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AI in Manufacturing

From pilots to scale: Maturity, impact, barriers, and trends

Deloitte Survey
June 2026

THE NEXT WAVE OF MANUFACTURING AI WILL BE DEFINED BY SCALE, TRUST, AND EXECUTION

Manufacturing companies are already realizing **measurable benefits from AI investments**. Survey results show that AI is no longer a question of technical feasibility or business value - both are largely established.

The primary challenge has **shifted to execution at scale**. While most organizations have **successfully implemented initial and piloted AI use cases**, many **struggle to scale** them consistently across sites and operations.

AI adoption is strongest in areas such as **quality, production, and intralogistics**, where data is abundant, process signals are clear, and impact can be directly measured. In these domains, AI delivers the highest value, particularly in **complex and parameter-intensive environments**.

At the same time, **operational risks are becoming a critical factor**. A large majority of respondents highlight concerns around disruptions caused by unstable or incorrect AI outputs, particularly with respect to quality, throughput, and safety.

To unlock the full value of AI, organizations need to move beyond experimentation and **focus on robust data foundations, scalable deployment models, and strong governance**.

The ability to scale defines AI leaders in manufacturing
Although ~84% of surveyed manufacturers see measurable value delivered by AI in their operations, only ~20% of use cases are actually scaled across sites today.

AI adoption concentrates where data density and impact are highest
Quality and Production clearly lead AI usage with ~61% of use cases, reflecting sensor-rich environments and direct links to throughput, quality and cost – while support functions trail behind.

The value potential is tangible and consistent
Across industries, participants report average AI-driven improvement potential of around 20% across core operational KPIs, confirming that AI impact is no longer theoretical.

Trust and reliability are becoming the gating factors for the next wave of adoption
As AI moves closer to the shop floor and decision-making, concerns around reliability, security, compliance and user acceptance increasingly shape what gets deployed – and what scales.

The next frontier is process augmentation, not parameter optimization
The greatest AI value will not come from optimizing isolated parameters, but from augmenting end-to-end processes across production, quality, maintenance, energy, and planning. This requires rethinking how processes are designed, controlled, and continuously improved with AI.

AI MATURITY IS ADVANCING IN MANUFACTURING, YET SCALED DEPLOYMENT REMAINS UNEVEN ACROSS SECTORS

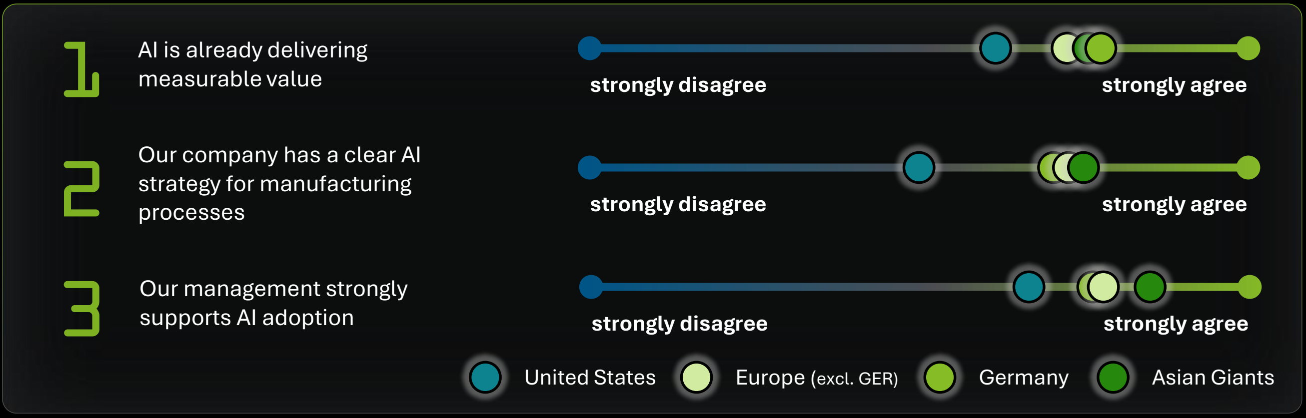

***Figure 3:** Self-reported perspectives of study participants on AI strategy, value, and leadership support*

1. **Strategic commitment is high, but scaling remains limited:** Manufacturers report strong leadership support and clear AI strategies. While first use cases have progressed beyond pilots into production, only a smaller share are scaled consistently across sites and operations.
2. **Deployment maturity varies across industries:** Differences in reported use case volumes reflect not only AI maturity, but also portfolio breadth, industry characteristics, and sample composition. As a result, leading industries differ depending on whether maturity is measured in absolute scale or relative advancement.
3. **AI in manufacturing has clearly moved beyond experimentation:** Across industries, organizations report productive AI deployments. However, broad industrialization remains gradual, with scaling constrained by operational, organizational, and technical factors.
4. **Clear sector patterns emerge in both scale and maturity:** Within this sample Metals, Forging, and Casting lead in absolute volume of scaled AI deployments. Medical Devices and Electronics stand out on relative maturity. Automotive & Industrial Machinery show broad AI activity but remain predominantly pilot-heavy. Chemicals and Petrochemicals appear less advanced overall

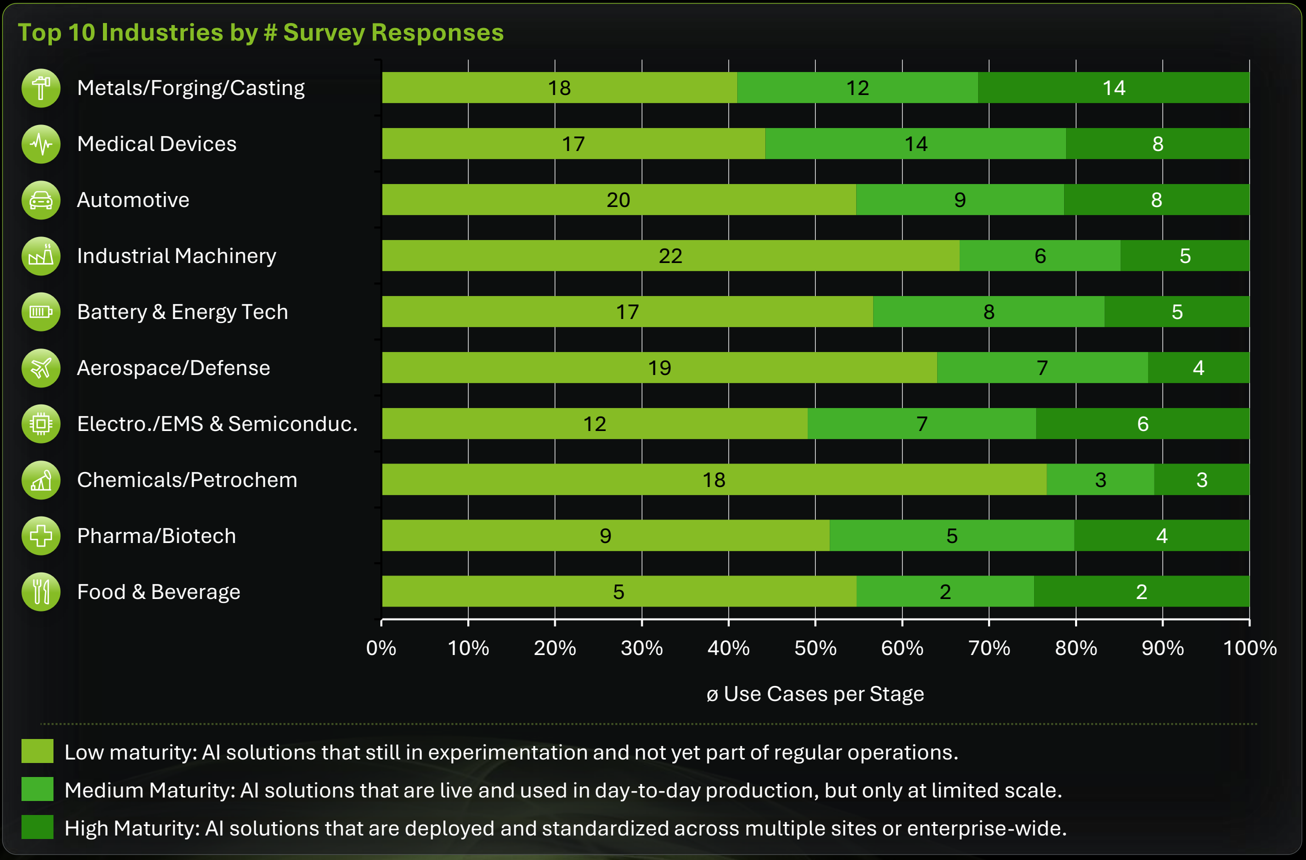

***Figure 4:** Average of reported AI use cases per industry and maturity stage*

SCALING INDUSTRIAL AI NOW DEPENDS ON TRUST, RESILIENCE, AND GOVERNANCE AS MUCH AS ON TECHNICAL CAPABILITY

Main Challenges When Implementing AI

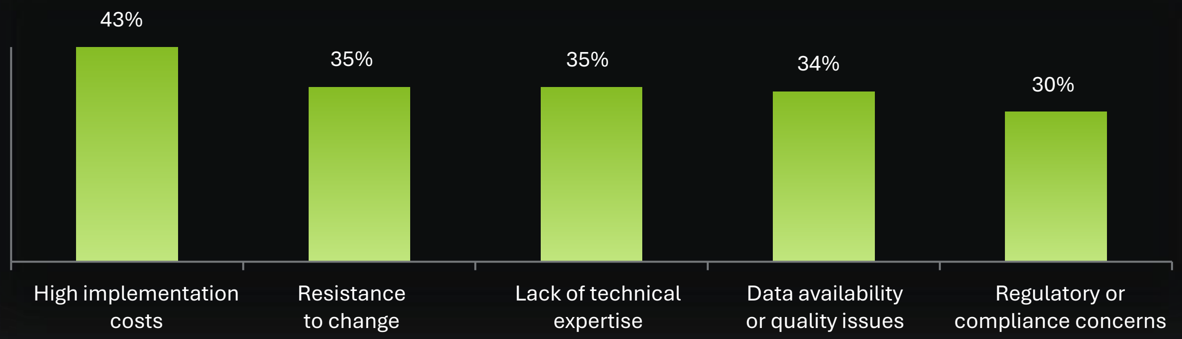

Figure 5: *Main challenges participants are confronted with when implementing AI*

As adoption advances, manufacturers are moving beyond basic feasibility questions and increasingly **confronting the realities of industrial deployment at scale**. High implementation costs, limited technical expertise, and data availability remain important constraints. On the other hand, growing concerns around operational disruption, cybersecurity, and regulatory compliance point to a deeper integration of AI into production-critical environments rather than isolated pilots.

As a result, scaling AI now requires **more than strong use cases from a business perspective**. It depends on **robust data foundations, industrial-grade deployment models, clear governance**, and **systems** that can be trusted **under real operating conditions**. Building confidence among those who run and maintain daily operations is therefore essential. Actively navigating these challenges is not simply about risk mitigation - it is a prerequisite for moving from pilots to **trusted, large-scale industrial AI deployment.**

79% **Operational Disruption Risks**
Unstable or incorrect AI outputs may trigger wrong parameter settings, unplanned downtime, or disruptions in production flow. Companies fear that unreliable AI could directly impact quality, throughput, or safety.

51% **Cybersecurity & Data Protection Risks**
AI in factory systems increases exposure to cyberattacks, data breaches, and unauthorized access. Companies worry that compromised models or systems could lead to operational critical failures.

29% **Change Resistance & User Acceptance Risks**
Employees may hesitate to trust AI-based recommendations or feel a loss of control. Low transparency & confidence in AI decisions can significantly slow down adoption and reduce the impact of AI initiatives.

27% **Compliance & Regulatory Exposure Risks**
AI results must remain explainable and compliant with strict industry regulations. Organizations fear non-compliant decisions, missing auditability, or difficulties justifying AI behavior to regulators.

15% **System & Model Reliability Risks**
Models may drift, behave inconsistently, or fail under new conditions. Companies worry that unreliable predictions could destabilize critical processes and require constant re-calibration.

Figure 6: *Most frequently cited and perceived risks among participants (multiple mentions possible)*

MANUFACTURERS DEPLOY AI WHERE DATA IS RICHEST AND OPERATIONAL IMPACT IS EASIEST TO PROVE

AI adoption is already visible across the manufacturing value chain, but it is most advanced in a few operational hotspots. Quality, Production, and Intralogistics lead the current adoption pattern, reflecting areas where **data is richer, process signals are more structured, and business value can be demonstrated more directly**. These domains also stand out in maturity terms: Quality is the most established entry domain for AI, while Production becomes particularly prominent once use cases scale.

At the same time, AI is also present in functions such as Compliance, Energy & Utilities, Maintenance, and Health & Safety, showing that adoption is extending beyond the traditional production core. The current picture is therefore not one of uniform end-to-end deployment, but of clear centers of gravity along the value chain - anchored above all in the domains **where operational impact is most immediate, measurable, and most likely to support earlier scaling.**

Functional Areas

Figure 7: *AI deployment per functional areas*

Used Technology

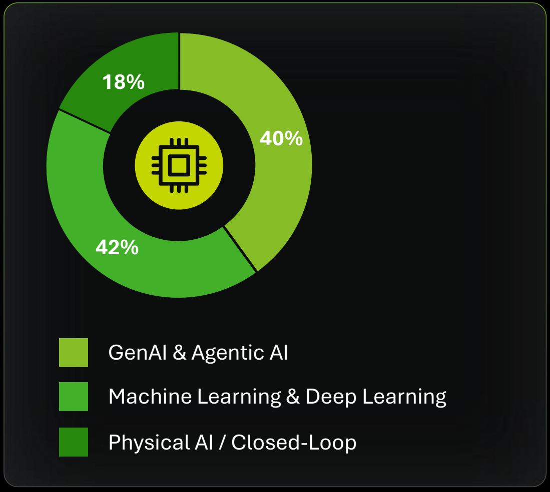

Figure 8: *Used AI Technology*

Technology Description

GenAI & Agentic AI

AI systems that generate content or recommendations and support decision-making, planning, and interaction with complex systems.

Machine Learning & Deep Learning

Data-driven models that learn from historical and real-time data to predict outcomes, detect patterns, and optimize processes.

Physical AI

AI embedded in physical systems such as machines, sensors, vision, and robotics to perceive, decide, and act in real-world manufacturing environments.

Exemplary Use Case of Study Participants

Autonomous Incident Resolution — Quality

AI agents analyze logs, quality events, and system signals to identify root causes and automatically trigger corrective actions with minimal human intervention.

ML Production & Throughput Optimization — Production

Machine-learning models continuously optimize production parameters in real time to stabilize throughput, reduce bottlenecks, and improve overall line performance.

Closed-Loop Defect Detection & Sorting — Quality

AI embedded in cameras, sensors, and machines detects defects in real time and immediately triggers physical actions such as sorting, rejection, or line adjustment.

AI CREATES THE MOST VALUE WHERE MANUFACTURING PROCESSES ARE COMPLEX, VARIABLE, AND HARD TO CONTROL

AI value potential is **broadly consistent across both discrete and process manufacturing**, with most core KPI improvements clustering around a band of roughly **20%**. The differences in impact are about where the value is most visible: discrete manufacturers report slightly stronger effects in asset and productivity metrics, while process manufacturers show a modest tilt toward cost and resource efficiency.

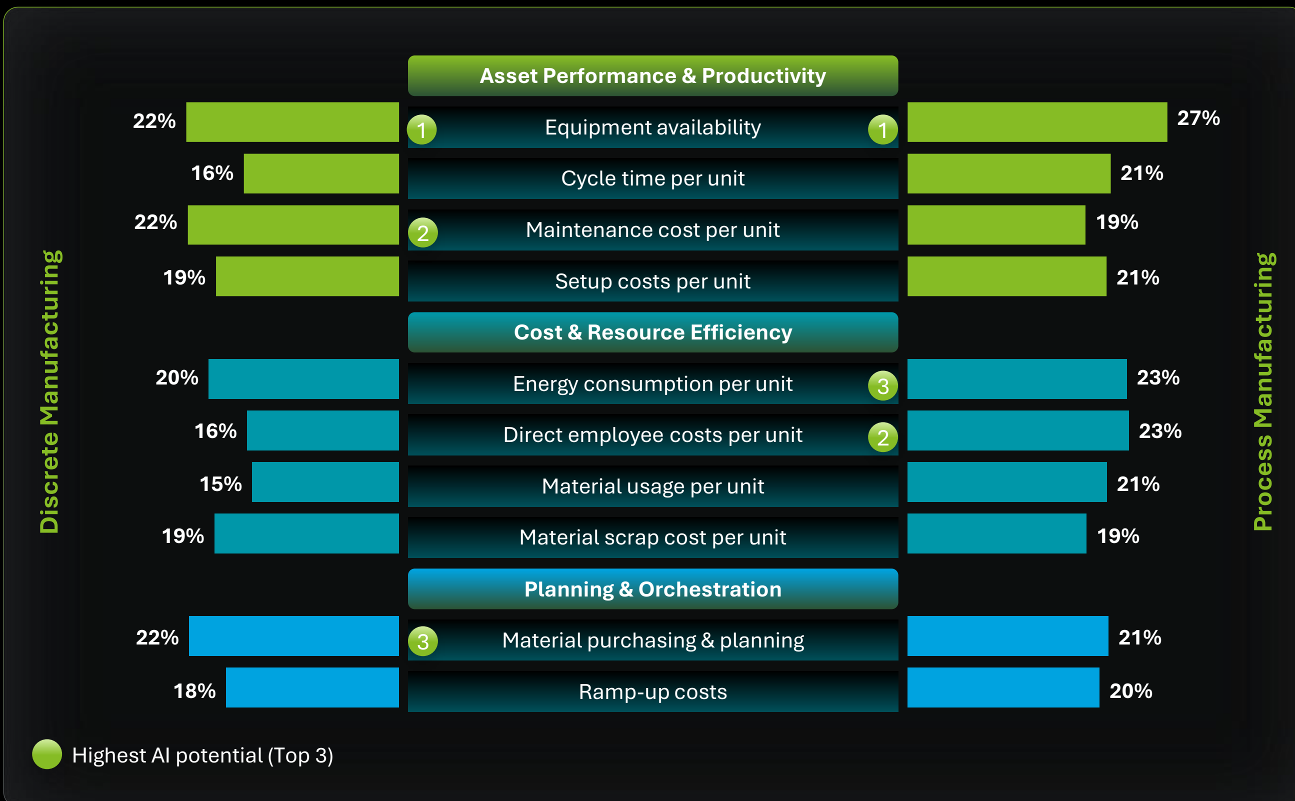

Figure 9: *Average efficiency potential of AI across key manufacturing KPIs, based on KPI impact assessments of selected and described AI use cases across industry areas.*

A process-step view of AI impact shows that value potential is not evenly distributed along the manufacturing value chain. This helps explain why AI adoption tends to cluster in certain operational hotspots: the **strongest impact appears in stages that are more complex, parameter-sensitive, and shaped by greater variability**, whereas more standardized steps generally show lower improvement potential. Looking at AI through the lens of individual process steps therefore provides a practical basis for identifying where it can deliver the greatest operational value in both discrete and process manufacturing.

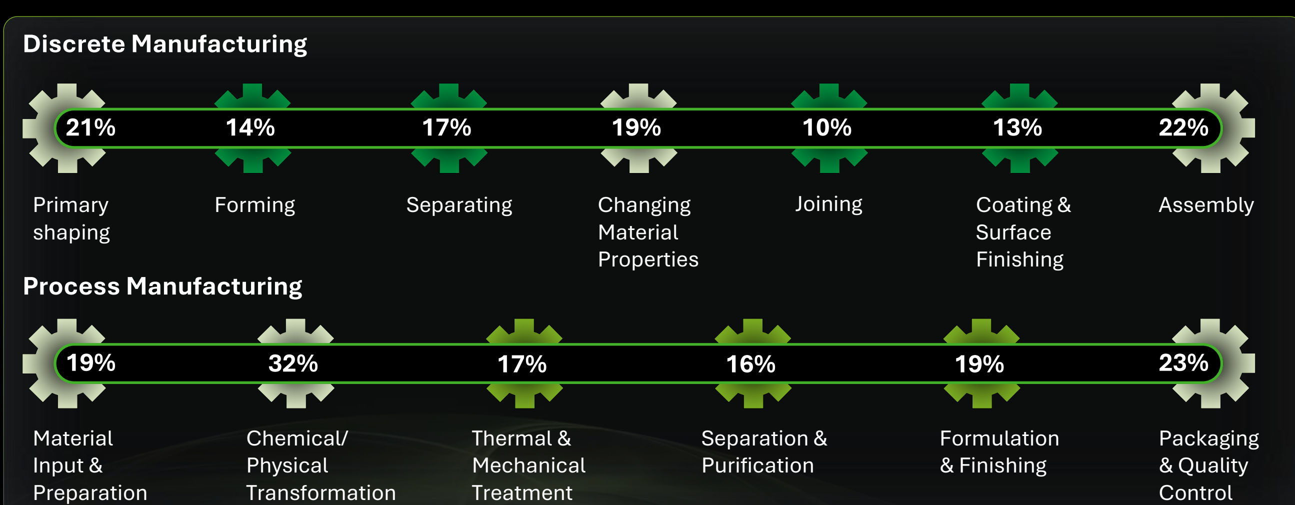

Figure 10: *Average AI-driven efficiency potential across key manufacturing process steps across all industry areas.*

FUTURE AI LEADERS WILL INDUSTRIALIZE END-TO-END PROCESS AUGMENTATION INSTEAD OF OPTIMIZING ISOLATED USE CASES

Trends for AI in Manufacturing

1 From pilots to scalable deployment

The main challenge is no longer proving that AI can create value, but scaling proven use cases consistently across lines, plants, and regions. Future AI leaders will be those manufacturers that can industrialize AI - not those with the largest number of pilots.

Recommendations for Manufacturers

A. Build a **structured AI scaling pipeline** from pilot to production to multi-site rollout

B. Reduce fragmented pilot portfolios and **focus on fewer, higher-value use cases with clear KPI impact**, defined process ownership, and replication potential

C. **Define common rollout assets** such as reference architectures, data templates, validation methods, and operating procedures

2 AI value concentrates in complex, data-rich processes

AI does not create equal value across the entire manufacturing value chain. The strongest impact appears where processes are data-rich, variable, and parameter-intensive - for example in quality, production, and selected logistics or process-control environments.

Recommendations for Manufacturers

A. **Focus AI use cases on operational KPIs** where AI can create measurable impact, such as throughput, quality, equipment availability, and cycle time

B. Use process-step analysis to **identify where AI has the highest improvement potential** instead of applying AI uniformly across all areas

C. Start where **data quality** and **operational ownership** are strongest, then expand toward adjacent processes

3 From parameter optimization to process augmentation

Many AI initiatives still focus on optimizing individual parameters, machines, or inspection steps. While this creates value, the next frontier is broader: using AI to augment entire processes. This means connecting prediction, recommendation, automation, and human decision-making across production, quality, maintenance, energy, and planning. AI will not only improve existing process parameters - but will help redesign how processes work.

Recommendations for Manufacturers

A. Move beyond isolated parameter optimization and **design end-to-end AI-enabled process loops** that detect deviations, identify root causes, recommend actions, trigger adjustments, and learn from outcomes

B. Combine different AI technologies where needed: **Machine learning** for prediction, **GenAI** or **agentic AI** for decision support, and physical AI for interaction with machines and equipment

C. **Redesign selected workflows** around AI-enabled decisions rather than adding AI as a layer on top of existing processes

WHY DELOITTE

Deloitte supports manufacturers end-to-end – from AI strategy and use-case prioritization to scalable implementation across plants, processes, and value chains. With deep expertise in manufacturing operations, data & AI engineering, and risk-aware transformation, we help organizations move from AI ambition to measurable operational impact.

Let's turn AI potential into scaled, trusted, and measurable manufacturing performance.

ABOUT THIS STUDY – OBJECTIVES & METHODOLOGY

Artificial intelligence is becoming a **central driver of productivity and quality** improvement **in manufacturing**. After years of experimentation, many companies are increasingly **moving AI into core operational processes**, enabled by improved data availability, more advanced sensor technologies, and maturing AI platforms. At the same time, **scaling AI remains challenging**: common constraints include data readiness, talent and skill gaps, and fragmented application and system landscapes.

Objectives

This study provides an evidence-based view of how manufacturing organizations **assess their AI adoption in 2026** - and where they see the greatest potential for value creation across operations.

Based on participant responses, the analysis focuses on three objectives:

- ***Assess*** *the current level of AI maturity and adoption across manufacturing sectors*
- ***Identify*** *where AI is already delivering measurable operational impact*
- ***Quantify*** *the main barriers that limit scaling and value realization*

Methodology

This study is based on a quantitative survey of more than **140 manufacturing organizations across industries, regions, and company sizes**.

Respondents provided structured input on AI maturity, adoption across value-chain areas, use-case scaling, KPI definition and achievement, technology usage, and perceived barriers. Qualitative comments were included to enrich interpretations with practical examples.

The survey captured input from **different organizational roles**, with the majority of responses coming from **senior decision-makers**, ensuring findings reflect strategic and operational leadership perspectives.

Study participants across regions

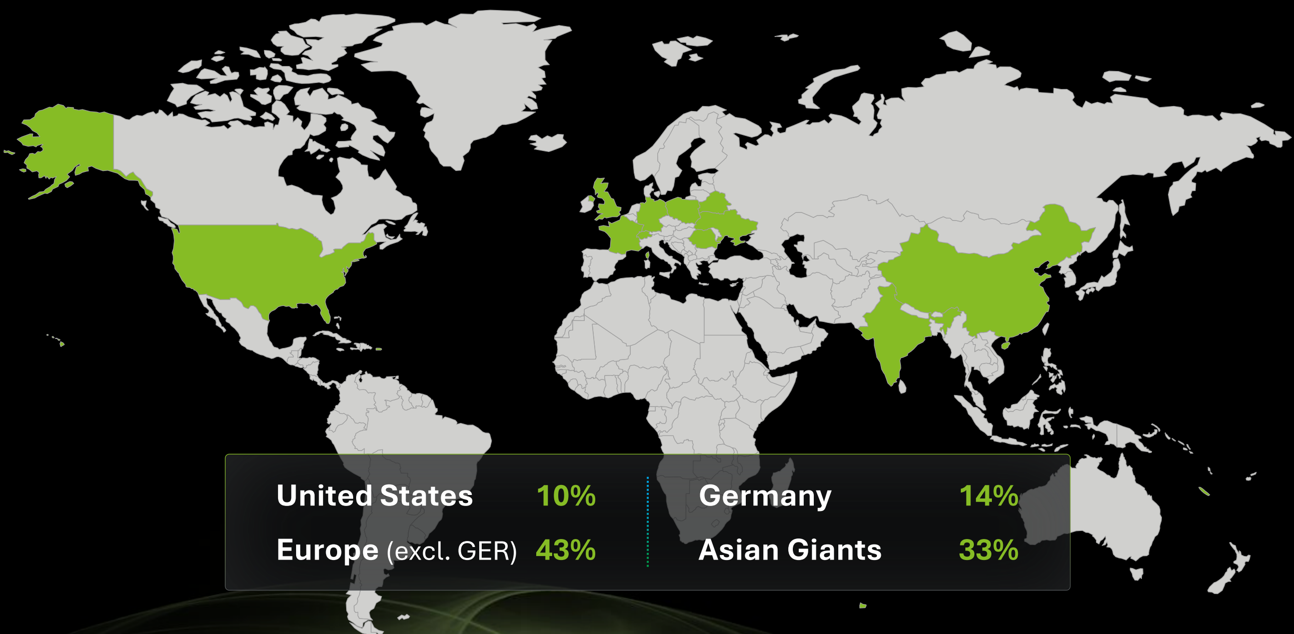

Figure 1: *Distribution of participants across regions*

ABOUT THIS STUDY – COMPANY DISTRIBUTION

This study draws on responses from **manufacturing organizations** across a broad range of **industries** and company **sizes**, providing a robust foundation for interpreting the results. Participants include **small and mid-sized** companies as well as **large** and **very large** enterprises, reflecting different organizational structures and operating environments.

The resulting sample composition ensures that the findings capture perspectives from organizations with **varying levels of scale, complexity, and resource availability**, all of which influence how AI is adopted, scaled, and embedded in manufacturing operations.

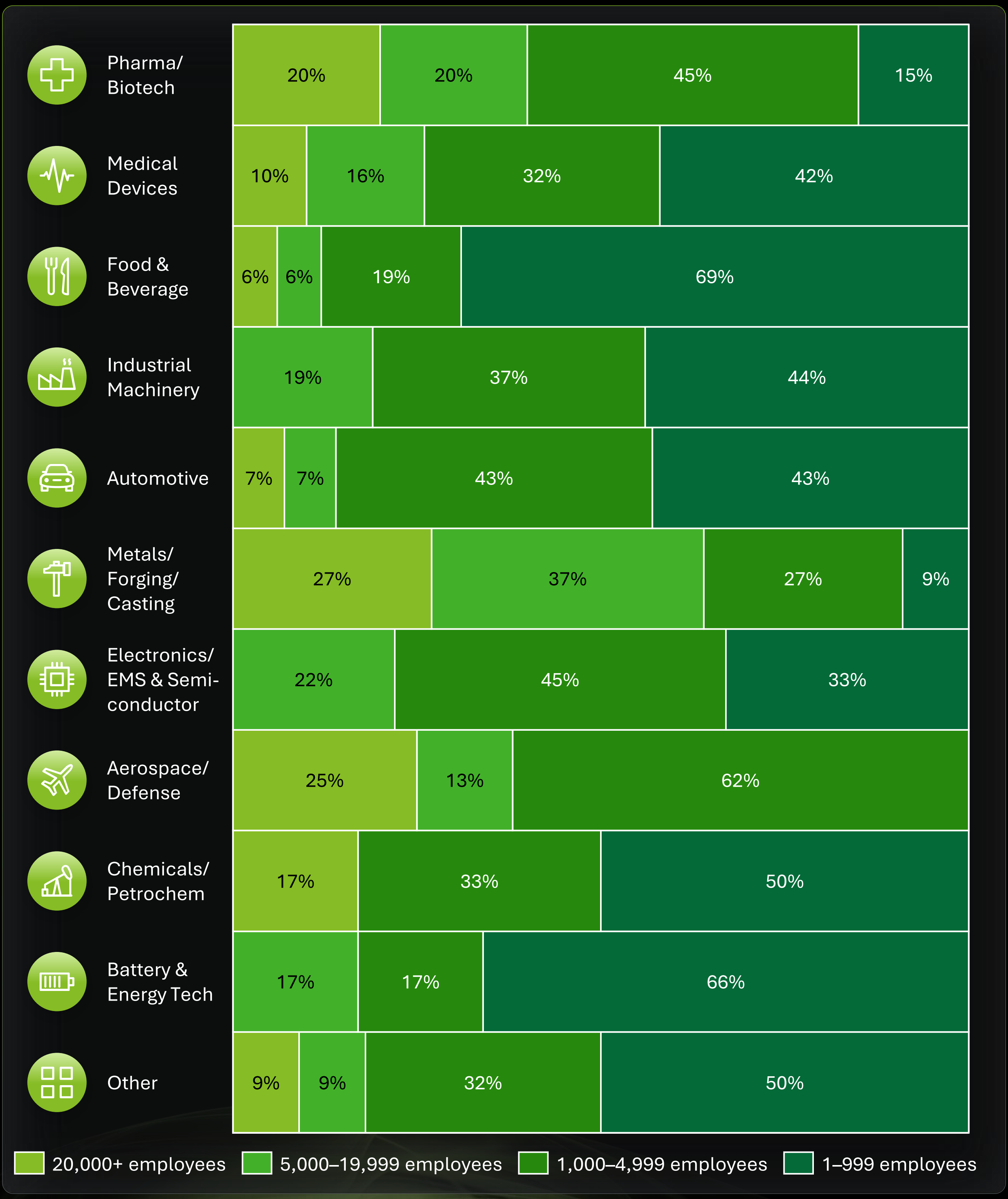

***Figure 2:** Distribution of company sizes per industry*

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