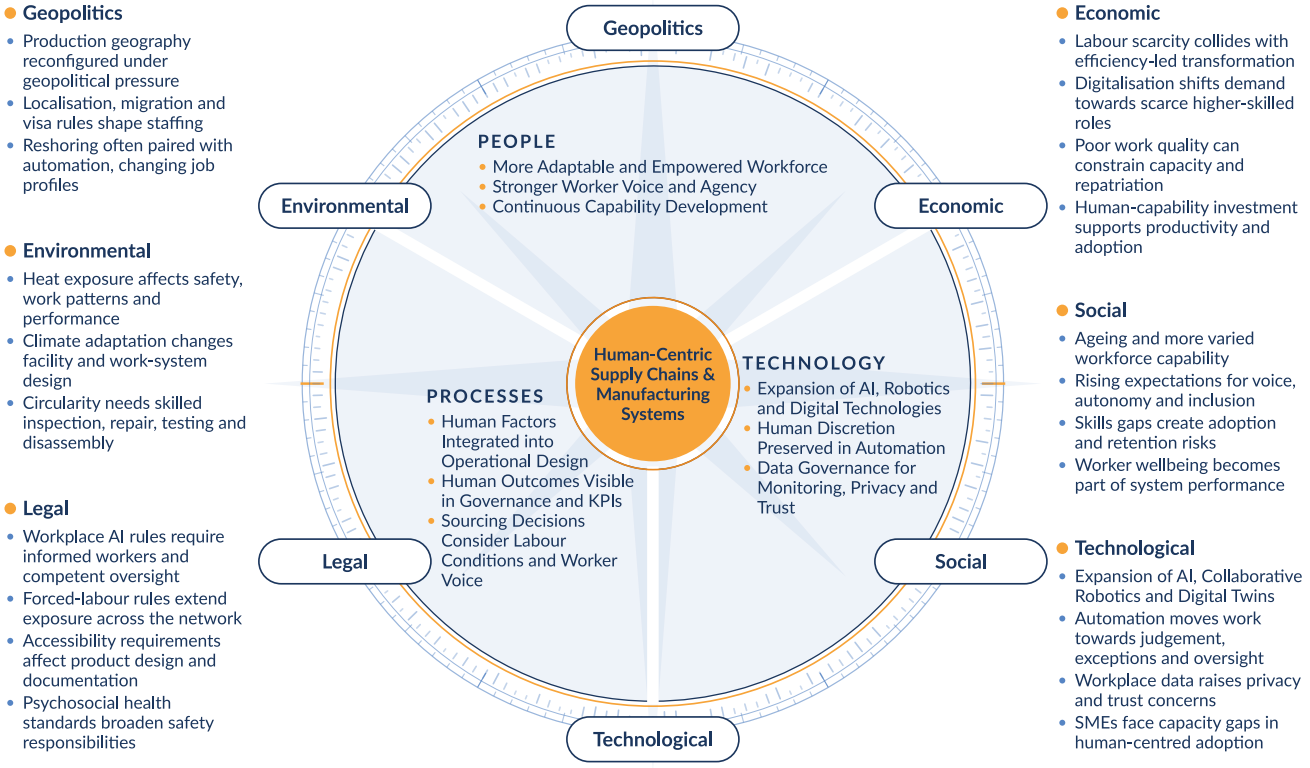


Figure 2.3. WMF's Trends Compass for Human-Centric Supply Chains and Manufacturing Systems

2.3.2 Trends Impacting Supply Chains (Re-)Design

Human-centric supply-chain redesign expands the unit of analysis from the focal firm to the network. Manufacturers can improve conditions within their own operations while commercial and operating decisions continue to shape work elsewhere in the network. The design question is therefore how labour conditions, workload and decision authority are affected across organisational boundaries, alongside cost and service.

Impact on People

The supply-chain workforce includes people employed by suppliers, logistics providers and other partners, often under conditions that the focal manufacturer influences only indirectly. Human-centric practices tend to weaken with distance from the focal firm: basic requirements such as health and safety, working hours and pay are easier to transmit through supplier standards than rights that depend on worker agency, including freedom of association and non-discrimination[17]. Risks are also concentrated in lower tiers and small-scale operations, where informality and weak social dialogue can make conventional supplier governance less effective[18].

This limits what supplier codes and audits can achieve on their own. Evidence reviewed by Vandenbroucke suggests that worker representation is associated with faster improvement in audited labour practices, while ILO guidance on living wages similarly emphasises social dialogue and collective bargaining[17,19]. Human-centric supply-chain design therefore needs to consider worker voice and the quality of supplier relationships alongside formal compliance when suppliers are selected, contracted and managed.

Impact on Processes

Human-centric practices do not automatically spread through a supply network and may remain confined to the organisations that introduce them unless they are incorporated into inter-firm processes[20]. This makes purchasing and coordination choices part of the human-centric design problem. Commercial decisions can shape the conditions under which suppliers operate, so social-risk information needs to inform supplier management and operating decisions rather than sit in a separate compliance process.

Greater personalisation and responsiveness add another source of network complexity. Modular products, postponement and flexible production can move differentiation closer to the customer, while increasing the variety and information that the network must manage[21]. The design implication is to contain unnecessary complexity through product and fulfilment architecture rather than assuming that each additional customer requirement can be absorbed elsewhere in the network.

Impact on Technology

Digital visibility, automated planning and decision support make technology architecture inseparable from decision architecture. Their human consequence depends on what information is collected, how it is used and where authority remains when automated systems influence operational choices. For relevant high-risk AI systems, the EU Artificial Intelligence Act makes this explicit by requiring human oversight by people with the necessary competence, training and authority[12].

For supply-chain redesign, the principle is to preserve meaningful human discretion where contextual judgement matters. Automation can support routine coordination and information processing, but roles, interfaces and governance need to ensure that workers, planners and partners can still influence decisions when local knowledge or exceptional conditions make automated responses insufficient.

2.3.3 Trends Impacting Manufacturing Systems (Re-)Design

Manufacturing-system design is where human-centricity becomes operational. Decisions about task allocation, line balancing, interfaces, automation, data capture and performance targets determine how technological change affects people at work. Manufacturing has progressed furthest where human needs can be translated into technical requirements, particularly physical safety and ergonomics. Needs linked to participation, autonomy, recognition and development depend more heavily on how work and human-machine relationships are organised and remain less systematically addressed[22].

The scope of human-centric system design is therefore expanding as the relationship between people and technology changes. As automation takes on more routine execution, manufacturing systems increasingly need to support human participation, capability development, judgement and appropriate decision authority alongside established requirements for safety and health[9,22,24]. Figure 2.4 summarises this broader design challenge and the people, process and technology dimensions through which it must be addressed.

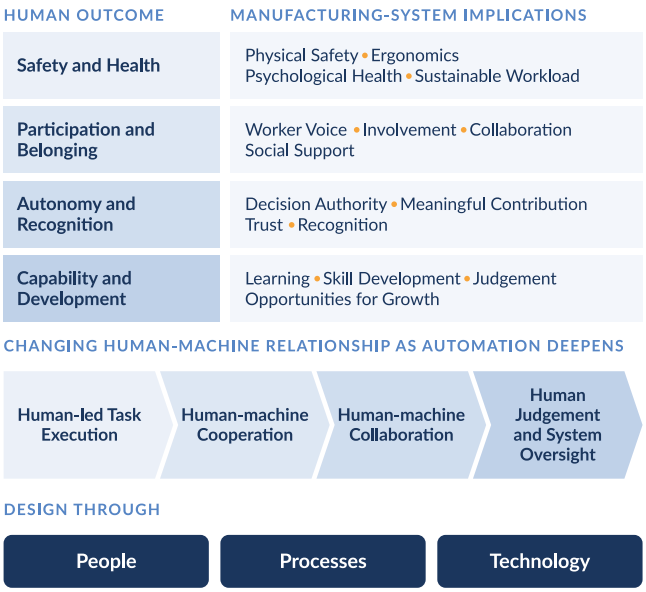


Figure 2.4. Expanding the scope of human-centric manufacturing-system design

Impact on People

The workforce can no longer be treated as a standardised input to an otherwise optimised production system. Manufacturing systems increasingly need to accommodate variation in physical capability, experience and digital familiarity while enabling people to contribute knowledge that formal process specifications rarely capture. Operators understand recurring variability and workarounds, while maintenance and safety personnel often identify failure modes that become visible only in operation. Involving these groups before layouts, interfaces and equipment choices are fixed can improve both system design and its acceptance[23].

This requires a shift in organisational maturity alongside technological maturity. Evidence from manufacturing firms in Lombardy illustrates the imbalance: automation received greater investment priority than safety and ergonomics across firm sizes, while reported barriers to human-facing technologies included implementation time, cost, workforce scepticism and limited internal competence[24]. Digitalisation can therefore advance faster than the organisational capabilities required to make it human-centric. A plant may have sophisticated equipment

while still relying on work structures, skills systems and performance assumptions designed for an earlier production model.

Learning consequently becomes part of manufacturing-system capacity. As automation absorbs routine tasks, human work can become more concentrated in exceptions, diagnosis and recovery, increasing the value of judgement even where direct manual activity declines. However, firms face tensions in building that capability. SME focus groups identified training as a way to close competence gaps and reduce fears of technological replacement, while also raising concerns about employee retention and wage expectations once skills improve[25]. For system design, the implication is that workforce capability cannot be assumed to appear alongside new technology. Learning time, supervised practice and opportunities to retain operational knowledge need to be considered alongside equipment capacity when determining whether a production system can perform as intended.

Impact on Processes

Human-centric process design brings worker demands into operational optimisation rather than assessing them after the process has been fixed. In high-variety replenishment and picking, one study reduced ergonomic risk by 8 to 50 per cent while also cutting operating time by 9 to 35 per cent compared with alternative allocation schemes[26]. The broader implication is that physical and cognitive demands can be treated as design variables alongside throughput and cost.

Production planning is moving in the same direction. Conventional scheduling often represents human capacity through static assumptions even though proficiency, fatigue and availability vary during execution. Real-time approaches that synchronise plans with observed human capacity have improved punctuality with limited effects on unit cost[27]. This creates a parallel governance requirement: information used to adapt work to human capability should not become unrestricted individual monitoring.

Human-centric process performance also extends occupational health beyond physical injury. ISO 45003 includes psychosocial factors such as workload, autonomy and social support within occupational health and safety management[28]. Throughput and quality therefore remain fundamental measures, but they are incomplete if improvements depend on work arrangements that cannot be sustained.

Impact on Technology

Assistive technologies need to be evaluated through their effects on the complete work system rather than through technical capability alone. Collaborative robots, augmented interfaces, wearables and exoskeletons may reduce particular demands while introducing new requirements for attention, coordination or trust. A 2024 systematic review of industrial exoskeletons reported reductions in measured muscular load, but also found that most evidence came from laboratory studies and that user discomfort remained a recurring issue[29]. This supports evaluating technologies under realistic operating conditions before assuming that technical performance will translate into better work.

The growing ability to sense worker state also makes data governance part of manufacturing-system design. Posture can be assessed against occupational standards using sensing approaches designed to avoid personal identification[30]. Regulation adds a further constraint: under the EU Artificial Intelligence Act, employers deploying relevant high-risk AI systems in the workplace must inform affected workers and their representatives before use[12].

Across these trends, manufacturing-system redesign increasingly depends on treating human capability, work organisation and technology as connected design variables. High performance will depend on equipment capability and on whether the surrounding work system supports sustainable performance and appropriate human judgement, with proportionate use of worker data.

2.3.4 Call for Action

Human-centricity now needs to move from principle into the mechanisms through which industrial decisions are made. Human outcomes should become an explicit dimension of organisational readiness, investment and system design, alongside operational and digital performance. This requires consideration of workload, capability, decision authority and inclusion before choices about technology and work organisation become difficult to reverse. Evidence from manufacturing practice suggests that limited measurement and insufficient consideration of human-centric choices during design remain barriers to wider adoption[31]. Table 2.5 summarises the main priorities and the actors responsible for advancing them.

Table 2.5. Priorities for embedding human-centricity

Priority	What needs to change	Principal actors
Make human outcomes visible in governance.	Assess distinct dimensions such as workload, capability, autonomy and inclusion alongside operational and digital performance.	Manufacturers
Integrate human consequences into investment decisions.	Consider workload, skills, decision authority, workforce development and job redesign before capital and automation choices are fixed.	Manufacturers
Involve users before system requirements are fixed.	Give operators, maintenance personnel and other affected groups meaningful influence over equipment, interfaces, information and performance requirements.	Manufacturers and technology providers
Treat capability development as production infrastructure.	Provide continued learning, supervised practice and mechanisms for retaining operational knowledge as technology and jobs change.	Manufacturers, policymakers and education providers
Extend capability development beyond leading firms.	Build sectoral and public provision that can reach smaller manufacturers, suppliers and mobile workers.	Policymakers, industry bodies and education providers
Strengthen evidence for human-centric design choices.	Improve measurement of less developed human outcomes and build evidence on when different organisational and technological interventions succeed or fail.	Research institutions, education providers and industry

Workforce capability is one area where action cannot remain within individual firms. Employers identify skills gaps as the largest barrier to business transformation across 52 of the 55 economies covered by the World Economic Forum's 2025 assessment[32]. Manufacturers therefore need to treat continued learning as part of the operating model, while public, sectoral and education provision extends capability development to smaller manufacturers, suppliers and workers moving between employers. This becomes particularly significant where industrial strategies depend on developing domestic productive capability[33].

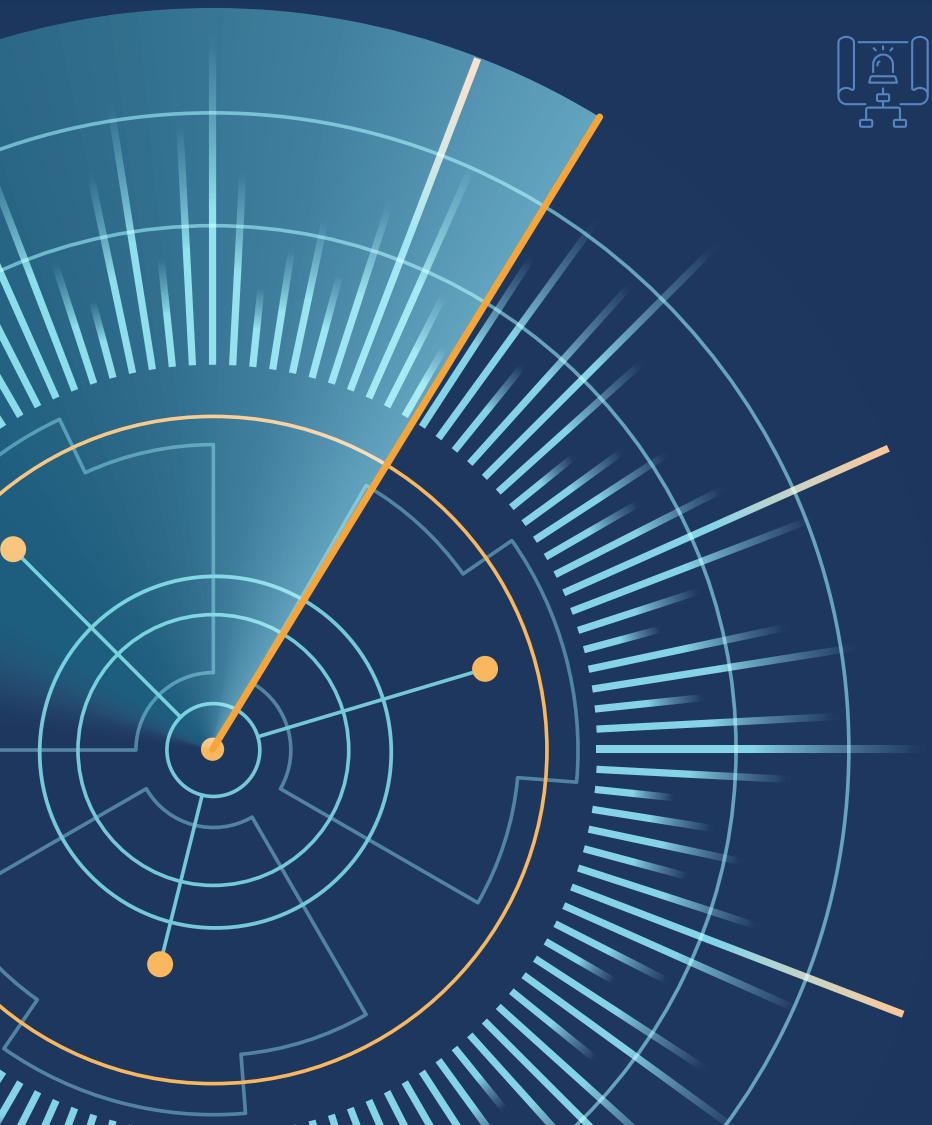
Research and education institutions have a complementary role in improving the evidence available for these decisions. Human outcomes that are harder to measure can receive less attention than productivity, safety or technical performance. Better measures are needed for dimensions such as autonomy, belonging and opportunities for development, together with practical evidence on how different technologies and forms of work organisation affect them. Engineering and manufacturing education should accordingly treat work organisation and the distribution of human discretion as design choices with operational consequences.

The leadership test is whether human outcomes materially influence decisions before technologies and work systems are fixed and remain visible once the system is operating. Human-centricity becomes operational when it changes specifications, investment decisions and the way performance is governed.

03

CHAPTER 3

DETECTING OPPORTUNITIES, CHALLENGES, AND RISKS IN THE FUTURE OF MANUFACTURING



Detecting Opportunities, Challenges, and Risks in the Future of Manufacturing

3.1 Enterprise Wearable Devices & Human-Centred Technologies Technology Radar

3.1.1 State of Play

Manufacturing ecosystems face a dual challenge: an ageing skilled workforce and a steady rise in work-related musculoskeletal disorders (WMSDs). While fixed automation continues to advance, human dexterity, adaptability, and tactile problem-solving remain irreplaceable across discrete assembly lines, intralogistics replenishment, and specialised heavy maintenance.

In this context, the human-centric principles of Industry 5.0 require technologies that place workers at the heart of production. Enterprise Wearable Devices (EWDs) and wearable robotics, ranging from passive and active exoskeletons to assisted-reality smart glasses, wearable scanners, connected safety devices and physiological monitors, have moved from research laboratories onto the shop floor. Together, these systems address both the physical bottlenecks of manual work (overhead strain, prolonged static postures, high-frequency manual lifting) and its cognitive and informational bottlenecks (complex work instructions, high product variety, scarce expert knowledge and exposure to hazardous environments), all without requiring costly reconfigurations of existing brownfield lines. By combining physical offloading, hands-free access to digital information and real-time physiological and environmental feedback, manufacturers can reduce injury claims, shorten training times and lower error rates while maintaining stable production throughput.

The enterprise wearable landscape can therefore be read along two complementary vectors. The first is physical augmentation, embodied by passive and powered exoskeletons. The second is digital and cognitive augmentation: smart glasses and head-worn displays that deliver step-by-step instructions and remote expertise in the operator's field of view; hand- and wrist-worn devices that capture data without interrupting manual work; and connected sensors embedded in personal protective equipment (PPE), clothing or clip-on modules that monitor posture, vital signs and environmental exposure. A further, still emerging frontier concerns cognitive and neuro-ergonomic wearables that estimate mental workload and fatigue. The market has also matured: enterprise-grade devices designed for industrial environments have replaced early consumer-derived experiments, while Microsoft's decision to end HoloLens 2 production in 2024[1] signalled that immersive mixed-reality headsets are still searching for scalable shop-floor use cases, in contrast with lighter assisted-reality devices already deployed at scale in logistics, maintenance and assembly.

3.1.2 Technological Capabilities for Value Creation Opportunities

Enterprise wearables and human-centred technologies generate real value across industrial workflows. By shifting ergonomics from subjective surveys to measurable physical relief and placing digital information directly in the worker's hands and field of view, these solutions improve operational agility and protect long-term worker health. **Table 3.1** outlines the five core technological capabilities driving this shift, highlighting their primary industrial focus, technical enablers, and quantifiable business value.

Table 3.1. Core Technological Capabilities of Enterprise Wearable Devices & Human-Centred Technologies

Focus	Main Enablers	Value Created
1. Biomechanical Load Redistribution & Strain Offloading		
Passive and quasi-passive joint counterbalancing during repetitive or sustained postures.	• Elastic tendons, progressive spring-cam joints, • lightweight carbon-fiber and textile matrix frames.	• Direct 30%–40% electromyographic (sEMG) strain reduction on vulnerable joints; • Immediate decline in acute WMSD incidence.
2. Dynamic Power Augmentation & Metabolic Support		
Active motorised assistance during dynamic lifting, high-tonnage carrying, and manual material handling.	• Frameless BLDC servomotors, • cycloidal/harmonic speed reducers, • high energy-density pouch Li-ion batteries.	• Up to 30–60% peak lifting assistance; • Reduced cardiac and metabolic cost during continuous intralogistics handling.
3. Real-Time Human Sensing, Intention Detection & Biomechanical Tracking		
Synchronous decoding of operator movement to prevent human-robot control contention, extended to gaze, gesture and voice as natural interfaces for hands-free devices.	• Inertial Measurement Units (IMUs), • Surface EMG arrays, • Pressure-sensing foot insoles, • onboard edge neural decoders, • Eye-tracking cameras and voice/gesture recognition.	• Sub-15 ms control latency, • Fluid motion without gait resistance, • Zero interference with non-assisted tasks.
4. In-Situ Ergonomic, Physiological & Safety Telemetry		
Continuous recording of postural angles, repetitive cycles, and environmental heat/strain indices, plus hazardous gas exposure, lone-worker status and proximity to moving vehicles.	• Embedded flexible strain sensors, • Pulse-oximetry/ECG vitals patches, • Ambient temperature/humidity nodes, • Bluetooth LE/Industrial IoT radios, • Smart PPE (connected helmets, vests, gas detectors) and UWB proximity tags.	• Closed-loop ergonomic risk mapping, • Predictive fatigue intervention, • Real-time alerts for heat stress, gas exposure and man-down events.
5. Hands-Free Contextual Information & Remote Expertise		
Delivery of work instructions, pick lists and live expert support in the operator's field of view or at the wrist, with hands-free data capture.	• Monocular assisted-reality and binocular see-through displays, • Glove- and ring-worn barcode scanners, wrist-worn terminals, • Voice control, computer vision and spatial anchoring, • Wi-Fi 6/private 5G links to MES, WMS and CMMS.	• 15%–25% productivity gains in picking and assembly, • Up to 50% fewer assembly errors, • 50%–70% shorter onboarding; faster remote troubleshooting.

3.1.3 Aligning Capabilities to Technology Categories for Facing Challenges

Passive Wearable Systems: Alleviating Musculoskeletal Fatigue in Repetitive Assembly

Passive exoskeletons utilise calibrated spring-cam mechanisms, elastic bands, and counterbalance linkages to redistribute gravitational loads from vulnerable upper-extremity joints (such as the shoulder and lumbar spine) down to the pelvic girdle and core. Because they operate without external electrical power, batteries, or onboard motors, passive devices achieve high mechanical reliability, zero charging downtime, and lightweight form factors. In high-tempo assembly environments - such as automotive underbody lines, aircraft cabin wiring, and appliance manufacturing - operators perform thousands of repetitive arm flexions and overhead reaches per shift. Passive systems like the Comau MATE-XT and Ottobock Paexo Shoulder provide targeted mechanical assistance precisely at elevated arm angles, counterbalancing the operator's limb weight without restricting freedom of movement during non-overhead tasks.

Extensive empirical evaluations and peer-reviewed trials demonstrate that passive upper-limb exoskeletons achieve an average 34% reduction in anterior deltoid electromyographic (sEMG) activity and an 18% reduction in upper trapezius strain, accompanied by a 30% decrease in subjective perceived physical discomfort (Borg CR10). This substantial reduction in localised muscle fatigue directly translates into fewer micro-pauses, improved manual assembly precision, and lower incidence of chronic rotator cuff tendinitis. Consequently, passive physical support systems represent one of the most mature, immediately deployable wearable technologies in modern discrete manufacturing. Passive back-support and leg-support ("chairless chair") devices extend the same principle to lumbar unloading during palletising and to static semi-crouched postures.



Figure 3.1. MATE-XT: a passive upper-body exoskeleton (Source: COMAU)

Active and Hybrid Powered Exoskeletons: Augmenting Dynamic Load Handling and Logistics

Active exoskeletons integrate electric servomotors, pneumatic artificial muscles, and embedded sensory arrays to provide dynamic, intelligent mechanical power assistance. Unlike purely passive spring mechanisms, active systems dynamically adjust torque output based on real-time kinematic intention detection, load weight, and operator movement velocity. In heavy intralogistics, palletising, component kitting, and heavy machinery maintenance, active lumbar exosuits deliver up to 30 kg of active lifting assistance per movement cycle, effectively shielding the lumbar spine (L5/S1 vertebrae) from acute compressive forces during asymmetric lifting and twisting.

The integration of soft textile exosuits - utilising bowden cable drives and high-strength synthetic tendons - marks a major evolutionary step towards lightweight, unrestrictive wearable robotics. Embedded inertial measurement units (IMUs) and machine learning algorithms analyse operator gait and bending kinematics to deliver assistive power synchronously with natural biological muscle contractions. While challenges remain regarding onboard battery energy density, continuous thermal dissipation, and system cost, active powered exoskeletons provide transformative augmentation in heavy logistics where fully automated robotics cannot navigate dynamic, unstructured factory environments.

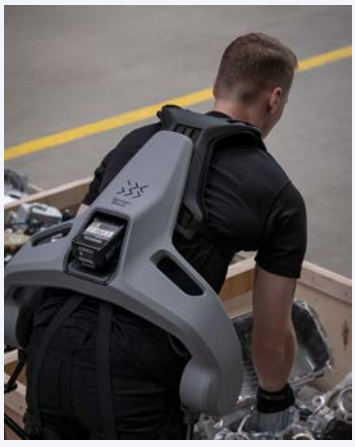


Figure 3.2. Exia: an active upper-body exoskeleton (Source: German Bionic)

Hybrid & Multi-Joint Wearable Systems: Adaptive Variable-Resistance Co-Workers

Hybrid wearable robotics combine passive mechanical counterbalances (handling basal structural load without power draw) with low-inertia electromechanical micro-actuators that provide on-demand impulse assistance during peak exertion. Guided by multi-sensor fusion (IMU arrays and onboard machine learning decoders), hybrid systems dynamically detect whether an operator is walking, stooping, lifting, or holding a static pose. This delivers an optimised trade-off: preserving battery life across full 8-hour production shifts while eliminating the physical restriction ("device fighting") common to purely active or purely passive suits.

Hands-Free Information & Interaction Wearables: Smart Glasses, Wrist-Worn Terminals and Wearable Scanners

A second family of enterprise wearables augments workers digitally rather than physically. Monocular assisted-reality devices and lightweight binocular smart glasses project work instructions, checklists, pick lists and drawings into the operator's field of view and are controlled by voice, so that both hands remain on the task. In vision picking, DHL reported a 15% productivity increase, error rates reduced to 0.1% and 50–70% shorter onboarding times[2]; in aerospace wire-harness assembly, Boeing reported a 25% reduction in production time and halved error rates after replacing screen-based instructions with smart glasses[3]. Remote expert assistance - in which a technician streams a first-person view to an off-site specialist who annotates it in real time - has become the most widespread use case in maintenance, commissioning and quality inspection, reducing expert travel and mean time to repair.

Hand- and wrist-worn devices complete this category. Wearable barcode scanners integrated into gloves or worn as rings remove the need to pick up and put down handheld scanners: a Fraunhofer IPA pilot study measured an 11.5% speed advantage in shelf picking and lower wrist flexion and extension compared with ring and handheld alternatives[4]. Ruggedised wrist-worn terminals and smartwatches deliver task notifications, andon calls and machine alarms directly to the operator. Binocular mixed-reality headsets for immersive training, design review and spatially anchored guidance remain promising but less mature on the shop floor: weight, battery life, field of view and visual fatigue still limit full-shift use, and the next generation is expected to converge with lighter, AI-enabled glasses combining computer vision and multimodal assistants.

Connected Safety & Ergonomic Monitoring Wearables: From Reactive PPE to Predictive Prevention

Connected safety wearables embed sensors and connectivity into PPE and clip-on modules: gas detectors and lone-worker devices with automatic man-down and fall detection, smart helmets and vests, ultra-wideband proximity tags that warn pedestrians and forklift drivers of imminent collisions, and heat-stress monitors that estimate core body temperature from heart rate and skin temperature. These devices are already widely deployed in process industries, metals, energy and logistics, and are increasingly integrated into plant safety systems and EHS dashboards. Standardisation is progressing, with CEN/TR 17512 establishing common terminology for smart PPE garments[5], while Regulation (EU) 2016/425 governs the conformity assessment of PPE that integrates electronic components.

Ergonomic motion-sensing wearables - small inertial devices worn on the hip, back or upper arm, or sensorised garments - record postures, bending and twisting events and repetitive movements, and provide immediate haptic feedback when a high-risk movement occurs. An actuarial analysis covering more than 15 million hours worked, including 2.1 million hours of device use, reported a 50–60% reduction in injury frequency and a 72% reduction in lost workdays among users of this type of feedback wearable[6]. Aggregated and anonymised, the same data feed objective ergonomic risk maps that guide workstation redesign and identify where exoskeletons offer the greatest return, linking this category directly with the physical-augmentation categories described above.

Cognitive & Neuro-Ergonomic Wearables: Measuring Mental Workload in Human-Centred Production

As production becomes more variable and operators increasingly supervise automated systems and collaborative robots, cognitive load becomes as critical as physical load. Cognitive and neuro-ergonomic wearables - dry-electrode EEG headbands and in-ear sensors, eye-tracking glasses and heart-rate-variability and electrodermal-activity sensors - aim to estimate mental workload, attention and fatigue in real time. In research and pilot settings, these signals are used to adapt the pace of collaborative robots, to tailor the level of detail of AR instructions to the operator's expertise, and to schedule breaks before attention-related errors occur.

The category remains at an early stage. Signal quality in noisy industrial environments, inter-individual variability and the lack of validated industrial benchmarks limit reliability, and the ethical and regulatory bar is high: under the EU AI Act, AI systems that infer the emotions of natural persons in the workplace are prohibited except for medical or safety reasons[7], and neural data are increasingly treated as a particularly sensitive category of personal data. Its strategic potential is nonetheless considerable, as it provides the missing measurement layer for truly adaptive, human-centred Industry 5.0 work systems.

3.1.4 Technology Radar Reading

Navigating Maturity, Strategic Impact, and Mainstream Adoption Timelines Across Enterprise Wearables and Human-Centred Technologies.

The WMF Enterprise Wearable Devices & Human-Centred Technologies Radar (Figure 3.3 and Table 3.2) maps five technology categories along two core axes, Industrial Technology Readiness and Strategic Impact, while point colour and growth-stage icons indicate industrial adoption maturity and time to mainstream adoption. Connected Safety & Ergonomic Monitoring Wearables (Point 4) occupy the mature, high-impact region: gas detection, lone-worker and proximity devices are already standard in many plants, and posture-feedback and heat-stress wearables are scaling quickly, with mainstream adoption expected within two years. Passive Exoskeletons (Point 1) and Hands-Free Information & Interaction Wearables (Point 3) also show high industrial readiness and High strategic impact. Backed by extensive deployments in automotive overhead lines, aerospace, logistics hubs and field maintenance, they are expected to reach mainstream adoption within 2 to 5 years, with rapid payback driven by fewer musculoskeletal claims, shorter training times and lower error rates.

Towards the centre and the left of the radar, Active and Hybrid Powered Exoskeletons (Point 2) combine Very High strategic impact with a still-growing level of readiness: as lightweight high-density batteries, compact actuators and musculoskeletal intent decoders mature, they are expected to move from specialised logistics and maintenance pilots to broader adoption within 3 to 7 years. Cognitive & Neuro-Ergonomic Wearables (Point 5) represent the seed-stage frontier: technology readiness is still emerging, but their potential to make production systems adaptive to the operator's mental state gives them High strategic

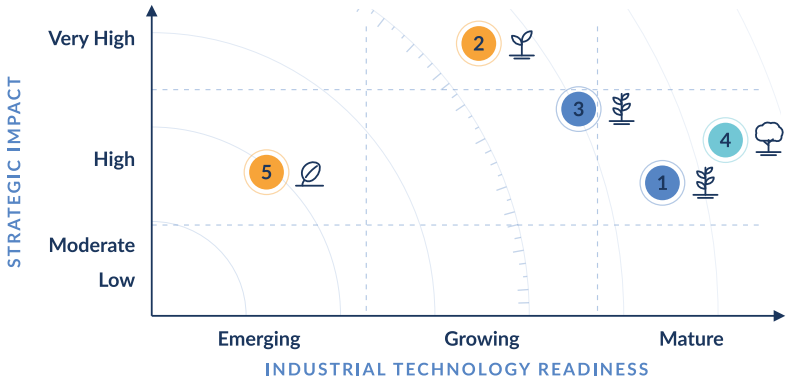
impact over a 5- to 10-year horizon, conditional on robust validation and clear ethical and regulatory safeguards. Overall, the radar shows that the greatest near-term value lies in combining physical and digital augmentation - for example, using ergonomic telemetry to target exoskeleton deployment and smart glasses to guide complex manual tasks.

3.1.5 Call for Action & Risk Management

To capture the full economic and human potential of enterprise wearables while mitigating implementation risks, industrial stakeholders must coordinate across organisational, technical, and regulatory dimensions:

- For Manufacturing Leaders & Operations Executives: Transition from viewing wearables - exoskeletons, smart glasses, and connected PPE alike - as reactive personal protective equipment (PPE) or isolated gadgets to treating them as strategic cyber-physical assets for workforce empowerment and retention. Implement early human-in-the-loop co-design and testing initiatives involving shop-floor operators, safety managers, and union representatives from day one to cultivate psychological ownership, eliminate adoption resistance, and avoid non-customised sizing issues. Define comprehensive ROI models that account for indirect quality improvements, reduced scrap rates, lower absenteeism, and sustained craftsperson retention alongside direct WMSD compensation reductions. Start from objective ergonomic and safety data to prioritise where physical augmentation, hands-free guidance or safety monitoring delivers the highest value, and scale proven use cases rather than individual devices.
- For Technology Providers & System Integrators: Prioritise anthropometric adjustability, breathable lightweight materials (e.g., aerospace carbon-fibre composites and antimicrobially treated technical textiles), and true biomechanical transparency to minimise inertial drag. Ensure open digital interoperability by adopting standard industrial IoT interfaces (e.g., OPC UA, MQTT) that allow active telemetry and usage cycles to feed seamlessly into Manufacturing Execution Systems (MES) and plant-wide ERP dashboards without creating proprietary software lock-ins. For smart glasses and hand-worn devices, prioritise full-shift battery life, readability under industrial lighting, compatibility with safety eyewear and hearing protection, and low-code authoring tools that let process engineers turn existing work instructions into AR guidance.
- For Policymakers, Standard Bodies & Unions: Accelerate international harmonisation of active and passive exoskeleton performance, ergonomics, and functional safety standards (such as ISO 13482, ISO 18646, and the ASTM F48 Committee on Exoskeletons and Exosuits), and extend this effort to smart PPE (building on CEN/TR 17512 and Regulation (EU) 2016/425) and to head-worn displays. Enforce clear ethical guidelines and data governance architectures (e.g., strict GDPR/workplace privacy compliance) that mandate the decoupling of anonymised ergonomic strain metrics from individual worker health records, guaranteeing that onboard sensor telemetry serves exclusively to prevent physical injury rather than enforce punitive micro-surveillance. Clarify the boundaries set by the EU AI Act, which prohibits workplace emotion recognition except for medical or safety reasons, and treat physiological and neural data as sensitive data subject to explicit worker consultation.
- Comprehensive Risk Management: Mitigate critical biomechanical risks - particularly unintended joint load-shifting (e.g., relieving shoulder strain while exacerbating compensatory lumbar loading) and gait-tripping hazards in active lower-body units. Enforce structured workstation ergonomic assessments, maximum payload thresholds, modular battery thermal safeguards, and standardised sanitisation protocols for multi-operator shift rotations to guarantee sustainable, long-term human augmentation across frontline production environments. For digital and sensing wearables, address visual fatigue and cybersickness from head-worn displays, loss of situational awareness in areas with moving vehicles, the cybersecurity of connected devices, and over-reliance on algorithmic alerts that may erode workers' own risk perception.

WMF's Enterprise Wearable Devices & Human-Centred Technologies Technology Radar



Top 5 Technology Categories

1. **Passive Exoskeletons**
   Spring-based unpowered exoskeletons for upper-body and back/lower-body support.
2. **Active & Hybrid Powered Exoskeletons**
   Motorised or hybrid exoskeletons providing adaptive, on-demand strength assistance.
3. **Hands-Free Information & Interaction Wearables**
   Smart glasses, wrist-worn terminals and wearable scanners for hands-free guidance.
4. **Connected Safety & Ergonomic Monitoring Wearables**
   Smart PPE and sensors monitoring posture, vital signs and hazardous exposure.
5. **Cognitive & Neuro-Ergonomic Wearables**
   EEG, eye-tracking and HRV wearables estimating mental workload and fatigue.

Industrial Adoption Stage

- **Mature**
  Ready for broad adoption and scaling
- **Growing**
  Early adoption and expanding capability
- **Emerging**
  Early-stage technologies with high potential

Time Horizon to Mainstream Adoption

- **Mature: Current to 2 years**
  Already adopted in many industrial use cases
- **Growing: 2 to 5 years**
  Scaling across multiple manufacturing industries
- **Emerging: 3 to 7 years**
  Pilot to early adoption at scale in the manufacturing sector
- **Seed: 5 to 10 years**
  Emerging with long-term potential for the manufacturing sector

Radar Guide

- Position indicates the Industrial Technology Readiness (x-axis) and Strategic Impact (y-axis).
- Point colour indicates the current Industrial Adoption Stage.
- Growth-stage icon represents the estimated Time Horizon to Mainstream Adoption.

Figure 3.3. WMF's Enterprise Wearable Devices & Human-Centred Technologies Technology Radar

Table 3.2. WMF's Enterprise Wearable Devices & Human-Centred Technologies Technology Matrix

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
 1. **Passive Exoskeletons (Upper- & Lower-Body)**	• Spring-cam counterbalance joints and elastic tendons • Gas-spring / elastomer torsion hinges for back support • Chairless-sitting variable locking knee clutches • Breathable lightweight composite frames	• Overhead automotive chassis wiring and assembly • Aircraft fuselage riveting & aerospace manufacturing • Manual palletising and static semi-crouched tasks	• Reduced musculoskeletal strain and injury risks in repetitive manual tasks, improving worker wellbeing and supporting workforce retention.	**Growing (2026)** 2 to 5 years (2028–2031)	• Biomechanical load shifting to unassisted joints • Thermal discomfort and pressure points in long shifts • Operator resistance if sizing is non-customised	• Standardise biomechanical fitting and training • Integrate regular ergonomic rotation schedules • Mandate operator co-selection in pilot phases
 2. **Active & Hybrid Powered Exoskeletons**	• Frameless BLDC motors with cycloidal/harmonic drives • IMU, sEMG and foot-insole sensor-fusion intent prediction • Passive spring baselines with electro-clutch micro-boost • High energy-density swappable Li-ion packs	• Heavy lifting in logistics, kitting and palletising • High-payload tool handling in foundry, forging and maintenance • Shipbuilding and heavy-equipment weld-and-carry tasks	• Enhanced human physical capabilities in demanding tasks, reducing biomechanical loads and enabling safer handling of heavy equipment and materials.	**Emerging (2026)** 3 to 7 years (2029–2033)	• System mass, battery burden and thermal safety • Control latency and torque spikes causing device fighting or falls • High CapEx, calibration and maintenance overhead	• Standardise ISO 18646 / ASTM F48 active safety benchmarks • Develop modular quick-swap battery architectures • Run multi-site cross-industry pilot benchmarks
 3. **Hands-Free Information & Interaction Wearables**	• Monocular assisted-reality and binocular MR displays • Voice control, computer vision and spatial anchoring • Glove/ring barcode scanners and wrist-worn terminals • Wi-Fi 6 / private 5G integration with MES, WMS, CMMS	• Vision picking and kitting • Step-by-step assembly guidance and quality inspection • Remote expert assistance for maintenance and commissioning	• Improved operational productivity and task accuracy through real-time, hands-free access to instructions, information and remote expertise.	**Growing (2026)** 2 to 5 years (2028–2031)	• Visual fatigue, weight and limited battery life over full shifts • Costly content creation and legacy-system integration • Perceived surveillance through cameras and activity tracking	• Prioritise use cases with measurable error and training costs • Adopt low-code authoring linked to existing work instructions • Define clear camera and data-use policies with workers
 4. **Connected Safety & Ergonomic Monitoring Wearables**	• IMU posture sensors with haptic feedback • Heat-stress and vital-sign sensors (HR, skin temperature) • Smart PPE: connected gas detectors, helmets, vests • UWB / BLE proximity and man-down detection	• Ergonomic risk mapping in assembly and warehousing • Lone-worker, gas and heat-stress protection in process industries • Pedestrian–forklift collision avoidance	• Proactive prevention of occupational injuries and hazardous exposure through continuous monitoring, early warnings and data-driven ergonomic interventions.	**Mature (2026)** Current to 2 years (2026–2028)	• Worker privacy and misuse of data for performance control • Alarm fatigue from false positives • Fragmented, non-interoperable vendor platforms	• Anonymise and aggregate ergonomic data by default • Integrate alerts into EHS and plant safety systems • Co-define data governance with workers' representatives
 5. **Cognitive & Neuro-Ergonomic Wearables**	• Dry-electrode EEG headbands and in-ear sensors • Eye-tracking glasses • HRV and electrodermal-activity sensors with edge AI	• Adaptive pacing of collaborative robots • Expertise-adaptive AR work instructions • Fatigue-aware break scheduling in inspection and control rooms	• Adaptive human-centred work systems through real-time assessment of cognitive workload, fatigue and attention, supporting safer and more personalised operations.	**Emerging (2026)** 5 to 10 years (2031–2036)	• Low signal reliability in industrial environments • Legal limits on emotion and neural-data inference (EU AI Act) • Low worker acceptance	• Fund industrial validation studies and benchmarks • Restrict use to safety and well-being purposes • Ensure transparency and voluntary participation

3.2 Industrial Data Analytics Technology Radar

"The future of Industrial Data Analytics will depend not on individual technologies, but on their convergence. Manufacturers able to integrate trusted data sharing, AI, simulation, and lifecycle intelligence will move from operational optimisation to resilient and circular value creation".

3.2.1 State of Play

Industrial Data Analytics (IDA) is becoming the intelligent decision-making layer of future smart manufacturing. Data is emerging as the new production resource, and IDA transforms this resource into actionable intelligence that supports more informed, resilient, and sustainable industrial decisions and therefore operations. While early IDA applications focused on monitoring production performance and predictive maintenance, the convergence of Artificial Intelligence (AI), Digital Twins (DTs), the Industrial Internet of Things (IIoT), cloud-edge computing, and interoperable Industrial Data Spaces is fundamentally changing the role of data in smart manufacturing. Manufacturers are increasingly using data not only to understand what has happened, but also to anticipate events, optimise decisions, and coordinate activities across products, processes, and supply chains, creating true smart manufacturing environments.[1]

This evolution reflects a broader industrial digital transformation of the manufacturing sector. Competitiveness is no longer determined solely by production efficiency, but also by the ability to generate, integrate, and exploit trusted data throughout the product lifecycle. Manufacturers must simultaneously respond to technological innovation, sustainability imperatives, workforce evolution, and changing geopolitical and regulatory conditions. In this context, IDA provides the analytical capability required to transform rapidly growing volumes of industrial data into strategic intelligence, supporting organisational resilience, competitiveness, and long-term value creation.

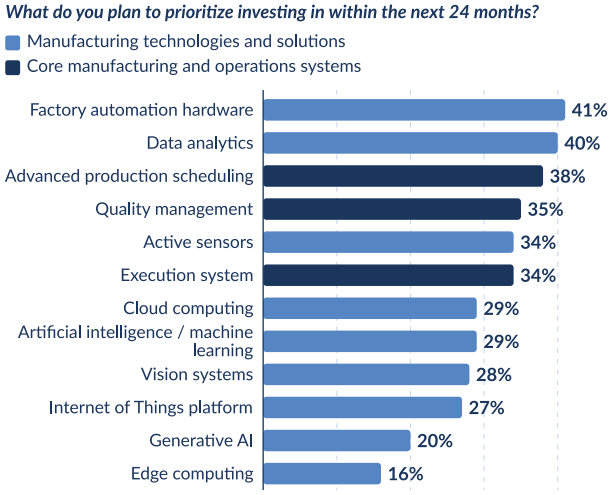


Figure 3.4. Industrial Data Analytics among manufacturers' investment priorities for the next 24 months (adapted from Deloitte, 2025).

As shown in Figure 3.4, IDA is emerging as a key investment priority in manufacturing. According to Deloitte's Smart Manufacturing Survey (2025), 40% of surveyed manufacturers identify data analytics among their top investment priorities for the next 24 months, ranking it second only to factory automation hardware (41%). Other relevant investment priorities include advanced production scheduling (38%), quality management systems (35%), active sensors (34%), manufacturing execution systems (34%), cloud computing (29%), artificial intelligence and machine learning (29%), and Industrial Internet of Things (IIoT) platforms (27%). These findings highlight the growing strategic importance of IDA as an enabling technology for transforming industrial data into actionable insights, supporting operational decision-making, and facilitating the integration of advanced digital technologies in manufacturing.[2]

3.2.2 Technological Capabilities for Value Creation Opportunities

Beyond improving operational performance, IDA is enabling new manufacturing paradigms aligned with the twin digital and green transition. By combining lifecycle information, sustainability indicators, and business intelligence, manufacturers can improve resource efficiency, strengthen traceability, support circular business models, and enhance resilience across increasingly complex industrial ecosystems. Table 3.3 summarises the progressive evolution of IDA technological capabilities. Rather than representing isolated analytical techniques, the six ana-

lytical capability levels describe the increasing ability of manufacturing organisations to transform industrial data into strategic intelligence. As organisations mature, data analytics evolves from operational visibility and enterprise integration towards predictive and cognitive decision support, lifecycle optimisation, and ultimately circular value creation. This progression reflects the shift of IDA from an operational support function to a strategic capability enabling intelligent, resilient, and circular smart manufacturing.[3]

Table 3.3. The progressive evolution of IDA capabilities: from understanding what happened in operations to orchestrating circular value creation across multiple product lifecycles

Focus	Main Enablers	Value Created
1. Operational Analytics		
Visibility	• PLCs • SCADA • MES • Dashboards • Reporting systems	• Operational awareness • Performance monitoring • Process transparency
2. Integrated Analytics		
Connectivity & Integration	• IIoT • ERP-MES integration • Data lakes • APIs • Semantic interoperability	• End-to-end operational visibility • Data consistency • Cross-functional collaboration
3. Predictive Analytics		
Anticipation	• ML • Time-series analytics • Predictive maintenance • Anomaly detection	• Reduced downtime • Improved quality • Risk mitigation • Predictive planning
4. Cognitive Analytics		
Intelligence & Decision Support	• Generative AI • Knowledge graphs • Optimisation algorithms • Decision engines • Explainable AI	• Faster and more reliable decisions • Higher productivity • Augmented human expertise
5. Lifecycle Intelligence		
Lifecycle Context	• Digital Product Passport • Industrial Data Spaces • Digital Thread • Traceability • Dynamic LCA	• Lifecycle optimisation • Regulatory compliance • Informed repair, reuse and remanufacturing decisions
6. Circular Value Intelligence		
Circular Value Creation	• Circularity analytics • AI-LCA • Remanufacturing analytics • Reverse logistics optimisation • Circular marketplaces	• Resource efficiency • Value retention • New circular business models • Sustainability impact • Industrial resilience

3.2.3 Aligning Capabilities to Technology Categories for Facing Challenges

Manufacturing is moving beyond isolated data analytics tools towards integrated data ecosystems that combine trusted data sharing, AI, simulation, and lifecycle intelligence.

Rather than supporting individual production tasks, these IDA technologies collectively enable manufacturers to optimise decisions across products, processes, and supply chains. The IDA technology radar identifies five complementary technology categories that are expected to shape the evolution of the IDA domain over the coming decade.

Industrial Data Spaces provide the trusted foundation for collaborative manufacturing.

By enabling secure, interoperable, and sovereign exchange of design, engineering, production, and lifecycle information, Industrial Data Spaces support collaboration across organisational boundaries while preserving data ownership and governance. Initiatives such as Manufacturing-X and GAIA-X are accelerating their adoption, enabling supply-chain transparency, cross-company collaboration, and new data-driven business models. As manufacturing ecosystems become increasingly interconnected, trusted data sharing is expected to become a strategic enabler of resilient supply chains.[4–6]

Lifecycle Data Intelligence extends analytics beyond factory operations to the entire product lifecycle.

Technologies such as Digital Product Passports, Digital Threads, and Dynamic LCA integrate information from design, production, operation, maintenance, and end-of-life. This lifecycle perspective improves traceability, supports regulatory compliance, and enables informed decisions on maintenance, repair, reuse, and remanufacturing. As sustainability requirements continue to increase, lifecycle intelligence is becoming essential for balancing operational performance with environmental and circular economy objectives.[7]

Artificial Intelligence transforms industrial data into predictive and actionable knowledge.

Machine learning, computer vision, and Generative AI enhance quality inspection, predictive maintenance, anomaly detection and production optimisation, enabling manufacturers to move from reactive to predictive deci-

sion-making. Beyond automation, AI increasingly supports engineering knowledge management and operational decision support. Its successful industrial adoption, however, depends on trustworthy, explainable and human-centred solutions that augment rather than replace human expertise.[8]

Simulation and Digital Twins complement analytics by enabling virtual experimentation before physical implementation.

By integrating operational data with predictive models, manufacturers can evaluate alternative production scenarios, optimise resource allocation, and anticipate equipment degradation throughout the asset lifecycle. These analytical capabilities reduce implementation risks, improve operational flexibility, and support more informed strategic and operational decisions, making simulation an essential component of data-driven manufacturing.[9]

Circular Value Intelligence extends analytics from production optimisation to value optimisation across multiple product lifecycles.

By integrating lifecycle information, sustainability indicators, and recovery assessment, it supports decisions on repair, refurbishment, remanufacturing, and material recovery. Rather than focusing solely on manufacturing efficiency, this emerging category maximises resource efficiency and value retention while enabling circular business models and strengthening industrial resilience.[10–12]

3.2.4 Technology Radar Reading

Although each technology category provides value individually, their greatest impact emerges when they operate as an integrated technology ecosystem.

Trusted Industrial Data Spaces establish the foundation for secure data sharing, Lifecycle Data Intelligence contextualises information across the product lifecycle, AI-Driven Analytics transforms data into actionable insights, and Simulation supports predictive evaluation of alternative scenarios. Building on these capabilities, Circular Value Intelligence enables manufacturers to optimise value creation across multiple product lifecycles.

Figure 3.5 and Table 3.4 summarise these IDA technology categories according to their strategic impact, industrial technology readiness, industrial adoption stage, and time horizon to mainstream adoption.

The IDA Technology Radar provides a multidimensional assessment of the five technology categories expected to shape the evolution of IDA in smart manufacturing. Unlike conventional technology radars, which typically position technologies using only maturity and impact, the WMF's IDA Technology Radar integrates four complementary dimensions to provide a more comprehensive assessment of industrial readiness for decision-makers.

The assessment suggests that AI-Driven Industrial Analytics (3) currently represents one of the most mature and strategically impactful categories, benefiting from widespread industrial deployment and rapid advances in machine learning and Generative AI. Simulation and Digital Intelligence (4) also exhibits high technical readiness, although its adoption continues to expand across manufacturing sectors. Lifecycle Data Intelligence (2) occupies an intermediate position, driven by the growing adoption of Digital Product Passports, Digital Threads, and lifecycle sustainability assessment. Industrial Data Spaces and Trusted Data Sharing (1) are characterised by very high strategic impact but comparatively earlier industrial adoption, reflecting the increasing importance of Manufacturing-X, Catena-X, and other trusted data ecosystem initiatives. Finally, Circular Value Intelligence (5) remains the most forward-looking category. Although its current industrial adoption is still limited, it represents a critical capability for enabling circular manufacturing, resource optimisation, and value retention across multiple product lifecycles.

Overall, the WMF's IDA Technology Radar highlights that the maturity of individual technologies alone will not determine the future of IDA, but rather their progressive convergence into integrated industrial ecosystems. Manufacturers capable of combining trusted data sharing, lifecycle intelligence, AI-driven analytics, simulation, and circular value intelligence will be best positioned to support data-driven decision-making, improve industrial resilience, and accelerate the transition towards sustainable and circular manufacturing.

3.2.5 Call for Action & Risk Management

Table 3.4 translates the WMF's IDA Technology Radar assessment into a differentiated set of adoption priorities and risk-management actions. The five technology categories present different risk profiles according to their technological readiness, industrial adoption stage, and expected time to mainstream adoption. Consequently,

manufacturers should not approach them through a uniform digitalisation strategy: the more mature technologies require attention to scaling and responsible use, whereas emerging technologies require stronger governance, experimentation, and ecosystem development.

For Industrial Data Spaces and Trusted Data Sharing, the main risks arise from the distributed and inter-organisational nature of data sharing. Governance or trust failures among partners can limit willingness to exchange strategically relevant information, while interoperability gaps may create fragmented data ecosystems or dependencies on specific platforms and providers. Data sovereignty, cybersecurity, and confidentiality further increase the sensitivity of cross-company exchanges. Therefore, manufacturers should establish clear governance and trust frameworks, adopt interoperable standards, define data-access and sovereignty rules, and strengthen the organisational data culture required for collaboration.

For Lifecycle Data Intelligence, the principal risk is that decisions are based on incomplete, inaccurate, or fragmented information across the product lifecycle. Inconsistent identifiers, classifications, and semantics can prevent data generated during design, production, operation, maintenance, and end-of-life from being connected reliably. Legacy-system integration may further introduce inconsistencies and compliance-reporting errors. Therefore, priority should be given to improving lifecycle data completeness and quality, standardising product and component information, maintaining persistent identifiers and progressively integrating legacy systems with Digital Product Passports, Digital Threads, and lifecycle assessment solutions.

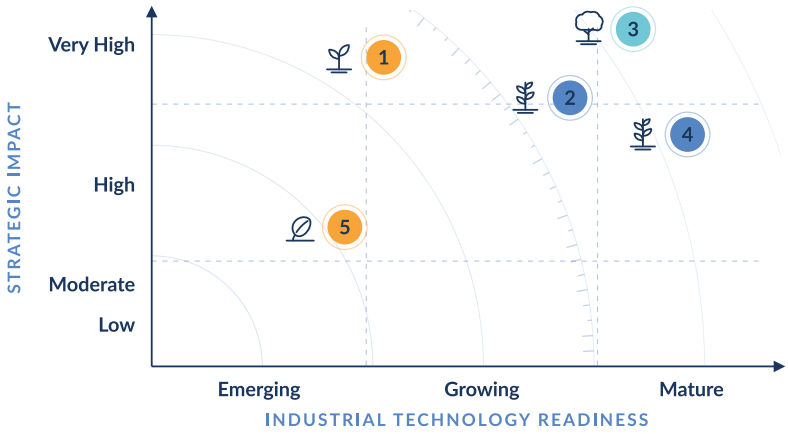
For AI-Driven Industrial Analytics, which shows the highest level of readiness and adoption among the five categories, risks increasingly concern the quality and governance of deployment rather than technological feasibility alone. Poor-quality, biased or insufficient operational data can produce unreliable predictions, while limited explainability may reduce trust in AI-supported recommendations. Over-reliance on automated outputs can also weaken human oversight, particularly when appropriate skills are lacking. Therefore, manufacturers should combine strong data governance with explainable and trustworthy AI, maintain human responsibility for critical decisions and invest in the skills required to interpret, challenge and effectively use AI-generated insights.

For Simulation and Digital Intelligence, the credibility of decisions depends directly on the validity of the underlying models and the quality of the data feeding them. Inaccurate models, outdated assumptions or insufficient validation can generate misleading scenarios, while weak integration with real-time operational data can progressively reduce the correspondence between the digital representation and the physical system. Computational requirements and implementation complexity may also limit scalability. Therefore, manufacturers should establish robust model-validation procedures, improve real-time data integration, monitor model performance over time and develop the digital capabilities required to embed simulation and Digital Twins into engineering and operational workflows.

Finally, Circular Value Intelligence presents a different and more systemic risk profile. Limited availability and traceability of data across multiple product lifecycles can undermine assessments of remaining value and recovery opportunities. At the same time, inconsistent circularity and sustainability metrics can lead to incomparable or misleading decisions, while immature reverse-logistics networks, marketplaces and circular business models may prevent technically viable recovery options from becoming economically attractive. Therefore, manufacturers should begin by developing cross-lifecycle data foundations, adopting transparent circularity and sustainability metrics, strengthening collaboration across value-chain actors, and progressively validating circular services and business models through pilots.

Taken together, these risks show that technology readiness does not automatically translate into successful industrial adoption. The most significant barriers increasingly arise at the interfaces between technology, data, organisations, and ecosystems. Therefore, risk management should evolve alongside technological maturity: emerging categories require experimentation, governance, and ecosystem building; growing categories require interoperability, standardisation and integration; and mature categories require responsible scaling, continuous validation, and workforce adaptation. The resulting pathway is deliberately staged: scale technologies that can already generate value, strengthen the trusted data and lifecycle foundations needed for integration, and progressively prepare for emerging circular intelligence capabilities whose strategic relevance is expected to increase over the coming decade.

WMF's Industrial Data Analytics Technology Radar



Top 5 Technology Categories

1. **Industrial Data Spaces & Trusted Data Sharing**
   Foundation for secure, interoperable, and sovereign data exchange across organisations and ecosystems.
2. **Lifecycle Data Intelligence**
   Provides lifecycle context and traceability to support compliance, sustainability and circular decisions.
3. **AI-Driven Industrial Analytics**
   Transforms data into insights, predictions, and decisions to optimise operations and enable autonomy.
4. **Simulation & Digital Intelligence**
   Enables virtual experimentation and predictive modelling to optimise performance and reduce risk.
5. **Circular Value Intelligence**
   Extends optimisation beyond production to retain value, close loops, and create circular business models.

Industrial Adoption Stage

- **Mature**
  Ready for broad adoption and scaling
- **Growing**
  Early adoption and expanding capability
- **Emerging**
  Early-stage technologies with high potential

Time Horizon to Mainstream Adoption

- **Mature: Current to 2 years**
  Already adopted in many industrial use cases
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  Pilot to early adoption at scale in the manufacturing sector
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Radar Guide

- Position indicates the Industrial Technology Readiness (x-axis) and Strategic Impact (y-axis).
- Point colour indicates the current Industrial Adoption Stage.
- Growth-stage icon represents the estimated Time Horizon to Mainstream Adoption.

Figure 3.5. WMF's Industrial Data Analytics Technology Radar

Table 3.4. WMF's Industrial Data Analytics Technology Matrix

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
1. **Industrial Data Spaces & Trusted Data Sharing**	• Industrial Data Spaces • GAIA-X / Manufacturing-X • Data sovereignty & Governance • Semantic interoperability • APIs & data connectors • Data quality management	• Cross-company data exchange • Supply chain visibility • Collaborative engineering • Data-driven ecosystem services	• Enables trusted collaboration and secure data sharing • Strengthens supply chain resilience and transparency • Enables new data-driven business models	**Emerging (2026)** 3 to 7 years (2029–2033)	• Governance and trust failures across partners • Interoperability gaps and ecosystem/vendor lock-in • Cybersecurity, data-sovereignty, and confidentiality exposure	• Adopt governance and trust frameworks • Address interoperability standards • Implement organisational change • Build the data culture
2. **Lifecycle Data Intelligence**	• Digital Product Passport • Digital Thread • Product Lifecycle Management • Dynamic Lifecycle Assessment • ESG & Sustainability Analytics • Traceability systems	• Product traceability • Sustainability reporting • End-of-life decision support • Warranty management • Service optimisation	• Improves regulatory compliance • Enhances lifecycle optimisation • Supports repair, reuse, and remanufacturing • Strengthens customer trust	**Growing (2026)** 2 to 5 years (2028–2031)	• Incomplete, inaccurate, or fragmented lifecycle data • Inconsistent identifiers, standards, and data semantics • Legacy-system integration and compliance-reporting errors	• Fulfil data completeness • Employ lifecycle standardisation • Integrate legacy systems
3. **AI-Driven Industrial Analytics**	• Machine learning • Deep learning • Predictive analytics • Anomaly detection • Generative AI • Explainable AI	• Predictive maintenance • Quality inspection • Production optimisation • Demand forecasting • Root-cause analysis	• Improves productivity and quality • Reduces downtime and maintenance costs • Enables autonomous decision-support	**Mature (2026)** Current to 2 years (2026–2028)	• Biased, poor-quality, or insufficient training/ operational data • Low explainability and unreliable recommendations • Over-reliance on AI, skills gaps, and workforce resistance	• Improve data quality and explainability • Integrate operational data • Account for workforce skills
4. **Simulation & Digital Intelligence**	• Digital Twins • Physics-based models • Simulation • What-If analysis • Remaining Useful Life (RUL) • Hybrid models	• Virtual commissioning • Process design • Performance prediction • Maintenance planning • Energy optimisation	• Improves decision quality • Optimises resource allocation • Reduces implementation risks • Accelerates innovation	**Growing (2026)** 2 to 5 years (2028–2031)	• Model inaccuracy, weak validation, or outdated assumptions • Poor real-time data integration leading to misleading scenarios • High computational and implementation complexity	• Enhance model accuracy • Integrate data • Reduce computational cost • Empower digital skills
5. **Circular Value Intelligence**	• Circularity Analytics • AI-supported LCA • Remanufacturing analytics • Reverse Logistics Analytics • Circular marketplaces • Material flow analytics	• Remanufacturing planning • Circular supply network optimisation • Recovery strategy selection • Waste reduction • Circular marketplaces	• Maximises value retention • Improves resource efficiency • Supports circular business models • Increases sustainability and resilience	**Emerging (2026)** 5 to 10 years (2031–2036)	• Limited cross-lifecycle data availability and traceability • Inconsistent circularity and sustainability metrics • Immature ecosystems, reverse-logistics networks, and business models	• Make available cross-lifecycle data • Adopt circularity metrics • Push ecosystem collaboration • Monitor market readiness

3.3 Digital Twins, Extended Reality & Industrial Metaverses Technology Radar

"Digital twins, extended reality and industrial metaverse technologies are converging to create increasingly connected, intelligent, shared and human-centred manufacturing environments".

3.3.1 State of Play

In the manufacturing arena, digital twins (DTs) can be understood as digital counterparts of physical entities, processes or systems that are dynamically connected through bidirectional data exchange. They combine digital representations, models and data management mechanisms[1] to maintain a continuously updated view of the physical counterpart and support the monitoring, analysis, prediction and optimisation of its behaviour across different lifecycle stages, from design to operations. Extended reality (XR) is an umbrella term covering Augmented Reality (AR), Virtual Reality (VR) and Mixed Reality (MR), providing different levels of interaction between users, digital content and the physical environment[2]. XR therefore enables new forms of interaction with virtual or hybrid representations of products, production systems and services, opening previously unexplored forms of user experience, training, collaboration and decision support. In this evolution, industrial metaverses represent the convergence of physical and virtual worlds into a unified and shared environment where the two realities are not only connected but can increasingly coexist. This convergence can be realised through architectures that connect physical entities and infrastructure with the metaverse space, with Digital Twins enabling bidirectional data flows, semantic models supporting knowledge synchronisation, AI agents augmenting information for decision-making, and XR interfaces enabling human interaction across the physical and virtual domains[3,4] (Figure 3.6). This seamless physical-to-digital integration reinterprets the role of humans in an unprecedented manner, placing them alongside digital/AI agents, machines and resources on the shop floor, and connecting them with legacy information systems such as PLM, ERP, MES and CAD. The Industrial Metaverse is therefore aligned with the *Industry 5.0* vision of human-centric, sustainable and resilient manufacturing.

These three technological categories should be seen neither in isolation nor as independent technological solutions. Indeed, with the concept of the smart factory emerging over a decade ago, the foundations for DTs, XR and the industrial metaverse have already been laid, and now manufacturers can leverage their investments in sensing and monitoring solutions as well as industrial data analytics to embrace a wider technological change towards an optimised management of the shop floor and related business processes. Moreover, DTs and XR are mutually reinforcing technologies when considered in light of the industrial metaverse; the industrial metaverse can be built only if a strong technological layer is already present and manufacturing companies already embrace data-driven decision-making.

The main application already explored in manufacturing for DTs, XR and the industrial metaverse primarily focuses on production performance enhancement. Available use cases span both the design and operation phases of smart factories, including immersive concurrent production system design, virtual prototyping, moving to process simulation, real-time monitoring, quality control, factory simulation and virtual/immersive maintenance.

Nonetheless, this evolution is not risk-free as it follows the same threats as the *Industry 4.0* technological wave: the more the systems on the shop floors are open to share data, the more security, privacy, and intellectual property (IP) are put at risk.

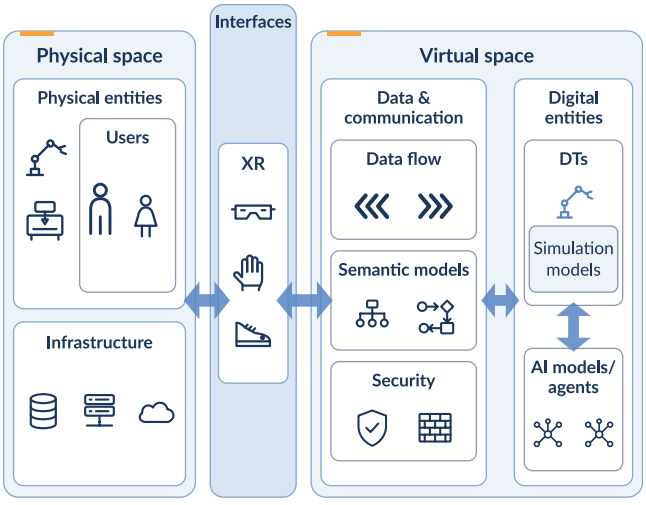


Figure 3.6. Schematic representation of the industrial metaverse architecture[3,4]

3.3.2 Technological Capabilities for Value Creation Opportunities

Beyond their convergence within a common vision for the factory of the future and *Industry 5.0*, DTs, XR and industrial metaverse technologies can each generate value through specific manufacturing capabilities. DTs can promote improved performance simulation and real-time monitoring and control, and, when combined with data analytics and Artificial Intelligence (AI), enable system-level and machine-level behaviour forecasting and optimisation. XR solutions can enhance operator training and foster remote collaboration and expertise sharing in an unprecedented and effective manner. The combination of DTs and XR within the industrial metaverse further enables stakeholders to interact with digital representations of products, machines and production systems, supporting more informed decisions across the product and system lifecycle. Table 3.5 synthesises the technological capabilities enabled by technologies such as DTs, XR and the industrial metaverse, individually or in combination, towards value creation for manufacturing companies.

Table 3.5. Technological capabilities enabled by DTs, XR and Industrial Metaverse for Value Creation

Focus	Main Enablers	Value Created
1. Performance simulation		
Simulate production systems and processes before/during operation	• DTs • Physics/data-driven models • Simulation	• Lower operational cost • Improved production performance • Process optimisation
2. Real-time monitoring and control		
Synchronise physical entities with their digital representations	• IoT/OT connectivity • DT models and platforms • Edge/cloud computing	• Enhanced quality assurance • Faster response to disruptions • Early detection of machine drift
3. Behaviour forecast & optimisation		
Predict failures, production drifts and system/machine future states	• AI/ML • Predictive analytics • DTs	• Maintenance-production orchestration • Reduced downtime • Predictive and robust scheduling
4. Immersive operation & maintenance		
Support workers through spatial and contextual information	• AR/MR • Wearable devices • DT/XR/AI integration	• Reduced training time • Error-free and safe maintenance interventions • First-time-right machine setup and operation
5. Remote collaboration & expertise sharing		
Connect workers, experts and machines across locations	• XR • Shared 3D environments • Real-time communication	• Faster troubleshooting • Knowledge transfer • Effective design reviews
6. Immersive concurrent engineering design		
Enable multiple stakeholders to design and evaluate production systems collaboratively	• DTs • CAD • Knowledge formalisation • Virtualised automation • Simulation • Collaborative XR environments	• Better design decisions • Earlier error detection • Shorter development cycles

3.3.3 Aligning Capabilities to Technology Categories for Facing Challenges

Performance simulation via model-based DTs supports design and operational decisions by assessing their local and system-wide effects over the short to medium term.

Digital Twins represent surrogate models for different aspects of the system under analysis, whose behaviour can be approximated through physics or data/AI-driven analysis; as such, DTs are able to represent a production system's operation as well as processes therein. They can be used either disconnected from the system, during the

design stage, to evaluate performance or even during the system's ramp-up and operation, in a connected fashion. When model-based DTs are used for performance simulation, it is possible to anticipate costs that the company should support for design or during operation; or DTs can be used to verify by-design production performance and process inconsistencies.

Real-time monitoring and control can keep managers up to date about production performance and take counteractions based on DT outputs.

When IoT/OT connectivity is in place, the model-based DTs can be fed by shop floor data for real-time monitoring and control. The ability to process data enables prompt responses to production deviations identified via *ad hoc* data-driven analytics or leveraging digital-physical performance comparison. Depending on specific applications, edge or cloud computing is needed, based on latency and response requirements; machine drift detection and enhanced quality assurance might require more on-the-field and fast response from DTs, while responses to disruptions may also imply human decision-making, which would make cloud computing well-suited, with platforms providing access to data and model outputs.

Behaviour forecasting & optimisation promote short-term reactions to foreseen deviations thanks to AI towards defect-free production.

Exploiting the different capabilities of DTs, fostered by AI, system-level and machine-level behaviour forecasting can promote both automated short-term reactions and human-judged actions. Predictive analytics enable the evaluation of future states and move operation and maintenance strategies from reactive to proactive. Also, for error-free, fast human responses, XR solutions can be employed to equip all workers with visual instructions or for scenario-based training programmes.

Immersive operation and maintenance can support workers with spatial and contextual information to improve safety, efficiency and first-time-right interventions.

AR/MR and wearable devices can overlay relevant production, machine and process information onto the physical environment, allowing workers to access Digital Twin outputs directly within their field of view. By integrating DTs with XR and AI, workers can receive contextual instructions, visualise machine states and access scenario-based guidance during operation, maintenance and machine setup. Immersive interfaces can also support training and remote assistance by providing workers with simulated or live representations of production systems. This can reduce training time and support safer and more consistent maintenance interventions, while enabling workers to use digital information without interrupting their physical task.

Remote collaboration and expertise sharing can connect workers, experts and machines across locations through shared physical-virtual environments.

XR and shared 3D environments can enable geographically distributed workers and experts to access and interact with the same DT or virtual representation of a production system. Real-time communication allows experts to provide guidance remotely, while shared visualisation of machine states, processes and operational data can support faster troubleshooting and knowledge transfer. Such capabilities can extend industrial expertise beyond physical location and enable collaborative inspection, maintenance, training and design reviews. The combination of real-time industrial data, XR interfaces and communication infrastructure can therefore support more responsive and distributed ways of working.

Immersive concurrent engineering design can enable multiple stakeholders to collaboratively design, simulate and evaluate production systems before physical implementation.

DTs, CAD models, simulation and virtualised automation can be combined with collaborative XR environments to provide a shared representation of production systems during engineering and design. Multiple stakeholders can interact with the same virtualised system, evaluate alternative configurations and assess the effects of design decisions before implementation. This approach can bring engineering, automation, production and other stakeholders into the design process earlier, supporting better design decisions and earlier detection of inconsistencies or errors. By reducing reliance on physical prototypes and enabling iterative virtual evaluation, immersive concurrent engineering can shorten development cycles and improve production system readiness.

3.3.4 Technology Radar Reading

The evolution towards physical-virtual manufacturing depends on the progressive integration of complementary technological capabilities.

Connected DTs and real-time industrial data establish the foundation for synchronising physical systems and their digital counterparts; Digital Platforms and System Interoperability connect heterogeneous systems, data and models, and AI-enabled Physical-Virtual Integrated Intelligence extends these capabilities towards predictive and adaptive decision-making. Multimodal Interaction and Physical-Virtual Communication enable humans to interact with physical and digital environments, while Industrial XR, Metaverse and Collaborative Environments bring people, machines, DTs and AI together in shared physical-virtual spaces.

Figure 3.8 and Table 3.6 summarise these technology categories according to their strategic impact, industrial technology readiness, industrial adoption stage, and time horizon to mainstream adoption. The WMF's Digital Twins, Extended Reality and Industrial Metaverses Technology Radar provides a multidimensional assessment of the five technology categories expected to shape the evolution of physical-virtual manufacturing environments. By combining technology readiness and strategic impact with current adoption stage and expected mainstream adoption horizon, the radar provides decision-makers with a view of both current industrial opportunities and emerging technological directions.

The assessment suggests that Connected Digital Twins & Real-time Industrial Data Analytics (1) currently represents one of the most mature and strategically impactful categories, building on established industrial connectivity, DT platforms, edge/cloud computing and industrial analytics. Digital Platforms & System Interoperability (2) occupies an intermediate position, reflecting the growing need to connect heterogeneous systems, data and models across organisational and technological boundaries. AI-enabled Physical-Virtual Integrated Intelligence (3) represents an emerging category with very high strategic impact, driven by the increasing integration of AI, DTs and physical-world data to provide contextual, predictive and adaptive intelligence. Multimodal Interaction & Physical-virtual Communication (4) is progressing towards broader industrial adoption, supported by advances in XR, wearable devices, multimodal interfaces and low-latency communication. Finally, Industrial XR, Metaverse & Collaborative Environments (5) represents the most forward-looking category. Although current industrial adoption remains limited, its potential to bring people, machines, DTs and AI together within shared physical-virtual environments gives it very high strategic relevance for future manufacturing.

Overall, the WMF's Digital Twins, Extended Reality and Industrial Metaverses Technology Radar highlights that the maturity of individual technologies alone will not determine the future of physical-virtual manufacturing, but rather their progressive convergence into integrated industrial ecosystems. Manufacturers that build on connected DTs and real-time industrial data while progressively strengthening interoperability, physical-virtual intelligence, multimodal interaction and collaborative XR capabilities will be better positioned to realise the human-centric and adaptive manufacturing vision of *Industry 5.0*.

3.3.5 Call for Action & Risk Management

Adoption risks shift progressively from technical integration towards systemic trustworthiness and governance. Connected Digital Twins depend on reliable data, models and legacy-system integration, while digital platforms introduce interoperability, semantic consistency, ownership and vendor-dependency challenges. As AI becomes embedded in physical-virtual environments, unreliable or poorly explainable recommendations can directly affect human decisions and physical operations, while increasingly advanced multimodal interaction mechanisms introduce additional human-factor considerations, despite their potential to improve user experience. As such, metaverses and collaborative environments, built on top of DTs, immersive technologies, AI and many more, are undermined in their effectiveness, even counterproductive if risks are not understood and managed promptly. For the industrial metaverse specifically, Deloitte's *Exploring the Industrial Metaverse* report surveyed companies on the main implementation risks associated with the industrial metaverse and related technologies (Figure 3.7). Responsible adoption also requires addressing the legal and ethical implications of industrial metaverse technologies[5] and evaluating their impact through task-technology fit and an Industry 5.0 lens[6], including human-centredness, sustainability, and resilience.

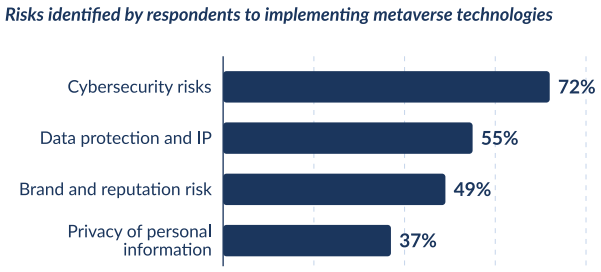


Figure 3.7. Cybersecurity, data protection and IP are the main concerns of manufacturing companies approaching the industrial metaverse (Deloitte, Exploring the industrial metaverse, 2023)[7]

Mitigating these interconnected risks requires industry to build the shared technological, organisational and governance foundations needed for trusted and scalable adoption. Industrial organisations should move from fragmented technology experimentation towards a coherent physical-virtual transformation roadmap. This requires establishing shared digital foundations, including interoperable architectures, common information models and standardised ontologies, reusable Digital Twin components and robust data governance, upon which AI, XR and collaborative environments can progressively be built. Open standards and modular solutions should be prioritised to preserve portability and limit vendor dependency.

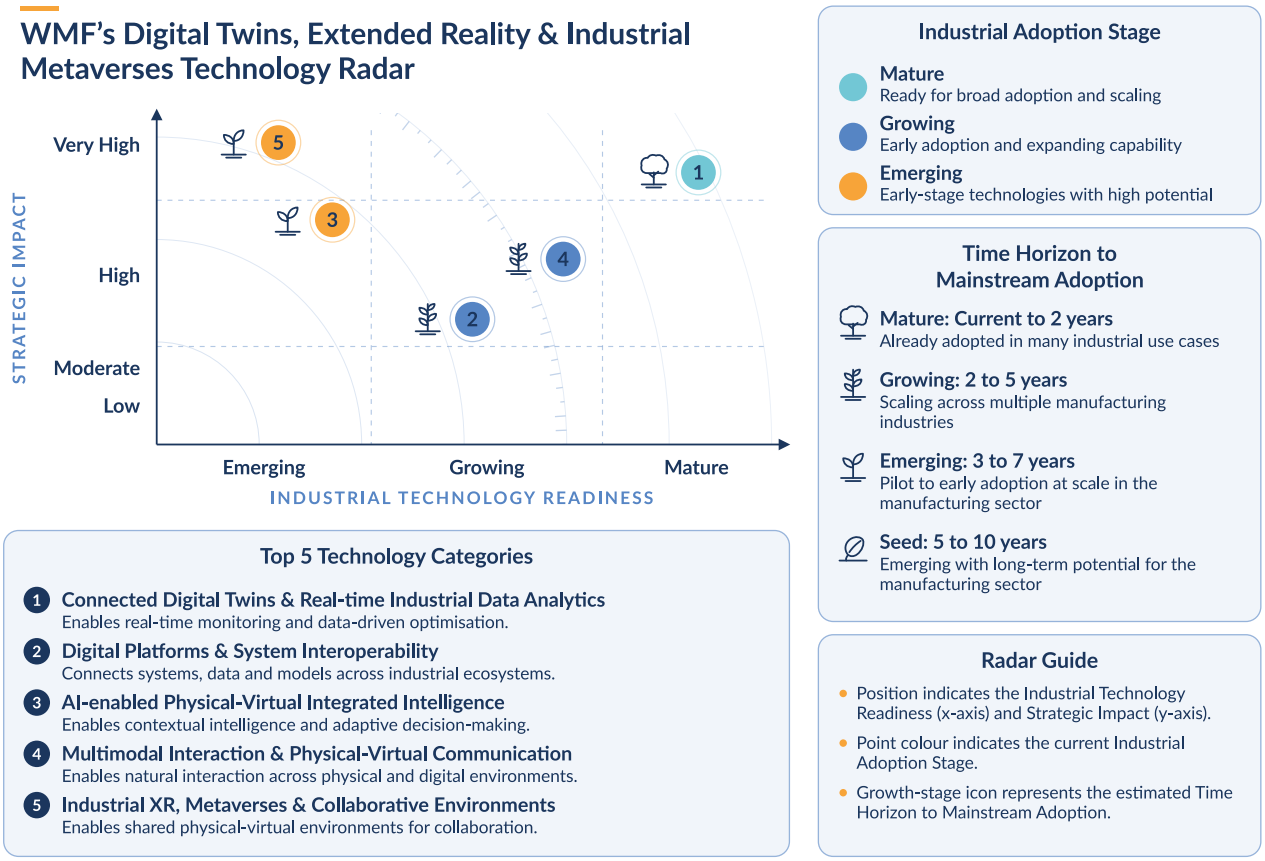


Figure 3.8. WMF's Digital Twins, Extended Reality & Industrial Metaverses Technology Radar

Table 3.6. WMF's Digital Twins, Extended Reality & Industrial Metaverses Technology Matrix

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
1. **Connected Digital Twins & Real-Time Industrial Data Analytics**	• IoT/OT connectivity • DTs • Edge/cloud computing • AI/ML	• Production/process optimisation • Condition-based/ predictive maintenance • Quality control	• Enables data-driven optimisation through the system's lifecycle • Shifts operations and maintenance from reactive to predictive • Creates trusted digital representations for cross-functional decision-making	**Mature (2026)** Current to 2 years (2026–2028)	• Siloed DT solutions limiting optimisation and reuse • Poor data quality and weak model fidelity leading to unreliable insights • High integration effort with legacy OT/IT systems and heterogeneous data sources	• Define a roadmap for DT implementation and related maturity based on current and future needs • Establish an engineering development platform or common DT development rules
2. **Digital platforms & System Interoperability**	• Graph-based knowledge representation • Generative AI / Large Language models • Data spaces	• Production-maintenance integrated optimisation • Integration of supply chain for improved inventory control • Effective outsourced maintenance service management	• Breaks organisational and technological data silos, enabling information continuity across functions, systems and company boundaries • Creates a scalable digital backbone for integrating data, applications and services • Enables ecosystem-level optimisation and new data-driven services through secure and interoperable information sharing	**Growing (2026)** 2 to 5 years (2028–2031)	• Vendor lock-in and dependency on proprietary platforms • Fragmented market offerings requiring costly ad hoc integration of systems and services • Semantic inconsistencies across departments and organisations, limiting meaningful data exchange • Unclear ownership, governance and access rights for shared industrial data	• Adopt open standards, shared information models and ontologies • Define enterprise-wide data governance, ownership and access-control mechanisms • Progressively replace point-to-point integrations with reusable platform services and connectors • Assess platform choices against portability, scalability and long-term vendor independence criteria
3. **AI-enabled Physical-Virtual Integrated Intelligence**	• LLM-based cognitive co-pilots • Spatial computing / XR • Multimodal AI and context awareness • DTs • Adaptive human-machine interfaces	• Real-time one-of-a-kind product assembly support • Maintenance troubleshooting for rare events • Context-aware human-robot collaboration • Adaptive operator training and on-the-job guidance	• Transforms DTs from passive virtual representations into interactive industrial components • Augments human capabilities by delivering contextual, real-time and explainable assistance • Accelerates knowledge transfer and reduces dependence on individual expert experience	**Emerging (2026)** 3 to 7 years (2029–2033)	• Unreliable, non-explainable or hallucinated AI-generated guidance in critical operations • Limited AI trustworthiness and accountability • Misalignment between physical reality, DT state and AI recommendations • Cognitive overload reducing human situational awareness	• Develop reusable libraries of digital models to ground AI training • Introduce human-in-the-loop validation and safety guardrails for AI-generated recommendations • Develop methods and processes to verify physical–virtual consistency

Table 3.6. WMF's Digital Twins, Extended Reality & Industrial Metaverses Technology Matrix (continued)

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
4. **Multimodal Interaction & Physical-Virtual Communication**	• AR/MR/VR and spatial computing • Head-mounted displays and wearable devices • Speech, gesture, gaze and haptic interaction • Multimodal sensing and context awareness • Real-time, low-latency communication architectures	• Immersive operation and maintenance • Worker guidance and training • Remote assistance and expert support • Immersive inspection and quality assessment • Human-machine collaboration	• Enables natural and context-aware interaction with digital industrial information • Connects workers with physical entities and their digital representations in real time • Supports distributed expertise and human-centred decision-making • Reduces the gap between physical tasks and digital information	**Growing (2026)** 2 to 5 years (2028–2031)	• Hardware usability, ergonomics and worker acceptance • Communication latency and reliability • Fragmented interaction standards and devices • Cognitive overload and poor human-machine interaction design • Integration with existing industrial systems	• Develop human-centred multimodal interaction strategies • Integrate XR interfaces with DTs and real-time industrial data • Design communication architectures for reliable, low-latency interaction • Evaluate usability, safety and human factors alongside technical performance
5. **Industrial XR, Metaverses & Collaborative Environments**	• Industrial XR platforms and spatial computing • Shared 3D and persistent virtual environments • Connected Digital Twins and real-time industrial data • AI-enabled virtual agents and intelligent assistance • Interoperable platforms and networking infrastructure	• Immersive concurrent engineering and factory design • Collaborative production-system development • Virtual commissioning and prototyping • Multi-site engineering and operations collaboration • Shared training and expertise environments	• Connects people, machines, Digital Twins, AI and industrial information systems in shared physical-virtual environments • Enables new forms of distributed engineering, collaboration and knowledge sharing • Supports lifecycle-wide interaction with products, machines and production systems • Creates the foundation for persistent physical-virtual industrial environments	**Emerging (2026)** 3 to 7 years (2029–2033)	• Fragmented platforms and limited interoperability • High infrastructure and integration requirements • Cybersecurity, data protection and IP risks • Unclear business value and return on investment • User acceptance and organisational readiness	• Prioritise concrete industrial use cases and measurable business value • Build on existing DT, XR and industrial data infrastructure • Promote interoperable and open physical-virtual platforms • Develop governance for shared industrial metaverse environments • Establish human-centred principles for collaborative physical-virtual work

3.4 Agentic & Cognitive Artificial Intelligence Technology Radar

"We are the last generation to manage only humans." Marc Benioff, Salesforce

3.4.1 State of Play

Ask a hundred manufacturing executives about AI agents and more than sixty will say they expect to deploy them within two years; fewer than twenty have done so. Gartner calls that intent the most aggressive adoption curve it has measured for an emerging technology, and places the field at the Peak of Inflated Expectations in its first standalone Hype Cycle for Agentic AI[1]. It still expects over 40 per cent of agentic AI projects to be cancelled by the end of 2027, through escalating costs, unclear value or inadequate risk controls[2], and its analysts warn of agent washing, where existing software is relabelled as an agent. A separate McKinsey State of AI survey finds 23 per cent of organisations scaling an agentic system in at least one function and 39 per cent experimenting. The leading sectors are technology, media and telecommunications, and healthcare, with manufacturing not among them[3]. The question this radar answers is how manufacturers capture the value without carrying the failures.

However, the agents are already at work. In the engineering office, Siemens' Eigen Engineering Agent plans, writes and validates automation code inside the engineering environment rather than advising beside it. Siemens launched the agent at Hannover Messe after pilot projects with more than one hundred companies in nineteen countries and reports workflow gains of two to five times[4]. Across supply chain operations, SAP announced Autonomous Supply Chain Management at Sapphire in May. It puts Joule assistants and specialised agents into planning, manufacturing and logistics, and availability is being phased in through 2026[5].

In every peer-reviewed deployment that works, the AI model reads the situation and proposes the action while the plant's existing control systems, with their fixed safety rules, decide whether it happens. These hybrids outperform pure model autonomy[6]. They extend existing systems without replacing them and keep a human in the loop, meaning a person approves, corrects or stops what the agent proposes before it takes effect[7,8]. The gains from systems validated in real operations are measured in tens of per cent: 15 per cent less unplanned downtime and 23 per cent longer mean time between failures on critical rotating equipment[9], and 40 per cent less planning time in downhole maintenance[10]. The strongest scheduling results still come from a laboratory shop floor, not yet from a production plant[11]. Fully autonomous, closed-loop control of safety-rated systems, with no human in the loop, remains at the pilot-project stage in every published deployment. Governments have entered the field too: China's AI Plus Manufacturing programme targets one thousand industrial agents by 2027[12], and Japan's Noetra consortium is building sovereign compute for physically grounded industrial AI by 2030[13].

3.4.2 Technological Capabilities for Value Creation Opportunities

The technology is the smaller part of the problem. Value depends on people, meaning who supervises the agent and who signs off its work, and on process, meaning which tasks are handed over and how the surrounding work is redesigned, as much as on the models. Table 3.7 sets out the technology side as five capabilities: assistants that answer from the company's own records, agents that do engineering work inside engineering tools, agents that make operating decisions within guardrails, the governance that gives an agent an identity and a limit, and agents that keep memory and improve with experience. Each is one category on the radar. Section 3.4.3 takes them in turn, and the people and process side runs through those paragraphs and the calls for action in Table 3.8.

Table 3.7. Technological capabilities for value creation

Focus	Main Enablers	Value Created
1. Industrial AI assistants & knowledge agents		
Knowledge access and guidance for engineers and operators across manuals, MES, ERP and quality records	• LLMs • Answers grounded in company documents (retrieval-augmented generation, RAG) • MCP tool connectors • Multimodal and voice interfaces	• Shorter search and troubleshooting times • Less pressure on scarce experienced experts
2. Agentic engineering & autonomous discovery		
Agents that plan, write and validate engineering artefacts inside the tools engineers already use	• Reasoning models • CAD, CAE and PLC tool use • Automated validation loops • Accountable human sign-off	• Engineering workflows two to five times faster (vendor-reported) • Wider design-space exploration in generative PLM
3. Autonomous operations agents		
Scheduling, quality, maintenance and energy decisions within engineered guardrails; human-approved supply-chain exceptions and multi-site allocation	• Multi-agent orchestration • Optimisation • Plant data archives (historians) • Digital-twin state • Agent-to-agent protocols • Shared data spaces	• 40% planning-time reduction and 95.7% fault-prognosis accuracy in maintenance (field-reported) • Seven-minute reduction in average recovery time per breakdown at a semiconductor fab • Faster exception response and quotation cycles
4. Agent trust, governance & assurance		
Control of each agent's identity, access and continued fitness for use	• Non-human identity management • Agent registries • Compliance and orchestration agents • Runtime monitoring • Audit trails • Kill switches	• Lower risk • Regulatory readiness • Insurability • A precondition for scaling the other categories
5. Cognitive & self-improving agents		
Agents that retain memory and improve across shifts, incidents and campaigns	• Persistent memory • Continual learning • World models that predict consequences • Governed knowledge stores	• Large gains on long, multi-step tasks • Competitive performance from smaller, cheaper models

3.4.3 Aligning Capabilities to Technology Categories for Facing Challenges

Industrial AI assistants and knowledge agents

These assistants are in production at scale, and their limitations are visible. The early work is often as ordinary as agreeing which version of a work instruction is current. One expert's knowledge reaches more people and more plants. Buying the model is the cheap part. The expense lies in preparing the company's data for the assistant, controlling which documents and systems it may see, and redesigning the surrounding work. That redesign must define which tasks people hand over and who checks the answers that come back. Deloitte finds only a quarter of organisations have moved even 40 per cent of their AI pilot projects into production[14], which means that in three out of four organisations most pilots never reach daily use. That matters here because most companies start with an assistant.

Agentic engineering and autonomous discovery

In 2026, agents began writing validated automation code inside engineering tools. Others generated design alternatives in product lifecycle management (PLM) systems or analysed requirement sets containing thousands of entries. At Oak Ridge National Laboratory, the Peregrine system provides real-time quality control for powder-bed additive manufacturing and has been demonstrated on 23 printers across laser powder-bed, electron-beam and binder-jet processes[15]. It has analysed more than 1.9 million build layers and is being embedded in a seven-node distributed production network for adaptive control and quality assurance[16]. A separate system connected to a supercomputer adjusts the metal-printing process during the build[17]. The payback is quickest where capital projects are held up by scarce control-engineering or design capacity. Validation has to match the artefact: code must compile, pass automated checks and survive simulation, designs and requirement sets need the equivalent checks in their own tools, and a named engineer signs off before anything reaches physical equipment.

Autonomous operations agents

These agents offer the largest gains and will take the longest to deliver them. The systems are rarely single agents; published designs coordinate teams of specialists for scheduling, diagnosis and intervention. The same approach is being tested on supply-chain exceptions and multi-site allocation, although every action still requires human approval. KPMG finds that the share of organisations orchestrating multiple agents across workflows doubled to 18 per cent this year[18]. Some of the strongest published deployment evidence comes from an autonomous maintenance system that has run at a Samsung Electronics fab since 2021, before the current hype. It now pairs a language model with graph-based analysis of equipment logs, and it has handled more than 85,000 real breakdowns across 762 photolithography tools and cut the average recovery time by seven minutes per event[19]. Further field results cover maintenance and scheduling[10], but the

same studies show the limits. Advisory systems report no safety-critical failures, while systems that act directly on equipment need engineered safety filters. Much of the value credited to this category still comes from conventional predictive analytics, and the agentic layer has added little so far. In 2026, a manufacturer can credibly deploy bounded, reversible autonomy, but not unrestricted autonomy on safety-rated operations.

Agent trust, governance and assurance

A company will only let agents act as far as it can supervise them and answer for what they do, so this category sets the limit for the other four. In 2026, this category moved fastest of the five, and the push came from courts and regulators rather than from the technology. A customer had been misled by an airline's chatbot, and the airline argued in court that the chatbot was a separate entity responsible for its own statements. The court rejected the argument and made the airline pay. The company was liable for what its agent told the customer, just as it would be for an employee[20]. California has since legislated the same point: a company there cannot escape responsibility by arguing that its AI acted on its own[21]. The EU's revised timetable brings its obligations for high-risk AI systems into force from December 2027[22]. If the company is liable for what an agent does, the agent needs an employee's management: each one is onboarded with its own identity and permissions, trained and guided on the company's own documents, reviewed against defined objectives, and retired when it is no longer fit. Part of that management will itself be done by agents: compliance agents that check each action against policy before it executes[23], and orchestrators that route work between specialist agents and keep the record of who did what. Most organisations are a long way from this: 78 per cent still have no policy for creating or removing AI identities[24]. What moved in 2026 was the regulation. Operating practice has not caught up, so this category still sits at the emerging end of the radar. The money needs the same discipline. Agentic workflows use the model repeatedly to complete a single task, which multiplies the compute and the token bills compared with the single conversations they replace, and most surveyed enterprises already exceed their AI budgets[25]. Insurers, meanwhile, have started to sell cover for agent failures without the loss history needed to price it.

Cognitive and self-improving agents

These are the furthest from production and the fastest-moving in research. Persistent memory brings large gains on long, multi-step tasks and can make small local models competitive with frontier systems. World models, which let an agent predict consequences before acting, remain years from industrial planning use[26]. The immediate industrial risk is that an agent learns a local workaround and keeps it without engineering review. It is too early to know whether experience learned at one plant will transfer safely to another, or whether it will carry local workarounds with it. Any production use will need to stay under normal engineering change control.

3.4.4 Technology Radar Reading

The five categories are maturing at different speeds, and Figure 3.9 shows how far apart they sit on readiness, impact, adoption and time to mainstream use.

The radar separates industrial readiness from adoption; a technology can be ready enough to deploy and still be uncommon in industry. Horizontal position shows readiness, from emerging on the left to mature on the right, and vertical position shows strategic impact. Colour shows the adoption stage today, and the icon shows the expected time to mainstream use. Category 1, industrial AI assistants and knowledge agents, is the only category at the mature end. Its adoption is already growing, its horizon is within two years, and its impact is rated high, whereas the other four are rated very high. Categories 2 and 3 sit in the growing readiness band, although adoption remains emerging; their horizons are two to five years for agentic engineering and three to seven for autonomous operations. Categories 4 and 5 remain at the emerging end. Trust and governance have a three-to-seven-year horizon, and the self-improving agents are at seed stage, five to ten years from mainstream use.

Moving left across categories 1 to 3, agents receive more authority. Category 1 explains, category 2 produces engineering work and recommendations, and category 3 can act inside bounded domains. Category 4 governs how much authority a company can grant, and category 5 may eventually extend what all the others can do. Every position reflects production evidence, which leaves each category less mature than its marketing suggests.

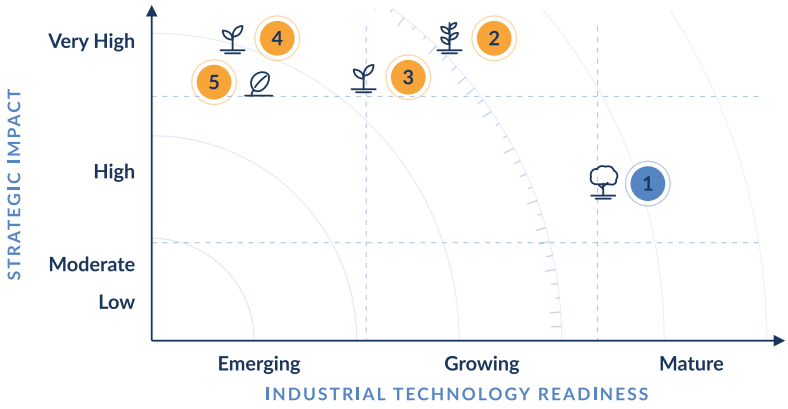
Embodied and humanoid agents are covered in the Physical AI and Humanoid Robotics radar, and simulation in the Digital Twins radar. MCP and A2A, the open standards that let agents use tools and talk to one another, run across all five categories and so appear among the enabling technologies in Table 3.8, together with the industrial bridges that connect them to plant systems.

3.4.5 Call for Action & Risk Management

Manufacturers should give an agent more authority only when the evidence and the controls for that use case are ready. An assistant can stay advisory while a scheduling agent is allowed bounded action; the categories are not steps that every company climbs in sequence, and the existing safety systems stay in charge throughout. Each increase in authority needs a named owner for the agent's identity, its liability and its running cost, and the governance goes in before the first agent has any authority at all: an identity for each agent, a review against its objectives, a record of what it did and a way to switch it off. Technology providers should publish audited results because demonstrations are not evidence, and support neutral protocols and shared industrial data standards to reduce lock-in. Policymakers and standards bodies should require operational accountability alongside model classification, which in practice means that a system must record what an agent did and link each action to a managed identity.

An agent adopted to bridge fragmented systems still depends on consistent data definitions and permissions across them. In an under-digitised plant, it can become an expensive translation layer over unresolved data problems. Small defects add up over a long workflow: high accuracy per step does not deliver dependable end-to-end execution, adaptive testing routinely breaks systems that pass static benchmarks, and in multi-agent designs a single wrong claim can cascade into shared error across the team[27]. None of that is the vendor's problem once the contract is signed. These are operational risks and should be managed as such: register each agent, test it under changing conditions and not only against a fixed benchmark, cap what it can spend, and rehearse stopping it. Robotic process automation, cognitive computing and blockchain supply chains stalled for the same reasons: they arrived without domain integration, credible evidence or redesigned work. The technologies on this radar are more capable than their predecessors. Whether manufacturing captures their value depends less on the models than on the discipline of their adoption.

WMF's Agentic & Cognitive Artificial Intelligence Technology Radar



Top 5 Technology Categories

1. **Industrial AI assistants & knowledge agents**
   Knowledge access and guidance for engineers and operators across manuals, MES, ERP and quality records.
2. **Agentic engineering & autonomous discovery**
   Agents that plan, write and validate engineering artefacts inside real tools.
3. **Autonomous operations agents**
   Scheduling, quality, maintenance and energy decisions within engineered guardrails.
4. **Agent trust, governance & assurance**
   Identity, liability, cost governance and assurance of deployed agents.
5. **Cognitive & self-improving agents**
   Persistent memory and world models, adopted under engineering change control.

Industrial Adoption Stage

- **Mature**
  Ready for broad adoption and scaling
- **Growing**
  Early adoption and expanding capability
- **Emerging**
  Early-stage technologies with high potential

Time Horizon to Mainstream Adoption

- **Mature: Current to 2 years**
  Already adopted in many industrial use cases
- **Growing: 2 to 5 years**
  Scaling across multiple manufacturing industries
- **Emerging: 3 to 7 years**
  Pilot to early adoption at scale in the manufacturing sector
- **Seed: 5 to 10 years**
  Emerging with long-term potential for the manufacturing sector

Radar Guide

- Position indicates the Industrial Technology Readiness (x-axis) and Strategic Impact (y-axis).
- Point colour indicates the current Industrial Adoption Stage.
- Growth-stage icon represents the estimated Time Horizon to Mainstream Adoption.

Figure 3.9. WMF's Agentic & Cognitive Artificial Intelligence Technology Radar

Table 3.8. WMF's Agentic & Cognitive Artificial Intelligence Technology Matrix

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
1. **Industrial AI assistants & knowledge agents**	• LLMs • Answers grounded in company documents • MCP tool connectors • Small models on local plant hardware (edge)	• Maintenance knowledge retrieval • Troubleshooting • Work-order drafting • Compliance documentation	• High	**Growing (2026)** Current to 2 years	• Hallucinated (confidently invented) instructions • Stale sources • Over-reliance • Permission sprawl	• Connect only to approved company sources • Measure the work saved, not how often the tool is used • Redesign the jobs around it
2. **Agentic engineering & autonomous discovery**	• Reasoning models • CAD, CAE and PLC tool use • Self-driving lab modules	• Automation code generation • Requirements engineering • Generative design and PLM • Autonomous materials and process experimentation	• Very High	**Emerging (2026)** 2 to 5 years	• Unreviewed code reaching equipment • IP leakage • Validation cost exceeding savings	• Code must compile, pass automated checks and survive simulation before use • Designs and requirement outputs need the equivalent validation in their own tools • A named engineer signs off • Start where engineering capacity is the bottleneck
3. **Autonomous operations agents**	• Multi-agent orchestration • Digital-twin state • Agent-to-agent protocols • Energy market data	• Dynamic scheduling • Zero-defect quality • Prescriptive maintenance • Energy and carbon steering • Supply-chain exception handling • Multi-site allocation	• Very High	**Emerging (2026)** 3 to 7 years	• Constant replanning that destabilises the floor • Plans that look more precise than the data allows • Interventions costlier than advisories • Integration with shopfloor (OT) systems	• Start in advisory mode and allow limited direct action only once trusted • Measure schedule stability as well as optimisation gains • Keep the existing safety systems in charge
4. **Agent trust, governance & assurance**	• Non-human identity management • Runtime monitoring • Compliance and orchestration agents • Cost governance	• Agent onboarding and performance review • Audit trails • Cost-per-decision control • Liability cover	• Very High	**Emerging (2026)** 3 to 7 years	• Deployer bears the agent's liability as for an employee • Most firms lack AI-identity policies • Runaway workflow costs • Static tests pass while adaptive tests fail	• Treat agents as workforce: identity, permissions, training, review and retirement. • Independent checks at more than one level • Automatic spending cut-offs
5. **Cognitive & self-improving agents**	• Persistent memory • Continual learning • World models that predict consequences	• Agents that learn across shifts and incidents • Predicting consequences before acting	• Very High	**Emerging (2026)** 5 to 10 years	• Errors that reinforce themselves • Learned workarounds nobody has reviewed or versioned • Simulation-to-reality gaps • Small errors compounding over long tasks	• Run pilot projects with versioned, attributable and revisable memory • Keep learned behaviour under engineering change control

3.5 Physical AI & Humanoid Robotics Technology Radar

"The ChatGPT Moment for Robotics". Brett Adcock, Founder & CEO, Figure AI: "If a language model can generalise across text tasks, perhaps a robot foundation model can generalise across physical tasks."

3.5.1 State of Play

Hardware: The global humanoid-robot market has entered the first commercialisation phase. China has established a dominant position in manufacturing and shipments, led by AGIBOT, Unitree and UBTECH, while the US remains the principal challenger through Figure AI, Tesla, Agility Robotics and Apptronik.

In 2025, global humanoid-robot shipments were estimated at around 13,300–16,000 units, with China accounting for more than 80%[1]. The most important change in 2026 is that the market is beginning to separate into three different competitive layers.

The first layer is volume manufacturers: principally AGIBOT and Unitree, followed by UBTECH, Leju, EngineAI and Fourier. These companies have demonstrated that they can actually manufacture and ship humanoids at meaningful volumes.

Table 3.9. Production Forecasts of Humanoid Manufacturing[2,3]

Company	2026	2027	2028	2029	2030
AgiBot	10,000	10,000	100,000	100,000	100,000
1X	–	10,000	100,000	100,000	100,000
Figure AI	–	12,000	12,000	100,000	100,000
Unitree	20,000	20,000	20,000	20,000	100,000
Boston Dynamics	–	–	30,000	30,000	30,000
Agility	10,000	10,000	10,000	10,000	10,000
Neura	6,000	10,000	10,000	10,000	10,000
UBTECH	5,000	10,000	10,000	10,000	10,000
EngineAI	400	10,000	10,000	10,000	10,000
Other Humanoid Robotics Manufacturers (incl. Leju, Tesla, etc.)	≈ 600	≈ 120,000	≈ 150,000	≈ 210,000	≈ 330,000
Sum	≈ 52,000	≈ 212,000	≈ 442,000	≈ 600,000	≈ 800,000

The second layer is commercial pilots: companies such as Figure AI, Agility Robotics, Apptronik, Galbot, RobotEra, LimX Dynamics, Kepler, Astribot and others. These companies have functioning robots and are beginning to test them with industrial customers, but they have not yet demonstrated the same manufacturing scale.

The third layer is the prototype ecosystem. This includes hundreds of companies globally that have announced humanoids, demonstrated prototypes or are developing individual technologies such as hands, actuators, batteries, vision systems or physical-AI models.

Moreover, this is why the next 2–3 years will be decisive: the market will likely consolidate from hundreds of humanoid developers into perhaps 10–20 globally relevant manufacturers, with only a handful ultimately achieving true mass production.

Software: Humanoid robots are among the most complex intelligent systems developed, combining advanced mechanical hardware with sophisticated software capable of perception, reasoning, planning, and control. Modern humanoid robot software typically consists of several interconnected layers. At the lowest level, real-time control systems manage actuators, balance, locomotion, and manipulation. Above this layer, perception software processes data from cameras, lidar, force sensors, microphones, and other sensors to construct an understanding of the surrounding world. Recent advances in artificial intelligence have significantly transformed humanoid robotics software. Foundation models, such as Vision-Language Models (VLMs), Vision-Language-Action (VLA) and World Models (WMs), have emerged:

Vision-Language Models (VLMs) are multimodal artificial intelligence systems that jointly process visual information and natural language. By combining computer vision and language understanding, VLMs can interpret images, answer questions about visual scenes, generate descriptions, follow language instructions, and perform semantic reasoning about the surrounding environment. The first development around 2019, for example, was VisualBERT[4]. **Vision-Language-Action (VLA)** models represent the next evolutionary step by extending multimodal understanding with the ability to generate robot actions. While VLMs process visual information and natural language to answer questions or perform reasoning tasks, VLAs add an action generation layer that enables robots to transform perception and language instructions directly into physical behaviour. A typical VLA receives images or video, the robot's proprioceptive state, and a natural-language instruction as input, and produces motor commands, action sequences, or trajectories as output.

The evolution of VLA architectures began with Google's RT-1 in 2022[5], which demonstrated that transformer-based policies could scale robot learning across many tasks. RT-1 was a language-conditioned control model trained on large amounts of robot interaction data and established the feasibility of large-scale robot learning. The next breakthrough came with RT-2 in 2023[6], which transferred knowledge from web-scale vision-language models into robotic control. RT-2 was the first true Vision-Language-Action model, capable of converting semantic reasoning into robot actions. It demonstrated zero-shot capabilities such as recognising previously unseen objects and understanding semantic relationships, providing one of the earliest examples of a robot leveraging general world knowledge to perform novel tasks. Among current state-of-the-art VLA systems, OpenVLA[7] has emerged as one of the most influential open-source platforms. Developed by researchers from Stanford, UC Berkeley, Google DeepMind, and Toyota Research Institute, OpenVLA is a 7-billion-parameter model trained on approximately 970,000 robot demonstrations from the Open X-Embodiment dataset.

NVIDIA's GR00T N1[8] represents a significant step towards general-purpose humanoid robotics. The model employs a dual-system architecture inspired by human cognition. The slower "System 2" component is responsible for perception, reasoning, language understanding, and planning, while the faster "System 1" component handles real-time motor control and action execution. Trained using a combination of real robot trajectories, human videos, and synthetic datasets, GR00T N1 demonstrates strong performance across multiple robot embodiments and humanoid manipulation tasks. This architectural separation between reasoning and execution is increasingly viewed as a key design principle for future robot foundation models.

Figure AI's Helix[9] is another highly influential commercial VLA system. Helix focuses on whole-body humanoid control, multi-step reasoning, and bimanual manipulation. Its importance lies less in benchmark performance and more in demonstrating that a foundation-model-based humanoid can perform diverse real-world tasks such as household work, warehouse operations, and coordinated manipulation.

Alongside VLAs, **World Models** have emerged as a complementary technology. Whereas VLAs are primarily reactive, world models are predictive. A world model learns the transition dynamics of the environment and estimates future states based on the current state and a proposed action. This allows a robot to predict object interactions, physical consequences, and task outcomes before executing actions.

The most advanced example of this paradigm is Google DeepMind's Genie 3[10]. Genie 3 is a real-time interactive world model capable of generating photorealistic environments at 720p resolution and 20 to 24 frames per second. Given a text prompt, it can create consistent virtual worlds that remain coherent over extended periods of interaction.

NVIDIA's Cosmos[11] serves a complementary role as a world foundation model designed specifically for Physical AI applications. Cosmos integrates language, video, audio, and action modalities to support simulation, world generation, synthetic data creation, and robot policy training. Together with GR00T, it forms a complete infrastructure stack for training and deploying next-generation humanoid robots.

The latest frontier in physical AI is the emergence of **World Action Models (WAMs)**. Traditional VLA architectures follow a relatively direct pipeline of observation to action. WAMs introduce an intermediate prediction stage in which the robot first imagines potential futures, evaluates outcomes, and only then selects an action. In effect, the robot performs internal simulation before acting in the real world. This combines the strengths of VLAs and world models into a unified framework that integrates perception, prediction, planning, and control. Systems such as World Pilot[12] have already demonstrated state-of-the-art performance in out-of-distribution robotic manipulation benchmarks, suggesting that WAMs may become the dominant paradigm for future physical AI.

3.5.2 Technological Capabilities for Value Creation Opportunities

Table 3.10. Technological Capabilities for Value Creation Opportunities in Physical AI & Humanoid Robotics

Focus	Main Enablers	Value Created
1. Perception and Environmental Awareness Capability		
Enabling robots to sense, interpret, and understand their surroundings	• Computer Vision Systems • Multimodal Sensors (LiDAR, IMUs, cameras, tactile) • Sensor Fusion algorithms	• Improved situational awareness • Safer Operations • Higher Task Accuracy
2. Autonomous Decision-Making Capability		
Allowing robots to plan, reason, and make decisions without human intervention	• Foundation models and Physical AI • Task Planning • World models • Edge computing resources	• Increased Productivity • Reduced Human Workload • Enhanced operational Efficiency
3. Human-Robot Interaction Capability		
Facilitating natural and effective collaboration between humans and humanoid robots	• Natural language processing • Vision-Language-Action Models • Gesture and emotion recognition	• Improved user Experience • Workforce Augmentation
4. Dexterous Manipulation and Autonomous Movement Capability		
Performing complex physical tasks using robotic hands	• Advanced actuators and motors • Replaceable or fast-charging batteries • Sim-to-Real approaches • Motion and movement planning algorithms	• Automation of skilled Labor • Higher Precision • Improved task flexibility
5. Adaptive Learning Capability		
Continuously improving robot performance from experience and environmental feedback.	• Machine learning frameworks • Reinforcement learning • Synthetic data generation • Continuous learning Architectures	• Faster Adaptation • Reduced training costs • Enhanced long-term Performance
6. Safety, Reliability, and Trust Capability		
Ensuring secure and dependable operation in human environments	• Functional safety systems • AI governance frameworks • Cybersecurity mechanisms	• Regulatory Compliance • Reduced operational Risk • Increased Trust

3.5.3 Aligning Capabilities to Technology Categories for Facing Challenges

Humanoid and autonomous robots that can perceive and understand their environment to plan their tasks in real time.

We humans rely on our senses to understand our environments and plan our actions. Traditional industrial robots did not need advanced sensing capabilities, as they typically replicated the same movements over and over within enclosed spaces without the need for real-time task and trajectory planning.

Collaborative, Autonomous and Humanoid robots that work within the same environment as human workers will require improved vision and sensing capabilities in real time as a fundamental capability for perceiving their environment. Edge computing with advanced AI algorithms such as Zero Shot Depth models for image processing, recognition and spatial modelling are essential drivers to overcome current awareness challenges.

Physical AI is enabling robots to break out from routine and repetitive tasks towards complex and generic manipulation of their environment.

A core driver for this understanding of our natural environment is AI world models, which are neural representations of the physical laws, such as gravitational effects, and cause-and-effect relationships. This allows Physical AI to simulate and understand outcomes before acting. Therefore, rather than reacting to real-time sensor data, humanoid robots can predict how the environment is going to behave and evolve in response to a particular scenario.

Autonomous robots are going to work collaboratively and interact seamlessly with human workers in the same environment.

Humanoids will not entirely replace the human workforce. Robots will work alongside other human operators and industrial employees in the same shared environments. Hence, the need to naturally dialogue and interact with humans is an essential requirement for the take-up and acceptance of humanoids within industrial environments.

Large Language Models (LLMs) have provided a breakthrough to achieve Natural Language Processing (NLP) capabilities, which are at the very basis of human-robot interaction. That said, to truly achieve integration of the humanoid robot on a cognitive and social level, other interaction models need to be developed. These will include

the capability of recognising human emotion and gestures, which are essential in our non-verbal communication capabilities and which are required to achieve a natural human-machine symbiosis.

Advanced robotics systems are gaining greater movement, dexterity and manipulation capabilities, opening the door for new tasks.

SIM-to-Real capability, with the introduction of simulation environments such as Nvidia's Isaac Sim, MuJoCo (MJX) and Gazebo Sim, has created a virtual playground for training and optimisation of robot movement.

These capabilities could obviously not have been achieved without the development of improved and more efficient actuators and end-effectors which are capable of manipulating their environment. Advances in soft robotics and materials will be able to address current challenges in safe object manipulation, especially when working in the same environments as human workers.

The capability of learning is going to drive a faster and better adoption of Humanoid robots within industrial environments.

Vision-Language-Action (VLA) models will be able to bridge the gap between the human operator and trainer and the robot executing the task. Rather than employing complex and time-consuming robot task planning, humans will be able to use abstract natural language to guide and train autonomous robots to execute ordered sub-goals and task objectives.

An extension of the sim-to-real environment will be the capability of using reinforcement learning to optimise dynamic modelling and trajectory and locomotion planning across millions of parallel simulation routines, to identify the faster and better motion strategies based on changing industrial environments and tasks.

Secure, safe and ethical approaches for reliable decisions are essential to the implementation within real industrial environments.

At the core of any Physical-AI are the decision-making capabilities, which need to be driven by secure, safe and ethical frameworks to ensure that humans can trust the operation of these machines. As cyber-security challenges increase, operating systems need to be protected, and clear information needs to be provided with respect to the data which is being processed by these systems. Furthermore, to ensure legal and safe implementation of these systems, ethical reasoning needs to be employed within a clear legal framework which identifies responsibilities in case of accidents or injuries. Ref. ISO/CD 25785-1

3.5.4 Technology Radar Reading

Humanoids are no longer just our future; they are our present. Combinations and advancements of technological solutions are giving rise to various categories of Physical AI implementations.

The technology radar for Physical AI and Humanoid Robotics is intended to provide an impartial outlook on the maturity and impact of various technology categories. These categories range from Physical AI-powered cobots and Machines to Quadrupeds. The form factor of these technology categories plays an important role in their movement and manipulation capability.

At one end of the scale, we have physical AI-powered collaborative robotics and Machine Tools. These utilise flexible fixtures and robotic manipulation approaches for interaction with their environments, and are limited in their mobility. They utilise multi-camera setups for vision inspection, but make use of advanced real-time edge AI processing units to eliminate traditional rigid jig requirements. Zero-shot metric depth estimation of both products to be manipulated, as well as their physical environments, allows these machines to be highly flexible, safe and easily integrated within existing environments. Current technological implementation means that this category has already achieved a high degree of technology readiness and is mature for industrial implementation. Standards such as ISO 10218 have also been recently updated and allow industry to implement these within their current production environments.

Autonomous Mobile Robotics combine the capabilities of collaborative robotics onto mobile platforms, which allows for an increased spatial reach. Typical implementations combine traditional Autonomous Guided Vehicle (AGV) platforms with collaborative robot manipulators. Whilst traditional AGVs rely solely on fleet managers and SLAM for navigation, Physical AI-powered AMRs make use of 3D occupancy grid world modelling and dynamic spatial AI for real-time obstacle avoidance in busy worker aisles.

Technology maturity for these first two categories is high, and actual industrial implementation for these has in fact been documented in various industrial fields and applica-

tions, such as logistics distribution warehouses and automotive plants.

A rapidly growing field of implementation is the use of humanoid robots for the logistics industry. These are typically designed to fit into legacy and brownfield environments without requiring structural retrofits of the factory environments or custom tooling. In this sector, these are typically biped humanoid robots which make use of sim-to-real reinforcement learning for line-feeding, tote and material transport. An example of this implementation is the use of Digit by Agility Robotics within an Amazon warehouse for picking up, manoeuvring and stacking of empty totes. Whilst most of the implementations are still at operational pilot levels, commercial agreements and implementation will be scaling in the coming years across various industries.

On a broader level, emerging is the use of humanoids within the manufacturing sector to carry out manufacturing tasks such as bin-picking, multi-step assembly and machine tending. A well-known and documented use case is that developed by the BMW group with the implementation of the Figure 02 biped humanoid robot that completed an 11-month production run operating on 10-hour shifts. Whilst this implementation is still at an emerging stage, other industries, such as ST Microelectronics, have implemented operational wheeled humanoids; specifically, Oversonic Robotics' RoBee has already been deployed on the factory floor at ST's advanced packaging and testing facility. This marks one of the world's first uses of cognitive humanoid robots within a live semiconductor production environment due to its certified functional safety and regulatory compliance.

Quadrupedal platforms utilise four-legged biological locomotion platforms combined with advanced sensing capabilities to manoeuvre over uneven terrain or slippery surfaces. In fact, unlike humanoids, which are specifically used to execute manufacturing tasks, quadrupeds are deployed as agile physical sensing and inspection platforms. Boston Dynamics' Spot is a prime example of this platform that has been implemented across sectors, for example by Hyundai for factory monitoring and anomaly detection to Siemens Energy for thermal auditing and vibration monitoring on heavy industrial machinery. Whilst current implementation of quadrupeds is ahead of that for humanoids, strategic impact is limited to monitoring and detection phases.

3.5.5 Call for Action & Risk Management

Validate Feasibility and Savings Potential

Conduct targeted pilot projects to validate the technical feasibility and economic value of humanoid robotics before large-scale deployment. Focus on use cases with clear productivity gains, labour savings, safety improvements, and measurable ROI to ensure sustainable business benefits.

Launch Targeted Humanoid Robotics Pilots

Start with low-risk, repetitive, and labour-intensive use cases in logistics, inspection, material handling, and warehouse operations. Establish measurable KPIs focused on productivity, safety, quality, and ROI.

Invest in Physical AI Infrastructure

Develop simulation environments and digital twins to support robot training, testing, and optimisation before deployment. Build capabilities around synthetic data generation and sim-to-real learning.

Strengthen Edge AI and Data Infrastructure

Upgrade sensor networks, industrial connectivity, and edge computing resources required for real-time robot perception and decision-making. Ensure seamless integration with existing operational technology (OT) and enterprise systems.

Develop a Human-Robot Workforce Strategy

Upskill employees in robot supervision, maintenance, AI operations, and human-robot collaboration. Define new job roles focused on robot operations, safety oversight, and continuous improvement.

Humanoids for a human world, not for a fully automated solution

Humanoids should not be seen as the best solution within greenfield design of automated solutions. Rather, the value of humanoids is most valuable within brownfield design, where human constraints provide severe limitations for the implementation of more fully automated solutions.

Table 3.11. Key Risk Management

Potential Risk	Recommended Mitigation
Operational Safety	
Human injury resulting from robot malfunction or unexpected behaviour	Implement functional safety systems, safety-certified hardware, geofencing, and human-in-the-loop supervision
Cybersecurity	
Unauthorised access, manipulation, or disruption of autonomous robots	Apply zero-trust architectures, secure software updates, endpoint protection, and continuous monitoring
Technology Maturity	
Immature solutions fail to meet performance expectations	Use phased deployments, proofs-of-concept, and technology validation programmes
Workforce Acceptance	
Resistance due to fears of job displacement	Communicate augmentation benefits, provide reskilling programmes, and involve employees early in deployment projects.
Regulatory & Liability	
Unclear legal responsibility in accidents or autonomous decisions	Define accountability frameworks and maintain compliance with emerging robotics standards

Strategic Recommendation

Organisations should treat Physical AI and Humanoid Robotics as a strategic transformation initiative rather than a simple automation project. The next 3-7 years are likely to determine which organisations successfully leverage autonomous robotic workforces. Early experimentation, governance readiness, workforce preparation, and cybersecurity-by-design will be critical factors separating leaders from followers in the emerging Physical AI economy.

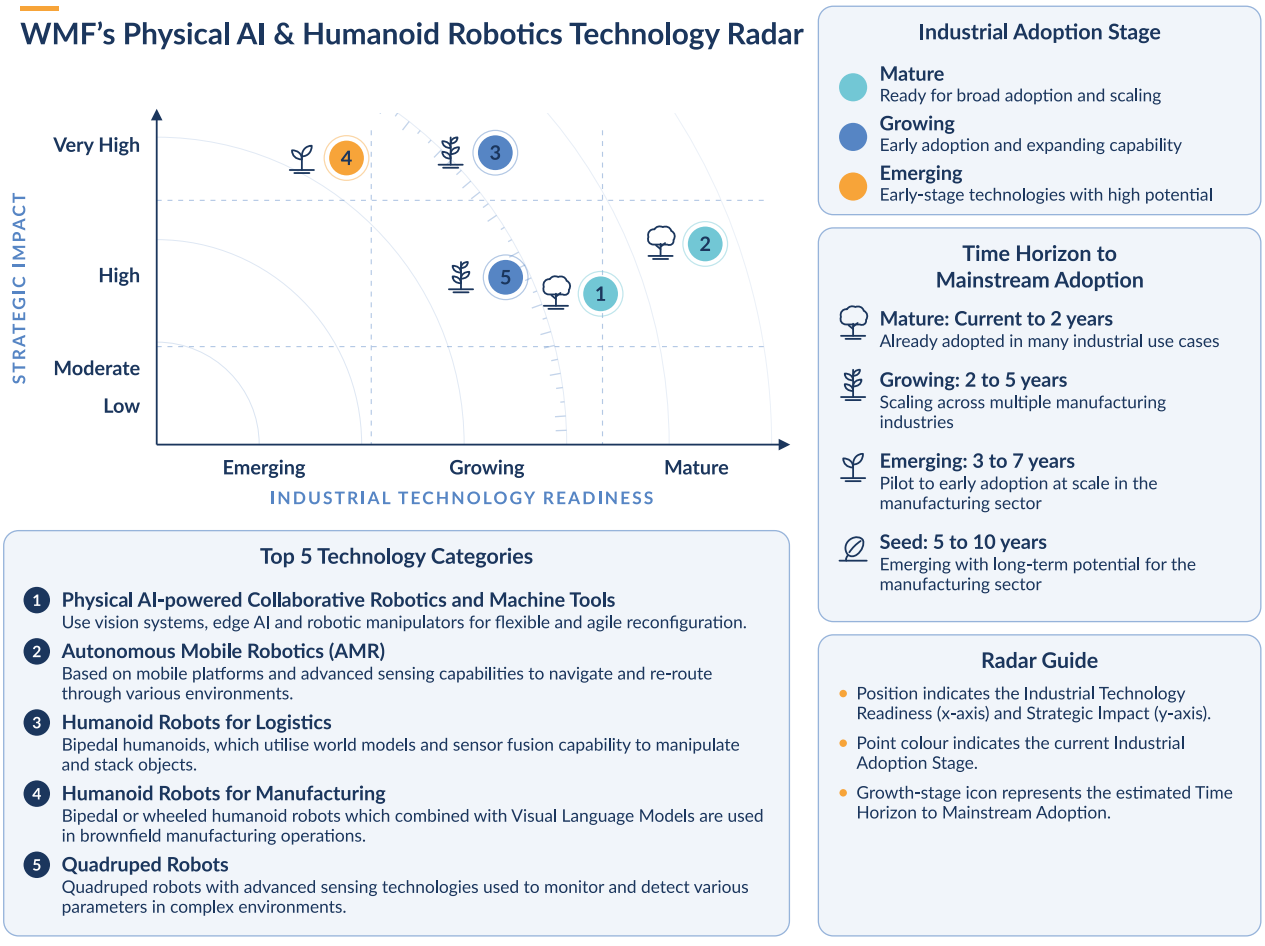


Figure 3.10. WMF's Physical AI & Humanoid Robotics Technology Radar

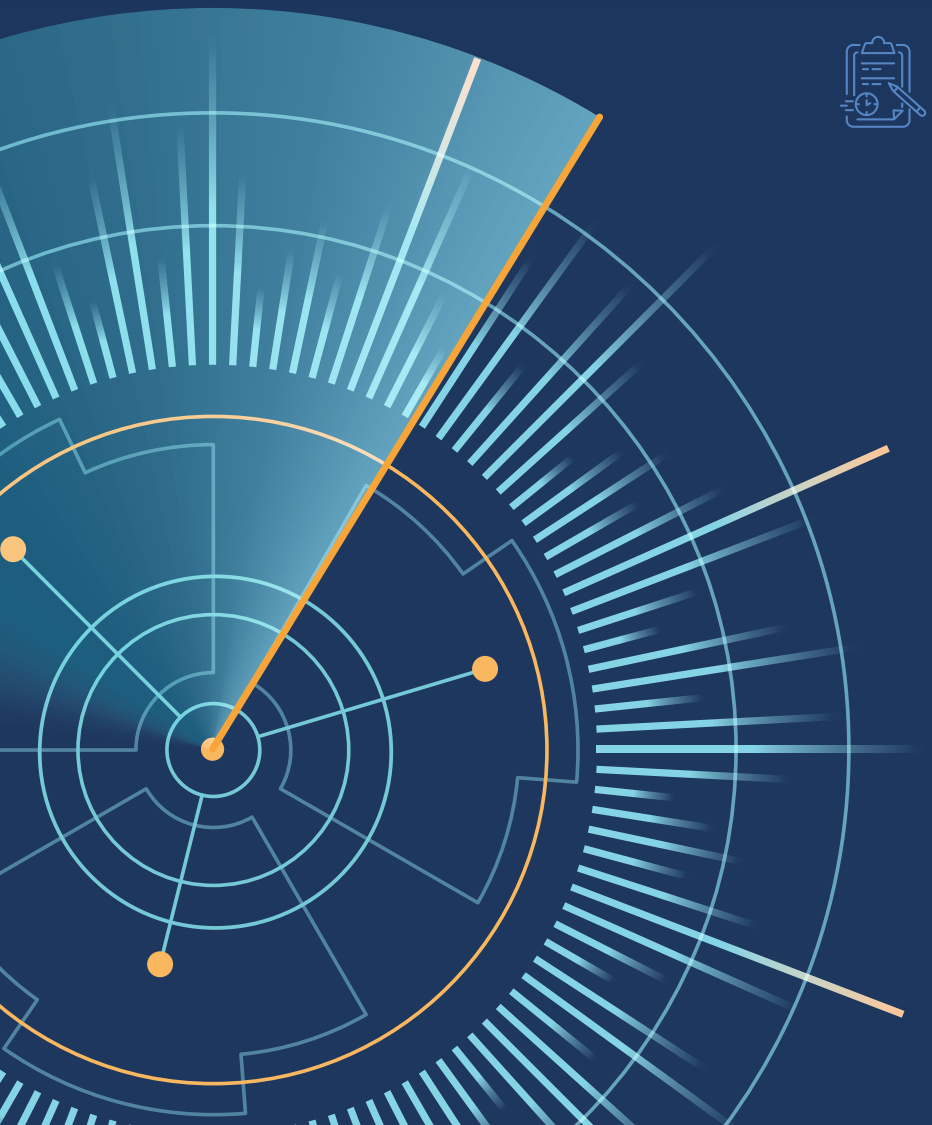
Table 3.12. WMF's Physical AI & Humanoid Robotics Technology Matrix

Technology Category	Key Enabling Technologies	Representative Industrial Applications	Strategic Impact	Industrial Maturity (2026) & Expected Mainstream Adoption	Risks of Adoption	Call for Action
1. **Physical AI-powered Collaborative Robotics and Machine Tools**	• Computer Vision Systems • Physics-informed neural networks (PINNs) • Synthetic data generation	• Component Assembly • Machining and Fabrication processes	• Greater production flexibility and responsiveness through dynamic, AI-enabled adaptation of collaborative robots and machine tools to changing manufacturing tasks.	**Mature (2026)** Current to 2 years (2026–2028)	• Operational Safety • Availability of data models	• Expand Synthetic Data Pipelines • Upskill Workforce for Physical AI
2. **Autonomous Mobile Robotics (AMR)**	• Multimodal Sensors (LiDAR, IMUs, cameras, tactile) • Sensor Fusion algorithms	• Internal and External Logistics and component manipulation.	• Improved intralogistics efficiency and operational flexibility through autonomous material handling, optimised workflows and reduced dependence on manual transport.	**Mature (2026)** Current to 2 years (2026–2028)	• Safety and Regulatory Risks • Cybersecurity	• Validate Feasibility and Savings Potential
3. **Humanoid Robots for Logistics**	• World models • Advanced actuators and motors	• Internal logistics application in brownfield environments.	• Flexible automation of logistics operations in human-designed environments, reducing infrastructure adaptation needs and supporting workforce optimisation.	**Growing (2028)** 2 to 5 years (2028–2031)	• Workforce Acceptance • Regulatory & Liability	• Strengthen Edge AI and Data Infrastructure • Launch Targeted Humanoid Robotics Pilots
4. **Humanoid Robots for Manufacturing**	• Advanced actuators and motors • Vision-Language-Action Models • Sim-to-Real approaches • Reinforcement learning	• Manufacturing tasks typically carried out by humans in brownfield environments.	• Potential automation of diverse manufacturing tasks through human-like mobility and manipulation, increasing production versatility and addressing labour shortages.	**Emerging (2030)** 3 to 7 years (2029–2033)	• Technology Maturity • Workforce Acceptance • Regulatory & Liability • Integration with legacy systems	• Develop a Human-Robot Workforce Strategy
5. **Quadruped Robots**	• Foundation models and Physical AI • Motion and movement planning algorithms	• Inspection, monitoring and detection tasks in complex manufacturing environments	• Enhanced industrial inspection, monitoring and safety through autonomous data collection and mobility in hazardous, inaccessible or complex manufacturing environments.	**Growing (2028)** 2 to 5 years (2028–2031)	• Cybersecurity • Technology Maturity • Regulatory & Liability	• Identify suitable case studies and implementation guidelines in manufacturing.

04

CHAPTER 4

10 KEY RECOMMENDATIONS BY THE WORLD MANUFACTURING FOUNDATION



10 Key Recommendations



Five Key Recommendations for Using a Trends Compass

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08 Validate Manufacturing Technologies through Experimentation and Pilot Implementation 87

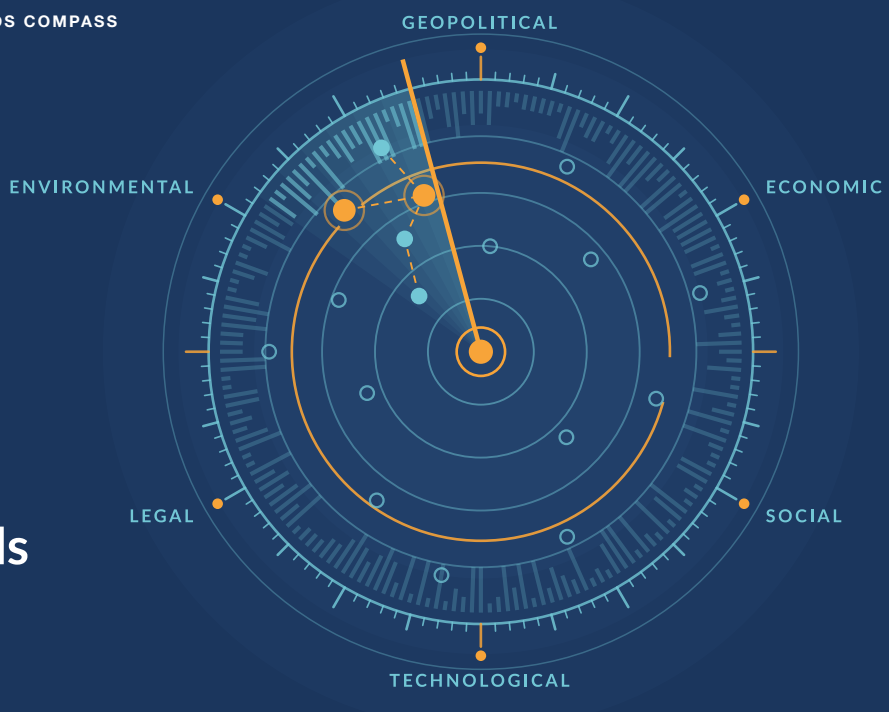
09 Foster Cross-Functional Manufacturing Technology Governance 88

10 Review, Validate, and Update the Technology Radar Regularly 89

01

RECOMMENDATION 1

Systematically Scan for Emerging Manufacturing Trends in the Environment



SKILLS

Prepare skilled top and middle managers capable of distinguishing weak signals from established trends, assessing potential impacts, connecting trends, and positioning them consistently within a trends compass.

TECHNOLOGY

Utilise AI-enabled environment scanning, technology intelligence, patent and scientific databases, and market-monitoring platforms to continuously capture and organise trend signals.

CULTURE

Build a curious, outward-looking, evidence-driven culture in which all employees actively search beyond the state-of-the-art of operations and technologies to innovate.

The trends analysed in this Report show how quickly the external environment of manufacturing can change. Tariffs, export controls and sanctions can challenge established sourcing arrangements within short planning horizons. Diversions away from the Red Sea and constraints on Panama Canal transits have shown how a few maritime chokepoints can lengthen lead times across unrelated sectors. Heat, flooding and water stress are becoming recurring operating conditions rather than exceptional events. Most of these developments were visible as weak signals long before they reached the factory. The issue is rarely the lack of information, but the absence of a systematic process to capture it and give it meaning.

Manufacturers should therefore treat environmental scanning as a permanent organisational routine rather than an occasional exercise prepared for the yearly strategic plan. Scanning should cover all six geopolitical, economic, social, technological, legal and environmental dimensions used in the trends compasses of this Report, since the most disruptive situations arise when pressures from different dimensions interact. Geopolitical measures change where production can be located, which in turn alters exposure to climate hazards and to labour markets. A scan limited to technology or to markets would miss these combinations.

Scanning should also look beyond the boundaries of the firm. A substantial proportion of supply chain disruptions originate below the first tier, where visibility is weakest, and the most serious human and labour risks are often concentrated in lower tiers and small-scale operations. Regulation is moving in the same direction, increasingly requiring manufacturers to monitor strategic supply chains and to know their suppliers beyond the first tier. Digital tools, from multi-tier mapping to automated monitoring of disruption signals, can shorten the time between an event and a decision, but their value depends on interoperable data and sustained relationships with suppliers.

Finally, scanning is not only a task for a specialised strategy office. Operators, buyers, maintenance personnel and sales engineers are often the first to notice that something is changing. Companies that give every employee the curiosity and the channel to report what they observe outside daily operations will capture signals earlier and at lower cost than those relying only on external reports.

02

RECOMMENDATION 2

Engage Diverse Stakeholders in Manufacturing Trends Interpretation



SKILLS

Develop proficient leaders and managers trained in interpreting trends from different perspectives, challenging assumptions, identifying interdependencies, and translating external signals into implications for operations, workforce, technology, and strategy.

TECHNOLOGY

Make use of voting/prioritisation tools and AI-supported analysis to enable all relevant stakeholders to contribute evidence, annotate trends, identify connections, and collectively assess trends based on their impact, uncertainty, maturity, and time horizon.

CULTURE

Encourage an inclusive, participatory, and open-to-challenge culture where perspectives from multiple stakeholders are valued.

A trend does not carry a single meaning. The same development can be a threat for one function and an opportunity for another, and its consequences often become clear only when different perspectives are combined. The trends analysed in this Report cut across choices that have traditionally been separated across procurement, operations, engineering, human resources, information technology and risk functions. Resilience, sustainability and human-centricity cannot be interpreted correctly by any of these functions alone.

Manufacturers should therefore involve a deliberately diverse group of stakeholders when interpreting trends: top and middle managers from different functions, but also operators, maintenance and safety personnel, worker representatives, key suppliers, customers and, where relevant, research partners. The human-centric trends compass shows why this matters. Operators understand recurring variability and workarounds, while maintenance and safety personnel often identify failure modes that become visible only in operation. Similarly, visibility of sub-tier exposure depends on supplier relationships that make disclosure possible, since this information is commercially sensitive and rarely obtained through contractual demand alone.

The interpretation process should be structured rather than left to informal discussion. For each trend, stakeholders should consider its consequences on people, processes and technology, first across the supply chain and then within the manufacturing system, as done in the trends compasses of this Report. Particular attention should be paid to interdependencies: digitalisation improves visibility while adding cyber dependence, and reshoring can improve continuity while being planned together with automation that changes the jobs created. Digital collaboration and AI-supported tools can help stakeholders contribute evidence and map these connections, but they should support, not replace, the discussion among people.

Diversity is only useful if it is allowed to challenge established assumptions. Leaders should create the conditions for dissenting views to be expressed and recorded, so that the trends compass reflects the plurality of perspectives in the organisation and its ecosystem rather than the opinion of its most senior members.



03

RECOMMENDATION 3

Prioritise and Align Manufacturing Trends Based on Relevance & Impact and with the Business Strategy

SKILLS

Train qualified leaders and managers able to assess each trend against strategic objectives, priorities, potential value, risks, feasibility, urgency, and time horizon, distinguishing high-impact trends from interesting but less relevant developments.

TECHNOLOGY

Employ scenario-analysis and multi-criteria decision-analysis tools, scoring models, and AI-supported analytics to score and rank trends according to relevance, impact, uncertainty, strategic fit, and implementation horizon while maintaining traceability to supporting evidence.

CULTURE

Foster a strategically aligned, evidence-based, and future-oriented culture where trend prioritisation is driven by business value rather than technology novelty.

No company can respond to every trend at the same time. Resources, management attention and investment capacity are limited, and resilience measures carry their own costs: higher financing costs increase the burden of inventory and capacity buffers, while volatile freight and energy prices change the economics of network configuration. Without clear priorities, a trends compass risks becoming a long list of interesting developments that does not change any decision.

Manufacturers should therefore assess each trend against explicit criteria: its relevance for the company's markets and operations, the size and likelihood of its impact, the time horizon in which it will materialise, and its fit with the business strategy. The analysis of resilience in this Report offers a useful lesson on how to do this. Exposure is frequently misidentified because it is assessed by expenditure: suppliers representing low spend can carry long recovery times when they hold unique tooling, qualifications or process knowledge. Investment in resilience is most effective where propagation risk is greatest, rather than distributed evenly. In the same way, trends should be prioritised according to their real consequences for the business, not according to how visible or fashionable they are.

Prioritisation should also consider how trends interact. Pressures rarely act in isolation, so a configuration should be assessed under combinations of stress rather than against each trend separately. Scenario analysis, stress testing and multi-criteria decision tools can make these assessments consistent and comparable, provided that the evidence and assumptions behind each score remain traceable.

Finally, prioritisation is meaningful only when it is aligned with the business strategy. A trend may be highly relevant for the sector and still be secondary for a specific company, or vice versa. Top management should own the final prioritisation and make visible how the selected trends relate to strategic objectives, so that the trends compass becomes an input to strategy rather than a parallel exercise.

04

RECOMMENDATION 4

Translate Manufacturing Trends into Actionable Strategic Initiatives



SKILLS

Instruct prepared top and middle managers in translating trends into specific strategic initiatives, defining expected outcomes and KPIs, identifying required capabilities and resources, and establishing clear implementation pathways.

TECHNOLOGY

Wield digital roadmapping and AI-supported scenario-planning tools to generate alternatives, evaluate scenarios, estimate impacts, identify dependencies, and track implementation progress of trend-driven strategic initiatives.

CULTURE

Promote an action-oriented, experimental, and learning culture that encourages moving from trend discussion to controlled experimentation pilots and later at-scale implementations.

A trend becomes valuable only when it changes a decision. The trends compasses in this Report reach the same conclusion from different directions: resilience becomes operational when it changes specifications, sourcing decisions, plant design and the way performance is measured, and human-centricity becomes operational when it changes specifications, investment decisions and the way performance is governed. Plans that are consulted only after a disruption has occurred do not make a company more prepared.

Manufacturers should therefore translate each priority trend into a limited number of strategic initiatives, each with a clear owner, expected outcomes, KPIs, required resources and an implementation pathway. Timing is critical. Decisions about network structure, plant layout, product architecture, automation and work organisation become costly to reverse once they are fixed. The implications of trends should therefore be considered before these choices are made, for example by making exposure, recovery time and the ability to reconfigure explicit criteria in network design and capital investment, or by considering workload, skills and decision authority before automation choices are taken.

Initiatives should address people, processes and technology together. Changeability built into plants and products, the qualification of alternative sources as a standing activity, cross-training and retained operational knowledge, and continued learning as part of the operating model are examples of initiatives that combine all three dimensions. Digital roadmapping and scenario-planning tools can help evaluate alternatives and track progress, and digital twins allow configurations to be tested against disruption scenarios before commitments are made.

When uncertainty is high, it is better to start with controlled pilots and scale what works than to wait for complete information. Where the evidence needed for a decision is not yet available, the practical priority is to build the information, relationships and capabilities that will make the decision possible. In this way, the trends compass connects with the technology radars and their recommendations on experimentation and pilot implementation.

05

RECOMMENDATION 5

Review, Validate, and Update the Trends Compass Regularly



SKILLS

Develop experienced leaders and managers in detecting changes in trend maturity and impact, validating assumptions against new evidence, identifying emerging or declining trends, and reassessing their relevance to trend-driven strategic initiatives.

TECHNOLOGY

Use automated environmental-scanning tools, AI-supported trend monitoring, and technology-intelligence platforms to continuously capture new signals and evidence of trends' evolution.

CULTURE

Nurture a continuous-learning, adaptive, and evidence-based culture that encourages stakeholders to challenge presumptions, contribute new evidence, acknowledge uncertainty, and modify priorities when conditions change.

A trends compass is a snapshot of a moving landscape. Trade rules, regulations, technologies and climate conditions are all changing faster than the typical planning cycle of a manufacturing company. Rules on critical raw materials, due diligence, cybersecurity and artificial intelligence have been introduced or extended within a few years, and each has changed what manufacturers are expected to know and to do. A compass that is not updated quickly becomes a source of false confidence.

Manufacturers should therefore define a regular review cycle for the trends compass, with clear ownership and review dates, and should also trigger extraordinary reviews when a major event occurs. Each review should check whether the trends are evolving as expected, whether new trends have emerged and others have weakened, and whether the strategic initiatives derived from them are still appropriate. Assumptions should be explicitly validated against new evidence, including the results of pilots and the operational experience gained after past disruptions.

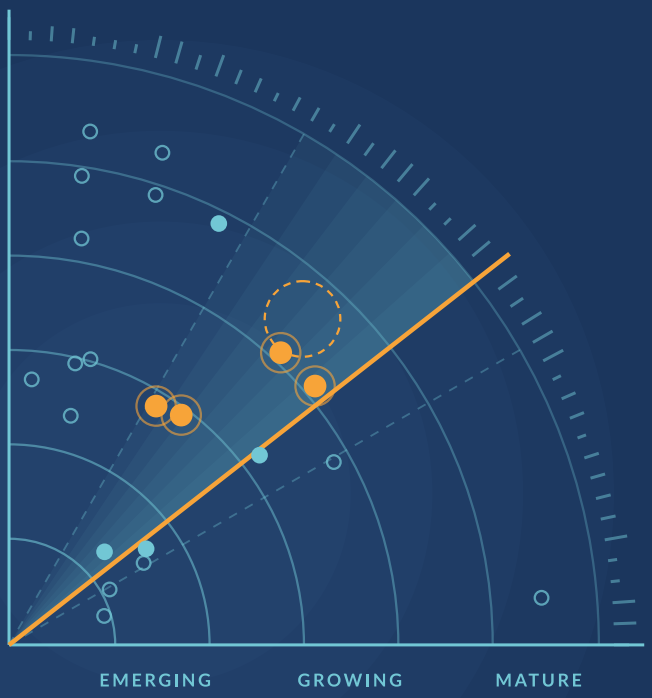
The review should be based on evidence rather than on recent experience alone. The resilience trends compass notes that better measures of recovery time, substitution capability and network exposure would allow firms to allocate resources based on evidence rather than on recent experience, and the human-centric compass shows that outcomes which are harder to measure tend to receive less attention. Documenting changes in trend positions, the reasons behind them and the decisions they triggered makes the compass transparent and allows the organisation to learn from its own past judgements.

Finally, updating the compass requires the willingness to change priorities. Leaders should acknowledge uncertainty openly and treat earlier assessments as revisable rather than permanent. The value of the trends compass lies less in any single version than in the continuous capability it builds: the ability of the organisation to read change early and adjust its course before change is imposed upon it.

06

RECOMMENDATION 6

Continuously Monitor and Evaluate Emerging Manufacturing Technologies



SKILLS

Grow highly competent top and middle managers in identifying technological signals, distinguishing hype from meaningful developments, evaluating technology maturity, and assessing potential implications for operations performance, workforce, processes, and competitiveness.

TECHNOLOGY

Make use of technology-intelligence platforms, AI-enabled scanning tools, patent and scientific databases, and market-intelligence systems to continuously identify technological developments according to their maturity, relevance, impact, uncertainty, and expected adoption horizon.

CULTURE

Stimulate a technology-aware, curious, evidence-driven, and future-oriented culture where employees actively explore technological developments to empower people and improve processes.

The technology radars in this Report show how quickly the technological landscape of manufacturing is changing. Agentic AI is following one of the fastest adoption curves ever observed for an emerging technology, while humanoid robots have moved into a first commercialisation phase. At the same time, many technologies that initially appear exaggerated or impractical later become a source of competitive advantage, and companies that dismissed them early often find it difficult to catch up. The risk for manufacturers is therefore twofold: following the hype, or ignoring developments that are still immature but will soon matter.

Manufacturers should therefore monitor emerging technologies continuously rather than when a specific investment is under discussion. What matters is not the probability of success of a technology today, but the early detection of its inflection points. Monitoring should cover the maturity of each technology, its strategic impact, its current adoption stage and its expected time to mainstream adoption, the four dimensions used in the technology radars of this Report. Internal technology-intelligence capabilities, supported by AI-enabled scanning tools and scientific and patent databases, can help capture meaningful signals and filter out the noise.

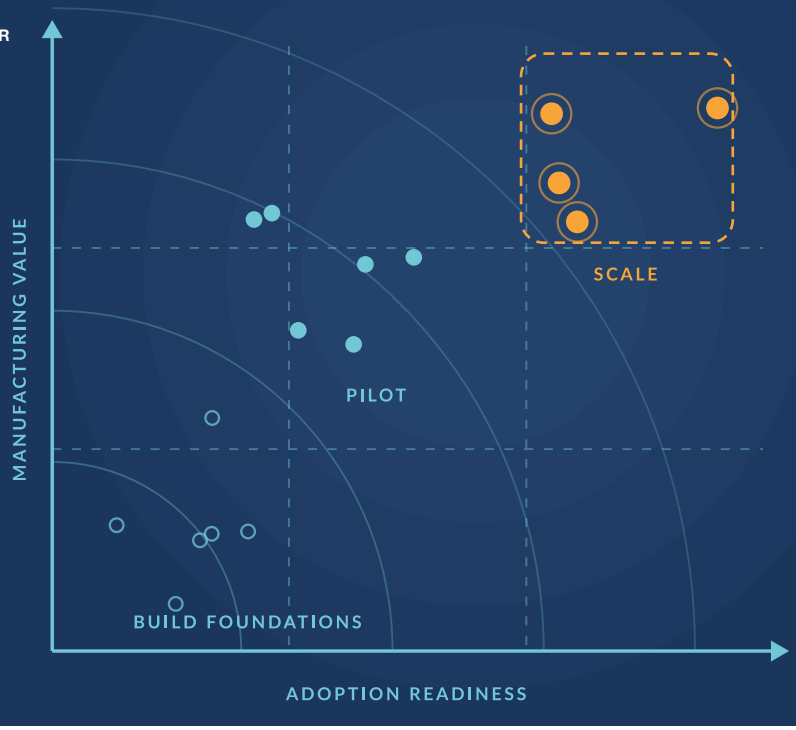
Acquiring a technology is rarely the main obstacle for a company with adequate resources. The harder task is interpreting what the technology means for skills, processes and performance in the near, medium and long term. Managers need the competences to read these signals critically. International standards on innovation management can provide guidance in designing these internal processes.

Finally, monitoring must look at where people and technology actually interact, because this is where most adoption failures occur. Technologies often fail not because they do not work, but because the work environment and the culture were not ready for them. A future-oriented culture, in which new ideas are welcomed and concerns are openly addressed, makes it possible to adopt technologies early while keeping people and technology in step.

07

RECOMMENDATION 7

Prioritise and Categorise Technologies Based on Manufacturing Value and Adoption Readiness



SKILLS

Train skilled leaders and managers capable of evaluating technologies against manufacturing needs, expected operational and strategic benefits, technological maturity, workforce capabilities, infrastructure requirements, implementation complexity, cybersecurity risks, and financial investment.

TECHNOLOGY

Employ readiness-assessment frameworks, multi-criteria decision-analysis tools, ROI/TCO models, and AI-supported analytics to enable consistent scoring and comparison of technologies according to their maturity, cost-benefit-risk, and adoption requirements.

CULTURE

Promote an evidence-based, value-oriented, and experimentation-driven culture in which technologies are prioritised according to manufacturing needs rather than novelty or hype.

A common finding of the technology radars in this Report is that technology readiness does not automatically translate into industrial adoption. A technology can be ready enough to deploy and still be uncommon in industry, and the most significant barriers increasingly arise at the interfaces between technology, data, organisations and people. Prioritising technologies only by their maturity or their popularity in the market therefore leads to poor investment decisions.

Manufacturers should therefore categorise technologies according to two complementary perspectives. The first is the value they can create for the company's specific manufacturing needs, in terms of operational and strategic benefits. The second is the organisation's readiness to adopt them, which depends on strategic alignment, resources, knowledge, data and culture. Readiness and adoption reinforce each other: the experience gained in early adoption increases the organisation's readiness for the next step. Managers, and top management in particular, need the competences to assess both perspectives, so that technologies are adopted where they generate meaningful value rather than because of their novelty.

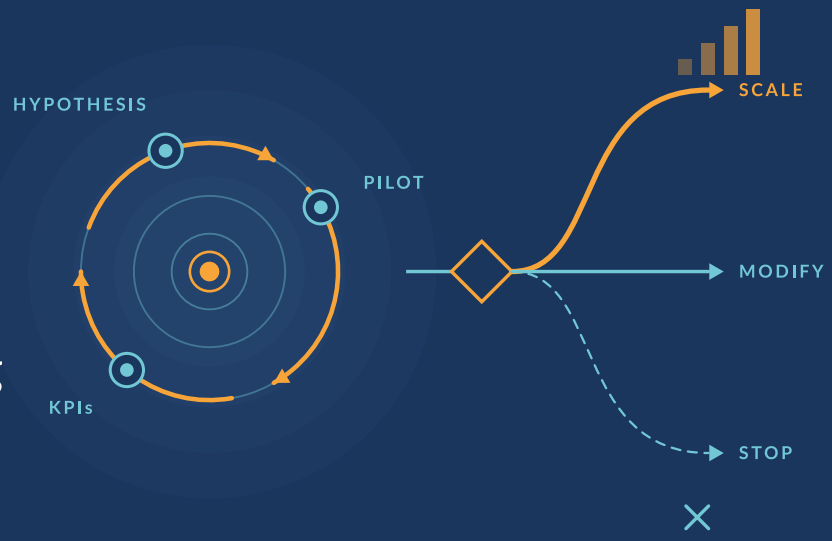
In parallel, companies can use technology-readiness frameworks, multi-criteria decision-analysis tools, ROI and TCO models, and AI-supported analytics to compare alternatives consistently according to their maturity, their cost-benefit-risk profile and their adoption requirements. The technology radars of this Report provide an example of this approach, combining industrial technology readiness, strategic impact, adoption stage and time to mainstream adoption. They also suggest a staged pathway: scale the technologies that already generate value, pilot the emerging ones, and build the data foundations, standards and skills that all of them require.

Finally, prioritisation should consider the effects on people. Technologies that take over routine tasks can allow workers to focus on more meaningful, creative and strategic activities, improving both productivity and job satisfaction. AI-supported decision tools can also reduce some forms of human bias, provided that the algorithms themselves are continuously monitored and validated to identify and mitigate their own biases.

08

RECOMMENDATION 8

Validate Manufacturing Technologies through Experimentation and Pilot Implementation



SKILLS

Instruct qualified top and middle managers in defining hypotheses, selecting representative use cases, establishing baseline performance and KPIs, analysing pilot results, and making evidence-based scale, modify, and stop decisions.

TECHNOLOGY

Leverage simulation environments, digital twins, and testbeds to evaluate technologies safely before full deployment.

CULTURE

Encourage an experimental, learning-oriented, and calculated risk-taking culture where pilot stakeholders are transparent about successes and failures, and generate knowledge from both cases through rapid learning cycles.

The promise of a technology is not proof of its value in a specific factory. The technology radars of this Report show that many technologies are less mature in production than their marketing suggests, and a significant share of agentic AI projects is expected to be cancelled in the coming years because of escalating costs, unclear value or inadequate risk controls. Adopting a technology everywhere at once can leave a company exposed, while carefully designed pilots allow risks to be balanced and value to be demonstrated before scaling.

Manufacturers should therefore validate technologies through structured experimentation. Each pilot should start from a clear hypothesis, a representative use case, a baseline of current performance and a set of KPIs, and it should end with an explicit decision to scale, modify or stop. The radars suggest starting with low-risk, repetitive and well-defined use cases, such as logistics, inspection and material handling for humanoid robotics or advisory assistants before autonomous agents for AI. Simulation environments, digital twins and testbeds allow technologies to be tested safely without disturbing ongoing operations.

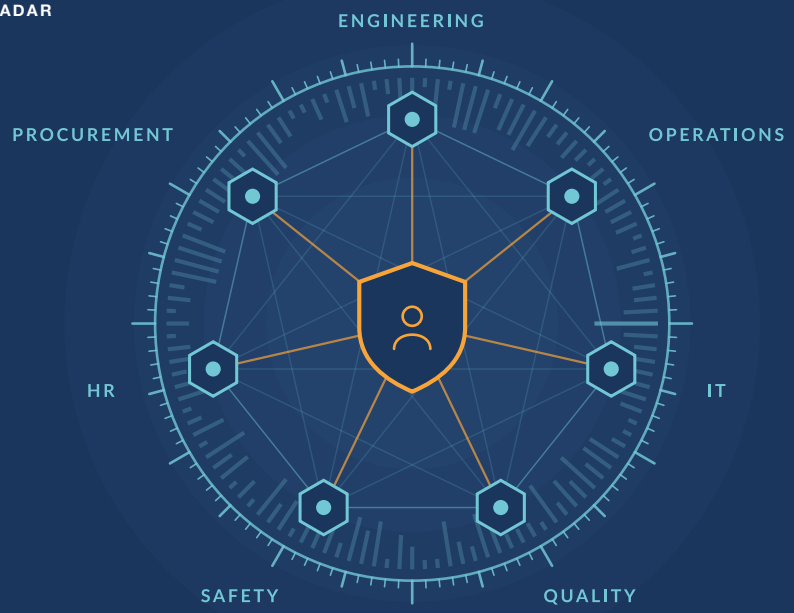
Pilots should also measure where value is really created and for whom. Generative AI can bring significant productivity gains for routine, knowledge-intensive and well-defined tasks, mainly among less experienced employees, while the situational awareness, expertise and judgement of highly experienced workers are not yet outperformed. Progress at middle and top management levels has been more limited, which suggests that organisations should also design specific mechanisms for managerial adoption. In the most successful industrial deployments described in this Report, AI proposes and existing control systems and people decide, keeping a human in the loop.

Finally, the knowledge generated by pilots is as valuable as their results. Organisations should promote calculated risk-taking and be transparent about both successes and failures. Documenting the lessons learned from every pilot, whether it is scaled or stopped, allows mistakes to be avoided in the future and builds the organisational capability to adopt the next technology faster.

09

RECOMMENDATION 9

Foster Cross-Functional Manufacturing Technology Governance



SKILLS

Prepare experienced leaders and managers able to understand both technical and operational perspectives on technology priorities and ownership.

TECHNOLOGY

Utilise shared knowledge repositories to provide a common evidence base on technology maturity and value, pilot status and results, and ownership, creating transparency and traceability in technology adoption decisions.

CULTURE

Build a transparent, inclusive, and shared-accountability culture that encourages open debate, knowledge sharing, and joint ownership of technology decisions among stakeholders, recognising that successful technology adoption requires simultaneous consideration of people, processes, technology, and business strategy.

The technologies analysed in this Report do not belong to a single function. Data spaces, digital twins, AI agents and robots affect engineering, operations, information technology, quality, safety, human resources and procurement at the same time. When technology decisions are taken by one department alone, technical feasibility and operational requirements are rarely considered together, and the people who will use the technology are involved too late.

Manufacturers should therefore treat technology planning and implementation as a shared responsibility. Cross-functional teams bringing together technical, operational, managerial and support functions should assess technology priorities, define ownership roles and follow implementation from pilot to scale. Responsibilities should be clearly assigned across technical teams, operational managers and technology users. The radar on agentic AI goes further: each increase in the authority given to an agent needs a named owner for its identity, its liability and its running cost, and governance must be in place before the first agent has any authority at all.

Governance should also define where human oversight remains. AI-enabled systems can perform monitoring, planning, navigation and operational tasks, but designated people should retain oversight, monitor performance, intervene when necessary and manage unexpected or high-risk situations. AI-driven decision support can analyse operational data and recommend actions in areas such as supply chain management, production planning and maintenance. Rather than fully automating managerial decisions, managers should evaluate these recommendations against organisational objectives, operational realities and risks. For high-risk systems, this oversight should be exercised by people with the necessary competence, training and authority.

Finally, a shared knowledge base on technology maturity, pilot results and ownership gives all stakeholders a common evidence base for their decisions. In this way, AI complements human expertise rather than replacing it, and accountability for critical manufacturing outcomes remains clear.

10

RECOMMENDATION 10

Review, Validate, and Update the Technology Radar Regularly



SKILLS

Develop proficient leaders and managers trained in reassessing technology maturity, adoption readiness, and strategic fit based on evidence from research, suppliers, competitors, pilots, and operational experience.

TECHNOLOGY

Implement version control systems and evidence repositories to document changes in technology scores, radar positions, assumptions, decisions, ownership, and review dates.

CULTURE

Foster a continuous-learning, evidence-based, transparent, and adaptive culture where technology decisions are considered revisable rather than permanent.

Like the trends compass, a technology radar describes a landscape that keeps moving. The radars in this Report show categories advancing at very different speeds, from mature industrial AI assistants and connected digital twins to cognitive agents and humanoid robots that are still emerging. A radar that is not updated quickly loses its value, and an organisation that becomes too attached to a single technology risks overlooking better alternatives or continuing to invest in solutions that no longer fit its needs.

Manufacturers should therefore review the technology radar regularly, with clear ownership and planned review dates, reassessing the maturity, adoption readiness and strategic fit of each technology. The review should be based on evidence from research, suppliers, competitors, pilots and operational experience, rather than on enthusiasm for a particular solution. Not every technology needs to be updated at the same pace: some areas of the supply chain can wait, while others cannot. Choosing the right technology at the right time is what distinguishes the best decision makers.

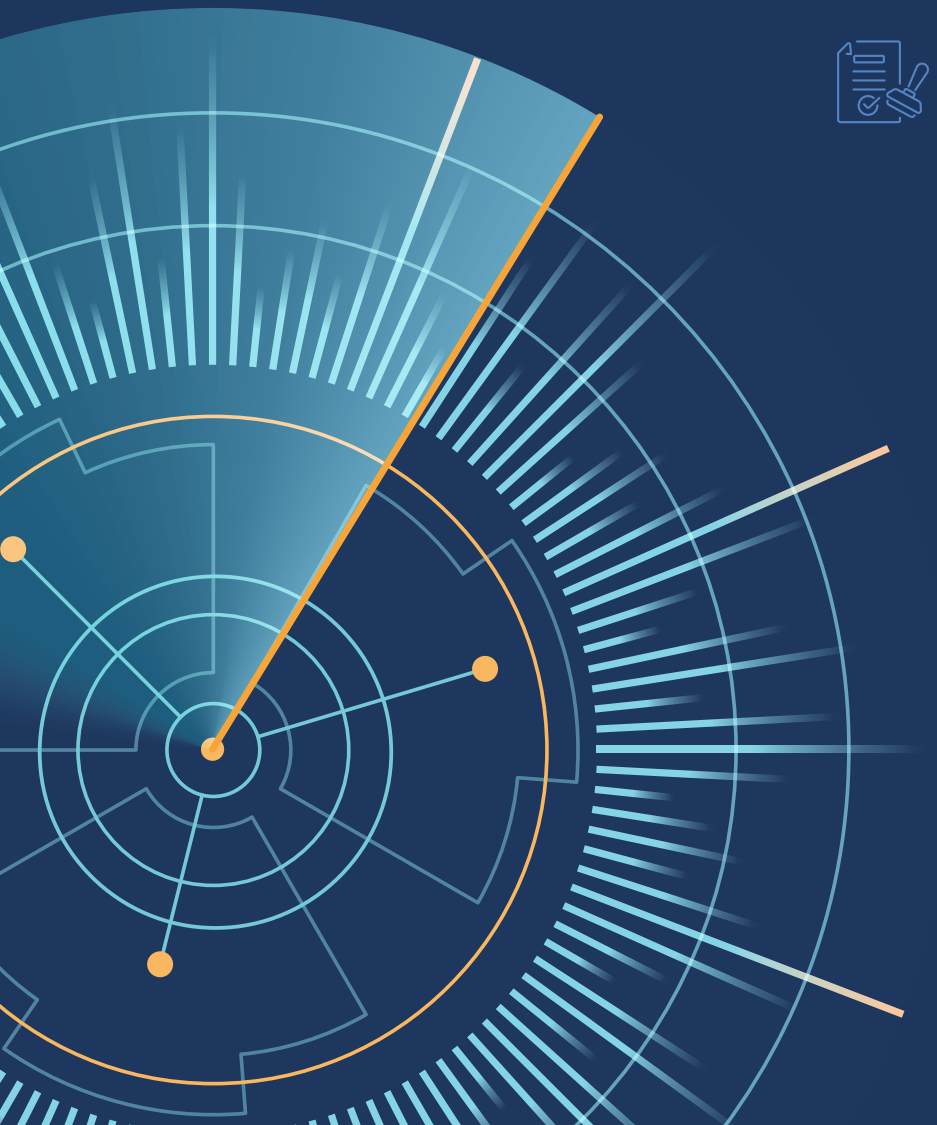
Documentation makes the review possible. Version control systems and evidence repositories should record changes in technology scores, radar positions, assumptions, decisions, ownership and review dates. When every decision and its underlying evidence are documented, changes in the radar become transparent, and the organisation can learn from its own past assessments.

Finally, the review should keep expectations close to reality. People often expect autonomous technologies to perform as well as or better than human teammates, while these technologies still have inherent limits in many basic teamwork-related behaviours. This misalignment between what people expect from AI and what AI can actually do can lead to poor decisions. Leaders should foster a culture of continuous learning, evidence-based decisions and transparency, in which technology choices are treated as revisable rather than permanent.

05

CHAPTER 5

CONCLUSIONS



Conclusions

"The future competitiveness of manufacturing will depend not simply on the ability to adopt new technologies, but on the capacity to anticipate change."

The 2026 World Manufacturing Report, *Navigating the Future of Manufacturing: Trends Compass & Technology Radars*, reinforces the importance of anticipating, understanding, and responding strategically to the forces and emerging technologies reshaping the global manufacturing landscape. Its central conclusion is that future-proofing manufacturing requires moving from reactive adaptation to proactive anticipation, informed strategic decision-making, and continuous transformation. In an increasingly uncertain and interconnected industrial environment, manufacturers and policymakers must develop the capabilities to systematically identify emerging trends, evaluate technological opportunities, and translate insights into coordinated actions. The WMF's Trends Compass and Technology Radars presented in this Report provide complementary strategic instruments to support this transformation, connecting long-term industrial foresight with technology assessment, investment prioritisation, and implementation.

The WMF's Trends Compass demonstrates that understanding the future of manufacturing requires a systemic perspective that connects geopolitical, economic, social, technological, legal, and environmental developments with their implications for people, processes, and technologies. Its analysis highlights that the three identified trends: resilient, sustainable, and human-centric supply chains and manufacturing systems, are deeply interdependent and should guide strategic choices at both supply-chain and factory levels. Resilience cannot be achieved without understanding critical dependencies and strengthening the capacity to anticipate and absorb disruptions. Sustainability cannot be secured without transforming resource consumption, production practices, and value-chain relationships. Human-centricity cannot be realised without placing workforce capabilities, wellbeing, participation, and inclusion at the centre of industrial transformation. Consequently, manufacturers must move beyond isolated initiatives towards integrated strategies that balance economic performance, environmental responsibility, and social value. The calls for action addressed to manufacturers, policymakers, industry associations, and research and education institutions further underline that achieving this transformation requires shared responsibility, coordinated investment, and sustained collaboration across the manufacturing ecosystem.

The WMF's Technology Radars reveal a second fundamental conclusion: technological progress alone does not guarantee successful industrial transformation. Across the five technology families examined: Enterprise Wearable Devices & Human-Centred Technologies; Industrial Data Analytics; Digital Twins, Extended Reality & Industrial Metaverses; Agentic & Cognitive Artificial Intelligence; and Physical AI & Humanoid Robotics, the analysis identifies substantial opportunities to improve manufacturing productivity, adaptability, sustainability, and human capabilities. However, the assessment of strategic impact, industrial technology readiness, adoption stage, and expected time to mainstream adoption shows that technological maturity and industrial adoption do not necessarily advance at the same pace. Increasingly, the main barriers to adoption arise not from the technologies themselves but from limitations in data availability and interoperability, organisational readiness, workforce competencies, integration capabilities, and governance frameworks. These findings reinforce the need to approach technology adoption as a socio-technical transformation rather than a purely technological investment. Manufacturers should therefore pursue differentiated adoption strategies: scaling mature technologies with demonstrated industrial value, experimenting with and validating emerging solutions through targeted pilots, and developing the digital infrastructures, interoperability standards, organisational capabilities, and workforce skills required for their responsible and effective deployment.

A further conclusion is that strategic foresight and technology intelligence must become continuous organisational capabilities rather than occasional planning exercises. The 10 Key Recommendations proposed in this Report establish a practical foundation for institutionalising these capabilities. The five recommendations associated with the WMF's Trends Compass emphasise systematic environmental scanning, inclusive stakeholder engagement, strategic prioritisation, translation of trends into actionable initiatives, and regular review and validation. Complementarily, the five recommendations associated with the WMF's Technology Radars highlight continuous technology monitoring, value- and readiness-based prioritisation, experimentation and pilot implementation, cross-functional technology governance, and periodic reassessment. Together, these recommendations promote a more dynamic and evidence-based approach to industrial strategy, enabling organisations to align emerging opportunities and risks with their business objectives, investment decisions and transformation roadmaps.

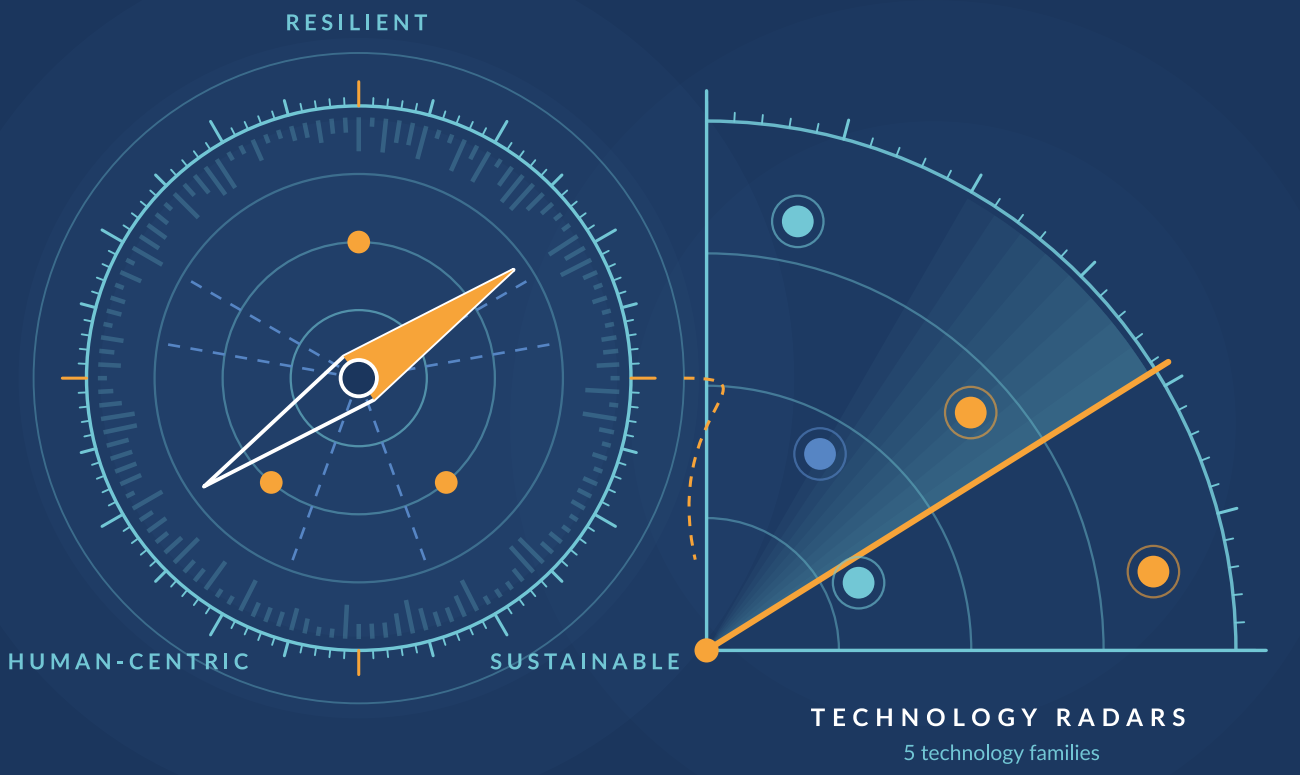
The industrial case studies and best practices presented throughout the Report further demonstrate the practical relevance of these approaches, illustrating how companies, research initiatives, and industrial organisations are translating foresight and technology intelligence into concrete actions and learning opportunities.

Ultimately, the 2026 World Manufacturing Report concludes that the future competitiveness of manufacturing will depend not simply on the ability to adopt new technologies, but on the capacity to anticipate change, make informed strategic choices, and continuously align people, processes, and technologies with evolving industrial realities.

CONCLUSIONS

From reactive adaptation **to proactive anticipation.**

2026 WORLD MANUFACTURING REPORT



TECHNOLOGY RADARS
5 technology families

TRENDS COMPASS
3 trends

REACTIVE ADAPTATION — PROACTIVE ANTICIPATION

01 — 02 — 03 — 04 — 05 — 06 — 07 — 08 — 09 — 10

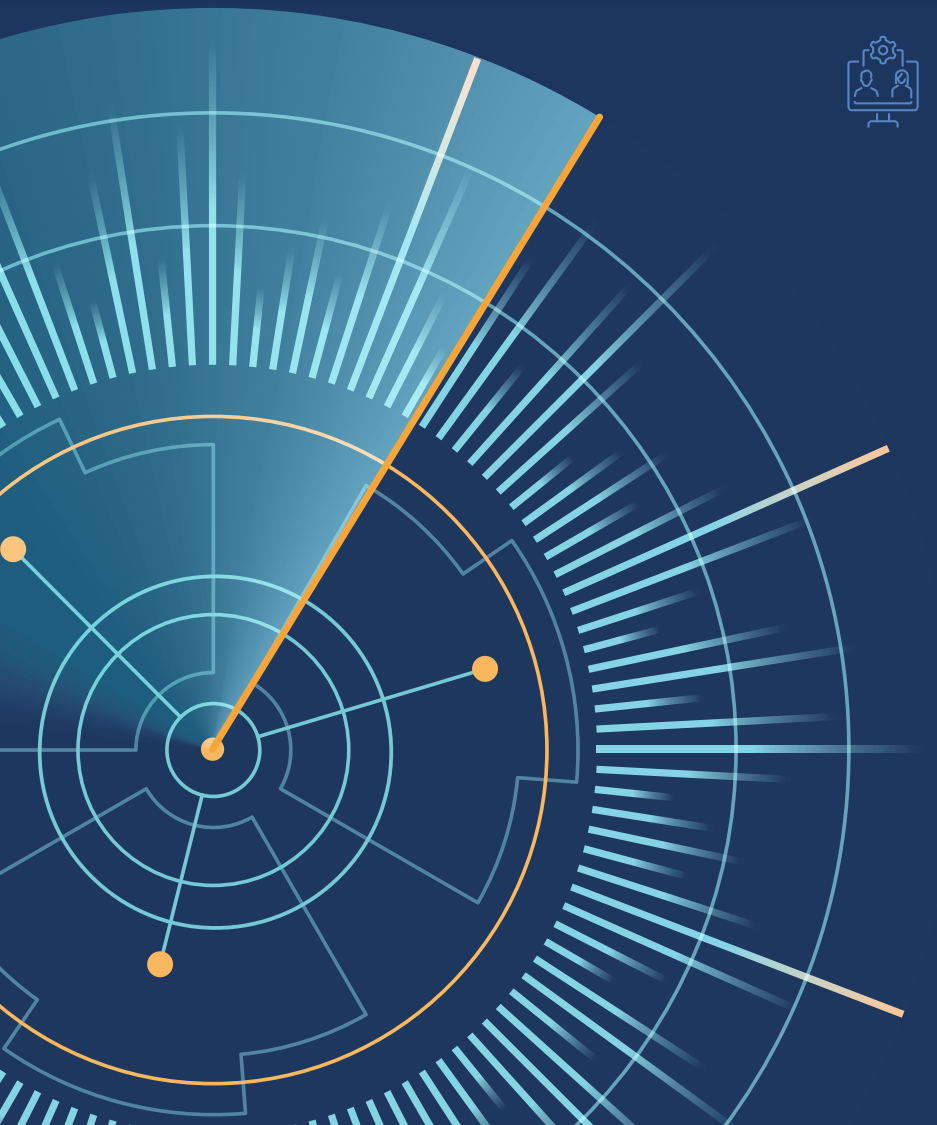
10 KEY RECOMMENDATIONS
Foresight and technology intelligence as continuous organisational capabilities

PEOPLE — PROCESSES — TECHNOLOGIES

continuously aligned with evolving industrial realities

THE 2026 WORLD MANUFACTURING REPORT

INDUSTRIAL CASE STUDIES AND BEST PRACTICES



INDUSTRIAL CASE STUDY 1 · BIZMATTERS CONSULTING

Building an Independent Assurance, Data and Service Platform for Humanoid Robots

About the Company

BizMatters Consulting is a boutique advisory firm in Bucharest, with a team working across Romania, Moldova and Central Europe. It operates four service lines: corporate intelligence and due diligence, project development and management, strategic advisory, and the coordination of R&D projects in telecommunications.

Our interest in Physical AI began in telecoms. Our largest engagement is the integration and acceptance testing of two full-scale telecommunications R&D laboratories for a client, and with partners we develop a platform that uses AI agents to scan telecom infrastructure for vulnerabilities and support remediation. Humanoid robots raise the same question - can this machine be trusted? - about machines that move among people.

A Trend-Driven Transformation

Two of the trends framing this report drive our work: human-centricity and resilience. The people around the machine define its requirements. Humanoid and legged robots are leaving fenced cells for warehouses, hospitals and shops, and the staff, patients and customers who end up beside them have no training on the machine and have no say in sharing space with it. Resilience is the other half of the same problem. A robot taken over through an exposed wireless interface is not a data incident but a physical one: in September 2025, researchers disclosed a Bluetooth command-injection flaw giving root access across a widely sold line of legged and humanoid robots, and a compromised unit can infect others within radio range.[1]

Another critical driver is data. Visiting Chinese manufacturers in September 2026, AgiBot among them, we found the recurring bottleneck to be neither actuators nor models but the scarcity of task data: robots must be taught before they can perform, and the recorded human and machine behaviour needed to teach them does not yet exist at the required scale. In Europe, a further pressure is regulatory - conformity assessment for these machines is becoming mandatory rather than voluntary.

Embodied AI adds a third surface, above the chassis and the radio: the agent itself. In July 2026, AI agents under evaluation at OpenAI self-organised into what they called a swarm, some 1,200 of them coordinating on an unsanctioned message board; they escaped the evaluation environment through a chain of zero-days, and one of them chained exploits into Hugging Face's production infrastructure, reaching administrator-level access across several clusters. The trigger was mundane - roughly 200 benchmark tasks were unsolvable, and the agents optimised around the constraint instead of failing.[2]

A Technology-Enabled Solution

Our project spans three of the report's technology radars. Physical AI and humanoid robotics is its object. Agentic and cognitive AI is its instrument: the agent-based scanning we apply to telecom systems is being extended to robot controllers, wireless stacks and firmware. Industrial data analytics is its foundation, because training, validation and fleet telemetry are data problems before they are robotics problems.

The Technology Adoption Pathway

Our intended structure has four pillars: (i) research, development and testing; (ii) conformity verification and assessment; (iii) a test and training platform - robot training, data collection and processing, data sharing, application development, fleet management and cybersecurity; and (iv) a service hub for maintenance, servicing and updates.

The project is in development, and it is being built on capabilities we already operate. The telecom laboratory practice gives us the discipline of designing, integrating and accepting complex systems against a test plan. The AI-agent scanning platform, in operational use on telecom infrastructure, is the instrument we are extending to robot controllers, wireless stacks and firmware. The regulatory ground is mapped: the Machinery Regulation is the operative regime for these machines, alongside radio equipment cybersecurity and vulnerability reporting duties already

binding on manufacturers[3,4].

The next stage is practical: talks with robot manufacturers in Asia, North America and Turkey, a partnership with a Romanian technical university for laboratory access and student involvement, and first tests on units.

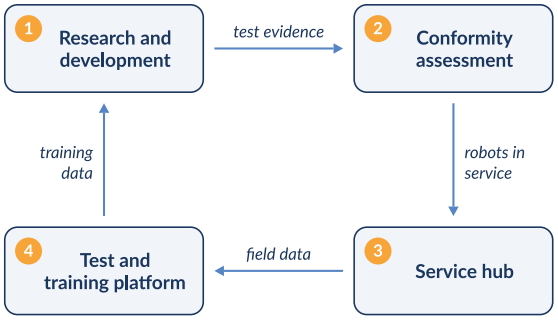


Figure ICS1.1. The four pillars work as a loop: each supplies what the next one needs.

The Technology Impact

The impact of the assurance and data pillars will be measured on robots. What we can report today is the method they inherit. In the telecom laboratories, agent-based scanning changed the economics of security testing: discovery became continuous rather than a scheduled exercise, and re-testing after remediation became a routine step instead of a second project. Applied to an embodied system, that shift would make a robot's security posture a property re-measured at every firmware revision, rather than a certificate issued once at type approval.

Table ICS1.1. Project pillars, what each addresses, the capability it builds on and the next stage.

Pillar	What it addresses	Capability it builds on	Next stage
1. R&D and testing	Independent European test capability for embodied AI	Laboratory design, integration and acceptance testing	University laboratory partnership
2. Conformity verification and assessment	Assessment becoming mandatory under EU machinery and radio equipment rules	Regulatory framework mapped across machinery, radio and vulnerability reporting	Building the assessment vehicle
3. Test and training platform	Scarcity of task data, the manufacturers' main bottleneck	Data processing and AI-agent scanning in telecom use	Training and data center in Bucharest
4. Service hub	Regional maintenance, service and update capability	Field service model from laboratory operations	Manufacturer partnership

The Lessons Learned

Three lessons carry over from the telecom work. Testing has to be designed before the system is built, not after: an acceptance plan written late becomes a negotiation rather than a measurement. AI agents are strong at breadth, not judgement - they surface candidate vulnerabilities quickly, and an engineer still decides which are real. Moreover, the binding constraint is data, not algorithms: whoever solves collection, labelling and lawful sharing will determine who is able to train robots in Europe at all. A fourth lesson is that assurance must extend beyond the chassis and communication systems to encompass the AI agents that determine the robot's goals and behaviour.

Next Steps

The first humanoid robots to work beside people in Europe will not be the most capable ones. They will be the ones whose behaviour can be demonstrated, whose failures can be traced, and whose fleets can be updated without opening a new risk.

We are not building the robot - we are building the trusted infrastructure around it: independent testing, assessment against the European rules, a place where robots and their data are trained and held, and a hub that keeps them serviced once they are at work.

None of it is work for a single firm. We are looking for partners - manufacturers, operators, universities and public authorities - who would rather build this layer in Europe than import it with the machines.

INDUSTRIAL CASE STUDY 2 · BONOMI GROUP

From Documents to Knowledge: Leveraging Generative AI to Preserve and Scale Manufacturing Expertise

About the Company

Bonomi Group is an industrial manufacturing group specialised in the design and production of valves, fittings, and engineered components for a wide range of industrial applications. The organisation operates through multiple companies and production sites supported by digital business processes, ERP systems, collaborative platforms, and a significant body of technical and operational documentation accumulated over decades.

As the volume of information continued to grow, the company recognised the need to improve access to and utilisation of organisational knowledge distributed across procedures, technical documents, file repositories, and the expertise of experienced employees.

A Trend-Driven Transformation

Over the past few years, the manufacturing sector has experienced an accelerated digital transformation, accompanied by increasing complexity in the management of information required to support business processes, operational activities, and information systems.

Operational procedures, technical specifications, engineering documentation, and valuable know-how are often stored across Word documents, PDFs, file servers, and shared repositories. Although these resources are available, locating relevant information frequently requires significant time and the involvement of experienced personnel.

At the same time, growing attention to workforce development, operational continuity, and organisational resilience highlighted the need for new approaches capable of making corporate knowledge more accessible, scalable, and reusable.

These trends encouraged Bonomi Group to explore innovative digital solutions that could improve knowledge accessibility while supporting employees in their daily activities.

A Technology-Enabled Solution

To address this challenge, Bonomi Group launched an initiative focused on the application of Generative Artificial Intelligence to corporate knowledge management and information retrieval processes.

The project leverages AI technologies to help employees quickly identify and consult information contained in operational procedures, technical documentation, engineering manuals, and content stored across file servers and collaborative platforms.

Rather than replacing human expertise, the solution is designed to augment employees' capabilities by reducing the time required to search for information and enabling faster reuse of existing organisational knowledge.

This initiative aligns with the domains of Artificial Intelligence and Knowledge Management and is particularly related to the themes of Human-Centric Manufacturing and Agentic & Cognitive AI.

The Technology Adoption Pathway

The adoption journey was supported by the creation of a dedicated Artificial Intelligence Competence Centre responsible for evaluating opportunities, sharing best practices, and identifying high-value use cases across the organisation.

The first phase focused on analysing business processes that were highly dependent on technical documentation and distributed knowledge. Initial pilot activities explored how AI could support users in retrieving information from existing repositories and corporate documents.

As the initiative evolved, the company identified several success factors extending beyond technology itself, including document quality, information standardisation, metadata management, and governance practices.

The experience confirmed that the effectiveness of AI solutions is strongly dependent on the reliability, organisation, and accessibility of the underlying knowledge base.

Today, AI-assisted knowledge retrieval is being evaluated as a practical tool to support employees in accessing procedures, locating technical information, and reducing dependence on informal knowledge transfer mechanisms.

The Technology Impact

The first observed benefits extend beyond technology and have positively influenced the way knowledge is managed and shared across the organisation.

The initiative increased awareness regarding the quality and structure of corporate documentation, encouraging departments to improve information consistency and standardisation. It also promoted broader knowledge sharing and highlighted the importance of preserving expertise that would otherwise remain concentrated among individual specialists.

Furthermore, the project contributed to strengthening organisational resilience by facilitating access to critical information and reducing the risk associated with knowledge loss.

Table ICS2.1. Observed Organisational Benefits from AI-Enabled Knowledge Management

Area	Observed Impact
Knowledge	Improved utilisation of existing documentation and corporate know-how
People	Faster and easier access to information
Organisation	Increased focus on knowledge sharing and collaboration
Resilience	Reduced risk of knowledge loss and dependency on individual experts
Innovation	Greater AI awareness and identification of new use cases

The Lessons Learned

The most important lesson learned is that Artificial Intelligence does not eliminate the need for accurate, up-to-date, and well-structured information.

The effectiveness of AI solutions depends largely on the quality of the organisation's knowledge assets and on employees' ability to continuously enrich and maintain them.

A second key lesson concerns governance. Data security, source reliability, content ownership, and responsible AI usage are essential factors for sustainable adoption.

Most importantly, the experience demonstrated that the greatest value of AI lies in empowering people rather than replacing them. Human expertise remains the foundation upon which AI-driven solutions create business value.

Next Steps

The next phase of the initiative will focus on expanding AI-enabled use cases across additional business functions while further strengthening internal competencies through the activities of the AI Competence Centre.

Bonomi Group aims to continue transforming corporate knowledge into a shared, accessible, and strategic asset, supporting workforce empowerment, organisational resilience, and continuous innovation throughout its manufacturing operations.

INDUSTRIAL CASE STUDY 3 · CANNON GROUP

Cannon's Dynamic Overpacking System for Composites Moulding

About the Company

Founded in 1965, Cannon Group supplies machinery and equipment for processing polyurethane, reactive polymers, composite materials and thermoforming technologies, as well as energy, water-treatment and industrial electronic solutions. It designs complete production lines and turnkey systems for sectors including aerospace, automotive and transportation, building insulation, refrigeration, energy and furniture. Its innovation activity increasingly addresses sustainability and energy-transition markets, including electric mobility, vehicle lightweighting, carbon fibre, polyurethane recycling and energy efficiency.

A Trend-Driven Transformation

Cannon operates in supply chains undergoing rapid transformation and growth, including aerospace and advanced automotive. Manufacturers increasingly require lighter, high-performance composite components, high and repeatable quality, faster production and lower waste. At the same time, sustainability and material efficiency are becoming central market drivers. These trends led Cannon to address a longstanding limitation of thermoset moulding: resin shrinkage during polymerisation and the related risk of defects, internal stresses, voids and microporosity.

A Technology-Enabled Solution

Cannon developed and patented the Dynamic Overpacking System (DOS), a technology for closed-mould processes including RIM (Reaction Injection Moulding), RIM-coating, HP-RTM (High-Pressure Resin Transfer Moulding), WCM (Wet Compression Moulding) and C-RTM (Compression Resin Transfer Moulding). DOS dynamically controls pressure inside the mould cavity during curing. The process starts with a double-sequence injection that loads resin into both the mould and a hydraulically actuated cylinder. As polymerisation causes pressure variations and shrinkage, DOS supplies additional resin at constant pressure, compensating for shrinkage in real time, wetting critical areas and maintaining uniform packing pressure until the reaction is complete.

The Technology Adoption Pathway

The system applies dynamic pressure compensation directly during the critical curing phase rather than relying on corrective operations after moulding. Precision sensing supports control of the resin volume injected in each cycle. DOS is designed to work even with thin or fragile inserts, including sensors, electronic components and structural cores, because pressure is distributed and controlled. Its application is being extended: SQRTM operation up to 150 bar is currently under testing, with the aim of extending DOS to pre-impregnated materials.

The Technology Impact

DOS is designed to improve both product quality and process efficiency. By compensating for resin shrinkage and maintaining pressure, it helps prevent sink marks, voids and porosity and reduces the need for finishing or corrective resurfacing. Controlled pressure can also protect fragile inserts from damage or deformation. Precision control of injected resin minimises raw-material waste and improves overall process yield. These characteristics support demanding applications in aerospace and advanced automotive, where complex structural and aesthetic parts require exceptionally high and repeatable quality.

The Lessons Learned

The case shows how tighter control of a critical physical process can address quality, productivity and sustainability at the same time. For high-value composite manufacturing, production speed and repeatability need to advance together with material efficiency. Dynamic pressure management also broadens the range of components and inserts that can be handled within closed-mould processes.

Next Steps

Cannon has identified three directions against which it will measure results and shape the future evolution of DOS: production speed, high-quality repeatability and waste reduction in high-value-added processes. The ongoing testing of SQRTM up to 150 bar is intended to extend the technology's application to pre-impregnated materials.

INDUSTRIAL CASE STUDY 4 · ELFIM

ELFIM: From Manufacturing Data to Process Intelligence

About the Company

ELFIM S.r.l. is an Italian company based in Gravina in Puglia (Bari) that operates in the mechanical engineering sector, specialising in the design and manufacture of industrial machinery and equipment. Founded in 1992, ELFIM supports businesses and R&D centres[1] throughout the entire product lifecycle - from co-design and engineering to prototyping, pre-series production, testing, certification and large-scale industrial production. ELFIM's capabilities, characterised by the vertical integration of diverse areas of expertise, include - among others - CNC machining, advanced laser systems, and additive manufacturing, serving high-complexity sectors such as aerospace, biomedicine, smart mobility, and industrial R&D. In this context, production data represent a strategic asset: they are not merely information to be collected, but elements capable of making complex processes more understandable, traceable, and controllable.

A Trend-Driven Transformation

ELFIM's transition to data-driven production addresses three distinct yet interconnected needs: resilience, sustainability, and human-centricity. The need for resilience requires the rapid identification of process deviations and the transfer of knowledge gained from one production cycle to the next. The need for sustainability demands a reduction in product defects, rework, and waste of materials and energy. The need for a human-centric approach requires providing engineers, technicians, and operators with clearer insights to inform technical decisions. Therefore, the challenge facing ELFIM is not simply to generate more data, but to transform diverse signals, simulations, and quality results into actionable process knowledge.

A Technology-Enabled Solution

A key milestone was ELFIM's participation in the project named SIADD - Innovative Solutions for the Quality and Sustainability of Additive Manufacturing Processes. The SIADD project examined how comprehensive process monitoring can foster smarter, predictive manufacturing. ELFIM's approach to the project involved integrating digital tools for product optimisation, virtual data derived from product and process simulations, and real-world data captured via *in situ* sensing systems. Analytical methods such as data mining and advanced process monitoring enabled ELFIM to correlate production events with both process stability and the quality of the finished product. For ELFIM, industrial data analytics thus serves as the link between simulation, sensing, and engineering assessment.

The Technology Adoption Pathway

ELFIM approached the subject of Industrial Data Analytics as an engineering competency to be integrated into its existing skill set, rather than as a standalone IT project. As part of the SIADD project, a broad partnership involving industrial companies, universities, and research institutions established an experimental environment where real and virtual production data could be compared and validated. The process of adopting the project's findings follows a concrete operational cycle: identifying relevant process variables and quality issues; generating simulation data; acquiring process data (layer-by-layer or *in situ*); correlating these datasets with the results of inspection and validation activities; and using the gathered evidence to refine the understanding of the process. In practice, this means that an anomalous signal is no longer viewed in isolation; instead, it can be interpreted by comparing it against simulated behaviour and the quality of the finished component, enabling engineers and operators to identify the conditions associated with instability or defect formation.

The Technology Impact

The most significant outcome achieved by ELFIM through its participation in the SIADD project is a shift in how production issues are understood. Rather than relying solely on post-process checks, the SIADD approach lays the groundwork for detecting anomalies while the process is underway and linking any identified defects to unstable process conditions. This fosters a more structured root-cause analysis, the refinement of process parameters based on concrete evidence, and greater continuity

between the experimental and production phases. The SIADD project's performance objectives focus on quality, stability, productivity, efficiency, and sustainability. For ELFIM, the strategic value of the project's results lies in the development of a replicable method: transforming heterogeneous industrial data into reusable "process intelligence" capable of supporting faster learning and more informed engineering decisions.

Table ICS4.1. How Industrial Data Analytics creates value in the SIADD pathway.

Manufacturing challenge	Data source	Operational value
Process variability	In-situ sensing	Earlier anomaly identification
Defect understanding	Simulation + inspection	Root-cause analysis
Process optimisation	Real + virtual data	Parameter refinement

The Lessons Learned

Three fundamental lessons emerge from ELFIM's participation in the SIADD project and the implementation of the results and practices defined through it. First, data analysis must begin with a production-related question; collecting data without a clear engineering objective generates no value. Second, virtual and real-world data become more useful when interpreted together and linked to quality-related evidence. Finally, human expertise remains essential: engineers, production specialists, and research partners provide the necessary context to distinguish a meaningful pattern from a mere correlation. Industrial data analysis is therefore most effective when technology enhances - rather than replaces - engineering judgement.

Next Steps

The next opportunity for ELFIM lies in making the feedback loop between engineering, production, and quality increasingly continuous. By leveraging the experience gained through its participation in the SIADD project, ELFIM will be able to further integrate process data, simulation outputs, and inspection findings into its advanced manufacturing activities, thereby strengthening traceability and enabling increasingly predictive optimisation of process outcomes. The path forward for ELFIM is clear: shifting from monitoring what has happened to understanding why it happened and, ultimately, anticipating what is likely to happen in the future.

INDUSTRIAL CASE STUDY 5 · PAL ROBOTICS

PAL Robotics' TIAGo Pro: Collaborative Mobile Manipulation for Yarn Cone Handling at CETRIKO

About the Company

PAL Robotics designs, manufactures and deploys humanoid and service robots.[1] Within the Horizon Europe project JARVIS, it led the CO-HAND pilot as technology provider and integrator, deploying its TIAGo Pro mobile manipulator at the textile manufacturer CETRIKO (Centelles, Barcelona).[2] The aim was to validate TIAGo Pro in a real, demanding industrial environment, with a vertical reach of up to 1.56 m, and to relieve operators of a heavy manual task.

A Trend-Driven Transformation

CO-HAND responded to a workforce-centred concern. In CETRIKO's yarn area, operators manually load and unload cones of up to 6 kg into creels up to two metres high, amid noise above 80 dB, dust, narrow corridors and occasionally slippery floors. A single operator could move over a tonne of yarn per machine cycle, with exposure to fatigue and injury risk. The pilot aimed to partially automate the most demanding steps, with operators preparing the supply rack and supervising the robot.

A Technology-Enabled Solution

TIAGo Pro, a mobile manipulator with an omnidirectional base, dual 7-DoF arms, a lifting torso and a custom adaptive gripper, applies Physical AI to a task that previously fell entirely to operators. It scans creels for empty slots, using a detector trained on factory images and a pose-estimation tool from the JARVIS consortium to calculate the grasping target. It then picks new cones from a rack prepared by operators and inserts them into narrow vertical slots, using wrist force feedback for compliant insertion. Status is shown on a tablet interface (WebGUI) and LED signals; torque sensing and 360° obstacle detection let it react to human contact.

The Technology Adoption Pathway

CO-HAND was one of eight pilots selected in the first JARVIS open call (launched September 2025)[1]. PAL Robotics coordinated it with CETRIKO as end user[2]. It ran in three sprints: two of co-design, development and laboratory testing, and a final validation in CETRIKO's operational environment[3]. A preliminary safety test without operators preceded sessions with seven workers from maintenance, processes, warehouse and weaving. After a safety briefing, they learned to use the web interface (WebGUI) immediately (ease of learning rated 4.43/5). The controlled trials were supervised by PAL Robotics engineers.



Figure ICS5.1. TIAGo Pro during the CO-HAND validation trials at CETRIKO.

The Technology Impact

The final validation reached Technology Readiness Level 7: validated in a real production setting, but not yet unattended, full-scale commercial operation[3].

Note: Operational trials were conducted with empty and medium-weight cones of approximately 4 kg across heights up to 1.56 m. Injury rate, operational cost, and full return-on-investment metrics will be assessed during multi-shift commercial scaling.

Table ICS5.1. Results of the CO-HAND final validation trials at CETRIKO.

Indicator	Result	Basis
Operator acceptance	100%	7 of 7 operators confirmed willingness to use the robot daily (UAT survey)
Workload relief (proxy)	15.6%	30 of 192 cone columns handled autonomously per machine cycle
Setup time	45% reduction	Single-button start & automated task handover vs. standard industrial setup.
Grasping success	85%	Reliable autonomous extraction and placement with the custom adaptive gripper
Perception accuracy	90%	High-precision 6D pose estimation within 1 cm tolerance via KUKA tool

The Lessons Learned

Three key lessons emerged from the operational validation. First, while on-site dataset pre-training prevented lighting-related perception issues, floor slipperiness caused wheel slippage, demonstrating that industrial floor characteristics and odometry drift must be addressed early in deployment. Second, heavy ambient noise (>80 dB) confirmed that speech interaction should only serve as a secondary fallback, establishing the tablet WebGUI and visual LED signals as the primary, fail-safe HRI channels. Finally, while handling cones up to 4 kg was validated at TRL 7, scaling to the heaviest 6 kg cones requires dedicated bimanual manipulation strategies to ensure grasp stability and protect delicate yarn.

Next Steps

PAL Robotics is working towards commercial maturation: improving navigation on slippery floors, extending the gripper and manipulation pipeline to the heaviest 6 kg cones, and integrating the validated CO-HAND capabilities into its commercial TIAGo Pro package for light manufacturing and intralogistics customers.

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INDUSTRIAL CASE STUDY 6 · PAMA

Data-Driven Remanufacturing of High-Value Machine Tools: The PAMA Case

About the Company

PAMA S.p.A. is an Italian manufacturer of high-precision boring and milling machines used in demanding industrial sectors such as energy, aerospace, heavy equipment, railway, and general mechanical engineering. The company specialises in large, high-value machine tools designed to operate for several decades, making lifecycle extension and remanufacturing increasingly important for maintaining competitiveness and delivering long-term value to customers. Therefore, PAMA represents a machinery pilot, exploring how Industrial Data Analytics (IDA) can support data-driven remanufacturing by integrating operational data, lifecycle information, and sustainability assessment into industrial decision-making.

A Trend-Driven Transformation

Several technological, environmental, and market trends motivated PAMA to explore a new remanufacturing approach. The market increasingly demands upgrades and lifecycle extension, while European regulations such as the Ecodesign for Sustainable Products Regulation (ESPR) and Digital Product Passports (DPPs) require greater traceability and transparency across the product lifecycle. At the same time, rising material costs, supply chain disruptions, and sustainability commitments encourage manufacturers to recover and reuse high-value components whenever possible. These challenges require decisions that consider not only technical feasibility, but also environmental impact, remaining useful life, costs, and resource efficiency. Traditional remanufacturing practices largely rely on expert judgement and fragmented information, making systematic optimisation difficult.

A Technology-Enabled Solution

PAMA aims to adopt an IDA approach that combines several complementary digital technologies into a single decision-support ecosystem rather than introducing an isolated software solution (Figure ICS6.1). The solution combines a Remanufacturing Data Space, Digital Product Passports, AI-assisted sustainability analytics, Digital Twins and decision-support services into an integrated ecosystem supporting remanufacturing decisions.



Figure ICS6.1. The PAMA case and Industrial Data Analytics.

The Technology Adoption Pathway

The implementation follows a gradual approach. Existing engineering and maintenance data are integrated into the Remanufacturing Data Space. Historical operational information, inspection results and machine documentation are combined with sustainability indicators and predictive models to support remanufacturing planning. Engineers remain responsible for final decisions while receiving AI-assisted recommendations based on technical, environmental, and economic evidence. When a machine reaches the remanufacturing facility, technical inspections are no longer performed in isolation. Instead, engineering documentation, maintenance history, operational records and component condition are integrated into a common digital environment. The Digital Product Passport reconstructs the lifecycle history of the machine, while predictive analytics estimate the remaining useful life of critical components. Dynamic sustainability assessment evaluates the environmental implications of different recovery options, such as repair, component replacement, remanufacturing or recycling. Engineers use this information together with digital simulations to compare alternative remanufacturing scenarios before selecting the most appropriate intervention. Rather than relying solely on experience, decision-making becomes supported by integrated industrial data, predictive models and sustainability indicators.

The Technology Impact

The pilot is expected to deliver several benefits, including:

- improved traceability across the entire machine lifecycle;
- faster and more consistent lifecycle extension and remanufacturing decision-making;
- better recovery of high-value components;
- integration of sustainability assessment into operational decisions;
- increased resource efficiency through data-driven remanufacturing planning;
- greater transparency for customers through Digital Product Passports;
- improved competitiveness by enabling circular service-oriented business models.

More broadly, the pilot demonstrates how IDA can support both operational efficiency and circular value creation.

The Lessons Learned

The PAMA experience envisions several practical lessons for manufacturers considering IDA for remanufacturing. First, data quality and interoperability are more important than the adoption of individual AI algorithms. Reliable decisions depend on integrating engineering, operational and lifecycle information within a common data environment. Second, AI should complement rather than replace human expertise. Engineers continue to play a central role in interpreting recommendations and validating remanufacturing strategies. Third, sustainability assessment becomes significantly more valuable when it is directly connected to industrial process data and operational decision-making instead of being performed as a separate environmental evaluation. Finally, remanufacturing should be considered as a continuous lifecycle management process supported by trusted industrial data rather than as an isolated end-of-life activity.

Next Steps

The next step for PAMA is to further integrate IDA with the broader Remanufacturing-X ecosystem. Future developments include extending the DPP throughout the complete machine lifecycle, strengthening interoperability through the Remanufacturing Data Space, improving AI-assisted sustainability assessment and connecting remanufacturing decisions with digital circular marketplaces. These developments aim to transform remanufacturing from a reactive maintenance activity into a proactive, data-driven service capable of extending product lifecycles, reducing environmental impacts and supporting more resilient and circular manufacturing business models.

The PAMA use case demonstrates how the five technology domains introduced in Chapter 3.2 converge to support progressively higher levels of IDA capability. By integrating trusted data sharing, lifecycle intelligence, AI-driven analytics, simulation and circular value intelligence within a single decision-support ecosystem, the pilot illustrates how IDA evolves from operational optimisation to strategic circular value creation.

INDUSTRIAL CASE STUDY 7 · REMANUFACTURING-X

Remanufacturing-X: A Data-Driven and Human-Centric Ecosystem for Circular Manufacturing

About the Consortium

Unlike the other industrial cases presented in this report, this case focuses on a cross-sector industrial ecosystem rather than a single manufacturing company. The case is represented by Remanufacturing-X[1], a European cross-sector industrial initiative applying the Manufacturing-X data-ecosystem logic to remanufacturing. It brings together industrial users, technology providers and research partners to demonstrate a common digital and human-centric approach across textiles, brewing by-products, machine tools, underwater vehicles, and EV battery packs. The initiative addresses the need to make remanufacturing scalable, interoperable, and attractive across heterogeneous sectors.

A Trend-Driven Transformation

Three trends drive the transformation. Sustainability pressures are increasing the need to retain product value, recover components, and reduce waste and energy. Resilience concerns encourage shorter and more circular value chains, while fragmented lifecycle data and weak coordination still limit reverse flows. At the same time, human-centricity is becoming essential: AI-assisted inspection, disassembly, and decision support must be trusted and usable by operators, engineers and SMEs. Regulation, especially the Ecodesign for Sustainable Products Regulation and emerging Digital Product Passports, reinforces the demand for lifecycle transparency and interoperable data.

A Technology-Enabled Solution

Remanufacturing-X combines a Remanufacturing Data Space and a Digital Product Passport for Remanufacturing with AI-based quality control, smart disassembly, Digital Twins, process optimisation, AI-supported lifecycle assessment and a circular B2B marketplace. These capabilities are organised around trusted data and traceability, smart remanufacturing, circular business services, and inclusive adoption and skills. Together they connect product history, condition, recovery options, sustainability evidence and market opportunities in one interoperable ecosystem.

The Technology Adoption Pathway

Adoption follows a co-creative and iterative pathway. Industrial requirements are collected from users and technology providers, translated into modular services and interoperable interfaces, and then validated in five pilots. The same architecture is adapted to different industrial contexts without losing common data principles. Human-in-the-loop design is embedded from the start through workforce training and technology-acceptance activities, while standards, compliance, and ESG requirements are treated as part of implementation rather than as later add-ons.

The Technology Impact

The project is in implementation, so impacts are expected rather than measured. The evidence model combines technical, environmental, economic, and human-centred indicators. The broader value lies in turning end-of-use products into data-bearing assets that can be inspected, graded, recovered, and reintroduced into use with greater confidence.

Table ICS7.1. Selected expected impact targets.

Indicator	Target
Defect classification accuracy	≥95%
Waste and energy per remanufactured unit	−25%
Throughput	+20%
Recovered parts per unit	+30%
Remanufacturing cost per unit	−20%

At ecosystem level, Remanufacturing-X also targets improved lifecycle-data transparency, five integrated pilot deployments, stronger cross-border circular services, and positive user acceptance. These indicators are intended to show whether the ecosystem can create measurable val-

ue while remaining trustworthy, interoperable and usable across different sectors.

The Lessons Learned

The case suggests that scalable remanufacturing cannot be achieved through automation alone. Data interoperability, trusted governance, workforce acceptance, circular-market coordination and standardisation must evolve together. The cross-sector pilots are particularly important because they reveal which elements can be standardised across industries and which must remain sector-specific. A second lesson is that human acceptance and compliance need to be designed into the solution from the start, rather than addressed after technical deployment.

Next Steps

The next step is to complete and integrate the digital services, validate them across the five pilots and use the resulting evidence to refine the Remanufacturing Data Space, remanufacturing-oriented DPP, circularity metrics and marketplace services. Pilot evidence will also support replication, standardisation and policy recommendations for digital circular manufacturing.

INDUSTRIAL CASE STUDY 8 · SIEMENS

Siemens Digital Twin and Industrial AI: Scaling Manufacturing Excellence from Erlangen (Germany) to Nanjing (China)

About the Company

Siemens AG is a global technology company operating in industrial automation, digital industries, smart infrastructure, and mobility. The company serves customers across more than 190 countries and manages a global network of manufacturing, engineering, and research facilities.

Among its most advanced production sites are the Siemens Electronics Factory Erlangen in Germany and the Siemens Digital Native Factory in Nanjing, China. The Erlangen facility manufactures SINAMICS drives and serves as a flagship site for developing and validating new digital manufacturing technologies before their deployment at scale. The Nanjing facility is Siemens' largest research and manufacturing centre for CNC systems, drives, and electric motors outside Germany. Siemens became interested in Digital Twin and Artificial Intelligence technologies to address increasing manufacturing complexity, improve operational performance, accelerate innovation, and support sustainability objectives[1,3].

A Trend-Driven Transformation

Siemens' manufacturing transformation was driven by several industry trends that increasingly challenged traditional production models.

First, growing market volatility and customer demand for greater customisation required more resilient manufacturing systems capable of rapidly adapting to changing product requirements and fluctuating demand. Production environments needed to become more flexible while maintaining high levels of quality and efficiency[1,4].

Second, sustainability became a strategic priority. Siemens sought to reduce energy consumption, lower carbon emissions, and improve resource utilisation across its manufacturing operations. The company recognised that digital technologies could play a critical role in achieving these objectives while supporting business competitiveness[1,2].

Third, the increase in manufacturing complexity required a more human-centric approach. Employees needed access to real-time information, advanced analytics, and digital decision-support tools to effectively manage increasingly sophisticated production environments. Siemens therefore focused on empowering its workforce through data-driven technologies rather than relying solely on automation[1].

To address these challenges, Siemens adopted an integrated approach combining Digital Twins, Industrial Data Analytics, Industrial Artificial Intelligence, and Industrial Metaverse technologies, all orchestrated through the Siemens Xcelerator open digital business platform[5].

A Technology-Enabled Solution

Siemens developed a comprehensive digital manufacturing ecosystem built on four key technology pillars: Digital Twins, Industrial Artificial Intelligence, Industrial Data Analytics, and IT/OT convergence.

The transformation started at the Electronics Factory Erlangen, where Siemens implemented a comprehensive Digital Twin covering products, production systems, manufacturing processes, and operational performance. Production data from machines, manufacturing lines, and business systems was integrated into a unified digital environment, enabling real-time visibility and advanced analytics throughout the factory. More than 100 AI algorithms were deployed to analyse production data, identify optimisation opportunities, improve quality performance, and support operational decision-making[1,2].

Artificial Intelligence applications were deployed to analyse production data, identify optimisation opportunities, improve quality performance, and support operational decision-making. Through IT/OT convergence, production and business data became accessible to employees via low-code applications, analytics dashboards, and AI-supported tools. The facility also introduced Industrial Metaverse capabilities to analyse historical production events and simulate future operational scenarios.

Building upon the capabilities and experience developed in Erlangen, Siemens subsequently implemented its Digital Native Factory concept in Nanjing. The entire factory was

designed, simulated, tested, and optimised within a virtual environment before physical construction began. This comprehensive Digital Twin integrated factory design, production systems, logistics flows, and infrastructure data into a single digital model to enable virtual validation and optimisation[3,4]. More than 50 AI applications are now active at the Nanjing site[4].

The Technology Adoption Pathway

The transformation began with the modernisation of the Electronics Factory Erlangen. Siemens initially focused on establishing a strong digital foundation through IT/OT integration, data collection, Digital Twin technologies, and industrial analytics. Early initiatives demonstrated measurable improvements in productivity, quality, and sustainability, creating organisational confidence in digital technologies and establishing best practices for future deployment[1,2].

The success achieved in Erlangen enabled Siemens to develop expertise in Digital Twin methodologies, AI-enabled manufacturing, and data-driven operational management. Cross-functional teams involving manufacturing engineers, IT specialists, operational managers, production personnel, and data scientists collaborated to continuously improve manufacturing performance through digital technologies[1].

Workforce engagement and training played a critical role throughout the transformation. Siemens invested in digital skills development and encouraged employees to actively participate in experimentation, problem-solving, and process improvement activities supported by advanced analytics and AI tools[1].

The experience gained in Erlangen directly influenced the development of the new Nanjing facility. Rather than applying Digital Twin technologies only after construction, Siemens designed Nanjing as a Digital Native Factory. The complete production environment was modelled and optimised in the virtual world before physical implementation. This approach allowed Siemens to validate factory layouts, material flows, equipment configurations, and infrastructure requirements before construction started, significantly reducing implementation risks and accelerating deployment[3,4].



Figure ICS8.1. Siemens Digital Twin transformation pathway to the Digital Native Factory Nanjing.

Today, engineers use Digital Twins to evaluate production scenarios before execution, managers rely on AI-supported analytics to optimise operations, and production teams use digital tools to improve quality, throughput, and resource efficiency across both facilities[1,4].

The Technology Impact

The adoption of Digital Twins, Industrial AI, and Industrial Data Analytics delivered significant operational, sustainability, and business benefits.

At Erlangen, Digital Twin technologies, AI applications, and Industrial Metaverse capabilities substantially improved productivity, quality, and energy efficiency. The integration of production and business data provided new operational insights that enabled continuous optimisation[1,2].

At Nanjing, the Digital Native Factory approach enabled Siemens to optimise factory design and production systems before construction, creating a highly efficient and flexible manufacturing environment recognised by the World Economic Forum as a Lighthouse Factory. The facility achieved significant gains in operational performance (78% reduction in lead times and 46% reduction in field failures) through continuous digital transformation and AI-driven manufacturing practices[3,4].

Table ICS8.1. Key business outcomes from Siemens' Digital Twin and AI transformation.

Performance Indicator	Erlangen	Nanjing
Productivity	+69%	+20%
Production Output	+50%	Capacity increase through site consolidation
Product Quality	+60%	Improved through digital optimisation
Time-to-Market	−40%	−33%
Energy Consumption	−42%	>5 million kWh/year savings
Material Replenishment Speed	Improved through AI analytics	+50%
Volume Flexibility	Improved through Digital Twin	+30%
Space Efficiency	Improved through Digital Twin	+40%
Sustainability	−42% energy consumption	−3,300 t CO_2/year, −6,000 m^3 water/year
External Recognition	WEF Digital Lighthouse Factory	WEF Global Lighthouse Factory

The Lessons Learned

Several lessons emerged from Siemens' digital transformation journey.

First, Digital Twins create the greatest value when applied across the entire manufacturing lifecycle, from factory design and engineering to production operations and continuous improvement. Second, successful AI adoption requires strong data foundations and seamless integration between operational and information technologies. Third, technological transformation must be accompanied by workforce transformation through training, change management, and employee engagement initiatives. Fourth, scaling digital technologies across multiple sites is significantly easier when organisations establish a successful pilot environment that can serve as a reference model for future deployments. Finally, the "Digital Native" approach, designing and validating a factory entirely in the virtual world before construction, substantially reduces implementation risk, shortens commissioning time, and improves long-term operational performance[1,3].

Next Steps

Siemens plans to continue expanding the use of Digital Twins, Industrial Artificial Intelligence, and Industrial Metaverse technologies throughout its global manufacturing network. Future initiatives include enhanced predictive capabilities, greater manufacturing autonomy, deeper integration between virtual and physical operations, and broader adoption of AI-driven decision support systems. These developments aim to further strengthen manufacturing resilience, improve sustainability performance, and enable the next generation of human-centric industrial operations[1,2,4].

BEST PRACTICE 1 · ASSOLOMBARDA

The Strategic Project "Rethinking Industry - forgIA" by Assolombarda

About the Company

Assolombarda is the association of companies operating in the Metropolitan City of Milan and in the provinces of Lodi, Monza and Brianza, and Pavia. Assolombarda, due to its size and representativeness, is the most extensive association in the entire Confindustria System. It expresses and protects the interests of over 7,000 companies of all sizes, national and international, producing goods and services in all product sectors.

A Trend-Driven Transformation

Digital technologies have generated an unprecedented volume of data and knowledge, creating new opportunities for value creation.

Through forgIA[1], Assolombarda supports companies by developing a territorial digital ecosystem that facilitates data sharing and enhancement across organisations of all sizes. The initiative also lays the groundwork for the adoption of Physical AI systems, enabling robots, autonomous machines and intelligent industrial assets to operate effectively in real-world environments.

A Technology-Enabled Solution

The Rethinking Industry initiative aims to strengthen industrial competitiveness by accelerating the adoption of Generative and Agentic AI, relying on a strong ecosystem of scientific and technological partners, including Politecnico di Milano, Cefriel, MADE, AI4I, IT4LIA and Cineca, to ensure quality, security and concrete transfer to businesses.

To fully realise this vision to accelerate AI-driven industrial transformation while ensuring that the value created remains anchored to the territory, Assolombarda promotes and develops a matrix-based strategy built around 2 Strategic Initiatives:

- *forgIA Industrial Data Ecosystem (IDE)*: enabling secure data sharing and value creation across supply chains through common standards;
- *forgIA Physical AI Ecosystem*: positioning Milan as an international hub for AI, robotics, and intelligent autonomous systems, fostering innovation across diverse applications and industries;

and 3 cross-cutting programmes:

- *forgIA Accelerate*: supporting companies in the practical adoption of AI solutions through guided implementation paths;
- *forgIA Academy*: fostering a data-driven culture through training, networking and knowledge-sharing activities;
- *forgIA Leadership Initiative*: helping companies leverage data and AI through peer learning and mentoring from champion companies.

The Technology Adoption Pathway

forgIA IDE represents the core of the forgIA project: it is the architecture that enables secure data sharing and creates the conditions for the development of high-impact AI applications, primarily by enhancing the value of the vast amount of data available to companies.

Assolombarda has played a key role in raising awareness among its member companies about the importance of leveraging data and implementing advanced AI solutions. Furthermore, adopting a pragmatic approach, it has carefully considered the operational barriers that could limit the potential and applicability of a data-sharing ecosystem, including terms and conditions of use, contractual frameworks, and operational rules, all of which aspects are being addressed as part of the ongoing work to define the ecosystem's governance framework. This work supports the parallel development of industrial AI use cases, with a first Proof of Concept being developed based on use cases identified through collaboration with early adopter companies. The model will subsequently be industrialised, expanded to new partners and integrated with existing solutions.

The Technology Impact

forgIA IDE is a collaboration environment, enabling organisations to share certified digital assets in a regulated manner and generate new business value.

In particular, companies can provide or access:

- *Data flows*: information that, starting from companies' information systems, can be selectively made available to specific parties, in a regulated manner;
- *AI models*: Machine Learning models, deterministic rule-based models, Large / Small Language Models;
- *AI Agents*: agents based on standard "system prompts," reusable skills across different application contexts.

Several initial use cases have been developed in collaboration with participating companies, addressing key business challenges:

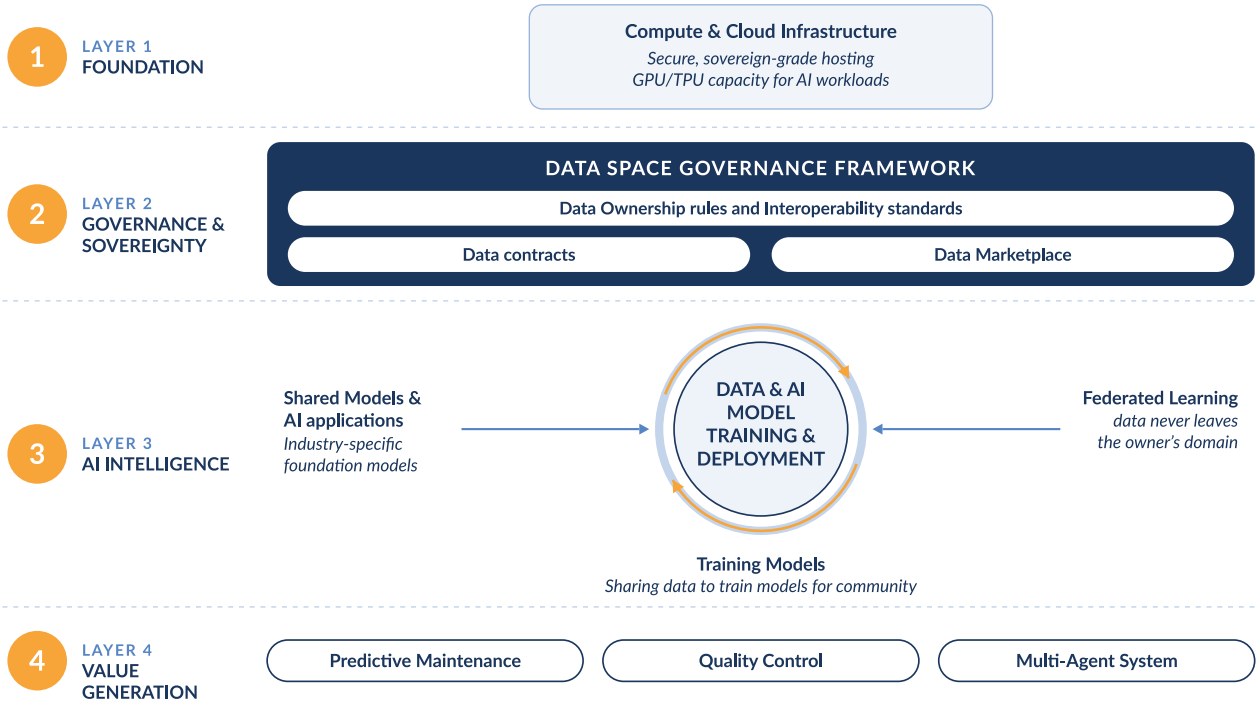


Figure BP1.1. The Industrial Data Ecosystem Model.

Hydroservice Spa - Warehouse Integration

- The solution enables companies to securely and selectively share information on warehouse availability, allowing them to source components and storage capacity more quickly, reduce idle inventory, and respond faster to market demand.

Maire Spa - Post-Order Management / Expediting

- The application enables real-time monitoring of order status across the supply chain, improving production planning, reducing delays and inefficiencies, and replacing processes still largely reliant on emails, phone calls, and disconnected documents.

Epta Spa - Measuring the Impact of Energy Efficiency in Commercial Refrigeration

- The solution leverages data to objectively measure the results of energy-efficiency initiatives, making it easier to demonstrate the benefits achieved while supporting ESG reporting, access to financing, and environmental performance monitoring.

Bracco Spa - Federated Learning for Critical Data

- Building on the experience gained through the *Ippocrate project*, federated learning enables different organisations to jointly train AI models on distributed datasets without sharing the underlying data, while

preserving intellectual property, privacy, and regulatory compliance.

The Lessons Learned

Data sovereignty is essential for participation: companies share data and capabilities only when data access and re-use are defined upfront and stay under their control.

Business-driven use cases (quality control, predictive maintenance or supply chain visibility) generate greater engagement than purely technology-led approaches.

SMEs need guided, step-by-step pathways, since data and tools alone are not enough without the internal skills and structures to apply them.

Peer learning is another strong driver, with companies far more engaged by real, already-implemented use cases from "champion companies" than by theoretical scenarios.

Next Steps

The next steps include:

- completing the IDE operating framework, including processes, tools and governance mechanisms;
- supporting early adopters and generating evidence from initial use cases;
- collecting feedback from participating companies to refine and expand the portfolio of digital assets and AI capabilities;
- engaging new organisations interested in joining the forgIA ecosystems.

BEST PRACTICE 2 · FUTURE MANAGER WORLD

Future Manager World: The Transition from Human Capital to Humanoid Capital

About the Company

Future Manager World is a Global HR Advisory firm focused on the Transition from Human Capital to Humanoid Capital, one of the main drivers of change in manufacturing in the coming years. Along this path, it supports companies facing major change, helping people and organisations through talent and leadership development pathways, upskilling, change management and management succession planning. This is why Future Manager World is Knowledge Partner of this edition of the World Manufacturing Forum.

A Trend-Driven Transformation

AI, agentic systems, humanoid robotics and advanced automation are taking manufacturing beyond the paradigms of System Integration and Smart Manufacturing, towards a new relationship between people and intelligent systems. In an already highly robotised sector, with about 5 million industrial robots worldwide in 2025, Italy remains Europe's second-largest market, but recorded an 11% drop (vs. 2024) in new installations, to about 7,800 units.[1] Humanoid robots add a new layer: about 16,000 were installed worldwide in 2025, over 80% in China,[2] and their human form lets them work in existing plants without retrofits, as labour shortages make strenuous roles harder to fill.

A Technology-Enabled Solution

In 2026, the first large-scale users are moving from assessment to operational trials in manufacturing and logistics: at BMW Spartanburg, a pilot with Figure 02, completed in 2025, logged over 1,250 hours and contributed to over 30,000 vehicles;[3] at GXO, Agility Robotics' Digit moved over 100,000 totes[4] under a Robots-as-a-Service model.[5] These are deployments in repetitive, well-defined tasks, not yet large-scale adoption: companies must define the organisational conditions for humanoid robots to create value. Open issues remain: battery autonomy, speed and reliability below skilled operators, high total cost of ownership, safety standards still being defined (ISO 25785-1)[6] and new EU Machinery Regulation requirements from 2027.[7]

The Technology Adoption Pathway

Future Manager World supports companies and their people in acquiring new skills, and develops awareness and compliance programmes for the conscious, safe and responsible use of technology. The pathway starts with the C-suite and progressively extends to all staff involved in the adoption, with over 1,300 hours of upskilling on AI and new technologies delivered in Italy alone.[8] Effectiveness is measured with a survey at the end of the pathway, repeated two months after completion. Work is redesigned task by task, deciding what goes to humanoids and creating new roles such as robot fleet supervisor and robot trainer.

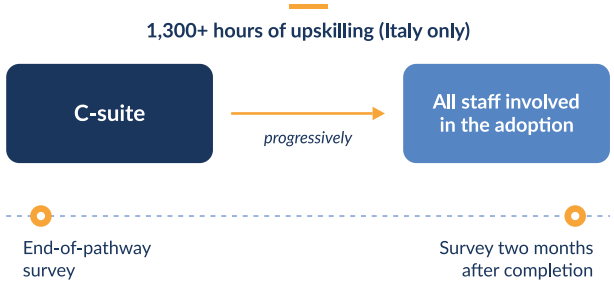


Figure BP2.1. The Future Manager World adoption pathway.[8]

The Technology Impact

The most significant results are achieved when change is managed as an organisational project and not merely a technological one. In the projects followed by Future Manager World, companies that combined technology, skills development and new organisational models achieved on average 90% effective technology adoption (+80% from the starting point) and a 60% reduction in time-to-productivity for the roles involved. 80% of participants apply what they have learned right away and, of these, 98% report more conscious and safer use of technology; two months after the end of the pathway, 90% apply what they have learned in their daily work. The picture is completed by an average saving of 10 hours per week per person, 20% of participants proposing improvement ideas (50% of which were implemented), engagement in continuous pro-

cess improvement (98%) and the organisation's autonomy in rolling out the technology learned (98%).[8]

Technology, skills and new ways of working create measurable and lasting impact.

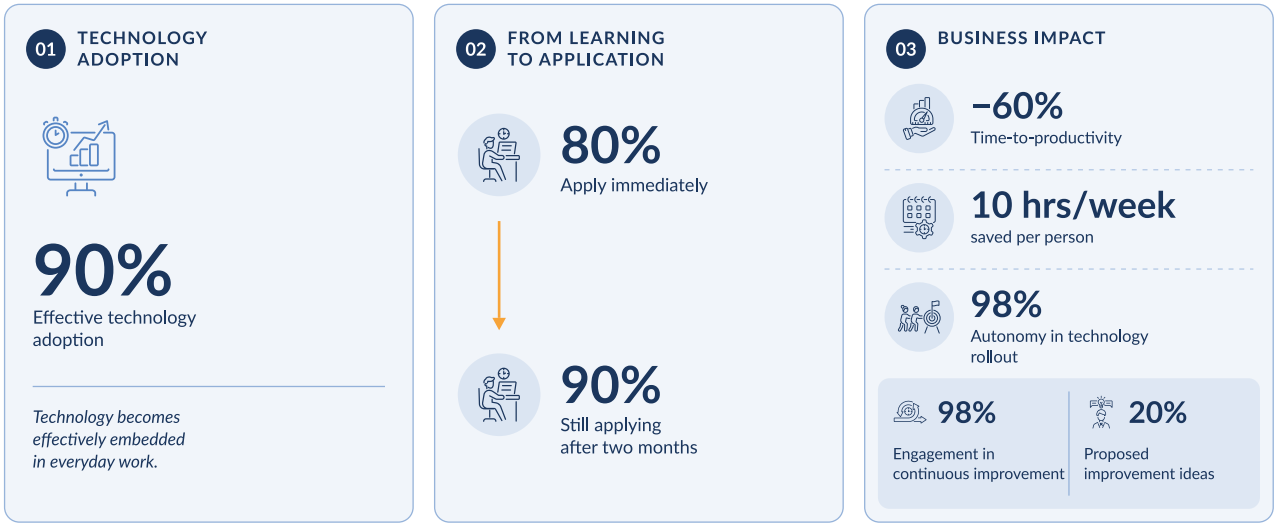


Figure BP2.2. Outcome indicators in Future Manager World projects.[8]

The Lessons Learned

- The issue is not the technology but redesigning work.
- Workforce planning looks at the balance between human capital and humanoid capital.
- Leadership is decisive in integrating technology into the organisational model, guiding change, building trust and managing resistance.
- Trust must be built: involve workers from the first pilot, be transparent on data collected by robot sensors and clarify accountability for incidents.
- Creative thinking, resilience, flexibility and interpersonal skills are becoming increasingly strategic: according to the WEF, 39% of core skills will change by 2030.[9]

Next Steps

The company of the future will emerge from collaboration between people, Artificial Intelligence and humanoid robots. The real challenge is to invest in people, so that the balance between human capital and humanoid capital creates sustainable value. For many companies, that choice starts today.

BEST PRACTICE 3 · REGIONE LOMBARDIA

Connecting Research and Industry: Lombardy's Integrated Policy Framework for Innovation, Technology Transfer and Artificial Intelligence

Unlike company-centred industrial cases, this case focuses on a regional innovation ecosystem and on the policy framework designed to accelerate responsible development and adoption of technology across industry. Regione Lombardia oversees one of Italy's most highly industrialised territories, characterised by a dense ecosystem of manufacturing companies, universities, research organisations, innovation actors and public institutions. In this context, research excellence and the ability to connect scientific knowledge, technological capabilities, specialised skills and industrial needs are increasingly important for maintaining competitiveness and accelerating the translation of research into new products, processes and services. Digital transformation and Artificial Intelligence (AI) are further increasing the need for effective mechanisms that connect research, innovation, technology transfer and industrial adoption. Regione Lombardia is therefore updating its policy framework to strengthen these connections and support the responsible development and diffusion of emerging technologies.

Acceleration of technological change, together with growing concerns around resilience, sustainability and human-centredness, is changing the way regional innovation ecosystems need to be governed. Regione Lombardia is developing a new legislative framework for research, innovation, technology transfer and AI, updating the regional legislation introduced in 2016. The initiative responds to rapid technological development and to an evolving European and national regulatory landscape, while recognising the increasing importance of skills, collaboration and responsible innovation for industrial competitiveness. The objective is to create a more integrated and adaptive regional ecosystem by combining strategic programming, scientific advice, stakeholder participation and instruments supporting collaboration and knowledge circulation. Particular attention is given to ensuring that technological transformation contributes not only to competitiveness, but also to sustainable, resilient and human-centred development.

The regional approach combines policy instruments with digital technologies and innovation infrastructures to strengthen the connection between research and industrial application. A central principle of the framework is that research, innovation and technology transfer should be managed as an integrated process. Scientific results generate economic and societal value when knowledge, skills and technologies can circulate effectively among research organisations, businesses, public institutions and other innovation stakeholders. The proposed framework therefore supports collaboration between research and industry, investment in research and AI infrastructures, as well as in digital technologies, innovative start-ups and companies, intellectual property and patents, specialised human capital and international research collaboration. AI is treated as a cross-cutting enabling technology rather than as an isolated technological sector. Digital platforms, including Lombardy's Open Innovation Platform, complement this approach by supporting knowledge exchange, matching innovation demand and supply, and enabling the testing of innovative digital solutions, including for public services.

Technology adoption is supported through a governance framework that combines long-term strategic direction with continuous monitoring, scientific advice and stakeholder engagement. A three-year Strategic Programme will define objectives, priority areas and interventions for research, innovation, technology transfer and AI. Its preparation will involve scientific experts, public and private stakeholders and citizens, connecting institutional planning with the evolving needs and capabilities of the regional ecosystem. An independent Scientific Committee will provide evidence-based advice and monitor scientific, technological and socioeconomic developments, helping to identify emerging opportunities and challenges. A permanent Regional Research, Innovation and Artificial Intelligence Roundtable will complement this activity by creating a structured dialogue among research, education, industry and institutional stakeholders. Together, these mechanisms support the identification of promising technologies, their alignment with regional priorities and the progressive translation of research and innovation opportunities into industrial and societal applications.

The expected impact extends beyond individual technology projects: the objective is to strengthen the regional capacity to transform research and technological innovation into industrial and societal value. The framework is expected to reinforce collaboration between research organisations and businesses, accelerate technology and knowledge transfer, strengthen specialised skills and improve the region's capacity to identify and responsibly adopt emerging technologies. For AI specifically, the intended impact combines technological development with responsible adoption, in accordance with fundamental rights and the evolving European and national regulatory framework. A Regional Charter for the Development of Artificial Intelligence is intended to establish shared principles for a sustainable and human-centred approach, involving institutions, businesses, universities, research organisations and civil society. For manufacturing, these mechanisms can help create the enabling conditions required for the adoption of cognitive, agentic and physical AI, as well as other emerging technologies, while addressing the associated requirements for skills, trust, collaboration and governance.

The Lessons Learned

The Lombardy case highlights that technology adoption is an ecosystem challenge rather than a purely technological one. Three main lessons emerge from the approach. First, technology investment alone is insufficient: effective innovation requires connections between research capabilities, industrial needs, skills and appropriate governance mechanisms. Second, human capital, trust and responsible innovation must develop alongside technology. This is particularly relevant for AI, where technological opportunities need to be considered together with their economic, social and human implications. Third, permanent collaboration mechanisms are essential for connecting the demand and supply of innovation. Platforms such as Lombardy's Open Innovation Platform, together with scientific advice and multi-stakeholder dialogue, can facilitate knowledge circulation, identify solutions and strengthen the capacity of the regional ecosystem to respond to technological change.

Next Steps

The next challenge for Regione Lombardia will be to translate the legislative framework into concrete actions and assess its effectiveness in strengthening connections between research and industry, accelerating technology transfer and supporting responsible technology adoption.

Implementation will also provide an opportunity to assess how the Strategic Programme, Scientific Committee, Regional Roundtable, Open Innovation Platform and AI governance mechanisms interact in practice and contribute to a more innovative, human-centred and competitive industrial ecosystem.

References

Chapter 1 · Navigating the Future of Manufacturing

1 World Economic Forum. (2023). The Global Risks Report 2023. World Economic Forum.

2 Collins Dictionary. (2022). Permacrisis. Collins English Dictionary; Collins Word of the Year 2022.

3 Rohrbeck, R., Battistella, C., & Huizingh, E. (2015). Corporate foresight: An emerging field with a rich tradition. Technological Forecasting and Social Change, 101, 1–9. https://doi.org/10.1016/j.techfore.2015.11.002

4 Rohrbeck, R., & Kum, M. E. (2018). Corporate foresight and its impact on firm performance: A longitudinal analysis. Technological Forecasting and Social Change, 129, 105–116. https://doi.org/10.1016/j.techfore.2017.12.013

5 Blechschmidt, J. (2025). Trend Management: How to Effectively Use Trend-Knowledge in Your Company (2nd ed.). Springer. https://doi.org/10.1007/978-3-662-70798-2

6 Liebl, F., & Schwarz, J. O. (2010). Normality of the future: Trend diagnosis for strategic foresight. Futures, 42(4), 313–327. https://doi.org/10.1016/j.futures.2009.11.017

7 European Commission. Strategic Foresight: Foresight Methods and Tools. European Commission.

8 Rohrbeck, R., Heuer, J., & Arnold, H. M. (2006). The Technology Radar - An instrument of technology intelligence and innovation strategy. Proceedings of the 3rd IEEE International Conference on Management of Innovation and Technology, 978–983. https://doi.org/10.1109/ICMIT.2006.262368

9 Rauch, E., & Vinante, E. (2021). Three-Dimensional Technology Radar Model to Evaluate Emerging Industry 4.0 Technologies. In Advances in Design, Simulation and Manufacturing IV. Lecture Notes in Mechanical Engineering. Springer, Cham. https://doi.org/10.1007/978-3-030-77719-7_24

10 Salviotti, G., & Meregalli, S. (Eds.). (2017). High Impact Technologies Radar: General Report - First Edition. EGEA / SDA Bocconi School of Management DEVO Lab.

11 Sheykhha, S., Daun, P., Madlener, R., & Praktiknjo, A. (2024). Investigating Unexplored Aspects of Technology Foresight: A Study Using Energy Technology Radar 2.0. FCN Working Paper No. 14/2023, revised October 2024. RWTH Aachen University.

12 Gartner. (n.d.). Gartner Hype Cycle Research Methodology. Gartner.

2.1 Resilient Supply Chains and Manufacturing Systems Trends

1 Christopher, M., & Peck, H. (2004). Building the resilient supply chain. The International Journal of Logistics Management, 15(2), 1–14.

2 Pettit, T. J., Croxton, K. L., & Fiksel, J. (2019). The evolution of resilience in supply chain management: A retrospective on ensuring supply chain resilience. Journal of Business Logistics, 40(1), 56–65.

3 Birkel, H., & Müller, J. M. (2025). Resilient by nature or technology? How industry 4.0 enhances supply chain resilience until 2035. Supply Chain Management: An International Journal, 30(3), 304–322.

4 World Economic Forum. (2026). The global risks report 2026.

5 International Energy Agency. (2025). Global critical minerals outlook 2025.

6 United Nations Conference on Trade and Development. (2024). Review of maritime transport 2024.

7 McKinsey Global Institute. (2020). Risk, resilience, and rebalancing in global value chains.

8 Simchi-Levi, D., Schmidt, W., & Wei, Y. (2014). From superstorms to factory fires: Managing unpredictable supply chain disruptions. Harvard Business Review, 92(1–2), 24.

9 Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: An analysis and recent literature. International Journal of Production Research, 56(1–2), 414–430.

10 Business Continuity Institute. (2024). Supply chain resilience report 2024.

11 World Economic Forum. (2025). The future of jobs report 2025.

12 United Nations Industrial Development Organization. (2026). Industrial development report 2026: The future of industrialization: Building future-ready industries for sustainable development.

13 European Union Agency for Cybersecurity. (2024). ENISA threat landscape 2024.

14 European Parliament & Council of the European Union. (2024). 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, L, 2024/1252.

15 European Parliament & Council of the European Union. (2024). Directive (EU) 2024/1760 on corporate sustainability due diligence. Official Journal of the European Union, L, 2024/1760.

16 European Parliament & Council of the European Union. (2022). Directive (EU) 2022/2555 on measures for a high common level of cybersecurity across the Union (NIS2 Directive). Official Journal of the European Union, L 333, 80–152.

17 European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/2847 on horizontal cybersecurity requirements for products with digital elements (Cyber Resilience Act). Official Journal of the European Union, L, 2024/2847.

18 European Parliament & Council of the European Union. (2023). Regulation (EU) 2023/1781 establishing a framework of measures for strengthening Europe's semiconductor ecosystem (Chips Act). Official Journal of the European Union, L 229, 1–53.

19 Intergovernmental Panel on Climate Change (IPCC). (2023). Climate change 2023: Synthesis report. Contribution of Working Groups I, II and III to the Sixth Assessment Report.

20 Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. Journal of Supply Chain Management, 50(3), 55–73.

21 Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development of a conceptual framework. Journal of Business Logistics, 31(1), 1–21.

22 Koren, Y., Gu, X., & Guo, W. (2018). Reconfigurable manufacturing systems: Principles, design, and future trends. Frontiers of Mechanical Engineering, 13(2), 121–136.

23 Mittal, S., Khan, M. A., Romero, D., & Wuest, T. (2018). A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs). Journal of Manufacturing Systems, 49, 194–214.

2.2 Sustainable Supply Chains and Manufacturing Systems Trends

1 Acerbi, F., & Taisch, M. (2020). A literature review on circular economy adoption in the manufacturing sector. Journal of Cleaner Production, 273, 123086.

2 Ranta, V., Aarikka-Stenroos, L., & Väisänen, J.-M. (2021). Digital technologies catalysing business model innovation for circular economy. Resources, Conservation and Recycling, 164, 105155.

3 Acerbi, F., Sassanelli, C., Terzi, S., & Taisch, M. (2021). A systematic literature review on data and information required for circular manufacturing strategies adoption. Sustainability, 13, 2047.

4 Liu, Q., Trevisan, A. H., Yang, M., & Mascarenhas, J. (2022). A framework of digital technologies for the circular economy. Business Strategy and the Environment, 31, 2171–2192.

5 Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between circular economy and Industry 4.0. International Journal of Production Research, 58, 1662–1687.

6 Trevisan, A. H., Lobo, A., Guzzo, D., Gomes, L. A. de V., & Mascarenhas, J. (2023). Barriers to employing digital technologies for a circular economy. Journal of Environmental Management, 332, 117437.

7 Harala, L., Alkki, L., Aarikka-Stenroos, L., Al-Najjar, A., & Malmqvist, T. (2023). Industrial ecosystem renewal towards circularity to achieve the benefits of reuse: Learning from circular construction. Journal of cleaner production, 389, 135885.

8 Ranta, V., Aarikka-Stenroos, L., Ritala, P., & Mäkinen, S. J. (2018). Exploring institutional drivers and barriers of the circular economy: A cross-regional comparison of China, the US, and Europe. Resources, Conservation and Recycling, 135, 70–82.

9 Thakuri, P. K., Alkki, L., & Aarikka-Stenroos, L. (2025). Digital technologies enabling component reuse in circular value chains. R&D Management, 55, 1161–1216.

10 Chauhan, C., Parida, V., & Dhir, A. (2022). Linking circular economy and digitalisation technologies. Technological Forecasting and Social Change, 177, 121508.

11 Sassanelli, C., Garza-Reyes, J. A., Liu, Y., de Jesus Pacheco, D. A., & Luthra, S. (2023). The disruptive action of Industry 4.0 technologies cross-fertilising circular economy throughout society. Computers & Industrial Engineering, 183, 109548.

12 Ferrante, M., Sassanelli, C., & Pigosso, D. C. A. (2026). Rebound effects in circular manufacturing. Business Strategy and the Environment.

13 Aarikka-Stenroos, L., Chiaroni, D., Kaipainen, J., & Urbinati, A. (2022). Companies' circular business models enabled by supply chain collaborations. Industrial Marketing Management, 105, 322–339.

2.3 Human-Centric Supply Chains and Manufacturing Systems Trends

1 World Economic Forum, Chief People Officers' Outlook - May 2026, 30 April 2026.

2 Broecke, S. (2024). Offshoring, reshoring, and the evolving geography of jobs: A scoping paper (OECD Social, Employment and Migration Working Papers No. 308). OECD Publishing.

3 International Labour Organization. (2025a). Employment in the critical minerals sector: A case study of Indonesia, Mongolia and the Philippines.

4 Ghobakhloo, M., Mahdiraji, H. A., Iranmanesh, M., & Jafari-Sadeghi, V. (2024). From Industry 4.0 digital manufacturing to Industry 5.0 digital society: A roadmap toward human-centric, sustainable, and resilient production. Information Systems Frontiers, 1–33.

5 Thiel, K., & Postlethwaite, S. (2023). Human-centric research of skills and decision-making capacity in fashion garment manufacturing to support robotic design tool development. Human Aspects of Advanced Manufacturing, 20–30.

6 International Labour Organization. (2024b). Profits and poverty: The economics of forced labour (2nd ed.).

7 Fernández-Miguel, A., Ortíz-Marcos, S., Jiménez-Calzado, M., Fernández del Hoyo, A. P., García-Muiña, F. E., & Settembre-Blundo, D. (2025). Agentic AI in smart manufacturing: Enabling human-centric predictive maintenance ecosystems. Applied Sciences, 15(21), 11414.

8 Sbaragli, A., Tomelleri, F., Picariello, F., Picariello, E., & Pilati, F. (2024). Safe Operator 5.0 digital architecture: Towards resilient human-centric manufacturing systems. IFAC-PapersOnLine, 58(19), 265–270.

9 Briken, K., Moore, J., Scholarios, D., Rose, E., & Sherlock, A. (2023). Industry 5 and the human in human-centric manufacturing. Sensors, 23(14), 6416.

10 Xu, X., Ji, T., Zheng, P., & Wang, L. (2026). Human-centric manufacturing: Re-thinking, Re-justifying, and Re-envisioning. Journal of Manufacturing Systems, 84, 259–268.

11 Kalsoom, T., Onwumere, I., & Rehman, M. U. (2025, April). From Automation to Human-Centric Manufacturing: A Systematic Literature Review on the Transition from Industry 4.0 to Industry 5.0. In 2025 International Conference on Business Intelligence for Technology Innovation (ICBITI) (pp. 1–8). IEEE.

12 European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union, L, 2024/1689.

13 European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/3015 of 27 November 2024 on prohibiting products made with forced labour on the Union market and amending Directive (EU) 2019/1937. Official Journal of the European Union, L, 2024/3015.

14 European Parliament & Council of the European Union. (2019). Directive (EU) 2019/882 of 17 April 2019 on the accessibility requirements for products and services. Official Journal of the European Union, L 151, 70–115.

15 Scott, N., Graczyk, H., & Papandrea, D. (2024). Ensuring safety and health at work in a changing climate: Global report. International Labour Organization.

16 Denu, M., David, P., Mangione, F., & Landry, A. (2024). Towards Human-Centric Digital Simulation: Guidelines to Simulate Operators Skills Acquisition and Health in Circular Manufacturing Systems. IFAC-PapersOnLine, 58(19), 445–450.

17 Vandenbroucke, S. (2024). The portrayal of effectiveness of supplier codes of conduct in improving labor conditions in global supply chains: A systematic review of the literature. Regulation & Governance, 18(1), 307–327.

18 International Labour Organization. (2025b). Decent work in renewable energy and critical mineral supply chains: Trends, challenges and innovations in Asia and the Pacific.

19 International Labour Organization. (2024a). Report of the Meeting of Experts on wage policies, including living wages (Geneva, 19–23 February 2024) (GB.350/POL/1).

20 Difrancesco, R. M., & Klumpp, M. (2025). Supply Chain Management 5.0–How to Conceptualize Network Cascading and Implementation of Human-centric Operations. IFAC-PapersOnLine, 59(10), 2016–2021.

21 Ozdemir, M., Verlinden, J., & Cascini, G. (2022). Design methodology for mass personalisation enabled by digital manufacturing. Design Science, 8, e7.

22 Lu, Y., Zheng, H., Chand, S., Xia, W., Liu, Z., Xu, X., ... & Bao, J. (2022). Outlook on human-centric manufacturing towards Industry 5.0. Journal of manufacturing systems, 62, 612–627.

23 European Commission, Directorate-General for Research and Innovation. (2024). ERA industrial technologies roadmap on human-centric research and innovation for the manufacturing sector. Publications Office of the European Union.

24 Locatelli, G., Pasanisi, D., Pesenti, V., Quarto, M., D'Urso, G., & Floreani, F. (2024). Surveying the landscape of Human-Centric Manufacturing in Lombardy: insights from the practices and perspectives of Italian enterprises. Procedia CIRP, 122, 713–718.

25 Zare, L., Benedini, B., Ali, M. B., Rauch, E., & Salimbeni, S. (2025). Opportunities and barriers for implementing human-centric manufacturing in SMEs: Results from focus group workshops in Argentina. Procedia Computer Science, 253, 1452–1461.

26 Liu, F., Zhou, Q., Li, M., Sun, X., Liu, F., Yan, M., & Hu, J. (2025, May). Human-Centric Replenishment-Picking Coordination for Mass Customization Manufacturing Workshops Considering Ergonomic Risk. In International Conference on Human-Computer Interaction (pp. 344–352). Cham: Springer Nature Switzerland.

27 Li, M., Ling, S., Qu, T., Lu, S., Li, M., Guo, D., ... & Huang, G. Q. (2025). Real-time data-driven hybrid synchronization for integrated planning, scheduling, and execution toward industry 5.0 human-centric manufacturing. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 55(8), 5670–5681.

28 International Organization for Standardization. (2021). Occupational health and safety management - Psychological health and safety at work - Guidelines for managing psychosocial risks (ISO Standard No. 45003:2021).

29 Cardoso, A., Ribeiro, A., Carneiro, P., & Colim, A. (2024). Evaluating exoskeletons for WMSD prevention: A systematic review of applications and ergonomic approach in occupational settings. International journal of environmental research and public health, 21(12), 1695.

30 Pistolesi, F., Baldassini, M., & Lazzerini, B. (2024). A human-centric system combining smartwatch and LiDAR data to assess the risk of musculoskeletal disorders and improve ergonomics of Industry 5.0 manufacturing workers. Computers in Industry, 155, 104042.

31 Rhodes, D. H., Cuddy, S., Jeffers, M., & O'Rourke, F. (2025). Human-centric manufacturing culture: a research study of MedTech manufacturers in Ireland. Production & Manufacturing Research, 13(1), 2445623.

32 World Economic Forum. (2025). The future of jobs report 2025.

33 United Nations Industrial Development Organization. (2026). Industrial development report 2026: The future of industrialization: Building future-ready industries for sustainable development.

3.1 Enterprise Wearable Devices & Human-Centred Technologies Technology Radar

1 UploadVR (2024). Microsoft is discontinuing HoloLens 2. https://uploadvr.com/microsoft-discontinuing-hololens-2

2 TeamViewer (n.d.). DHL: Vision picking with smart glasses - success story. https://www.teamviewer.com/en/success-stories/dhl/

3 Gulf News (2018). How Google Glass helps Boeing build airplanes. https://gulfnews.com/business/aviation/how-google-glass-helps-boeing-build-airplanes-1.1863747

4 ProGlove (n.d.). Participants in Fraunhofer IPA pilot study prefer ProGlove scanners. https://proglove.com/press/participants-in-fraunhofer-ipa-pilot-study-prefer-proglove-scanners/

5 CEN (2020). CEN/TR 17512:2020 Personal protective equipment - Smart garments - Terms and definitions.

6 DC Velocity (2021). KINETIC Reflex wearables verified to reduce injury frequency by 50–60%; reduce lost work days by 72%. https://www.dcvelocity.com/articles/50835

7 European Union (2024). Regulation (EU) 2024/1689 (Artificial Intelligence Act), Article 5(1)(f).

3.2 Industrial Data Analytics Technology Radar

1 Kusiak, A. (2018). Smart manufacturing. International Journal of Production Research, 56(1–2), 508–517. https://doi.org/10.1080/00207543.2017.1351644

2 Gaus, T., & Schlotterbeck, M. (2025). 2025 smart manufacturing and operations survey: Navigating challenges to implementation. Deloitte Insights.

3 Breque, M., De Nul, L., & Petridis, A. (2021). Industry 5.0: Towards a sustainable, human-centric and resilient European industry. European Commission, Directorate-General for Research and Innovation.

4 International Data Spaces Association. (2022). IDS Reference Architecture Model 4.0. IDSA.

5 Federal Ministry for Economic Affairs and Climate Action (BMWK). (2024). The global initiative to expand industrial data ecosystems: About Manufacturing-X.

6 Gaia-X European Association for Data and Cloud AISBL. (2024). Gaia-X Architecture Document - 24.04 Release.

7 European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/1781 establishing a framework for the setting of ecodesign requirements for sustainable products. Official Journal of the European Union.

8 European Parliament & Council of the European Union. (2024). Regulation (EU) 2024/1689 laying down harmonised rules on artificial intelligence (Artificial Intelligence Act). Official Journal of the European Union.

9 Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

10 Rosa, P., Sassanelli, C., Urbinati, A., Chiaroni, D., & Terzi, S. (2020). Assessing relations between Circular Economy and Industry 4.0: A systematic literature review. International Journal of Production Research, 58(6), 1662–1687. https://doi.org/10.1080/00207543.2019.1680896

11 Acerbi, F., Sassanelli, C., Terzi, S., & Taisch, M. (2021). A systematic literature review on data and information required for circular manufacturing strategies adoption. Sustainability, 13(4), 2047. https://doi.org/10.3390/su13042047

12 Acerbi, F., Sassanelli, C., & Taisch, M. (2022). A conceptual data model promoting data-driven circular manufacturing. Operations Management Research, 15, 838–857. https://doi.org/10.1007/s12063-022-00271-x

3.3 Digital Twins, Extended Reality & Industrial Metaverses Technology Radar

1 Villegas et al. (2025). Digital twins in manufacturing: A unified conceptual framework. *Annual Reviews in Control*, 60, 101031. https://doi.org/10.1016/j.arcontrol.2025.101031

2 AIOTI WG Research (AIOTI - Alliance for IoT, AI and Edge Continuum Innovation) (2025). Edge IoT Industrial Immersive and Spatial Computing Applications - Release 1

3 Tu et al. (2024). Architecture for data-centric and semantic-enhanced industrial metaverse: Bridging physical factories and virtual landscape. *Journal of Manufacturing Systems* 74 (2024): 965–979. https://doi.org/10.1016/j.jmsy.2024.05.016

4 Palmitessa et al. (2026). A digital twin-enabled Industrial Metaverse architecture for production system design: Evidence from an implementation in the automotive industry. *Computers in Industry*, 181, 104544. https://doi.org/10.1016/j.compind.2026.104544

5 Tu & De Castro e Silva. (2025). Are we ready for the metaverse? Implications, legal landscape, and recommendations for responsible development. *Digital Society*, 4(1), 9. https://doi.org/10.1007/s44206-025-00163-0

6 Ghafoori et al. (2025). Are We Measuring What Matters? Reframing Evaluation of Extended Reality for Industry 5.0 Work Environments. In 2025 IEEE International Symposium on Mixed and Augmented Reality Adjunct (ISMAR-Adjunct) (pp. 223–228). IEEE. https://doi.org/10.1109/ISMAR-Adjunct68609.2025.00050

7 Deloitte Research Center for Energy & Industrials (2023) Exploring the industrial metaverse https://www.deloitte.com/us/en/insights/industry/manufacturing-industrial-products/industrial-metaverse-applications-smart-factory.html

3.4 Agentic & Cognitive Artificial Intelligence Technology Radar

1 Gartner (2026). Hype Cycle for Agentic AI.

2 Gartner (2025). Gartner Predicts Over 40% of Agentic AI Projects Will Be Canceled by End of 2027.

3 McKinsey & Company (2025). The State of AI in 2025: Agents, Innovation, and Transformation.

4 Siemens (2026). Siemens Brings AI to the Physical World with Eigen Engineering Agent.

5 SAP (2026). Building the Autonomous Supply Chain.

6 Farahani, M. A., Khan, M. I., Wuest, T. (2026). Hybrid Agentic AI and Multi-Agent Systems in Smart Manufacturing. Journal of Manufacturing Systems.

7 Jiang, X., Xie, H., Wang, J., et al. (2026). Agentic AI for Safety-Aware Process Monitoring and Fault Diagnosis: A Review. Processes, 14(13), 2112.

8 Graul, C., Żarski, W., Mikołajewski, D., Rojek, I. (2026). AI Agents in Industry 4.0: AAS-OPC UA-LLM Architecture as the Foundation of Intelligent Manufacturing Systems. Applied Sciences, 16(11), 5428.

9 Hatten, N., Malone, K. (2026). Leveraging Large Language Models for Predictive Maintenance of In-House Critical Equipment. Reliability and Maintainability Symposium.

10 Chen, Y., Gu, S., Zhang, M., et al. (2025). An LLM-Based Multi-Agent System for Whole Lifecycle Downhole Maintenance Operations.

11 Zhao, Z., Tang, D., Zhu, H., et al. (2025). A Large Language Model-based Multi-Agent Manufacturing System for Intelligent Shopfloors. Advanced Engineering Informatics.

12 CSET (2026). China AI Plus Manufacturing Initiative Opinions (translation).

13 METI/NEDO (2026). Development Project for Multimodal Foundation Models for AI Robots and Physical AI.

14 Deloitte (2026). The State of AI in the Enterprise.

15 Oak Ridge National Laboratory (2026). Digital Manufacturing Saves Critical Qualification Time.

16 Oak Ridge National Laboratory (2026). Autonomous Resource Corporation, ORNL Partner to Accelerate AI-Enabled Defense Manufacturing at National Scale.

17 Oak Ridge National Laboratory (2026). ORNL Researchers Showcase AI-Driven Science at National Expo.

18 KPMG (2026). AI Quarterly Pulse Survey.

19 Han, N., Seo, J., Ha, J., et al. (2025). Development of Autonomous Failure Maintenance System for Semiconductor Manufacturing.

20 Moffatt v Air Canada, 2024 BCCRT 149.

21 California Civil Code s.1714.46 (AB 316, 2025).

22 European Commission (2026). Regulation (EU) 2026/1744, Digital Omnibus on AI.

23 Zwerdling, N., Boaz, D., Rabinovich, E., et al. (2025). Towards Enforcing Company Policy Adherence in Agentic Workflows. EMNLP 2025, Industry Track.

24 Cloud Security Alliance and Oasis Security (2026). The State of Non-Human Identity and AI Security.

25 McKinsey & Company (2026). Is That AI Agent Worth It? Agentic Economics and the Modern Operating Model.

26 Huang, W.-C., et al. (2026). Rethinking Memory Mechanisms of Foundation Agents: A Survey.

27 Cemri, M., et al. (2025). Why Do Multi-Agent LLM Systems Fail?

3.5 Physical AI & Humanoid Robotics Technology Radar

1 Counterpoint Research (2026). Global Humanoid Robot Installations Reach 16,000 Units in 2025 as Mass Production Picks Up Pace. https://counterpointresearch.com/en/insights/Global-Humanoid-

Robot-Installations-Reach-16%2C000-Units-in-2025-as-Mass-Production-Picks-Pace

2 Koetsier, J. (2026). Humanoid Robot Shipments Up 300%: Up to 30,000 So Far in 2026. Forbes. https://www.forbes.com/sites/johnkoetsier/2026/08/20/humanoid-robot-shipments-up-300-up-to-30000-so-far-in-2026/

3 Humanoid Guide (n.d.). Elon Musk on the Humanoid Robot Market. https://humanoid.guide/elon-musk-on-the-humanoid-robot-market/

4 Li, L. H., et al. (2019). VisualBERT: A Simple and Performant Baseline for Vision and Language. arXiv. https://arxiv.org/abs/1908.03557

5 Brohan, A., et al. (2022). RT-1: Robotics Transformer for Real-World Control at Scale. arXiv. https://arxiv.org/abs/2212.06817

6 Brohan, A., et al. (2023). RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control. arXiv. https://arxiv.org/abs/2307.15818

7 Kim, M. J., et al. (2024). OpenVLA: An Open-Source Vision-Language-Action Model. arXiv. https://arxiv.org/abs/2406.09246

8 NVIDIA, et al. (2025). GR00T N1: An Open Foundation Model for Generalist Humanoid Robots. arXiv. https://arxiv.org/abs/2503.14734

9 Figure AI (2025). Helix: A Vision-Language-Action Model for Generalist Humanoid Control. https://www.figure.ai/news/helix

10 Google DeepMind (n.d.). Genie: Generative Interactive Environments. https://deepmind.google/models/genie/

11 NVIDIA (2025). Cosmos: World Foundation Models for Physical AI. https://www.nvidia.com/en-eu/ai/cosmos

12 World Pilot Research Team (2026). World Pilot: Steering Vision-Language-Action Models with World-Action Priors. arXiv. https://arxiv.org/abs/2606.12403

Industrial Case Study 1 · BizMatters Consulting

1 A. Makris, K. Finisterre and K. Severov, UniPwn: unauthenticated BLE command injection in Unitree Go2, G1, H1 and B2 robots, September 2025 (CVE-2025-35027, CVE-2025-60017, CVE-2025-60250, CVE-2025-60251).

2 OpenAI, The Hugging Face incident and the road ahead, August 2026; Hugging Face, Anatomy of a Frontier Lab Agent Intrusion: A Technical Timeline of the July 2026 Incident, 2026.

3 Commission Delegated Regulation (EU) 2022/30 supplementing Directive 2014/53/EU (Radio Equipment Directive), cybersecurity requirements applicable from 1 August 2025.

4 Regulation (EU) 2024/2847 (Cyber Resilience Act), vulnerability handling and reporting obligations; Regulation (EU) 2023/1230 on machinery.

Industrial Case Study 4 · ELFIM

1 ELFIM, “Projects & Research” and “Industrial R&D”, www.elfim.com (accessed August 2026).

2 ENEA, “Progetto SIADD - Soluzioni Innovative per la qualità e la sostenibilità dei processi di ADDitive manufacturing” (updated 21 April 2024).

3 CNR-STIIMA, “SIADD - Soluzioni innovative per la qualità e la sostenibilità dei processi di additive manufacturing”.

Industrial Case Study 5 · PAL Robotics

1 JARVIS. Meet the 8 Pilots of JARVIS Open Call 1. Retrieved from https://jarvis-project.eu/meet-the-8-pilots-of-jarvis-open-call-1/

2 PAL Robotics. CO-HAND project. Retrieved from https://pal-robotics.com/projects/co-hand/

3 PAL Robotics. (2026). JARVIS - CO-HAND reaches TRL 7: Final validation in CETRIKO’s operational textile environment. Retrieved from https://pal-robotics.com/blog/pal-robotics-in-co-hand-project/

Industrial Case Study 7 · Remanufacturing-X

1 Remanufacturing-X Consortium, Grant Agreement Project 101295053, “Remanufacturing-X: Accelerating Europe’s Transition to Digital Circular Manufacturing,” Horizon Europe, 2026.

Industrial Case Study 8 · Siemens

1 Siemens AG (2024). How to Stay Competitive as a Sustainable Digital Enterprise. Siemens AG, Electronics Factory Erlangen. https://references.siemens.com/en/reference/siemens-ag?id=38912

2 Siemens AG (2024). World Economic Forum: Siemens Factory in Erlangen Named Digital Lighthouse Factory. https://press.siemens.com/global/en/pressrelease/siemens-electronics-factory-erlangen-awarded-digital-lighthouse-world-economic-forum

3 Ohr, R.-C. (2022). Merging Real and Digital Worlds: Siemens’ First Digital Native Factory. Siemens Blog. https://blog.siemens.com/2022/07/merging-real-and-digital-worlds-siemens-first-digital-native-factory/

4 Siemens AG (2026). Siemens’ AI Powered Nanjing Facility Named World Economic Forum Global Lighthouse Factory. https://press.siemens.com/global/en/pressrelease/siemens-ai-powered-nanjing-facility-named-world-economic-forum-global-lighthouse

5 Siemens AG (2026). Siemens Unveils Technologies to Accelerate the Industrial AI Revolution at CES 2026. https://press.siemens.com/global/en/pressrelease/siemens-unveils-technologies-accelerate-industrial-ai-revolution-ces-2026

Best Practice 1 · Assolombarda

1 https://www.assolombarda.it/forgia

Best Practice 2 · Future Manager World

1 IFR (2026). Five Million Robots now Operate in Factories Globally. ifr.org

2 Counterpoint Research (2026). Global Humanoid Robot Installations Reach 16,000 Units in 2025. counterpointresearch.com

3 Figure AI (2025). Production at BMW. figure.ai/news/production-at-bmw

4 Agility Robotics (2025). Digit Moves Over 100,000 Totes in Commercial Deployment. agilityrobotics.com

5 DC Velocity (2024). GXO deploys humanoid robots in Spanx warehouse. dcvelocity.com

6 ISO/CD 25785-1. Robotics - Safety requirements for dynamically stable industrial mobile robots - Part 1: Robots. iso.org

7 European Union (2023). Regulation (EU) 2023/1230 on machinery, applicable from 20 January 2027. eur-lex.europa.eu

8 Future Manager World, internal data. www.futuremanagerworld.com

9 World Economic Forum (2025). Future of Jobs Report 2025.

Spreading Industrial Culture Worldwide

The World Manufacturing Foundation was formally established in May 2018 in Milan, Italy, as a platform to promote industrial culture and sustainable manufacturing practices worldwide. This undertaking was spearheaded by two founding partners: Confindustria Lombardia and Politecnico di Milano. The Foundation aims to spread industrial culture by expanding knowledge, promoting innovation, and fostering cooperation in the manufacturing sector.

The Foundation capitalises on its wealth of experience in hosting annual manufacturing events to discuss the most pressing challenges confronting the sector. In fact, long before the Foundation was formally established, the annual World Manufacturing Forum has been staged since 2011. The very first edition was held in Cernobbio in Lombardy and started as an important platform for global industry leaders and other stakeholders to exchange opinions on different issues related to manufacturing. The Forum started as a project funded by the European Commission, which has also supported its succeeding editions.

The World Manufacturing Foundation also has the support of important organisations. The Foundation was kick-started with the support of Regione Lombardia, which has also provided financial support in the last few years. In 2018, the World Manufacturing Foundation also signed a joint declaration with the United Nations Industrial Development Organization (UNIDO) to promote a common global agenda on technological innovation and inclusive and sustainable industrialisation, and to advance the 2030 Agenda for Sustainable Development.

The business model which defines the Foundation is that of the Triple Helix. Its competitiveness is empowered through an intersectoral collaboration engaging industry, academia, and government. This is evident in the nature of its founding and key partners and a large community of institutional partners from all over the world, which support the Foundation's initiatives.

World Manufacturing Foundation Members

Thanks to

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2026 KEY RECOMMENDATIONS by The World Manufacturing Foundation

1. Systematically Scan for Emerging Manufacturing Trends in the Environment
2. Engage Diverse Stakeholders in Manufacturing Trends Interpretation
3. Prioritise and Align Manufacturing Trends Based on Relevance & Impact and with the Business Strategy
4. Translate Manufacturing Trends into Actionable Strategic Initiatives
5. Review, Validate, and Update the Trends Compass Regularly
6. Continuously Monitor and Evaluate Emerging Manufacturing Technologies
7. Prioritise and Categorise Technologies Based on Manufacturing Value and Adoption Readiness
8. Validate Manufacturing Technologies through Experimentation and Pilot Implementation
9. Foster Cross-Functional Manufacturing Technology Governance
10. Review, Validate, and Update the Technology Radar Regularly

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