Scaling AI in Manufacturing Operations: A Practitioners' Perspective

Executive Summary

AI in manufacturing is a game-changer. It has the potential to transform performance across the breadth and depth of manufacturing operations. However, the massive potential of this new Industrial 4.0 era will only be realized if manufacturers really focus their efforts on where AI can add most value and then drive the solutions to scale.

To understand whether organizations are focusing on the most promising use cases, and then achieving scale with the solution, we have undertaken significant research and analysis. We analyzed 300 leading global manufacturers from four key segments – automotive, industrial manufacturing, consumer products, and aerospace & defense - to understand the focus of their AI initiatives. We also spoke with 30 senior industry executives, all of whom are involved in their organization's AI initiatives. Finally, we analyzed 22 AI use cases in manufacturing operations. These use cases were spread across seven broad functional areas, from inventory management through to production and quality control.

The key findings that emerge from this analysis include:

- **Europe is leading the way,** with more than half of its top manufacturers implementing at least one AI use case in manufacturing operations (within Europe, Germany leads the pack, with 69% of its manufacturers implementing AI). Europe is then followed by Japan (30% implementing) and the US (28%).
- **Three use cases** stand out in terms of their suitability for kickstarting a manufacturer's AI journey:
  - **Intelligent maintenance**
  - **Product quality control**
  - **Demand planning**
- These use cases have an optimal combination of several characteristics, that make them an ideal place to start:
  - Clear business value/benefits
  - Relative ease of implementation
  - Availability of data e.g., performance data from machines and equipment for intelligent maintenance, pictures and videos capturing finished products for quality, etc.
  - Availability of AI know-how and/or existing standardized solutions
  - The opportunity to add features that aid visibility and explainability, allowing employees to understand how decisions are reached and easing adoption by operational teams.

In the final section of this report, we look at the critical success factors for scaling these use cases in operations:

- **Deploy successful AI prototypes in live engineering environments**
  The first step in achieving scale involves bringing the AI prototype up to speed with processing data in real time from the shop floor/production environment. To automate the collection of real-time, live data, the prototype needs to be integrated with legacy IT (such as MES and ERP) and industrial internet of things (IIoT) systems.

- **Put down solid foundations of data governance and AI/data talent**
  To create a robust foundation for scale, and to encourage new implementations, manufacturers should design a data governance framework that defines critical processes related to the generation, management, and analysis of data. In addition, they need to deploy a data & AI platform – a central platform to store and analyze data using AI and to make it available to issue-specific AI applications. Alongside governance and platform, talent will also be a key building block, including manufacturing-specific expertise in AI, data science, and data engineering.

- **Scale the AI solution across the manufacturing network**
  Once the AI platform is ready, AI applications can be deployed and made available across multiple sites/factories. Performance needs to be continuously monitored for value generated, output quality and reliability.
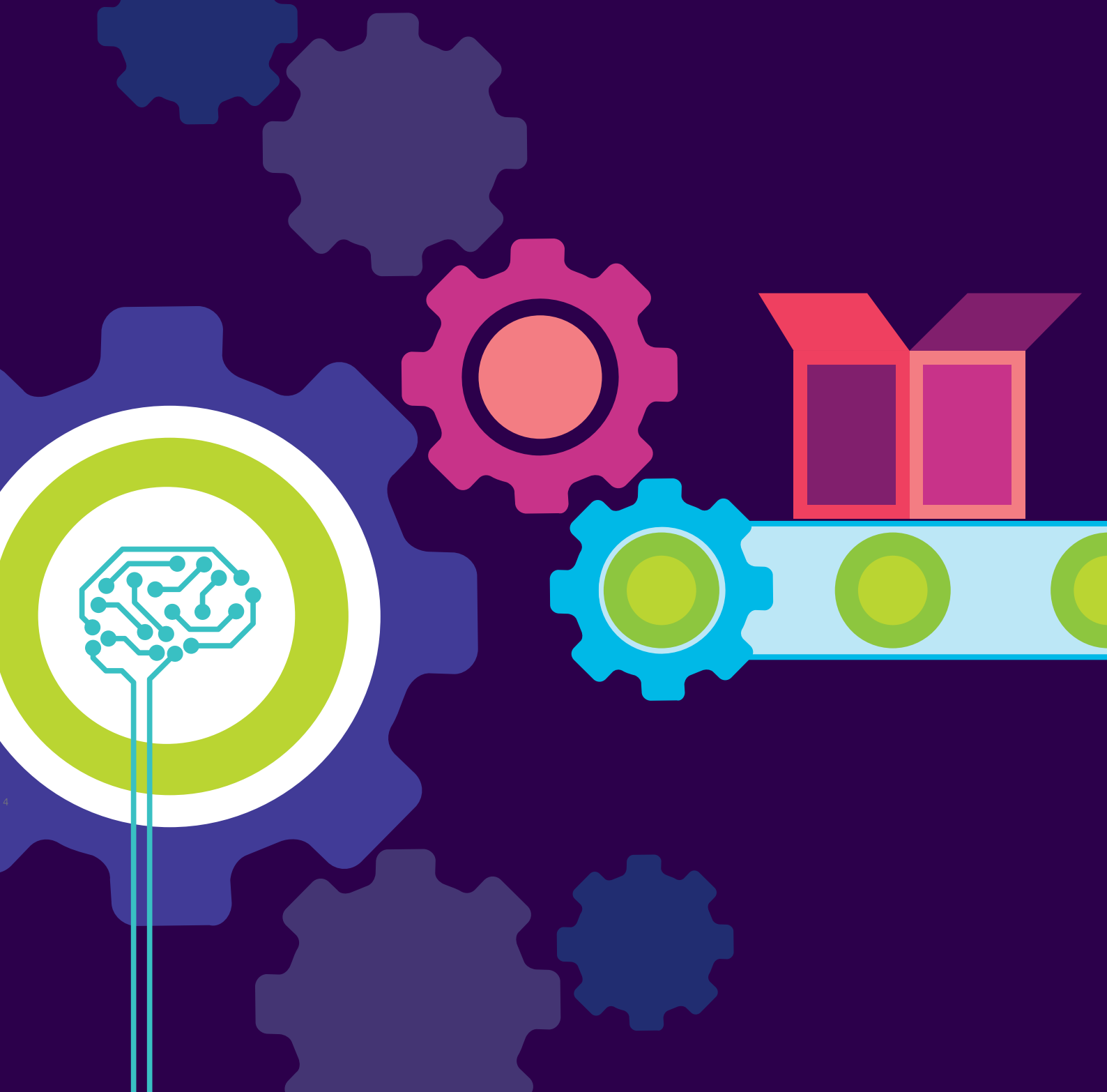
What is AI?

Artificial intelligence (AI) is a collective term for the capabilities shown by learning systems that are perceived by humans as representing intelligence. Today, typical AI capabilities include speech, image and video recognition, autonomous objects, natural language processing, conversational agents, prescriptive modeling, augmented creativity, smart automation, advanced simulation, as well as complex analytics and predictions.

In the context of manufacturing operations, we found most AI use cases centered around the following technologies:

1. Machine learning: The ability of algorithms and code to use data and automatically learn from its underlying patterns without being explicitly programmed.
2. Deep learning: An advanced form of machine learning that uses artificial neural networks to analyze and interpret images and videos.
3. Autonomous objects: Artificial agents – such as collaborative robots or autonomous guided vehicles – that can handle a task given to them on their own
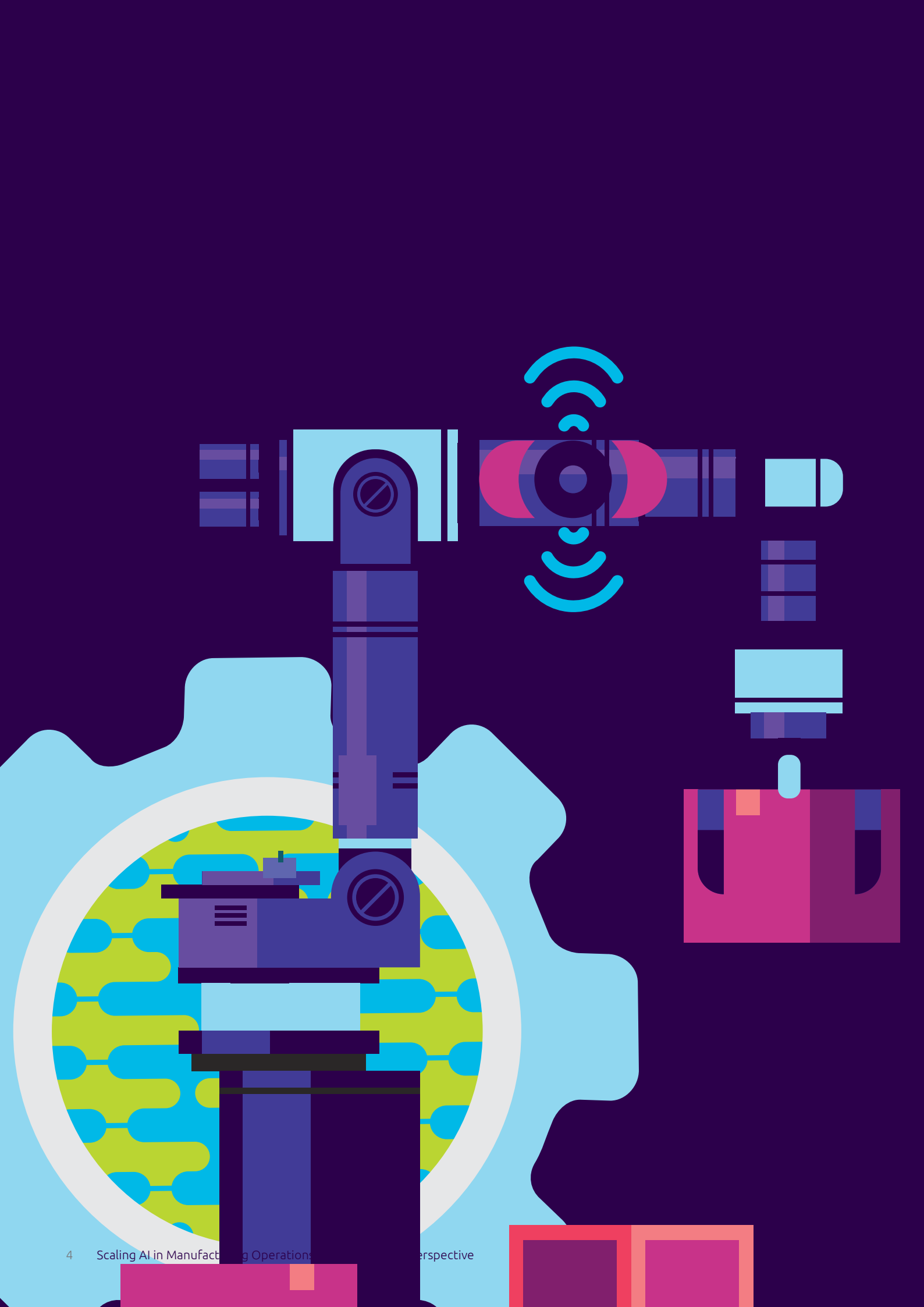
AI holds strong potential across the manufacturing value chain

A range of leading organizations are using artificial intelligence in their manufacturing operations – leveraging the benefits it offers over traditional methods:
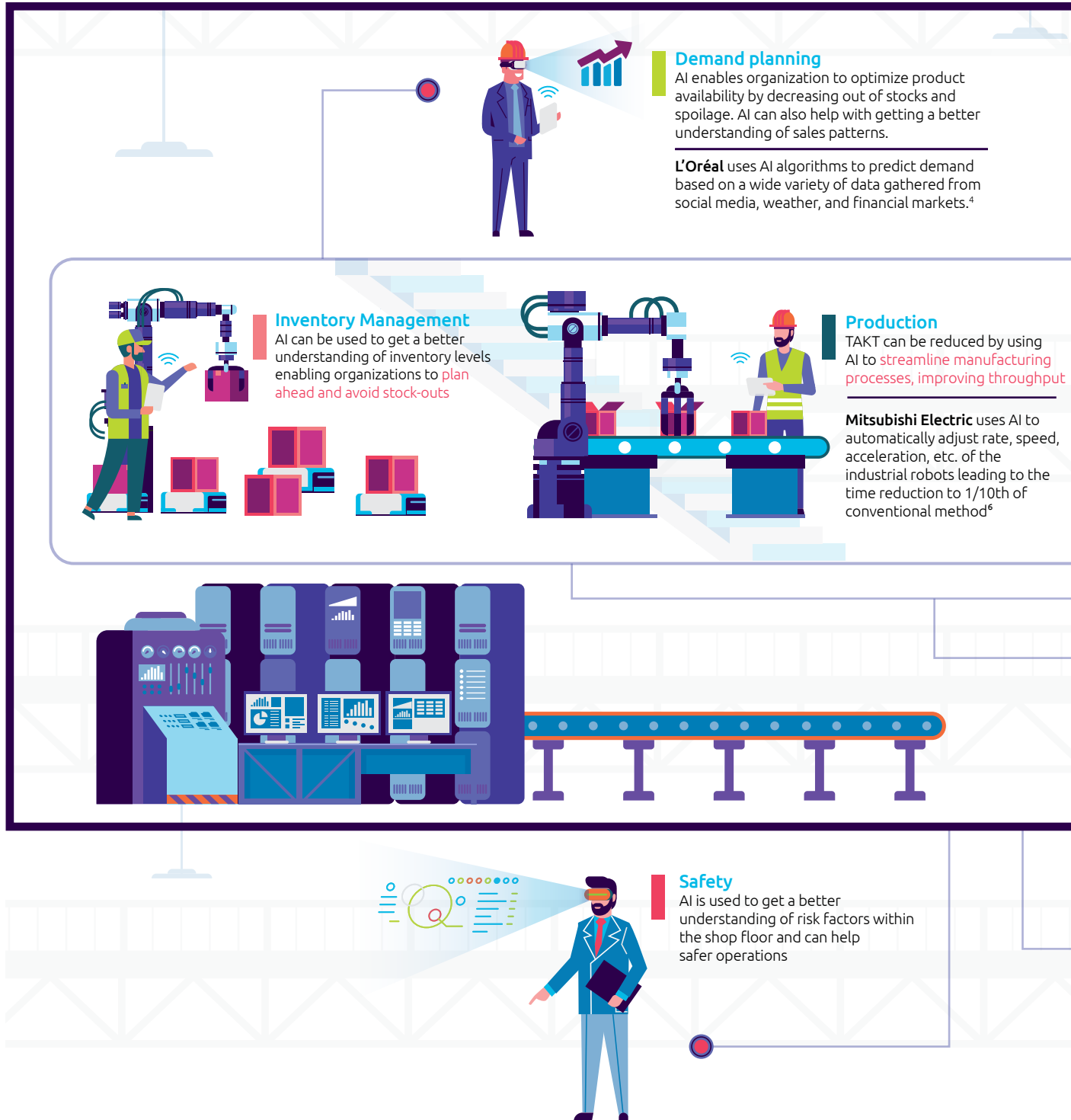
- **Bridgestone,** the Japanese tire manufacturer, introduced a new tire assembly system – "EXAMATION" – to improve the quality of its tires. This system provides automatic control of quality assurance in the production process – an approach that was previously dependent on human skills and judgement. This system is equipped with an artificial intelligence tool that uses sensors to measure the characteristics of individual tires based on 480 quality items. EXAMATION uses this information to control production processes in real time, ensuring that all components are assembled under ideal conditions. This system helps promote ultra-high levels of precision in tire manufacturing, resulting in an improvement of more than 15% in uniformity when compared to a conventional manufacturing process.[1]

- **Danone** uses machine learning to predict demand variability and planning. The new capability improved its forecasting process and led to more efficient planning between different functions, such as marketing and sales. It has led to a 20% reduction in forecast error and a 30% reduction in lost sales.[2]

- **General Motors' "Dreamcatcher"** system uses machine learning to transform prototyping. The solution was recently tested with the prototyping of a seatbelt bracket part, which resulted in a single-piece design that is 40% lighter and 20% stronger than the original eight-component design.[3]

These examples provide compelling evidence as to why artificial intelligence is being adopted across manufacturing sectors. And, as Figure 1 shows, AI offers applications across the breadth and depth of manufacturing operations, from product development to quality control.

To discover all potential applications of AI in manufacturing operations, we researched 300 global manufacturers. The 300 represented the top 75 global organizations in four manufacturing segments: automotive, industrial manufacturing, consumer products, and aerospace & defense. We also conducted in-depth interviews with 30 senior executives from these segments to understand how they are implementing and scaling AI (please see the research methodology at the end of the report for more details).

30%
reduction in lost sales achieved by Danone by using machine learning to predict demand

Figure 1: AI has potential across the breadth and depth of manufacturing operations

Demand planning

AI enables organization to optimize product availability by decreasing out of stocks and spoilage. AI can also help with getting a better understanding of sales patterns.

L'Oréal uses AI algorithms to predict demand based on a wide variety of data gathered from social media, weather, and financial markets.[4]

Inventory Management

AI can be used to get a better understanding of inventory levels enabling organizations to plan ahead and avoid stock-outs

Production

TAKT can be reduced by using AI to streamline manufacturing processes, improving throughput

Mitsubishi Electric uses AI to automatically adjust rate, speed, acceleration, etc. of the industrial robots leading to the time reduction to 1/10th of conventional method[6]

Safety

AI is used to get a better understanding of risk factors within the shop floor and can help safer operations

Source: Capgemini Research Institute analysis.

Product development/R&D

AI enables organizations to expediate product development and R&D by reducing the test times and driving more concrete insights from customer data and demands

Intel is using big data and AI platforms to create tests for hard to validate functionalities improving the targeted coverage by 230x compared to standard regression tests[5]
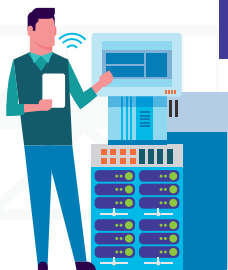
Process control

AI can help organizations optimize processes to achieve production levels with enhanced consistency, economy and safety

Unilever uses AI to influence operations by predicting outcomes and improving efficiency levels to optimise output.[7]

Quality control

Product quality inspections bring uniformity and efficiency in quality control, using image-based and sensor-based processes.

Bridgestone uses AI to promote high-level of precision in tire manufacturing, resulting in an improvement of more than 15% over traditional methods

Maintenance

Using AI, organizations can predict and prepare for asset failure, reducing (or even avoiding) downtime.

General Motors uses computer vision to analyse images from robot mounted cameras to spot early signs of failing robotic part[8]
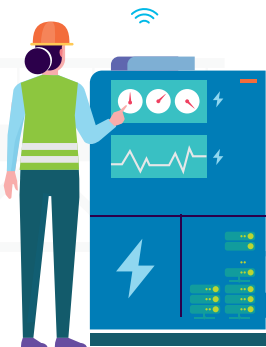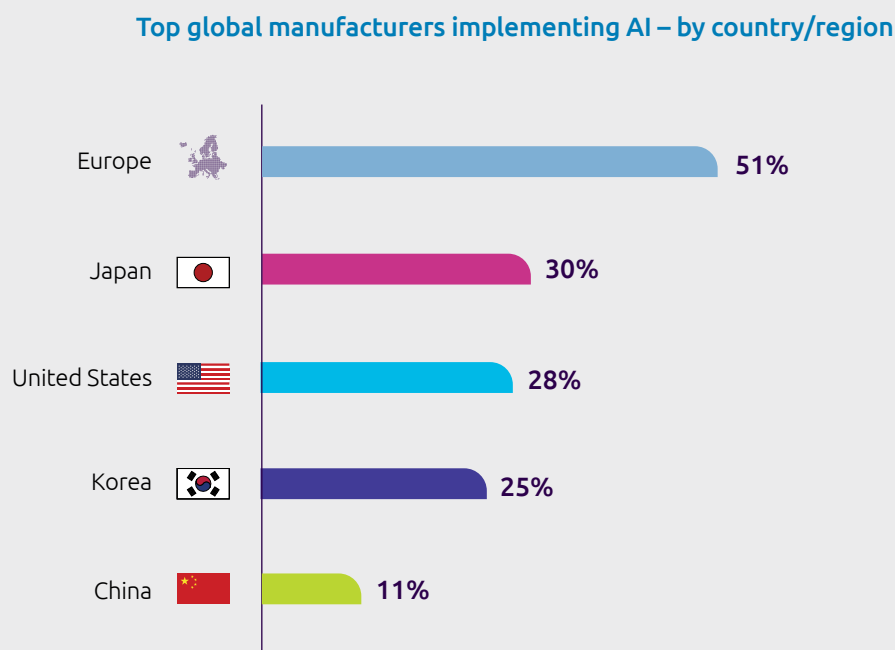
Energy management

AI allows organizations to gain deeper insights in the energy use throughout the production process, resulting in reduced bills and more sustainable production

Europe leads AI deployment in manufacturing operations

Our research of 300 major manufacturers found that Europe leads all major manufacturing countries in implementing AI in manufacturing operations. As Figure 2 shows, more than half of the European cohort are implementing AI solutions, with Japan and the US following in second and third. In Europe, Germany leads the way, with 69% of its manufacturers implementing at least one AI use case in manufacturing. Germany is followed by France (47%) and UK (33%). A growing realization of the scope of AI coupled with support from governments across countries is likely helping manufacturing companies in adopting AI in operations.

Figure 2: Europe leads in implementing AI in manufacturing operations

Top global manufacturers implementing AI – by country/region

Country/Region	Percentage
Europe	51%
Japan	30%
United States	28%
Korea	25%
China	11%

Percentages represent the share of organizations in each country/region that are implementing at least one AI use case, out of total organizations from that country/region in the top 300 global manufacturers (top 75 from each of the four focus sectors of the study). Number of organizations in top 300 global manufacturers that are in: US = 89, Europe = 73 (including France = 20, UK = 15, Germany = 13), Japan = 44, China = 32, and Korea = 12. Together these countries represent manufacturers with $3.8 trillion of annual revenues among the top 300 global manufacturers.
Source: Capgemini Research Institute analysis.

Three use cases to kickstart AI in manufacturing operations

As part of our research, we closely analyzed 22 unique use cases (please refer to appendix) against a range of characteristics, from whether there is a clear benefits case to the availability of relevant data. The aim was to identify the best use cases for organizations to begin their journey, and the assessment characteristics included:

a. Clear business value/benefits. Focusing on use cases where benefits are easily identified and quantified – including in financial terms – makes building the business case easier. For example, reducing downtime, improving OEE, reducing product defects and reducing inventory.

b. Relative ease of implementation. Focusing on less complex use cases leads to shorter payback periods (usually in a matter of a few months) and a higher return on investment. This further strengthens the business case.

c. Availability of data. For example, performance data from machines and equipment for intelligent maintenance, pictures and videos capturing finished products for quality, etc. Also, the data must contain enough occurrences of the particular issue that you want to predict in the future, such as a fault or substandard quality. When there are not enough occurrences, simulation data can be used. In many cases, the necessary data will come from machines equipped with IoT sensors.

d. Availability of the AI know-how, existing standardized solutions, and IT infrastructure required to deploy AI in production, at scale. Based on the popularity of these use cases, many vendors have been quick to translate those into AI offerings, which they bundle into packaged solutions, and which can be customized to specific use cases.

e. The opportunity to add features which aid visibility and explainability, allowing employees to understand how decisions are reached and easing adoption by operational teams.

We believe that three of these 22 use cases serve as a good starting point for manufacturers to focus their efforts, as they possess an optimal combination of the factors listed above. These three use cases are:

1. **Intelligent maintenance**
2. **Product quality inspection**
3. **Demand planning.**
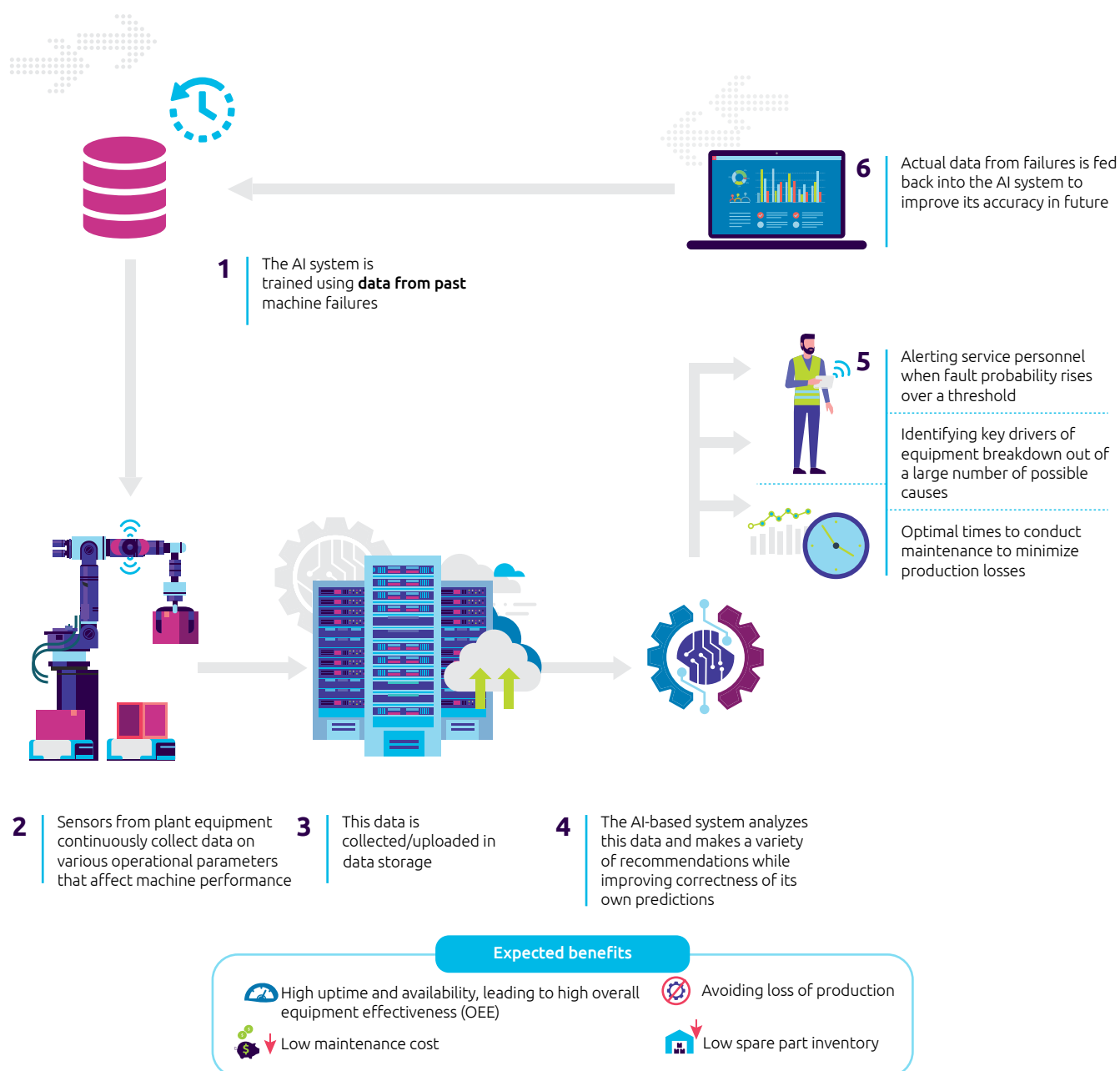
I. Intelligent maintenance

Intelligent maintenance of plant machinery and equipment is the "low hanging fruit" of AI adoption across industries. When applied to bottleneck resources, its ROI can be significant, as we saw in the industry examples earlier. Beyond minimizing downtime, AI-enabled intelligent maintenance also reduces maintenance costs and increases productivity. It is relatively easy to implement, given availability of good quality data and the expertise to analyze it in business context. Several integrated solutions are available, both from specialized startups and large players. Intelligent maintenance adds value in a few variants:

- Predicting when machines/equipment are likely to fail and recommending optimal times to conduct maintenance (condition-based maintenance).
- Analyzing root causes and identifying drivers of machine downtime to prevent future breakdowns. For instance, **General Motors** analyzes images from cameras mounted on assembly robots, to spot signs and indications of failing robotic components with the help of its supplier. In a pilot test of the system, it detected 72 instances of component failure across 7,000 robots, identifying the problem before it could result in unplanned outages. According to the Robotic Industries Association, the cost of just one minute of production-line downtime for a company like General Motors can be as high as $20,000.
- Correlating the impact of events and issues on machine efficiency and breakdowns. For instance, **Volvo** uses large-scale datasets in its Early Warning System. Every week, the system analyzes over one million events that occur during machine operations, such as temperature increases or abnormal pressure readings. This allows the organization to assess their impact on breakdown and failure rates.
- Minimize production losses and maximize OEE (overall equipment effectiveness)
- Ensuring you have the "right alerts at the right time". This is to avoid too many false positives that would render the solution unusable (a pitfall with many intelligent maintenance solutions). It also allows you to factor in the "time to action". In other words, when the alert should be raised to ensure the necessary steps can be taken to avoid a predicted failure.

The head of digital innovation of a large European engineering firm, outlines how intelligent maintenance creates benefits in multiple ways. "We have implemented predictive maintenance, using AI for our tuning machines, which run 24/7," he explains. "Previously, every unplanned stoppage resulted in lost production time – the time it took to complete maintenance and get the machine back up. Now, we have data on these past failures and their possible causes and can predict when the next issue is likely to occur. This allows us to save not only production hours lost, but also unplanned maintenance cost and man-hours, leading to big savings."

Figure 3: Using AI for intelligent maintenance in manufacturing

1 The AI system is trained using **data from past** machine failures

6 Actual data from failures is fed back into the AI system to improve its accuracy in future

5 Alerting service personnel when fault probability rises over a threshold

Identifying key drivers of equipment breakdown out of a large number of possible causes

Optimal times to conduct maintenance to minimize production losses

2 Sensors from plant equipment continuously collect data on various operational parameters that affect machine performance

3 This data is collected/uploaded in data storage

4 The AI-based system analyzes this data and makes a variety of recommendations while improving correctness of its own predictions

Expected benefits

High uptime and availability, leading to high overall equipment effectiveness (OEE)

Avoiding loss of production

Low maintenance cost

Low spare part inventory

Source: Capgemini Research Institute analysis.

The power of this approach can be seen in the example of a leading automotive manufacturer that was struggling to reduce machine stoppages and minimize production losses.[9] It wanted to identify machines and production lines in advance where faults are likely to occur, jeopardizing sales and final deliveries to customers. With an AI-enabled predictive maintenance solution, it was able to accurately identify machines and lines that were most likely to fail and take proactive remedial action. For instance, in a month where significant failures were anticipated, intelligent maintenance allowed 300 additional cars to be produced. This was in addition to the output that might otherwise have been lost because of downtime and maintenance.

To arrive at these predictions, the organization deployed a supervised machine learning model. The model analysed historical reasons for failure, focusing on information captured during stoppages. For example, it collected data on the duration of outages and the reasons for failure. Figure 4 shows how the AI model works in action – predicting a possible loss of approximately seven cars at Line "PUR", Station "CT229", in the first shift.

Figure 4: Predicting faults on production lines and their impact on car production

Case A: Predicting 'faults' resulting in maximum car loss per shift

Shift	Fault Code	Fault Description	Lost	Shift	Fault Code	Fault Description	Lost
1	215XX	Waiting output	3.1	2	215XX	Waiting output	3.2
1	C01KY	Issue	3.1	2	C01KY	Issue	3.0
1	C99YT	Code Action	2.6	2	C99YT	Code Action	2.7

Case A: Predicting 'lines' resulting in maximum car loss per shift

Shift	Line	Car Lost	Shift	Line	Car Lost	Shift	Line	Car Lost
1	12XXX	6	2	12XXX	5.6	1	12XXX	4.9
1	PUXX	4.2	2	PUXX	3.7	1	PUXX	2.9
1	TRABC	3.6	2	TRABC	3.2	1	TRABC	2.7

Predict feature values that would result in maximum 'Car Loss' for May

Deep Learning - Simulator

Disturbance_Month:	5
FAULT_DESCRIPTION:	GEEN BRUIKBARE FENOMEENCODE ZIE AKTIE !!
LINE:	PUR
SHIFT:	1
STATION:	CT229

Prediction

7.052
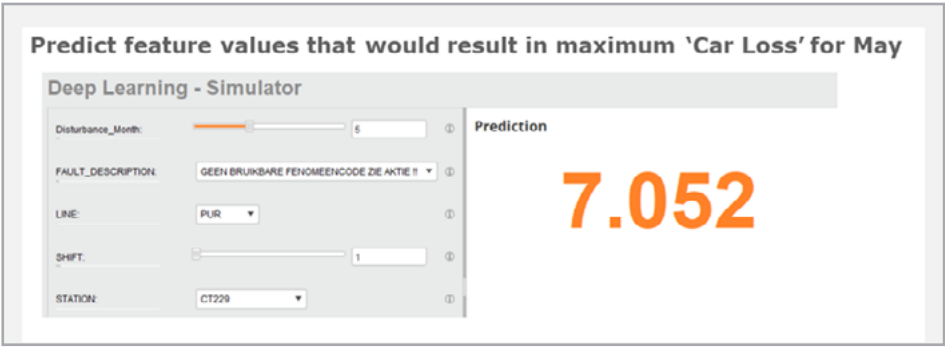
Source: Capgemini Research Institute analysis.

Similarly, a leading automotive manufacturer in the premium and commercial vehicle manufacturing space wanted to overcome maintenance challenges with welding and gluing robots.[10] Frequent changes in robot-driven welding programs were resulting in recurrent failures in areas such as chassis welding and glue leakage. With an intelligent maintenance solution, the manufacturer was able to predict the failure of robots one to two days in advance. This resulted in savings of about 500 minutes per week of operational downtime. The company had over 600 robots on this plant's assembly lines.

Interview with Luis Miguel del Saz Rodriguez, Head of Digital, Design, Manufacturing Services in Airbus Commercial Spain

Q. What AI use cases are you implementing in Airbus manufacturing operations

A. We are using artificial intelligence in several processes – manufacturing, quality, and supply chain are the most important. In manufacturing, we are very mature in asset maintenance. Our process involves several kinds of machines: ATL, trimming, non- destructive test, drilling. We monitor data from the parameters that directly impact the way these machines work. We use the data collected from the machine sensors (e.g., temperature, pressure, and humidity data) to predict when the output of the machine may lead to rework or scrap. The software helps by automatically raising a warning that allows us to stop the machine and save time and money.

Supply chain is other process that was largely manual and currently we are tracking the lead time required for the suppliers. We use machine learning to create the buffers to ensure the availability of the parts and reduce the assembly lead time.

Q. What benefits have you witnessed with AI vis-à-vis traditional methods?

A: One of the major benefits we see is in the area of quality. Our rate of production is not as high as other sectors, for example, automotive firms. In our case, we are talking about manufacturing four single-aisle aircraft per day of production. Thanks for artificial intelligence, we are able to detect the problem sooner and reduce the number of aircraft impacted. Other KPIs we have include reducing missing parts by four and the lead time by 20%.

Q. What is the process followed at Airbus for selecting AI use cases?

A: First, we organize a team workshop where we discover the pain points and the opportunities. We also consider the scale and impact in the business. Next, we take these pain points, or opportunities, and work on the digital solutions, analyze budget and the associated business case. Then, we launch a proof of concept to test if the solution is good and applicable in the other plant. The last step is the team selection. A good product owner and scrum master are key in the success of the project.

Q: What challenges did you face when scaling AI?

A: The challenge that we have is that it's not only a question of technology. It is also a question of people and cultural change and how we are going to deal with it. It's clear that with all these AI tools, we have significantly increased the level of information. But we need to convince the end user of the insights regarding the dependability of the data generated using AI. When it comes to the supply chain, even though people know that the inventory recommendations are correct, they feel more comfortable having this extra stock or to be a little more protective.

Another challenge is to select the right sponsor for the project. Manufacturing is a complex area where the selection of the sponsor is key to convince the project stakeholders.

II. Product quality inspection

In the same way that detecting subtle trends in certain parameters allows you to predict the potential failure of assets, analyzing process parameters can help you predict and prevent quality issues. In many processes, in-line visual inspection can capture trends that could not be detected otherwise. The widespread availability of high-resolution cameras, coupled with powerful image recognition technology, has dramatically cut the cost of real time in-line inspection.

This use case allows manufacturers to effectively deal with the stringent regulatory environment that exists in segments such as automotive and consumer products. In particular, it is helpful with regulations around product specifications and compliance. Any non-compliance can lead to significant losses, from dissatisfied customers to fines and class action lawsuits.

Eugene Kusse, factory director, Upfield (a spin-off of Unilever), says: "Working in the food industry, we have a responsibility to ensure that the food we produce is both safe for consumption and meets the toughest quality criteria. We have strict policy and procedures in place to ensure that we avoid any of the risks associated with not meeting those criteria"

A case in point is **Audi**, which has installed an image recognition system based on deep learning at its Ingolstadt press shop. Several cameras installed directly in the presses capture images of pressed sheet metal (see Figure 5). The images are then analyzed by the AI system to identify even the finest cracks on the metal sheets. The system was trained using several million test images, drawn from presses in Audi's Ingolstadt plant and several other Volkswagen plants. This helped achieve a very high accuracy.

Figure 5: **Quality inspection of metal sheets at Audi's Ingolstadt press shop**
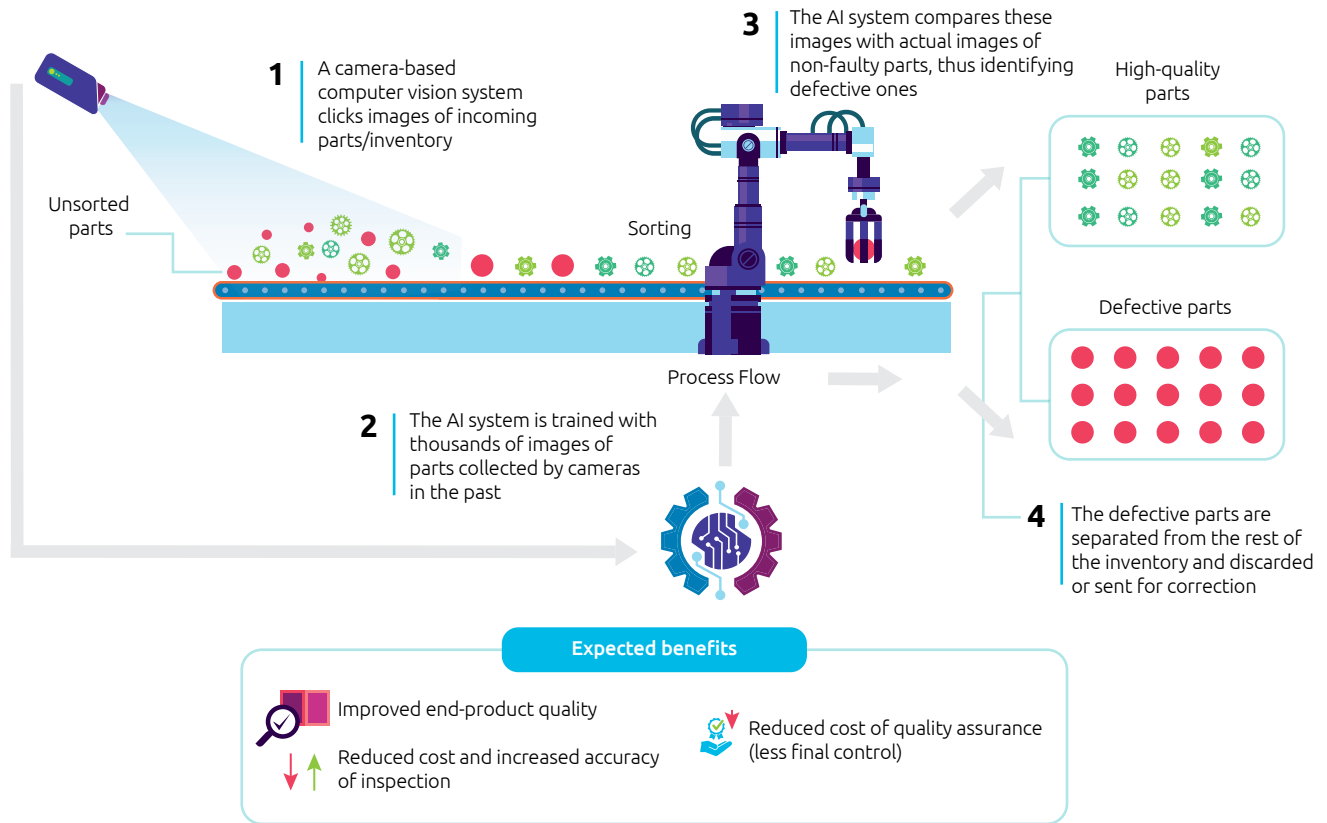

Source: Audi Media Center, "Audi optimizes quality inspections in the press shop with artificial intelligence," October 2018.

During the implementation of this use case, computer vision AI systems are trained on a large set of images, which are classified as "pass or fail." This then allows the system to spot whether a part is of requisite quality or not. AI-enabled quality inspection is being increasingly adopted to:

- Identify defects in parts and/or finished products (e.g. quality of paint). The director and global supply chain leader of a large European electronics organization said, "I think quality inspection is the area with the biggest potential. We are experimenting with automatic robotic inspection of coils. It is a big cost saver since it has the potential to eliminate 100% of wastage owing to poor inspections."
- Ensure that assembly operations are being executed properly (e.g., missing or misplaced components). Neeraj Tiwari, director manufacturing JV organization at Fiat

Chrysler China, explained how they employ computer vision to inspect the quality of power train assembly. "We trained an AI system to detect improper assemblies or missing components, such as small screws that are hard to detect for a human eye," he explained. "The system is extremely fast and efficient, allowing defective parts to be taken off the main conveyor on a separate line to the rework area where they can be corrected. The process not only saves a lot of quality issues at the end-customer but also loss of valuable production time."
- Predict the quality of the end-product for given input characteristics e.g., ingredients, raw material components
- Automatically track and document product quality
- Reduce manual intervention and errors in quality checks and increase scale and scope of quality inspection

Figure 6: Computer vision-based quality control in action

1 A camera-based computer vision system clicks images of incoming parts/inventory

2 The AI system is trained with thousands of images of parts collected by cameras in the past

3 The AI system compares these images with actual images of non-faulty parts, thus identifying defective ones

4 The defective parts are separated from the rest of the inventory and discarded or sent for correction

Unsorted parts

Sorting

Process Flow

High-quality parts

Defective parts

Expected benefits

Improved end-product quality

Reduced cost and increased accuracy of inspection

Reduced cost of quality assurance (less final control)

Source: Capgemini Research Institute analysis.

Neeraj Tiwari,
Director manufacturing JV organization at Fiat Chrysler China

"We trained an AI system to detect improper assemblies or missing components, such as small screws that are hard to detect for a human eye. The system is extremely fast and efficient, allowing defective parts to be taken off the main conveyor on a separate line to the rework area where they can be corrected. The process not only saves a lot of quality issues at the end-customer but also loss of valuable production time."

A large food processing organization implemented AI-enabled quality inspection of eggs on its production lines.[11] Its production output ranged from 30,000 to 270,000 eggs per hour. Inspecting eggs through sampling by operators is difficult to scale and minor defects are easily missed. The manual approach is also prone to errors on higher volumes, where even a 1% drop in quality represents several thousand eggs.

The organization devised a deep learning neural network-based AI algorithm using more than 70,000 images of eggs and classified them into ten categories depending on the kind of defect any egg might have (see Figure 7). In real time, every egg's image is compared with this system to identify whether it is defective. If found to include one of the categorized defects, the egg is taken off the conveyor and sent for recycling. The AI-enabled system also operates at high speed – scanning an egg in less than 40 milliseconds – to keep up with the speed of the production line.

Figure 7: Identifying defective eggs using computer vision
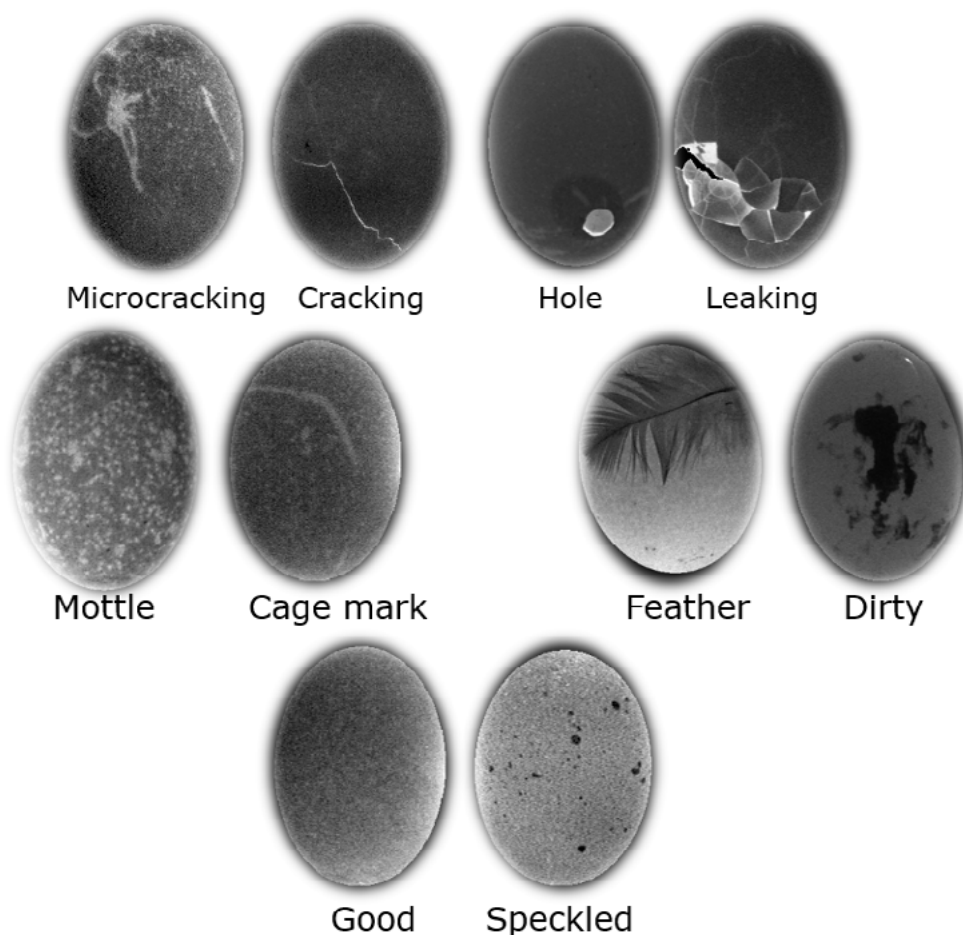
Source: Capgemini Research Institute analysis.

How BMW is using data to optimize processes across its operations

BMW realized early on that its future success would depend heavily on its ability to exploit big data. To address this imperative, BMW started building a data architecture that would be capable of handling vast amount of data generated by its production facilities in 31 countries and sales network in more than 140 countries. To kickstart the transformation, BMW put in place a data warehouse, creating a new data architecture that allowed it to deal with the massive amount of data it was generating and carry out timely analysis.[12]

At the time, Klaus Slaub, former CIO, BMW, said: "This is a big cultural change for the company because, in data terms we have been organized around functional lines: development, production, procurement and so on, all historically kept their own data to themselves. Now we are integrating this into a big data lake that will involve the whole organization. In the next five to ten years we will have the potential to use machine learning to optimize the quality of our processes or we can get more efficient. And that means data becomes the gold nuggets of the future, helping us to optimize our products, get better customer views, and optimize our business models."[13]

By 2017, BMW had developed an intranet-of-things platform to access the large quantity of sensor and process data from production and logistics quickly and easily.[14]

The new data foundation is yielding massive rewards for BMW:

• By creating an image database, BMW has built a neural network which evaluates the images in the production process. Once it's learning process is completed, the neural network can determine on its own whether a component meets the specifications.
• BMW is eliminating "pseudo" defects in its Steyr plant. It has trained analysis software, using pre-recorded test runs, which has learnt to distinguish between actual and presumed errors.
• BMW has also developed an AI control application at its Steyr plant, using stored image data annotated by employees, to highlight defects. With the help of the image data, an AI application recognizes whether a container needs to be bound onto a pallet or if no additional securing is required. If no additional binding is required, the AI application directs the container by the shortest route to the removal station.[15]
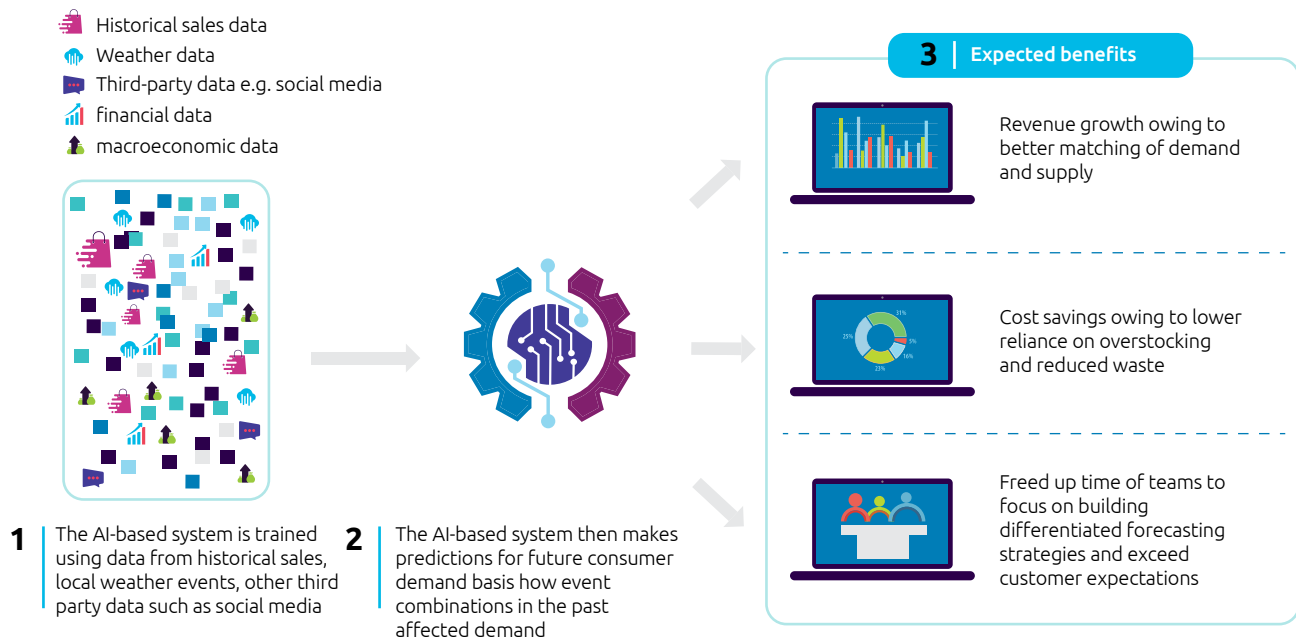
III. Demand planning

Organizations are using machine learning to predict changes in consumer demand as closely as possible. This means they can make the necessary changes to production schedules and raw material procurement. Better forecasting yields several benefits, from better client service to inventory reduction – WIP and finished goods.

Danone Group, a French multinational food products manufacturer, leverages a machine learning system to improve its demand forecast accuracy. This made a big difference in improving the forecasting but also improving planning between marketing, sales, account management, supply chain, and finance. For supply chain, this improved efficiency and inventory balance, allowing Danone to meet demand from product promotions and achieve its target service levels for channel or store-level inventories. The system led to a 20% reduction in forecast error, a 30% reduction in lost sales, a 30% reduction in product obsolescence, and a 50% reduction in demand planners' workload.

The global manufacturing engineering leader for a large American auto ancillary organization, spoke to us about how they are piloting AI in demand forecasting. "We have access to a lot of historical data on customer demand and also of what we have delivered to them in the past – such as what the demand was and how much we fulfilled," he says. "We are trying to use this data and the current forecast to create a demand planning model. This is because forecasting is becoming an extremely big challenge for us today. We need to be prepared in terms of our ability to meet volume fluctuations or demand fluctuations from our customers."

Figure 8: Using machine learning-based demand planning and forecasting

- Historical sales data
- Weather data
- Third-party data e.g. social media
- financial data
- macroeconomic data

3 | Expected benefits

Revenue growth owing to better matching of demand and supply

Cost savings owing to lower reliance on overstocking and reduced waste

Freed up time of teams to focus on building differentiated forecasting strategies and exceed customer expectations

1 The AI-based system is trained using data from historical sales, local weather events, other third party data such as social media

2 The AI-based system then makes predictions for future consumer demand basis how event combinations in the past affected demand

Source: Capgemini Research Institute analysis.

The head of digital product at one of the largest automobile manufacturers in Asia told us how they are using machine learning to incorporate micro and macro variables in the demand forecasting process. "Forecasting has been very heavy on statistics and has multiple modelling methods that have been used traditionally," he says. "The question that we are asking is how can one use machine learning which goes beyond specific variables and bring in macro and micro variables to generate a more meaningful forecast." **L'Oréal,** one of the world's largest beauty products manufacturers, which sells over seven billion products a year, uses information from various sources to predict changing customer demands, anticipate trends, and optimize sales. These sources include:

- social media
- data gathered at point-of-sale, such as reception, collection, and inventory
- data points such as weather and financial markets indicators.

Stéphane Lannuzel, operations chief digital officer at L'Oréal, says, "We harness this type of information to target end consumers more effectively and provide them with the products and services they need, anytime, anywhere."[16]

Eugene Kusse,
Factory director, Upfield
(a spin-off of Unilever)

"Working in the food industry, we have a responsibility to ensure that the food we produce is both safe for consumption and meets the toughest quality criteria. We have strict policy and procedures in place to ensure that we avoid any of the risks associated with not meeting those criteria"

Manufacturers focus their AI implementations on maintenance and quality

With AI offering potential across the entirety of manufacturing, we wanted to understand where organizations are focusing their efforts. As Figure 9 shows, our research across the four manufacturing segments found two areas with the greatest amount of activity – maintenance (29% of all AI implementations) and quality (27%).

Figure 9: **Maintenance and quality form majority of all AI implementations among top manufacturers**

Use-case distribution – by function

- Maintenance — 29%
- Quality — 27%
- Production — 20%
- Product development/R&D — 16%
- Supply chain management — 8%
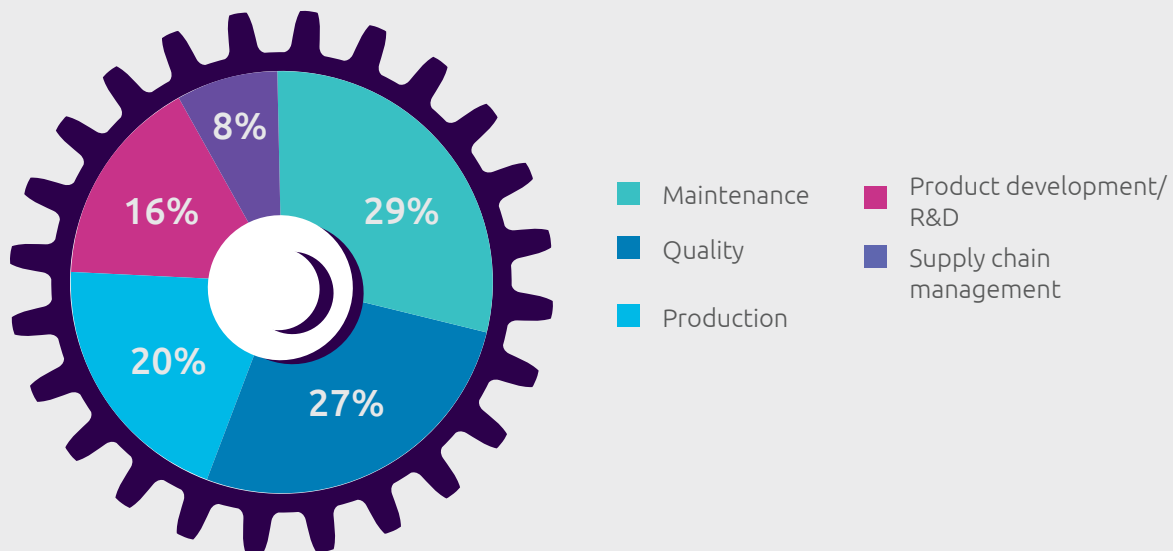
*Supply chain management includes supply chain, logistics, inventory management, and warehousing
Percentages depict the share of use cases implemented in a given function out of all use cases implemented
Source: Capgemini Research Institute, Artificial Intelligence in Operations, Secondary research of top 75 companies by revenue from automotive, industrial manufacturing, consumer products, and aerospace & defense.

29%
share of AI use cases
implemented in maintenance

How can organizations scale AI in manufacturing operations?

Our recent research on smart factories found that deployment and integration of digital platforms and technologies is the biggest challenge faced by manufacturers to achieve performance at scale.[17] For example, in the automotive industry, we found that only 14% of automotive OEMs have delivered AI implementations at scale as of January 2019. This has only climbed marginally from when we measured it in mid-2017, when it stood at around 10%.[18]

Our discussions with manufacturers as part of this research also confirmed that scaling AI implementations beyond the proof-of-concept (POC) level remains one of the biggest challenges. Based on our own experience of helping organizations scale AI, and discussions with industry experts, we have outlined the key actions that manufacturers can take to overcome this hurdle (see Figure 10). This assumes that they have at least reached POC/pilot stage – in other words, that a use case has proved its value in a controlled environment; that it can be prototyped, i.e. its development and implementation process are made standardized and repeatable; and the prototype is now ready to be deployed at scale.

Figure 10: Recommendations to scale AI in manufacturing operations

Deploy successful AI prototypes in live engineering environments

- Implement the AI application to **process real time data** from live environment
- **Create robust integrations** with legacy IT systems and industrial internet of things (IIoT) systems

Invest in laying down a foundation of data & AI systems and talent

- Design a **data governance framework** and build a data & AI platform
- Develop AI, data science and **data engineering expertise** with manufacturing knowledge

Scale the AI solution across the manufacturing network

- Deploy the AI application on the AI platform and make it **available across multiple sites/factories**
- **Continuously monitor** its performance for value generated, output quality, and reliability

Source: Capgemini Research Institute analysis.

I. Deploy successful AI prototypes in live engineering environments

a. Implement the AI application to process real-time data from the shop floor

So far, the implementation of the use case as a pilot/POC has happened in a sandbox or controlled environment. As a result, the system has been trained and tested on a limited set of data. Before the AI application can begin to handle many

possible scenarios, it needs to be trained to a level where its accuracy is sufficiently high for a production environment. Siddharth Verma – global head and VP, IoT Services, Siemens – pointed out that organizations need to be ready for a few false starts (a lesson they learned during the initial days of an intelligent maintenance implementation). "We used AI to predict failures in fans that handle exhausts from an autoclave," he explained. "In the early days, when the accuracy of the system was low, it predicted a few failures which turned out to be false alarms. At these points, it is important to remind everyone that it is a prediction which has a probability

of being right or wrong. As accuracy improved, the system was able to predict many failures in advance and saved a lot of cost and downtime, proving its worth." Testing on real time data not only builds accuracy, it also ensures the solution is up to the standards demanded by a factory floor environment.

b. Create robust integrations with legacy IT systems and industrial internet of things (IIoT) systems

Our research on scaling AI in the automotive industry found that integration issues with existing systems and tools is the biggest technological challenge standing in the way of at-scale AI.[19] We believe that organizations can overcome this hurdle by proactively building in legacy IT integration as a key ingredient of the scaling process. Legacy manufacturing systems – such as enterprise apps for product lifecycle management, manufacturing execution systems (MES), and enterprise resource planning (ERP) systems – have multiple data sources. These can be valuable inputs to the AI applications. Neeraj Tiwari, director manufacturing JV Organization at Fiat Chrysler China, explains how standardization of equipment and systems across the organization makes integration easier. "We have a centralized process for purchase of equipment, their subsystems, and associated software. This brings a level of standardization and makes integrating AI applications much easier and results in far fewer issues. Not only this, we are able to easily replicate the applications to new plants with a fraction of efforts, say 15 to 20% of the effort required for the first implementation. So, lessons learnt in continuous improvement drive are horizontally deployed."

In addition to these data sources, AI systems will sometimes need more granular data. This would come directly from machines and equipment, such as IoT systems. Industrial IoT

systems are increasingly emerging as a key source of data for AI applications, with two types of integrations needed:

1. Running AI computations at the edge, also known as "edge intelligence" (for instance, in the plant, in the assembly line, close to the asset) for making immediate tactical decisions
2. Collecting and processing IoT data in a central storage repository (for instance, strategic learning for optimization purposes).

II. Invest in laying down strong foundations: governance, platform and talent

a. Design a data governance framework and build a data & AI platform

Investing in foundational technology and AI skills is also key for long-term success. This allows organizations to maintain momentum when the value of AI has been proven by the first few use cases. It also helps in creating repeatable, faster, and easier rollouts of new AI applications in the future.

A data governance framework defines critical processes related to the generation, management, and analysis of data, which are crucial for the functioning of any AI application:

1. Who/which function generates the data, who is the owner and who manages access to it?
2. What data is useful for AI applications? And how is it captured and stored?
3. Which data standards/formats should we be following for ease of data integration?

In the absence of data governance, AI initiatives suffer a significant weakness – they do not have a single view of data, the right quality data, or enough training data. It takes the discipline brought by the data governance framework to get this right. The artificial intelligence lead for a large multi-national chemical organization, emphasizes the importance of working with common data standards across the organization. "Data collected and stored at different parts of the organization has to follow a set of standards while being captured or stored in a data repository," he says. "I think this makes life a lot easier. Following a well-rounded governance approach that propounds a set of standards can save you from the headache of figuring out where the data is and what the right data format is. It will also help you speed up data cleaning and data preparation before the final step of generating insights using AI." Data governance is essential to having a clean and structured dataset. Given that many organizations will find this challenging, having a well-planned and designed data management platform can simplify most of this effort.

To make the best and most effective use of the captured data, leading organizations deploy a robust data & AI platform to store it, govern access to it, and make it available to

issue-specific AI applications. A "data & AI platform" allows you to repeatedly and securely develop and scale solutions, from data acquisition to use case development and deployment. Figure 11 shows the building blocks of a data & AI platform.

As suggested above, the data & AI platform complements the existing manufacturing "stack," and the manufacturing execution system (MES) in particular. In this way, it provides operations optimization capabilities that are complementary.

Figure 11: **Building a data management foundation for scaling AI**
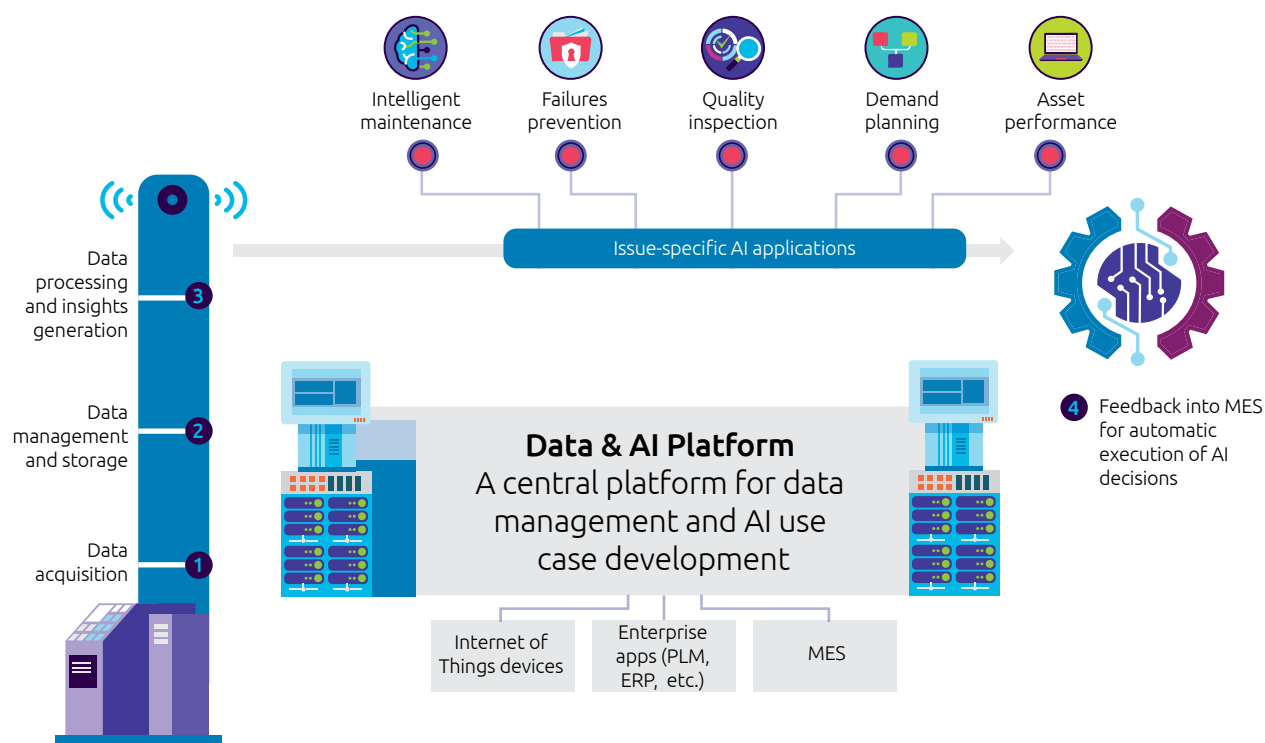
It collects data from existing machines, control systems, and the MES itself, as well as new sources (e.g., additional "context" sensors). Initially, it mostly provides insights into operations to suggest and support optimization decisions. Over time, the outcomes produced by AI models can be sent back into the MES for automated execution of optimization decisions (e.g., schedule a maintenance action and trigger a re-scheduling of the equipment). Such platforms are available either as vertically integrated solutions addressing a family of uses cases (e.g., asset performance) or as general-purpose platforms on which a variety of use cases can be developed.

For organizations that lack the necessary skills and expertise to implement and train AI in-house, buying an off-the-shelf solution could be a fast and efficient way to develop and implement AI. Custom-built solutions on a general-purpose platform, on the other hand, can act as a strong foundation

for organizations to build their AI expertise while also allowing to take advantage of the ecosystem of use case specific solutions.

b. Building AI, data science, and data engineering expertise with manufacturing knowledge

While gathering the right data to feed AI is the first step, manufacturers need a talent pool that can exploit this data. Generating insights requires this talent pool to have a deep understanding of the manufacturing domain as well, so that they understand the business problem the AI system is supposed to solve and the kind of solutions that would work. Many of these skillsets will not be found within a manufacturer's IT group and require dedicated hiring and upskilling programs. As part of their upskilling efforts, some organizations are working actively with academia and startups. The global automation manager for a large European

consumer products firm, told us, *"We are trying to build a group of people whom we call as 'citizens of data sciences.' For this, we have tied up with a university in England, which is conducting sessions on data sharing and knowledge every week for one hour. This is just the start. We are taking baby steps in this direction to have the right pool of talent."*

Alongside building the expertise to develop and implement AI, organizations need to train the users of AI applications. It is important to start this exercise as early as possible to ensure adoption is both quick and smooth. Since adopting AI requires fundamental changes in ways of working, change management becomes crucial as well. Leading organizations proactively train users of AI applications to interpret AI output, ascertain the trust they can place in AI recommendations, and when to use their own judgement to override AI if needed.

III. Scale the AI solution across the manufacturing network

The AI prototypes that have proven their value now need to be scaled to the plant level and across the broader manufacturing network of the organization. This is achieved by building on the foundations of data management and talent that have now been built.

a. Deploy the AI application on the AI platform and make it available across multiple sites/factories

Once organizations have developed their data & AI platform, existing AI implementations can be moved to the platform to capture the full value of available data and resources. This has several benefits:

- It helps scale the use case by giving it access to a wider set of data from multiple sites/plants, preparing it for use on those sites
- It helps identify the IT hardware and software resources needed for development of new use cases on the platform
- It allows you to use the output of the AI application as input to new AI apps hosted on the same platform (or, you can feed the output back into MES or control systems to automate decisions suggested by AI.)

The platform itself can be hosted on the cloud. This allows for centralized access to the AI application across the organization – as well as portability of applications and enterprise mobility – at a fraction of the cost.

b. Continuously monitor its performance for value generated, output quality, and reliability

The AI application is now capable of operating in a live environment, constantly generating value to users across the organization. To ensure a stable operation and avoid failures, it needs to be monitored for performance on various parameters, such as:

- Realization of overall business value
- Occurrences of failures, false positives and negatives
- Time bound operation and no degradation in performance over time
- Need for retraining, with new categories of data to improve accuracy of predictions.

This monitoring ensures that the AI application continues to deliver on its value promise and without any significant impact on plant operations over time.

Neeraj Tiwari,
Director manufacturing JV organization at Fiat Chrysler China

"We have a centralized process for purchase of equipment, their subsystems, and associated software. This brings a level of standardization and makes integrating AI applications much easier and results in far fewer issues. Not only this, we are able to easily replicate the applications to new plants with a fraction of efforts, say 15 to 20% of the effort required for the first implementation. So, lessons learnt in continuous improvement drive are horizontally deployed."

Conclusion

AI has the potential to revolutionize manufacturing operations. However, while we find that major global manufacturers have started experimenting with AI use cases, scaled deployment is rare. Unless more organizations move from pilots and proofs-of-concept to scale, then a new 4.0 era in manufacturing will still remain an elusive goal. By adopting a scale-driven strategy – which focuses efforts on the most valuable use cases and lays down strong governance, platform and talent foundations – manufacturers can turn the revolutionary potential of AI into the next industrial revolution.

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Research Methodology

We interviewed over 30 senior executives from the manufacturing sector, drawn from the following segments:

1. Industrial manufacturing
2. Automotive
3. Consumer products
4. Aerospace & defense

These executives fulfilled one of four specific roles and all were involved with their organization's AI initiatives:

1. Department/function head in one or more manufacturing plant(s) e.g., maintenance, production, quality
2. Plant leadership (plant manager/director)
3. Director/VP operations (corporate/multi-country responsibility)
4. AI heads/ heads of innovation/ chief digital officers

We also conducted extensive secondary research, examining the AI initiatives being tested and implemented by the top 75 organizations in each of the four segments (by annual global revenue). We analyzed company websites, annual reports, press releases and articles, investor and media presentations, earnings calls transcripts, leadership interviews, as well as official social media information. Our aim was to enlist as many AI use case implementations as possible.

We found 102 AI implementations among these 300 organizations, with some having several implementations underway. We found that many of the 102 had significant similarities. We were therefore able to identify 22 unique use cases among them. These use cases belong to different functions – from demand planning to maintenance (see appendix for details).

Executives interviewed by designation

Chief Digital Officer/AI Heads

Head of Operations

Departmental Managers

Plant Managers
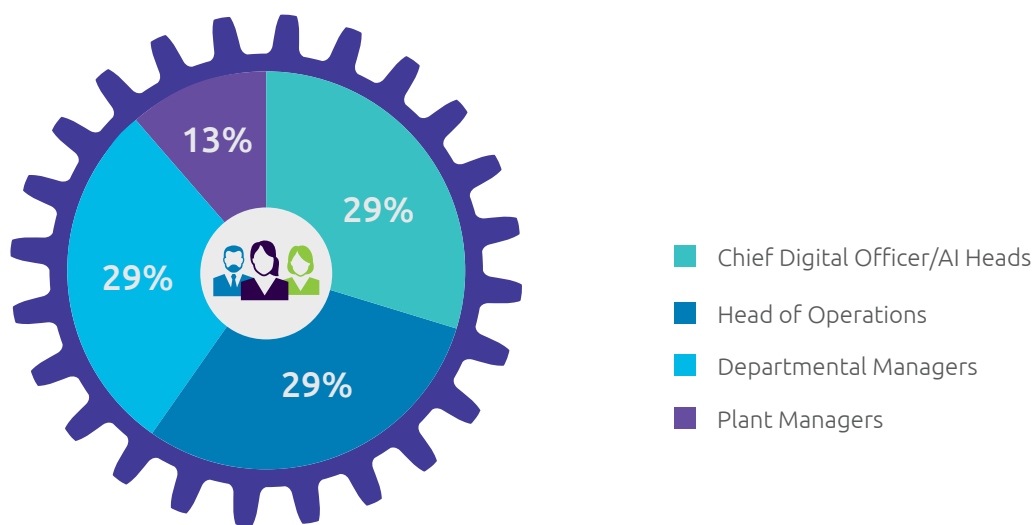
Appendix

All prominent AI use cases in manufacturing operations

Function	Use cases
Product development/R&D	• New product development • Product validation in R&D • Product enhancement
Demand Planning	• Demand planning/forecasting
Inventory Management	• Order optimization • Standardized communication with suppliers using NLP • Inventory planning
Process Control	• Real time-optimization of process parameters • Optimize equipment changeover
Production	• Optimizing overall productivity in the product line • Reduction in TAKT time • Computer vision for product identification • Layout planning • Collaborative robots (cobots)
Quality Control	• Product quality inspection • Predicting final product quality
Maintenance	• Intelligent maintenance • Energy management • Spotting anomalies in communications network • Worker safety • Scrap/wastage reduction • Increasing equipment efficiency

Most implemented use cases by sector

Automotive	**Product quality inspection**	The BMW Group uses AI to evaluate component images from its production line, allowing it to spot, in real time, deviations from the standard.[20]
	Intelligent maintenance	General Motors uses a computer vision system to analyze images from cameras mounted on assembly robots, to spot early indications of a failing robotic part. In the pilot phase, the system was mounted on 7,000 robots and was able to detect 72 instances of component failure. This helped them prevent massive potential downtime costs, which can reach at least $20,000 per minute for an organization of General Motors' size.
	Product validation	Nissan is in test phase of using AI to design its cars. To comply with new regulations (e.g., new safety specifications), AI is used to modify an existing car, while keeping in mind the knock-off effect of the modification.[21]
Consumer products	**Product enhancement**	Carlsberg has implemented a "Beer Fingerprinting" project, which is developing sensors that can differentiate between various flavours of beers. Today, no technology can effectively and quickly discriminate between flavors. Carlsberg processes the resulting data via AI and uses the information to develop new beers and enhance the quality of existing beers.[22]
	Product quality inspection	Canon is using AI in product quality. Its solution automatically identifies defects by analyzing images of the inspected parts.[23]
	New product development	Kellogg's has launched an AI system that helps customers decide which recipe should be chosen to make a product of their choice on their website Bear Naked. This technology helps the consumer giant come up with final products that the consumers actually want.[24]

Industrial Manufacturing	**Product quality inspection**	The process that Micron uses to produce memory technologies on its silicon wafers is highly complex and precise, with potential defects largely invisible to the human eye. As a result, there is a high potential for errors in the process. Micron spots any defects using computer vision, which has improved manufacturing efficiency and effectiveness.[25]
	Intelligent maintenance	Thales SA, a leading supplier of electronic systems to aerospace and defense companies, collects historic and current data on parts' failures. Drawing on the data, it has developed an AI algorithm to predict potential problems. This can be used to identify when parts might fail, allowing it to make proactive maintenance decisions for its customers. [26]
	Real time optimization of process parameters	Nokia launched a video application that uses machine learning to monitor an assembly line process in one of its factories in Oulu, Finland. It alerts the operator of inconsistencies in the process so that issues can be corrected in real time.[27]
Aerospace and Defense	**Intelligent maintenance**	Airbus is using AI to anticipate when its trimming machines are going to fail. Airbus uses this information to determine the root cause issue and plan maintenance, thereby avoiding expensive downtime.[28]
	Product quality inspection	Boeing is using computer vision for aircraft inspection. Ground crews scan various parts of an airplane with an augmented reality headset and other necessary hardware, capturing images. These images are then transmitted to a back-end processing platform where computer vision techniques are deployed to identify if certain abnormalities exist.[29]
	Real time optimization of process parameters	Bombardier has partnered with Aurora to strengthen its resource planning and scheduling using its AI enabled tools. As a result, Bombardier can schedule its airplane assembly operations more quickly and is able to handle production rate changes more effectively.[30]

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About the Capgemini Research Institute

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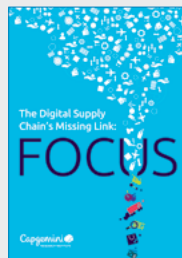

[Smart Factories @ Scale](#)

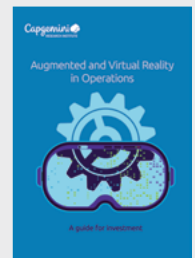[5G in industrial operations](#)

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Artificial intelligence has emerged as arguably the most debated, disruptive, and transformative business and technology trend facing today's enterprise. While the opportunities for material business performance improvement abound, the challenges to confidently realize the upsides and the multitude of risks along the way are far from insignificant.

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Perform AI

For Manufacturing

Manufacturing brings the power of Capgemini's Group's multi-disciplinary expertise to support our manufacturing clients as they invest in Industry 4.0, to secure and accelerate business outcomes. We lead through our expertise in Digital Engineering, Digital Manufacturing and AI technologies.

The goal is to move beyond traditional manufacturing techniques and accelerate the journey towards AI-powered intelligent operations. This involves making sense of the wealth of data produced by a connected factory, and implementing truly closed loop and ultimately autonomous operations. The Industry 4.0 ambition of self-optimizing manufacturing systems will require the systematic application of AI technologies and progressive transformation.
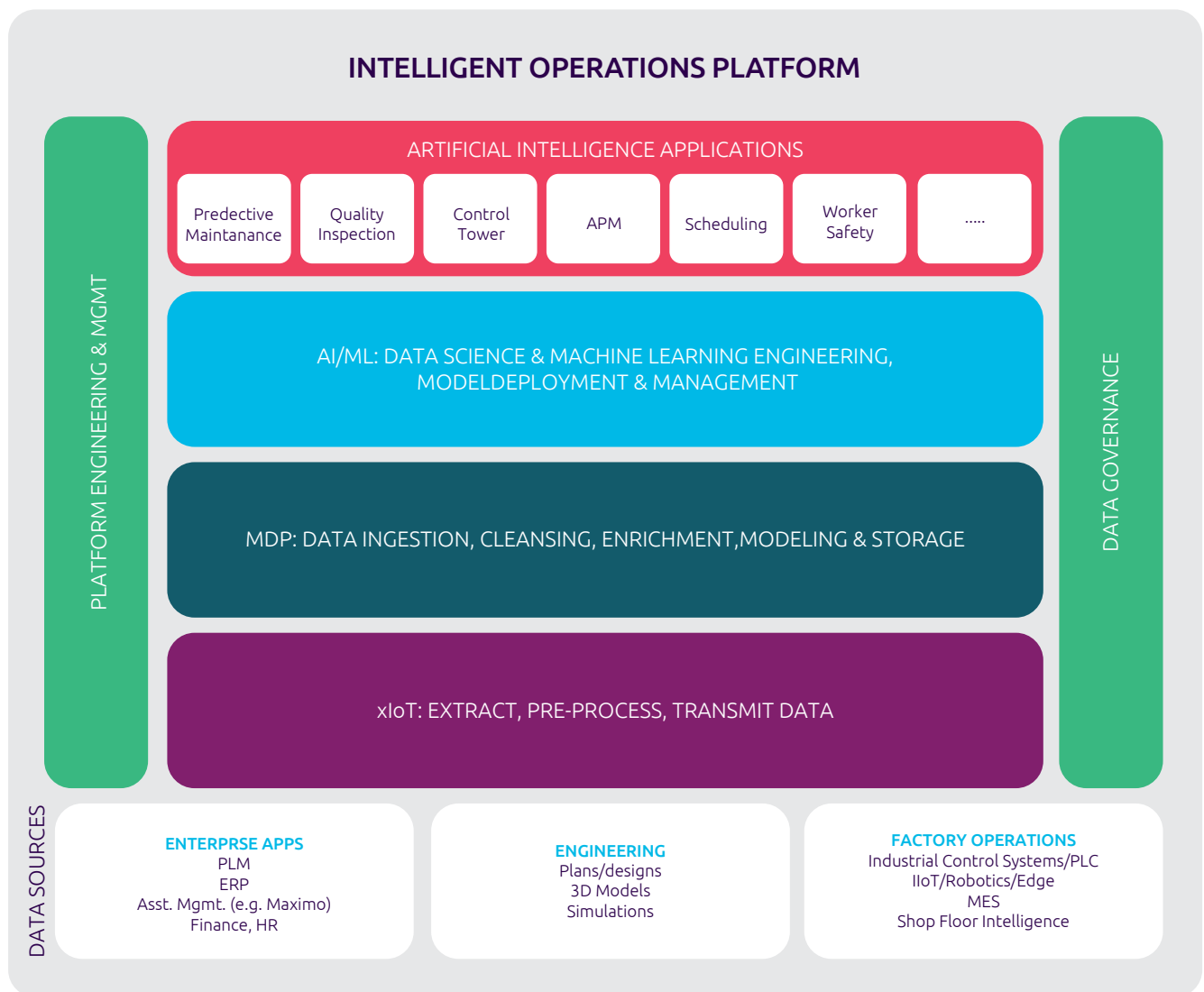
As we innovate with our clients, we are already seeing benefits like uptime improvement, productivity gain, reduced energy consumption, quality improvement, yield enhancement, and reduction in material wastage.

The ultimate goal of Capgemini's proven, gradual approach to Industry 4.0 implementation is AI-Powered Autonomous Operations.

Our Approach

Capgemini is pioneering new data centric and collaborative ways of designing, engineering, manufacturing and supporting products, assets and services – leveraging new technologies to create more value, what we call as the *Intelligent Industry.* For manufacturing operations, our approach seeks to address the Industry 4.0 implementation challenges and transition to autonomous operations – cost consciously, gradually, and with proven milestones.

Our approach binds a consulting led capability with cross-sector manufacturing process expertise and technology leadership to achieve this transformation to AI powered closed-loop operations and smart factory use cases. Digital continuity and data-centric digital thread is a pre-requisite for AI-powered closed-loop operations. Our offerings for AI in manufacturing are about applying AI to move from repeatable to transparent to optimized to autonomous operations, gradually.

INTELLIGENT OPERATIONS PLATFORM

PLATFORM ENGINEERING & MGMT

DATA GOVERNANCE

ARTIFICIAL INTELLIGENCE APPLICATIONS

Predective Maintanance	Quality Inspection	Control Tower	APM	Scheduling	Worker Safety	.....

AI/ML: DATA SCIENCE & MACHINE LEARNING ENGINEERING, MODELDEPLOYMENT & MANAGEMENT

MDP: DATA INGESTION, CLEANSING, ENRICHMENT,MODELING & STORAGE

xIoT: EXTRACT, PRE-PROCESS, TRANSMIT DATA

DATA SOURCES

ENTERPRSE APPS
PLM
ERP
Asst. Mgmt. (e.g. Maximo)
Finance, HR

ENGINEERING
Plans/designs
3D Models
Simulations

FACTORY OPERATIONS
Industrial Control Systems/PLC
IIoT/Robotics/Edge
MES
Shop Floor Intelligence

We support our clients at all stages of Industry 4.0 transformation:

- Initial AI pilots like machine-learning based predictive maintenance or visual inspection for quality, delivered in a few weeks thanks to accelerators, to experiment and mobilize the organization with early successes
- Industry 4.0 Advisory – advisory service to guide your transformation towards a platform-based Industry 4.0 Operating Model – people/process/technology
- Re-architecture of existing manufacturing systems, combining classical MES and AI-powered Intelligent Operations Platform, or improving Industrial Control Systems
- AI Use Cases Foundry to support deployment at scale of focused Intelligent Operations use cases, including development and transfer of supporting competencies.

For more details visit our webpage for Perform AI for Manufacturing

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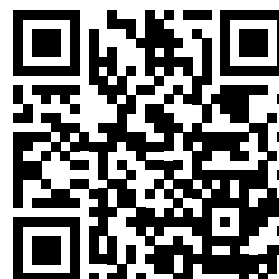
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