MIT Technology Review Insights

Produced in partnership with Microsoft

Reducing data, talent, and organizational barriers to achieve scale.

Taking AI to the next level in manufacturing

Preface

"Taking AI to the next level in manufacturing" is an MIT Technology Review Insights report sponsored by Microsoft. To produce this report, MIT Technology Review Insights conducted a global survey of senior executives at manufacturing organizations. The report also draws on in-depth interviews conducted with experts on the use of AI in manufacturing. The research took place in December 2023 and January 2024. Denis McCauley was the author of the report, Michelle Brosnahan was the editor, and Nicola Crepaldi was the producer. The research is editorially independent, and the views expressed are those of MIT Technology Review Insights.

We would like to thank the following executives for their time and insights:

Ben Armstrong, Executive Director, Industrial Performance Center and Co-leader, Work of the Future Initiative, MIT

Gunaranjan Chaudhry, Director, Data Science, SymphonyAI Industrial

Pavandeep Kalra, Chief Technology Officer of AI, Microsoft Cloud for Industry

Philippe Rambach, Chief AI Officer, Schneider Electric

Indranil Sircar, Chief Technology Officer of Manufacturing Solutions, Microsoft

About the survey

The survey forming the basis of this report was conducted by MIT Technology Review Insights in December 2023 and January 2024. The survey sample consists of 300 senior executives from operations, technology, production, design, engineering, and R&D. The respondents work in organizations headquartered in North America, EMEA (Europe, Middle East, and Africa), Asia-Pacific, and Latin America. Five manufacturing subsectors are represented in the sample: aerospace, automotive, chemicals, electronics and high technology, and industrial machinery and heavy equipment. All respondents work in organizations earning $100 million or more in annual revenue.

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Executive summary

Few technological advances have generated as much excitement as AI. In particular, generative AI seems to have taken business discourse to a fever pitch. Many manufacturing leaders express optimism: Research conducted by MIT Technology Review Insights found ambitions for AI development to be stronger in manufacturing than in most other sectors.

Manufacturers rightly view AI as integral to the creation of the hyper-automated intelligent factory. They see AI's utility in enhancing product and process innovation, reducing cycle time, wringing ever more efficiency from operations and assets, improving maintenance, and strengthening security, while reducing carbon emissions. Some manufacturers that have invested to develop AI capabilities are still striving to achieve their objectives.

This study from MIT Technology Review Insights seeks to understand how manufacturers are generating benefits from AI use cases – particularly in engineering and design and in factory operations. The survey included 300 manufacturers that have begun working with AI. Most of these (64%) are currently researching or experimenting with AI. Some 35% have begun to put AI use cases into production. Many executives that responded to the survey indicate they intend to boost AI spending significantly during the next two years. Those who haven't started AI in production are moving gradually. To facilitate use-case development and scaling, these manufacturers must address challenges with talents, skills, and data.

Following are the study's key findings:

- **Talent, skills, and data are the main constraints on AI scaling.** In both engineering and design and factory operations, manufacturers cite a deficit of talent and skills as their toughest challenge in scaling AI use cases. The closer use cases get to production, the harder this deficit bites. Many respondents say inadequate data quality and governance also hamper use-case development. Insufficient access to cloud-based compute power is another oft-cited constraint in engineering and design.

- **The biggest players do the most spending, and have the highest expectations.** In engineering and design, 58% of executives expect their organizations to increase AI spending by more than 10% during the next two years. And 43% say the same when it comes to factory operations. The largest manufacturers are far more likely to make big increases in investment than those in smaller – but still large – size categories.

- **Desired AI gains are specific to manufacturing functions.** The most common use cases deployed by manufacturers involve product design, conversational AI, and content creation. Knowledge management and quality control are those most frequently cited at pilot stage. In engineering and design, manufacturers chiefly seek AI gains in speed, efficiency, reduced failures, and security. In the factory, desired above all is better innovation, along with improved safety and a reduced carbon footprint.

- **Scaling can stall without the right data foundations.** Respondents are clear that AI use-case development is hampered by inadequate data quality (57%), weak data integration (54%), and weak governance (47%). Only about one in five manufacturers surveyed have production assets with data ready for use in existing AI models. That figure dwindles as manufacturers put use cases into production. The bigger the manufacturer, the greater the problem of unsuitable data is.

- **Fragmentation must be addressed for AI to scale.** Most manufacturers find some modernization of data architecture, infrastructure, and processes is needed to support AI, along with other technology and business priorities. A modernization strategy that improves interoperability of data systems between engineering and design and the factory, and between operational technology (OT) and information technology (IT), is a sound priority.

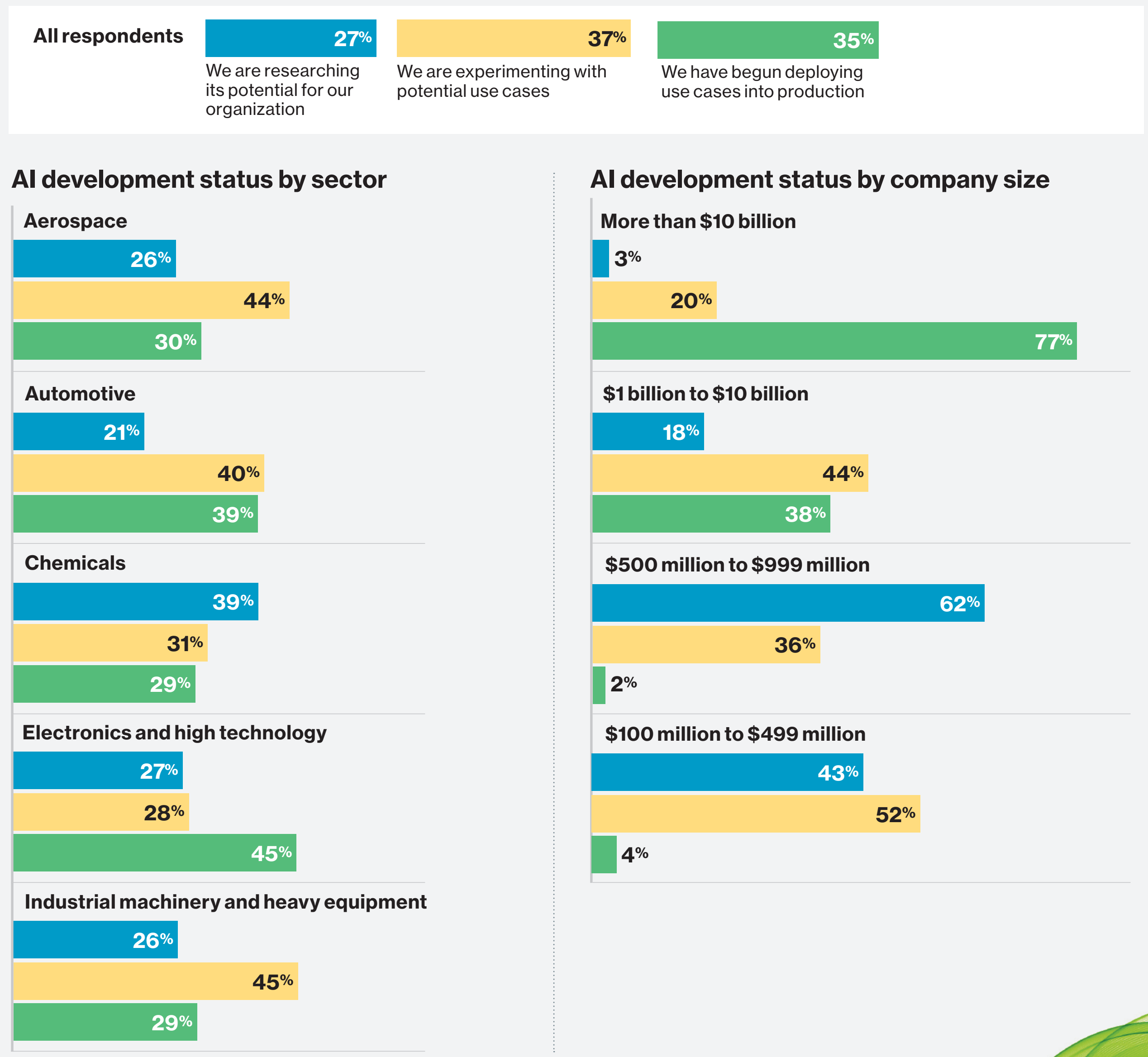
02 Introduction: Stepping on the AI accelerator

The advent of AI for the manufacturing sector is generating enthusiasm and ambitious plans across all sectors.[1] "Everyone in manufacturing is excited about AI," says Philippe Rambach, chief AI officer of Schneider Electric. "But relatively few are using AI at scale to transform the way they work."

This research, which surveyed executives at large manufacturers pursuing AI in some way – researching, experimenting with, or deploying it in engineering and design or on the factory floor – shows most companies (64%) are in the research or experimentation stage with AI. Considerably fewer (35%) have begun putting use cases into production and are deploying the technology. The survey's electronics/high-technology and automotive producers are more likely than others to have begun deploying.

Figure 1: Status of AI development

Respondents in different sectors indicated whether they are researching, experimenting with, or deploying AI in their organizations.



Source: MIT Technology Review Insights survey, 2024

> "The barriers to AI use-case development are falling."
>
> Pavandeep Kalra, Chief Technology Officer of AI, Microsoft Cloud for Industry

Within the much wider universe of large, medium-size, and small manufacturers, AI has so far had a lighter impact, according to Ben Armstrong, executive director of MIT's Industrial Performance Center. "While we see limited-impact uses of AI among some producers, there is little evidence of AI-led transformation," he says. "We've seen few manufacturers extend the use of AI techniques beyond the front office to production operations."

Among the select group of AI adopters, the pace of AI development is gradual. Evidence shows early adopters can struggle to meet AI objectives.[2] This is the case among those currently in the research or experimentation phase. About 5% of these manufacturers expect to start putting AI use cases into production in the next six months, and another 20% say it will be six to 12 months from now. Most are planning for the future, with 75% of executives in the survey saying the first deployments of AI will happen in one to two years or more.

This aligns with executives surveyed that plan to boos investment in developing AI capabilities. Many plan significant increases in AI spending in the next two years. This is particularly the case when it comes to engineering and design, where 58% of respondents expect spending growth of more than 10% during this period. Although fewer will boost spending to this degree in factory operations, the share (43%) is still considerable.

Pavandeep Kalra, chief technology officer of AI, Microsoft Cloud for Industry, sees an acceleration in use-case development on the near horizon. "Uses in areas like predictive maintenance or defect detection have typically required a lot of tuning and customization for different scenarios. That's made it extremely difficult to productionize such cases," he says. This is starting to change, he says, and could rapidly improve. "The foundation models that come with generative AI are reducing the need for customization. The barriers to AI use-case development are falling," he says.

Nearly two-thirds (65%) of surveyed manufacturers – and three-quarters of those in chemicals and electronics and high technology – are currently experimenting with generative AI.

> "Design engineering is becoming a lot more data-centric, and AI is enabling it through simulation."
>
> Indranil Sircar, Chief Technology Officer of Manufacturing Solutions, Microsoft

Figure 2: AI investment intentions

Respondents indicated how much they expect their companies' investment in AI to change during the next two years.

	Engineering/ design/R&D	Factory/ production
It will decrease	0%	2%
It will remain unchanged	10%	25%
It will increase 1% to 10%	32%	30%
It will increase 11% to 25%	29%	18%
It will increase 26% to 50%	19%	13%
It will increase 51% to 75%	7%	8%
It will increase 76% to 100%	2%	3%
It will increase more than 100%	1%	1%

Source: MIT Technology Review Insights survey, 2024

Use cases so far

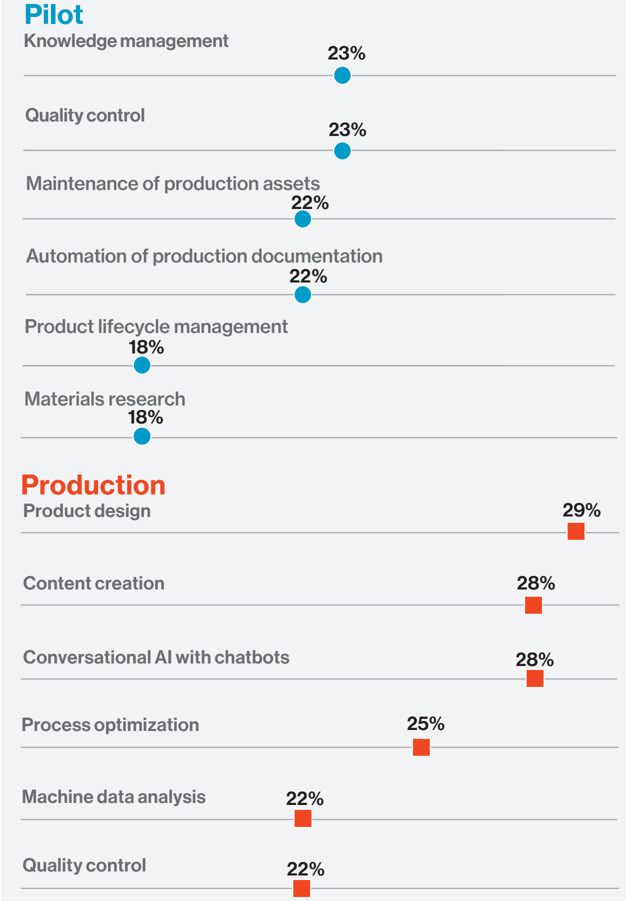
Among the survey sample, the AI use cases most likely to have progressed through to production involve product design, conversational AI (chatbots), and content creation. "Design is increasingly happening in simulated environments, which can greatly reduce cycle time," says Indranil Sircar, Microsoft's chief technology officer for manufacturing solutions.. "Design engineering is becoming a lot more data-centric, and AI is enabling it through simulation," he says. The other two frequently deployed use cases, conversational AI and content creation, have applications not just in design but also in production (for example, assisting with maintenance), supply chain (inventory management), and customer interaction. The most frequently cited projects at pilot stage are in quality control, knowledge management, equipment maintenance, and the automation of production documentation (see Figure 3).

When it comes to the factory floor, asset reliability is a common AI use case, according to Gunaranjan Chaudhry, director of data science at SymphonyAI Industrial. "Producers want to know if their assets are at risk of experiencing some sort of anomaly or failure, and when that's likely to happen, so they can plan around it," he says. Many discrete manufacturers (makers of physical, often assembled products), Chaudhry says, are using AI to enhance inspection, something that's been aided by improvement in computer vision models during the last decade.

Manufacturers have also spent time and resources developing AI-enabled process optimization – using AI techniques to improve productivity and efficiency. "These use cases, however, have proven harder to scale from one scenario to another, and the benefits are less tangible than in other use cases," says Chaudhry. The electronics and high-technology producers in the survey are the most likely to have deployed AI for process optimization, with chemical producers being the least likely.

Figure 3: Top AI use cases in pilot and production

Respondents rated top use cases currently in pilot and production stage.



Source: MIT Technology Review Insights survey, 2024

Figure 4: Expectations of AI spending growth

Respondents who expect AI spending to grow by more than 10% in the next two years, by company size.

	Engineering/ design/R&D	Factory/ production
All respondents	58%	43%
More than $10 billion	77%	77%
$1 billion to $10 billion	67%	44%
$500 million to $999 million	45%	21%
$100 million to $499 million	26%	10%

Source: MIT Technology Review Insights survey, 2024

When it comes to AI, company size and resources matter

It's no surprise larger companies are more likely than smaller ones to be investing in AI and developing use cases. What's striking is how big the gap is.

The divide is deep in use-case development: Whereas 77% of firms with more than $10 billion in annual revenue are deploying AI use cases, just 4% of those earning between $100 million and $499 million have done so (see Figure 1). The biggest businesses are also much more willing to spend: 77% of firms with more than $10 billion in annual revenue plan to boost AI investment in both engineering and design and the factory by more than 10% during the next two years. Among firms earning between $100 million and $499 million, 26% expect spend on AI in engineering and design to grow by 10%, and just 10% say the same about the factory. "Larger firms can obviously bring their financial resources to bear," says Sircar. "But the bigger ones are also better able to drive the other changes needed to support transformation."

Smaller companies say talent and skills shortages are the toughest impediment to scaling AI, and data quality issues are also a barrier. The smaller the manufacturer, the more respondents say the cost of maintaining and improving AI models are a hindrance to scaling.

03 The pressure to profit from AI

Given the sizable increases in AI spending planned by manufacturers, the pressure will be on executives to demonstrate return on investment. "Industrial manufacturers tend to be risk-intolerant when it comes to investment," says Armstrong. "They only like to spend on new technologies when there is a strong likelihood it will translate into profit."

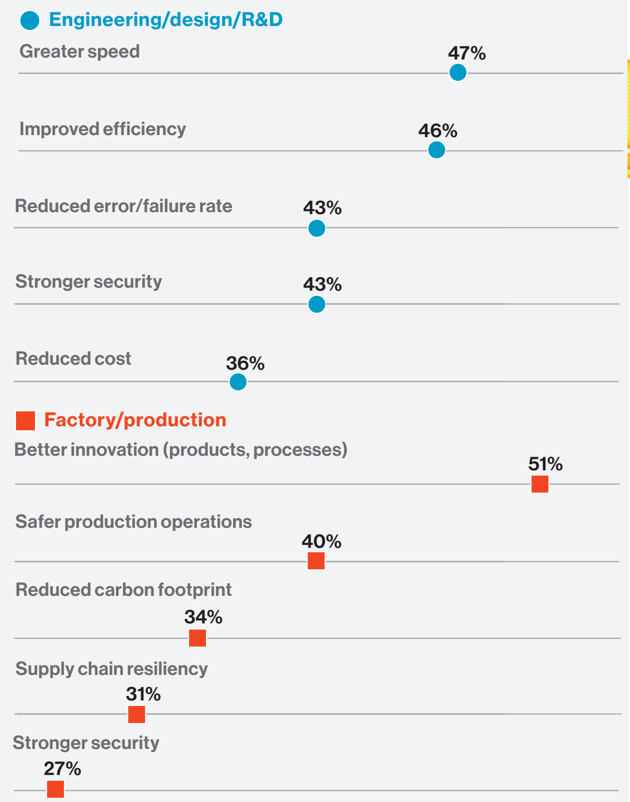
What gains do manufacturers seek from their AI investments? In engineering and design, returns are expected chiefly from greater speed (reduced design cycle time), improved process efficiency, reduction of errors and failures (through pinpointing machine defects or predicting failures, for example), and stronger security (identifying cyber risks to engineering IP or systems). In factory operations, the most valuable gains are expected from improved innovation (for example, in production and assembly processes), from safer operations (especially for aerospace and chemicals firms), and from a reduced carbon footprint (see Figure 5).

According to Chaudhry, manufacturers find it easier to quantify returns in engineering and design than in the factory. "A very tangible benefit in engineering and design is reduced cycle time for design iterations," he says. "AI speeds up the process by homing in on the specific parameters that you need to focus on. We've had design cycles being cut from 12 months to less than six months. That's an easily quantifiable benefit."

The gains are less quantifiable in factory operations. "Improvements in asset reliability are hard to prove when equipment breakdowns are infrequent, so it can be quite a while before the benefits become apparent," says Chaudhry.

Figure 5: Top benefits anticipated from AI implementation

What are the most valuable benefits your organization expects to see during the next two years from implementing AI in manufacturing?



Source: MIT Technology Review Insights survey, 2024

Understanding growth constraints

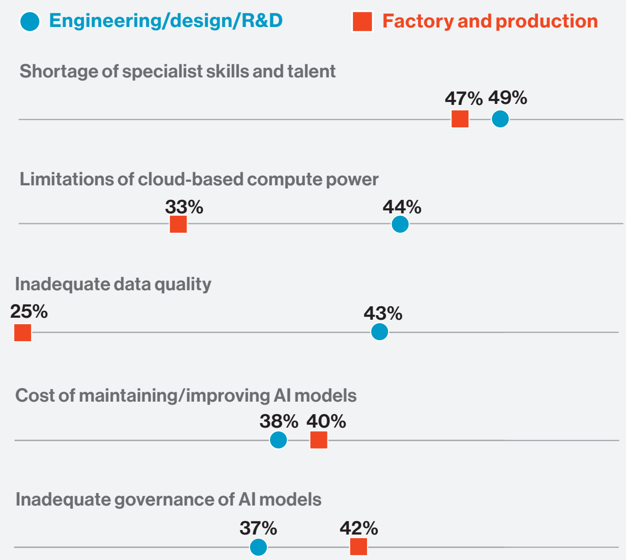
Realizing benefits requires scaling AI beyond a small number of sites or areas of operation. Even committed AI adopters in the survey have so far struggled here, as indicated by relatively low deployment rates.

The chief constraints are shortages of specialist skills, cited by 49% of executives in engineering and design and 47% in factory operations. In both areas, companies that are deploying use cases feel this crunch more keenly than others (see Figure 6).

Chaudhry agrees talent scarcity is often a barrier to scaling AI, but says its severity depends on the use case. "For example, with optimization cases, manufacturers often need a lot of in-house talent in order to update models and create new ones," he says. "Predictive maintenance cases, by contrast, don't require much human involvement once they're developed. When manufacturers are able to access capabilities such as automated model retraining, they'll have less need to involve their data science team to get their model pipeline running smoothly."

Figure 6: The toughest challenges in scaling AI

What are the biggest challenges your organization currently faces in scaling AI use cases?



Source: MIT Technology Review Insights survey, 2024

The AI skills challenge on the factory floor

Many economists and technology futurists, voicing concerns about AI's impact on jobs, emphasize the importance of re-skilling factory-floor workers as AI changes roles. The focus of this argument is often on training employees who lack advanced technology skills to use AI models. MIT's Ben Armstrong believes these calls are off target.

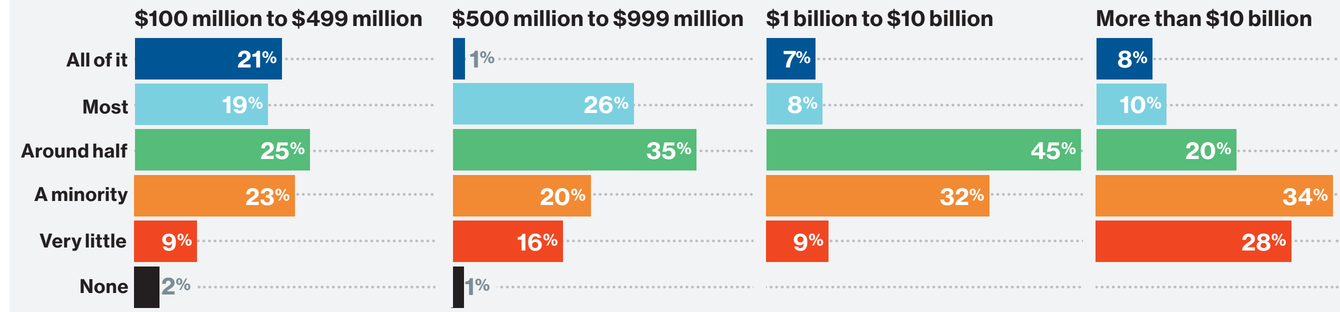
In the future, says Armstrong, AI factory workers will need more domain-specific skills. "The type of flexible LLM-based tools that are emerging now do not require a lot of skills to use," he says. "You offer a query, and it gives you a response. What will really be needed is the skill to tell whether the response is valid for the job at hand. For that, a lot of domain expertise is needed."

A worker using a given machine will need to know exactly what an error code means and whether it's relevant, Armstrong explains. "If the model issues an instruction, the worker will need to understand intuitively if it's a reasonable step to take."

These are high-stakes scenarios for people who work in manufacturing, says Armstrong. "And those scenarios require skills and knowledge that the worker will have but not the LLM in all situations." In this context, says Armstrong, the challenge is not so much in reskilling workers but in ensuring their core skills and domain expertise are maintained as AI becomes a bigger presence on the factory floor.

Figure 7: Higher-revenue companies are less likely to find data suitable for AI

Of the data your organization's production equipment and related assets generate, about how much is suitable for existing AI models?



Source: MIT Technology Review Insights survey, 2024

Kalra believes generative AI will help ease the talent and skills shortages manufacturers are experiencing. "We're seeing a breakthrough with the natural language interfaces of LLMs," says Kalra. "Some understanding of models is needed, but the skills required to use these are not at the level of data scientists or data engineers."

According to Armstrong, one of the most exciting implications of AI is its potential to help individuals learn what's working and what's not so they can do rapid experimentation. "I see this particularly benefitting the problem solvers and creative people on the shop floor who are trying to re-engineer processes to make production more efficient, higher quality, and faster."

In engineering and design, 44% of respondents say limitations on cloud-based computing power are a barrier to scale. Such constraints may come to bear, for example, in running LLMs that support factory simulation. Design teams increasingly use digital twins to aid simulation, and these can consume enormous amounts of compute power. Cloud-based providers can usually marshal the needed power, but not all manufacturers may be able to access them. And 38% (40% in terms of factory operations) say the costs involved in maintaining and improving AI models can limit their ability to scale.

Technical debt is another hindrance to manufacturers' use of AI, according to 45% of survey respondents. Technical debt can be caused by a technology stack that is siloed or unmaintained, or which has accumulated numerous patches and workarounds. (According to McKinsey, technical debt accounts for up to 40% of organizations' entire technology estate.[3]) Made to facilitate speed of delivery or to fix problems, technical debt hinders efficiency and integration in the long run. In AI models, technical debt can manifest itself in a number of ways. An example is undocumented algorithms, which not only make it difficult for teams to trace coding errors but also reduce the transparency of decisions made by models.

How good is my data?

Some of the toughest challenges manufacturers face in scaling AI involve data. In engineering and design, 43% of respondents highlight problems with data quality. In factory operations, 42% point to weaknesses in data governance.

The manufacturing industry generates enormous quantities of data, and research has shown manufacturers see growth in data volumes from their operations outstripping other industries.[4]

> "Some understanding of [large language] models is needed, but the skills required to use these are not at the level of data scientists or data engineers."
>
> Pavandeep Kalra, Chief Technology Officer of AI, Microsoft Cloud for Industry

But far from all of this data, particularly data generated by factory-floor equipment, is in a state useful to AI models. Fewer than one-quarter (23%) of survey respondents say all or most of the data their production assets generate is suitable for existing AI models. The bigger the manufacturer, the greater the problem of unsuitable data is (see Figure 7).

Chaudhry agrees poor production data hinders manufacturer efforts to scale AI. "This is particularly the case at older facilities and those where numerous machine sensors are broken," he says. Chaudhry adds that some manufacturers gather abundant data from their hardware but then lose it because of inefficient storage processes.

Manufacturers further along in deploying AI use cases in production feel this problem especially keenly. Just 17% say all or most production data is suitable for AI; as many as 57% say less than half of this data is suitable.

A related challenge is the limited interoperability between manufacturers' OT and IT systems. OT, such as programmable logic controllers (PLCs) and supervisory control and data acquisition (SCADA) systems hold large volumes of machine data that AI models would benefit from.

In efforts to improve the volume of AI-ready data their production assets generate, many manufacturers (57%) are looking to increase machine connectivity. Around two-thirds (65%) of respondents say their firms are also using AI in conjunction with IoT sensors. The latter are likely to include sensors embedded in production equipment, along with IoT sensors for supply-chain operations.

With many manufacturers ramping up spending on AI during the next two years, this and other data issues, if not rectified, will likely limit the returns on those investments. Manufacturers need to have the right data foundations in place to adequately support their AI ambitions.

04 Creating the data foundations

When it comes to developing AI capabilities, manufacturing executives surveyed leave no doubts about where their chief data challenges lie. More than half (57%) of all respondents name data quality as a top challenge; however, this number is higher in the chemical industry at 75%. Almost as many (54%) cite the need to improve data integration. A third major imperative (cited by 47%) is improving data governance (see Figure 8). These are closely interrelated challenges. The ability to meet any one of these hinges on success in addressing all of them.

Poor data quality results from a variety of factors. Errors in data entry, missing data points, inoperative sensors in plant equipment, and siloed data trapped in legacy systems are just some of the more common ones. Siloes, in turn, are a manifestation of inadequate data integration and are a significant impediment to scaling AI use cases. In the survey, automotive and industrial equipment producers appear to struggle more than others with integration issues.

"Especially if they were built decades ago, different parts of plants have different data systems associated with them," says Chaudhry. "The data is in vastly different

Figure 8: The toughest data challenges relating to AI
Which of these present your organization's biggest data challenges when it comes to AI?

	All	Aerospace	Automotive	Chemicals	Electronics and high technology	Industrial machinery and heavy equipment
Data quality	57%	60%	48%	75%	50%	57%
Data integration	54%	56%	58%	45%	53%	59%
Data governance/ compliance	47%	50%	54%	24%	51%	50%
Data growth	41%	34%	46%	45%	41%	38%
Data management	40%	40%	34%	47%	42%	36%
Securing data	38%	40%	43%	33%	36%	38%

Source: MIT Technology Review Insights survey, 2024

places and difficult to bring together to build good AI models." The situation is better in newer facilities, he says, "but even they were designed before people realized that having all this data in one place allows them to do a lot of things with it."

Modernization of data architecture is often needed to achieve major improvements in integration. Manufacturers, like organizations in all industries, struggle to integrate data from a multiplicity of disparate data and AI systems. Among other benefits, modern architectures promise to unify data repositories across the enterprise, including those in OT and IT systems. This is a tall order in the often-fragmented manufacturing environment, but some reduction in the variety of disparate data systems is realistic and will help to streamline data processing and management.

Modernization and simplification are vital if manufacturers are to scale AI use cases across design, engineering, production, the supply chain, and other enterprise functions. When assuming the role of chief AI officer at Schneider Electric, Philippe Rambach benefitted from the fact that the company had embarked on a major data modernization five years earlier. "We already had a data lake, and many aspects of our data operations were headed in the right direction," says Rambach. One result was that fragmentation of data systems had become less of a hindrance to AI development, he says.

Getting to good governance

The other part of the data modernization challenge is upgrading governance models. According to Kalra, many manufacturers are only now beginning to understand the importance of good data governance to their ability to scale AI. "They've realized that, in order to enable scale, they need to arrange their data in a way that it can be used in many different use cases," he says. The severity of this challenge becomes more apparent the closer that companies come to deploying use cases. In the survey, 61% of the manufacturers that have begun deploying say governance is a major data challenge, compared with 40% of those still experimenting with use cases and 37% of those in the research stage.

Manufacturers must adopt a wider view of what is useable data for AI, says Chaudhry. "People have only started realizing over the last couple of years that data is more than sensors," he says. For example, inspection logs, work orders, and maintenance reports are also data, but those have typically been retained only for compliance and audit purposes. "If you really want to build some sort of advanced reliability model, the maintenance history of an asset becomes really important," says Chaudhry.

As vital as modernization of the data estate is, manufacturers need not wait for perfect quality data or 100% sufficiency to move ahead with AI models. "There has to be enough good-quality data to get started," says Kalra. "The question is, how to get to that 70% or 80% fairly rapidly?" Kalra points out that modern architectural approaches such as retrieval augmented generation (RAG) can help to speed the population of AI models with data. RAG is a technique for enhancing the accuracy and reliability of LLMs with domain-specific data retrieved from external as well as internal sources.

Fine-tuning basic processes, such as data cleaning, can be just as effective as new tools in improving the accuracy and relevance of AI models. Use-case prioritization has helped Schneider Electric in this area, says Rambach. "Our approach is to accelerate some data cleaning work when we've identified a big AI business case," he says. "Other data cleaning work

05 Addressing organizational challenges

For 43% of the surveyed manufacturers, difficulties in changing organizational structures and processes are a major inhibitor to effective use of AI (see Figure 9). In the survey, the executives of the largest manufacturers, with over $10 billion in annual revenue, emphasize this point particularly strongly. (It's cited by 53% of surveyed executives of the largest manufacturers, compared with 32% in the smallest manufacturers, those earning between $100 million and $499 million.)

A key organizational weakness at many manufacturers is fragmentation – not just of data and siloed systems, but of use-case development overall, as well as of the functional expertise that develops cases and takes them into production. At many businesses, manufacturers included, use-case proofs of concept (PoC) and pilots are often driven by small engineering teams. These tend to focus on data science; for example, putting algorithms in place. "But that's just a small part of the challenge," says Chaudhry. "Getting the use case into production requires a platform, data ingestors, data storage, and a user interface, among other elements. At pilot and production stage, the IT team has a lot of work to do to put these technology elements in place," he says.

Figure 9: Top 5 organizational challenges for AI

Respondents chose their top three organizational challenges from 10 categories.

Talent shortages or upskilling complexity	48%
Technology debt/ problematic integration	45%
Difficulty selecting a solution	44%
Organizational and process changes	43%
Finding vendors or partners	41%

Source: MIT Technology Review Insights survey, 2024

To move use cases along the development path, it's important to create teams that bring together AI specialists, business owners, and IT people. Rambach says many companies in the industry separate these responsibilities. "Use-case development tends to be too focused on the innovation, the algorithms, and the modelling, and not focused enough on the practicalities of integration," he says. "That leads to failures, especially when AI or other specialists are outside the company."

Another organizational disconnect that can limit AI scalability is between engineering and design and the factory. To some extent, this relates to the limited interoperability of OT and IT systems. Engineers and designers at most large manufacturers tend to work mainly with IT, while OT predominates in the plant environment. “It’s not an easy divide to bridge,” says Chaudhry.

The ability to bridge that gap, Chaudhry says, will particularly benefit factory-floor teams. “Process facilities, for example, run at fairly steady condition most of the time, because of which there’s relatively little variation in historical data that AI models can learn from,” he says. “If production managers come across problems that haven’t happened before, AI won’t solve them unless there are engineering and physics models to fall back on.”

Hybrid models that combine AI with engineering and physics are a potential way to bring engineering and operations together, says Chaudhry, but they have yet to receive much attention in manufacturing.

Unified data is critical if AI is to help bring these two functional areas of manufacturing together, says Kalra. “Data must be able to span multiple domains in an interconnected way. It’s not very useful to say, ‘I have the data about production, I have the data about design,’ but you can’t actually interconnect those data sources.” These data nodes need to be connected across various data modalities, says Kalra. “It’s not only having the data accessible but also being able to thread the data through various modalities. If you have that, and if you have generative AI on top of it, it’s a very powerful combination.”

Schneider Electric | Taking a business-first approach to AI

Philippe Rambach was surprised to get a call two years ago from Schneider Electric’s CEO asking him to assume the role of chief AI officer. Rambach was a business manager with little expertise in AI. The CEO said that’s exactly why he wanted him for the job. “He wanted to avoid a risk of slow progress in scaling AI and getting small business benefits from it. In order to get us back on the fast track to scale AI, he needed somebody who understands the business and how it operates, not someone fascinated by the technology for technology’s sake,” Rambach says.

Putting a person with business experience in charge of AI development was the first step to executing the AI scale strategy at Schneider Electric. The next was building a team of specialists to drive the development. The company launched a massive recruitment drive, and Rambach says his team now employs around 300 AI and data specialists.

Those experts form the central core of a hub-and-spoke model that develops AI use cases in tandem with individual business units. The latter, the “spokes,” are the owners of AI use cases at Schneider Electric, he says. “All use-case development starts with the business case,” says Rambach. “From day one, our use-case development teams bring together the business owners, the AI specialists, and the IT people to integrate our solutions with our existing software and train the users. A team must be able to deliver a solution itself without much outside support.” Rambach is adamant that IT be involved from the start. “If IT integration is left to the end, it will often never get done,” he says.

Each development team must also be clear-headed about the project’s viability. “It must bring a project to an end if the potential points of failure are too numerous,” Rambach says.

For Schneider Electric, this approach makes it easier to progress AI use cases from PoC to minimum viable product (MVP) and ultimately to production, says Rambach. The company now releases five to six uses cases into production at scale each quarter, he says.

06 Conclusion: Setting the stage

While this research focuses on the experiences and plans of manufacturers committed to developing AI capabilities, there are many more manufacturers that have yet to begin. Some have likely determined that meeting their strategic objectives does not require mastering AI. Others believe they can benefit from its use but are unsure how to get started.

This MIT Technology Review Insights study suggests a few lessons these manufacturers should take to heart as they start exploring AI’s potential. These apply to organizations in any industry, and some may seem self-evident. But the experts we interviewed assure us that even mature AI adopters sometimes lose sight of these as they develop more and more use cases.

Start from the business need: At the outset, determine the business problem or challenge that technology could help address. Only then should technology solutions, including AI, be explored. “Asking ‘what can we do with AI?’ can generate lots of great ideas,” says Rambach, “but most will have limited impact if they don’t start with the actual business need.”

Embrace structural flexibility: Use-case development should not be the monopoly of AI experts. As expertise builds internally, it needs to be allied to, or integrated with, data science and engineering teams. Teaming these experts with business product owners and IT increases the likelihood of getting the desired results from AI use-case development and deployment.

Get the data in order: AI requires a level of data maturity. Determine how well the organization collects, stores, and processes data, and take concrete steps to redress weaknesses before taking AI use cases into production. Steps are likely to include the unification of data repositories to the extent possible. AI models require good-quality data, but the data need not be perfect to move use cases into production.

Use AI to develop skills: Manufacturers understandably worry about shortages of skills and talent to work with AI, but they should realize that AI can help develop such skills in their workforce. Generative AI, for example, makes it relatively easy for engineers and other non-IT staff to work with models. AI can also help production staff to perfect their problem-solving skills.

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About Microsoft

Microsoft (Nasdaq "MSFT" @microsoft) enables digital transformation for the era of an intelligent cloud and an intelligent edge. Its mission is to empower every person and every organization on the planet to achieve more.

Endnotes

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