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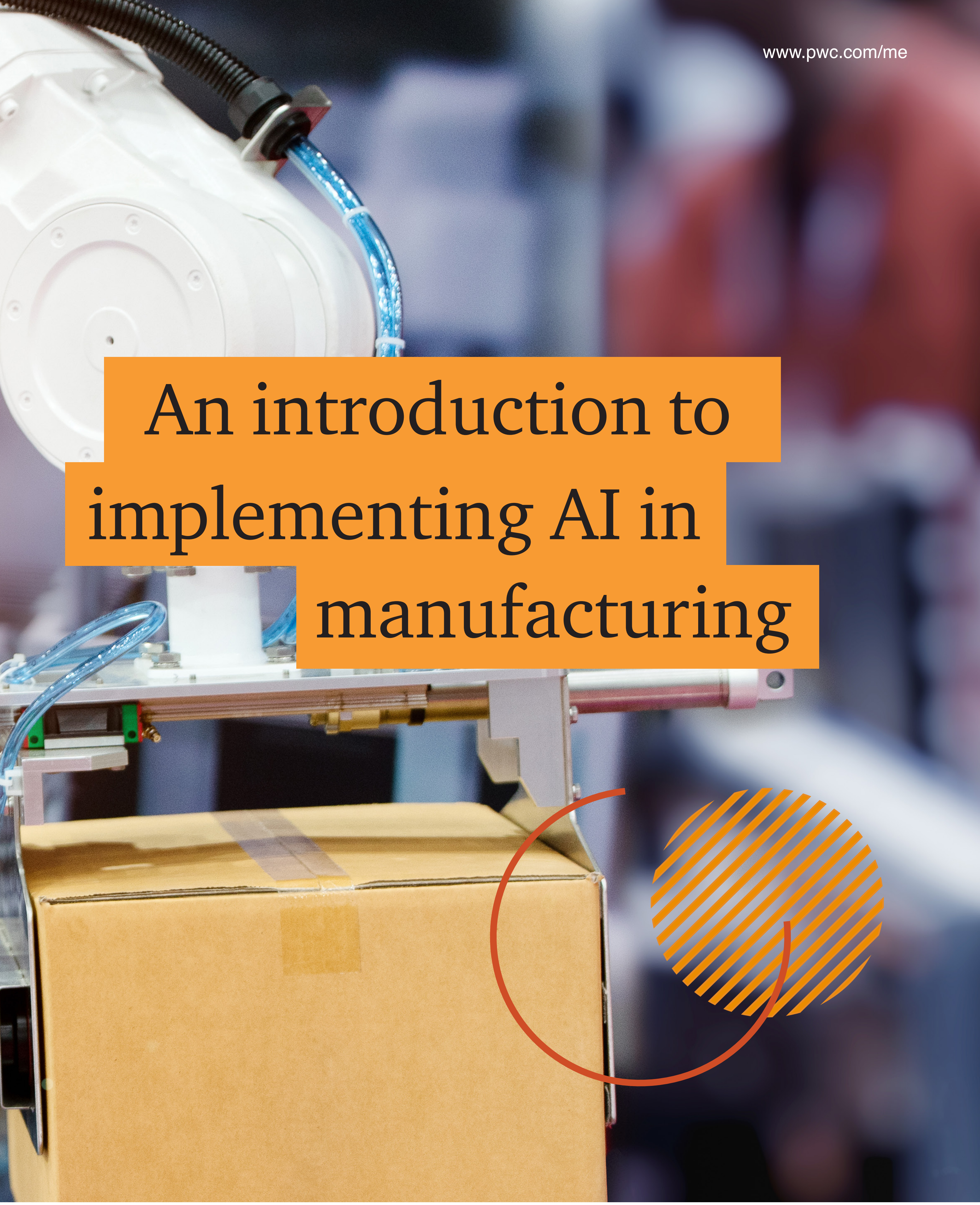

An introduction to implementing AI in manufacturing

pwc

GMIS | Global Manufacturing & Industrialisation Summit

Content page

Foreword

Artificial intelligence (AI) is gradually being implemented in almost every aspect of our lives. In medicine, geology, customer data analysis, autonomous vehicles and even art, its applications are everywhere and its uses are constantly evolving. However, AI has raised at least as many questions as it has answered, including how the technology is defined and used (assisted vs. augmented vs. autonomous intelligence, for example), whether computers are capable of thinking in the same way as humans (the so-called Turing test), the broader impact of automation on society, and the unanticipated ethical and moral dilemmas it may cause.

This white paper is the first in a global series on AI in manufacturing published by PwC, and is meant for executives in manufacturing and industrial companies who are looking to implement AI in their organisation. It focuses on the use of AI throughout the manufacturing value chain, including in production, testing and engineering. The aim is to address the business applications that can be supported by data, technology and automated processes, and how they are enabled by the right people, organisational structure and culture. We want to share recent developments, raise questions, pose challenges and bring cutting-edge research and ideas closer to industry.

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Foreword

From digital novices to digital champions: How AI can transform manufacturing

As we embark on a new decade, it is evident that the 2020s will shape up to be incredibly exciting for manufacturing as the digital world continues to transform – and, no doubt Artificial Intelligence (AI) will be at the heart of this transition.

For manufacturers, AI promises to be a game-changer at every level of the value chain. Direct automation, predictive maintenance, reduced downtime, 24/7 production, improved safety, lower operational costs, greater efficiency, quality control, and faster decision making are just some of the rewards on offer to organisations that embrace the transformation and master the implementation of AI throughout their entire business.

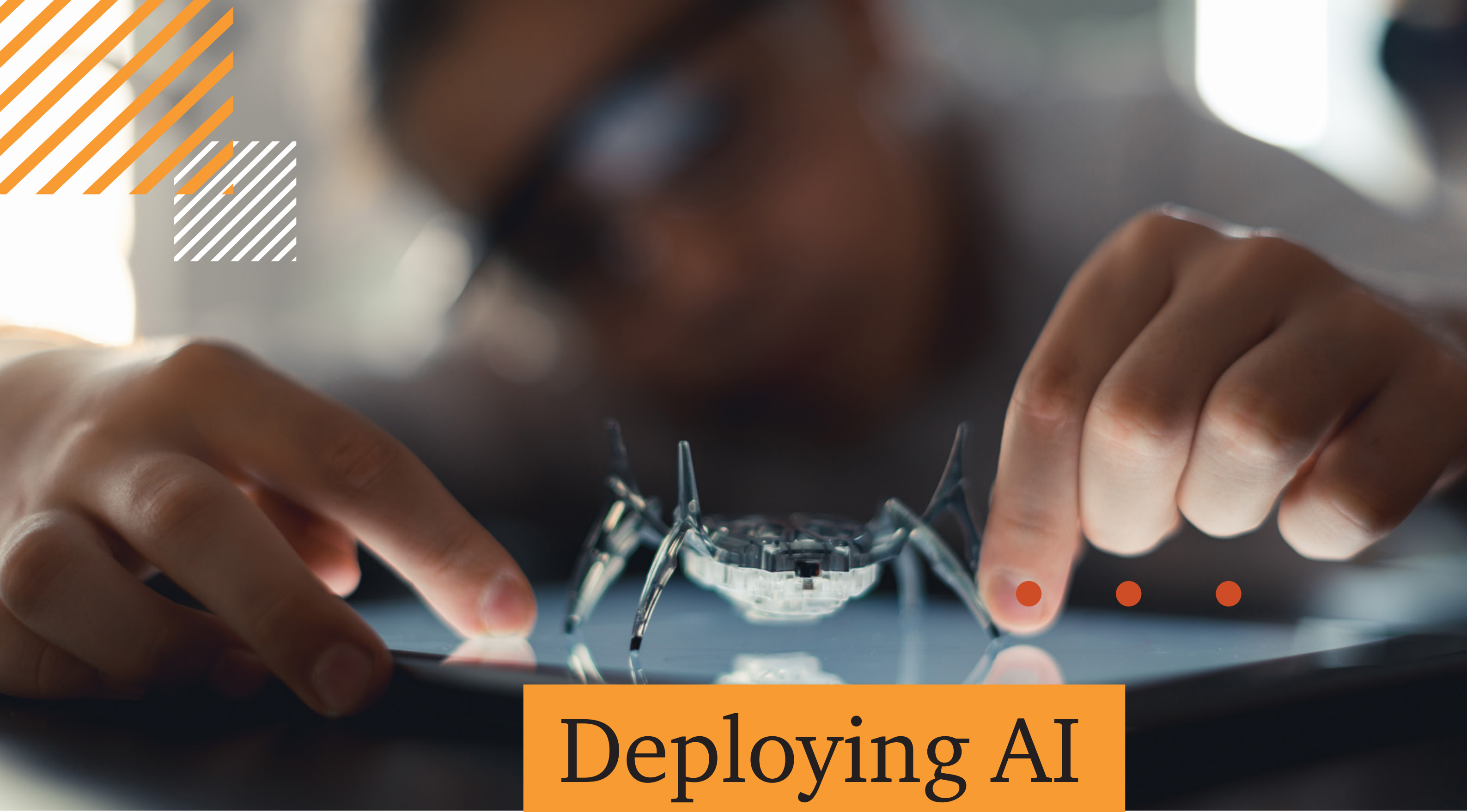
For those who have not yet made much progress with the adoption of AI, the good news is that it's not too late to start, nor are you alone. While manufacturing is often considered to be at the forefront of the application of new technologies, according to a PwC survey of manufacturing executives carried out across 26 countries in 2018, only 9% have implemented AI in their processes to improve operational decision-making. This is probably because the process of introducing AI is highly complex, time-consuming, and capital intensive, and requires a comprehensive, systematic approach if it is to prove successful.

Though it may be a daunting task, it is now widely accepted that every industry will be impacted dramatically by Artificial Intelligence (AI) within the next five years. Organisations and industries that embrace this technological revolution early on are going to reap huge benefits that will see them emerge ahead of their competitors, while companies that don't will risk losing their competitive edge.
The technology is now advancing so rapidly that organisations that don't make their move into AI soon will find themselves falling behind before they realise it.

This message on AI and 4IR technologies was one of the many that were stressed upon during the series of over 40 high-level panel discussions that took place at the second edition of the Global Manufacturing and Industrialisation Summit (GMIS) in July 2019 in Yekaterinburg, Russia. The Summit gathered over 3,000 visitors from all over the world to hear more than 80 leading experts drawn from government, industry, technology, finance, and academia to discuss and debate how the manufacturing sector can harness the power of AI and all other forms of Fourth Industrial Revolution technology to drive its development in the coming years. Exploring the opportunities and challenges that arise as the Fourth Industrial Revolution unfolds and plotting a path forward for the sector is at the heart of what the Global Manufacturing and Industrialisation Summit aims to achieve.

In a similar way, this report by PwC, 'AI in Manufacturing: Assessing the scale of opportunity' offers essential guidance for executives working in the manufacturing space who are looking to implement AI in their organisation, with a focus on the use of AI throughout the manufacturing value chain. Inevitably, one of the most influential factors in AI adoption is a company's overall progress in digitising its operations. By first assessing their current stage of progress, companies can take the next step in the transition from being digital novices to digital champions, and in the process play a part in the transformation of the manufacturing sector.

Badr Al-Olama
Global Manufacturing and
Industrialisation Summit (GMIS)



Deploying AI at scale

A glimpse into the future of manufacturing can be found at FANUC's plant in Oshino, Japan. Here, at one of the largest manufacturers of industrial robots in the world, the robots build, inspect and test themselves.

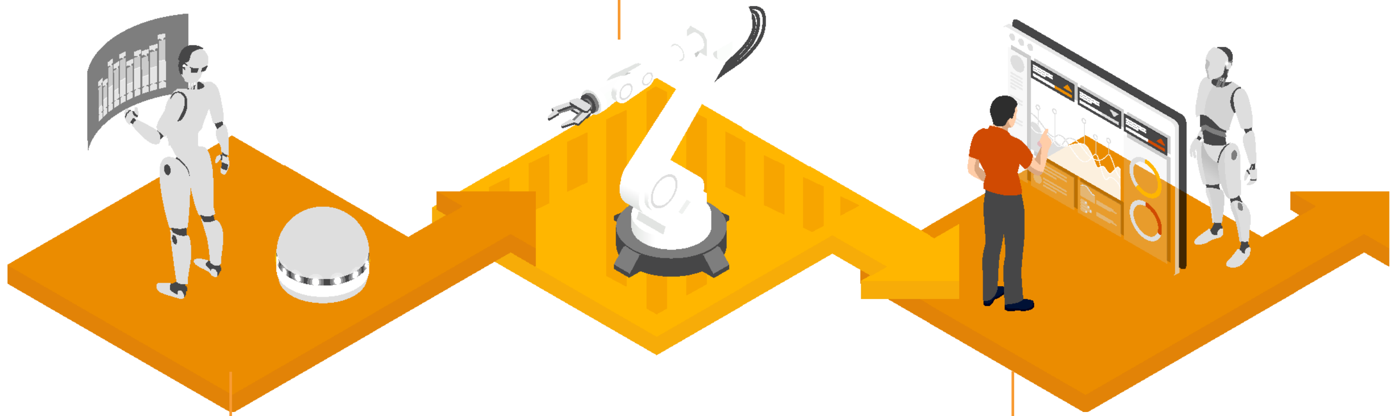
FANUC's complex of 22 sub-factories is significantly advanced. It is in fact the world's first factory complex with robots that create digitised "offspring" capable of machine learning and operates on a 24 hour basis. The company demonstrates just how far the use of AI in manufacturing processes has come since the 1960s, when 'Unimate', the first mass-produced industrial robot arm, joined the assembly line at General Motors, lifting hot pieces of metal and placing them in cooling liquid.

While FANUC exemplifies an AI-led future, many manufacturers today still struggle to deploy the technology at scale. In fact, a 2018 PwC Global Digital Operations study of 1,155 manufacturing executives across 26 countries showed that only 9% have implemented AI in their processes to improve operational decision-making[1]. So before we examine the applications and benefits of AI in manufacturing, we must examine what AI is, its potential and what drives its adoption.

> "Only **9%** of manufacturing executives have implemented AI

What is the potential of AI?

Simply put, AI is the simulation of human intelligence processes by computer systems[2]. Later in this paper we will look in more detail at the four main types of AI: assisted intelligence, augmented intelligence, autonomous intelligence and automation. Since the Industrial Revolution, factories have been rapidly and inexpensively mass-producing products to satisfy demand. However, manufacturers today are confronted with a wave of new challenges including:



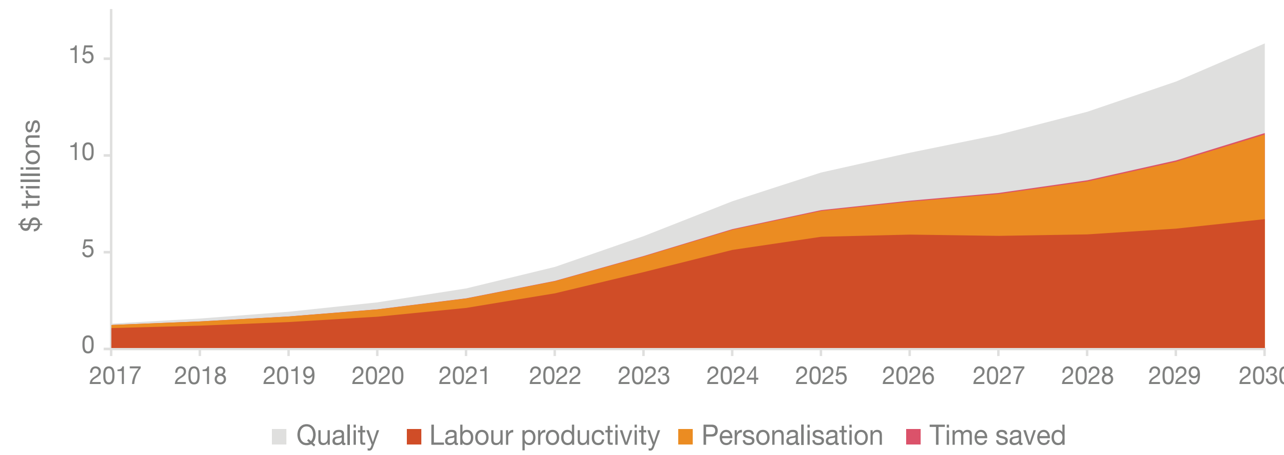
In addition, manufacturers are still contending with the problems they have always faced: higher production costs, equipment failure, and bottlenecks in the supply chain.

AI is helping to address some, if not all, of the above issues. PwC's AI analysis in 2017, *Sizing the prize – What's the real value of AI for your business and how can you capitalise*, showed that global economic output, as measured by gross domestic product (GDP), could be 14% higher in 2030 than baseline projections of $114 trillion, as a result of the expected growth of AI. This translates to an additional $15.7 trillion[3] (Figure 1).

The economic benefits of AI will be primarily the result of:

- Productivity gains from businesses that automate processes and augment the work of their existing labour force with different types of AI technologies.
- Increased consumer demand, resulting from the availability of personalised and/or higher-quality digital and AI-enhanced products and services.

Figure 1: How AI could contribute to additional global GDP growth

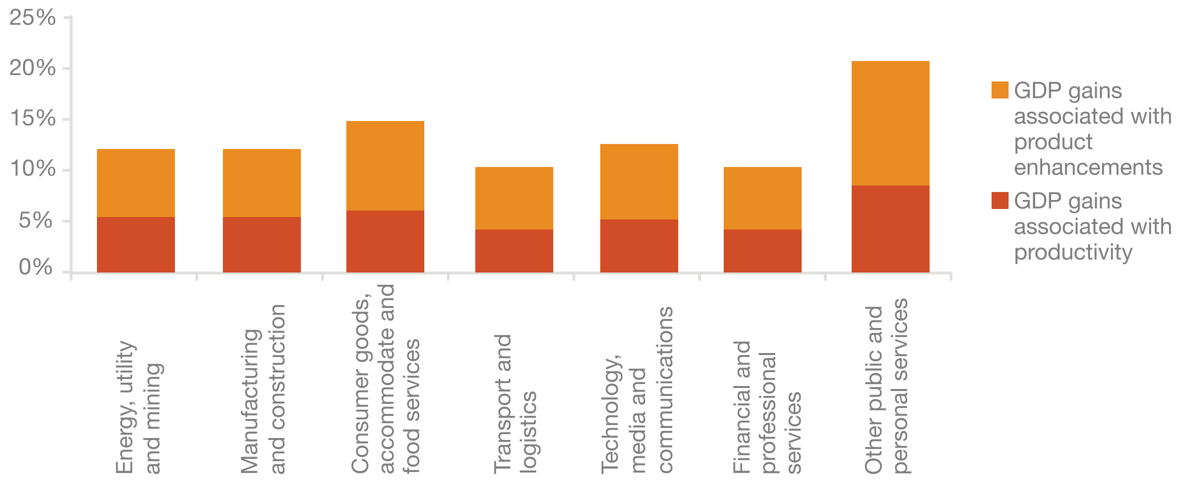


Source: PwC analysis

Potential by sector

Since the manufacturing and construction industries are capital intensive by nature, the adoption of AI applications may increase the sectors' contribution to GDP gains by more than 10% by 2030 (Figure 2).

Figure 2: GDP gains in 2030 resulting from AI by industry sector (% of GDP)

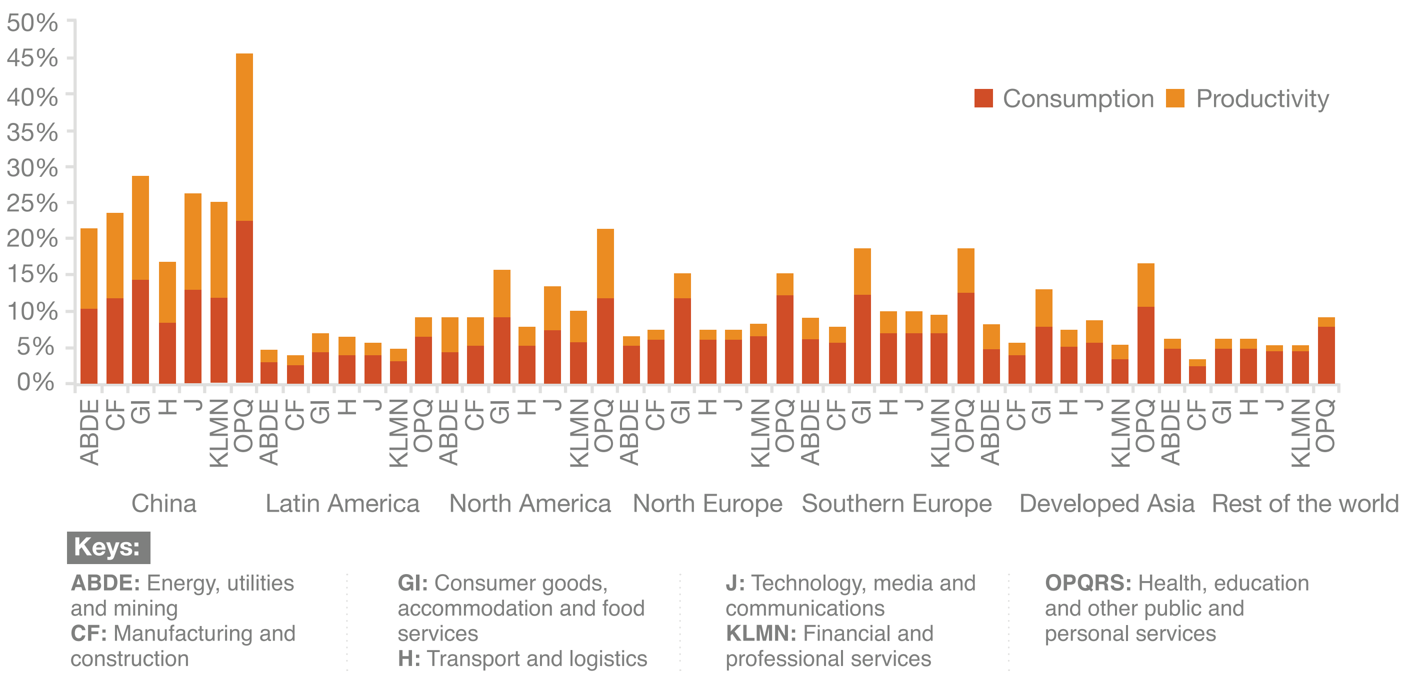


Source: PwC analysis

Potential by country

When we looked at the forecast GDP impact by country, we found that China is expected to experience a GDP impact of $2.5 trillion, the largest absolute GDP gain as a result of AI. This is largely due to the size of the country's manufacturing industry, as well as the significant emphasis China is placing on developing AI[4].

Figure 3: GDP impact from AI in 2030 by industry, region and channel of impact (% of GDP)

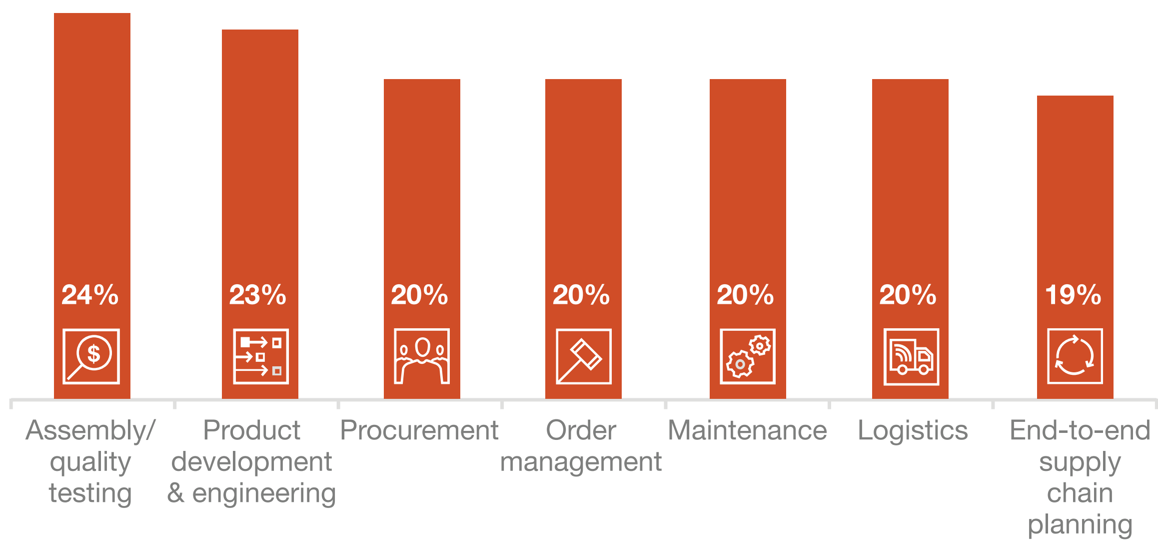


Source: PwC analysis

Potential within manufacturing organisations

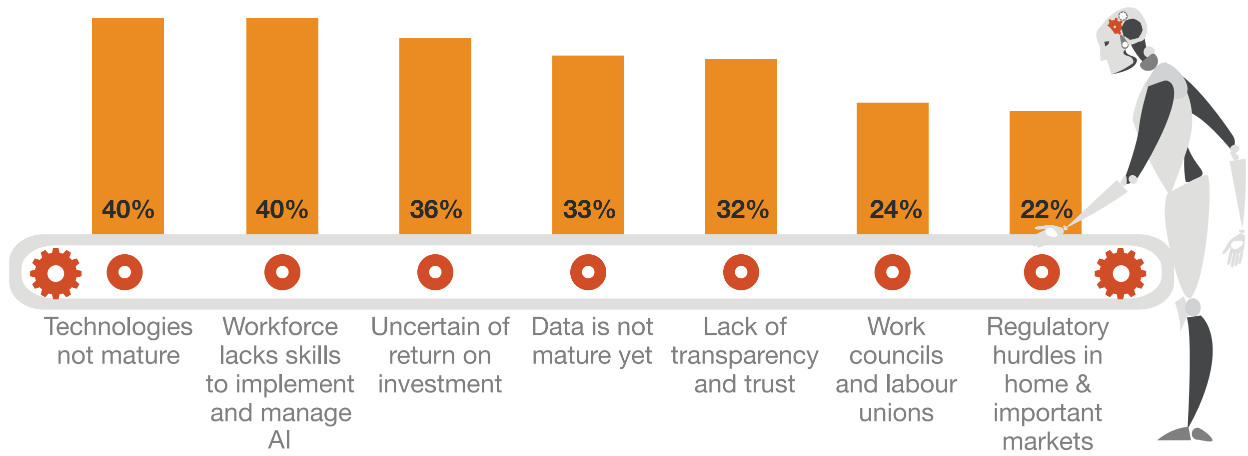
Figure 4 shows where AI capabilities are currently being used within manufacturing companies[5]. While the technology has been implemented throughout the key parts of the business, companies have put slightly more focus on adding AI solutions to their core production processes: product development, engineering, and assembly and quality testing.

Figure 4: AI implementation in manufacturing functions



The core use cases for AI in manufacturing are becoming clearer as companies learn to better quantify the value of the technology. However, PwC research has shown that uncertainty around return on investment (ROI) remains one of the major challenges to implementing it more widely[6]. As Figure 5 shows, many companies also struggle with collecting and supplying the data that an AI system needs to operate, and lack people in their workforce with the right skills to implement AI at scale.

Figure 5: Challenges for manufacturing companies with implementing AI at scale



Inevitably, one of the most influential factors in AI adoption is a company's overall progress in digitising its operations. The organisations that have made the most progress in digitising core business processes also lead on AI adoption. In the Global Digital Operations study, PwC ranked companies by digital maturity and grouped them into four categories: digital novices, digital followers, digital innovators and digital champions[7]. The study showed that 69% of digital champions have implemented, piloted or plan to use AI within their business, compared to 10% of digital novices.

Four different stages of digital maturity

Digital champions

The enterprise has a clear strategic position in the marketplace with complex and tailored customer solutions, offered via multilevel customer interactions. These companies have implemented near-real-time end-to-end integration and connectivity of their value chain across internal and external networks. These companies know how to leverage technology to connect customers, partners, operations and people to create value through ecosystems in new ways. Digital champions have built a digital culture by establishing new ways of working and making substantial investments in training, sourcing and developing new capabilities and skills.

Digital followers

Internal functions such as sales, manufacturing, sourcing and engineering are integrated and collaborate closely. But there is little activity beyond vertical digital integration within the company. The culture and workforce at these companies are not yet digitally oriented.

Digital innovators

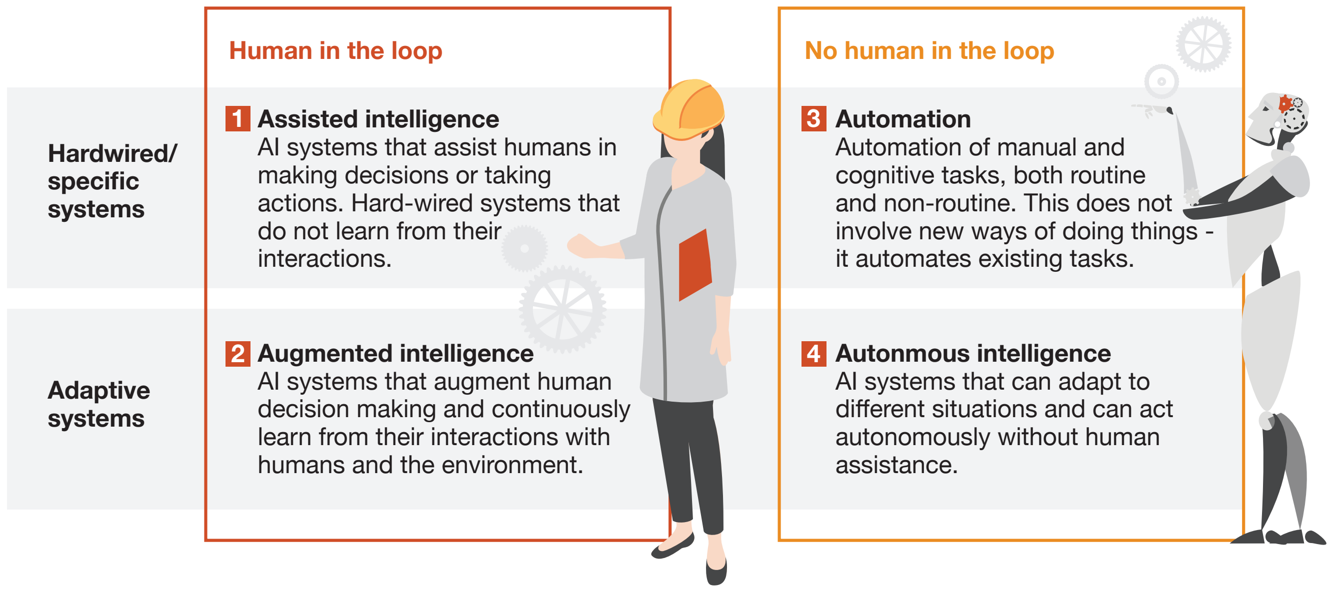
The enterprise is digitally connected to external partners and customers, using integrated platforms for information exchange and collaboration. But the horizontal digitisation is limited to the immediate supply chain, with no wider ecosystem for customer solutions, technology or people. Digital innovators prize digitisation and encourage the workforce to help identify new digital solutions, but their advances are limited in scope.

Digital novices

The company employs some isolated digital solutions and applications, but these exist at the functional or departmental level within the organisation.

For manufacturing companies considering introducing AI into their processes, it is important to define their goal from the outset: are they seeking to automate repetitive tasks or are they fundamentally changing the nature of work in their factories by having humans and machines collaborate with each other to make decisions? In our view, the following four types of AI[8] are in existence today:

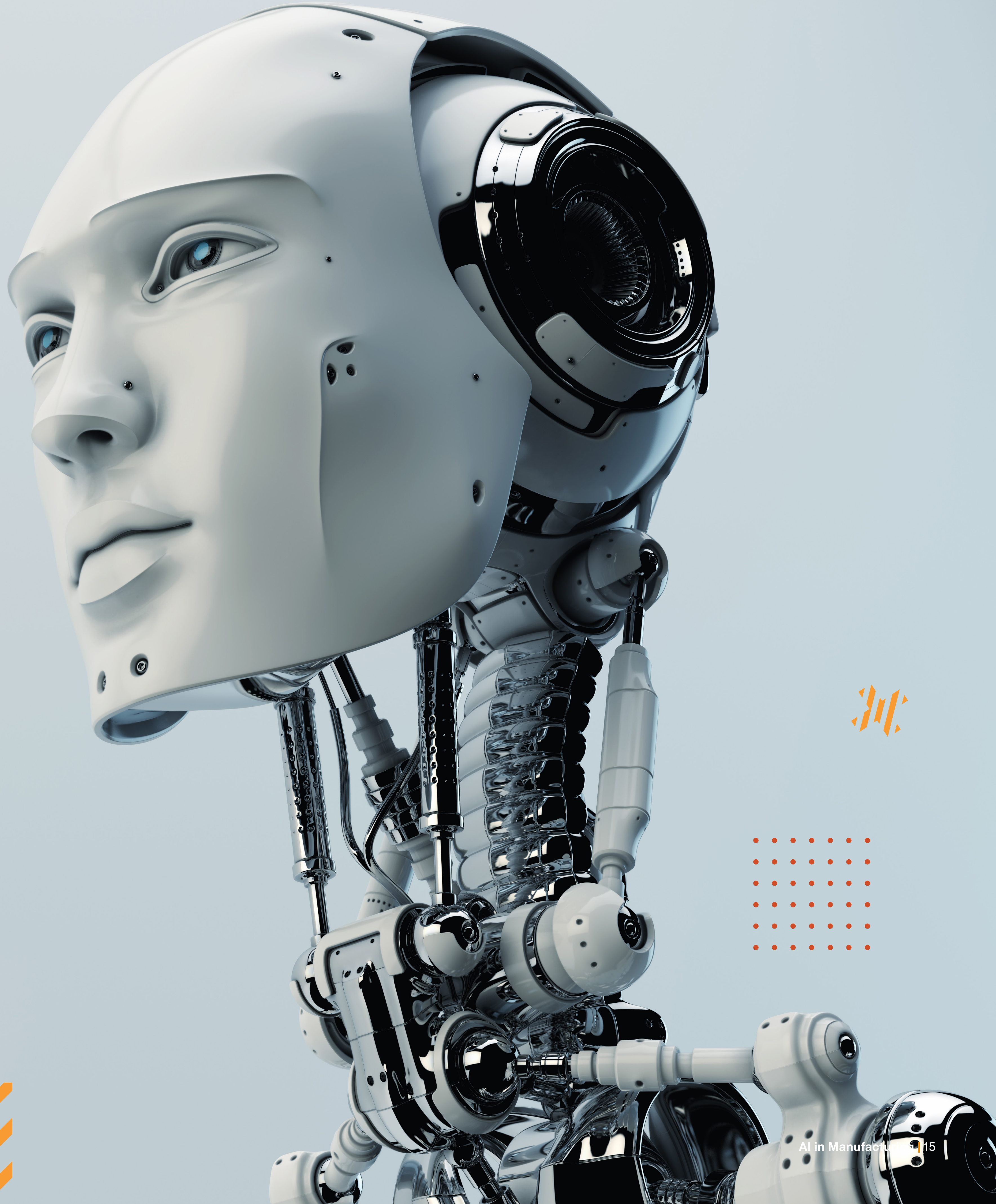
Figure 6: The four types of AI



Of course, companies may want to use different levels of automation and machine learning for different tasks. A step-by-step approach, i.e. starting with a ‘human-in-the-loop’ system and moving to a fully autonomous process, can be important for building up trust in the data and algorithms, and ultimately drive higher adoption of AI solutions throughout the organisation.

Implementing AI in the real world

In this section, we will look in detail at two companies PwC has worked with to implement AI in their manufacturing processes. Both examples started with augmented intelligence solutions and have now moved on to autonomous intelligence. In the future, we believe that the level of automation and machine learning will evolve further.



Case Study 1: 3B-Fibreglass

3B-Fibreglass (3B) is a developer and supplier of glass-fiber products and technologies to reinforce thermoplastic and thermoset polymers, which are used by the automotive and wind-power industries, and in high-performance composite materials. It operates three state-of-the-art manufacturing facilities located in Battice (Belgium), Birkeland (Norway) and Goa (India).

3B's manufacturing process consists of a hot phase and a cold phase. In the hot phase, silica sand, limestone, kaolin clay and a range of additives are melted and heated up to a temperature of approximately 1,400°C to create glass. The glass remains in the furnace for a highly variable amount of time - the first molecules leave the furnace after a couple of hours and some molecules remain for several days.

From the furnace, the stream of molten glass is guided through channels to bushings. These are plates made of precious-metal alloy, with anywhere from 4,000 to 6,000 very fine holes. To make glass fiber, the molten glass passes through the holes (each of which is typically just 9-25 micrometers in diameter) and comes out as fine filaments.

Every furnace feeds a couple of dozen bushings. As the molten glass passes out through the holes, a pulling force is applied to it, lengthening and thinning the fibers. As soon as the fiber leaves the bushing, the temperature drops instantly to room temperature over a distance of less than a meter.

Problem solving with AI: Identifying a break before it happens

A major source of inefficiency in the production of glass fiber is fibers breaking when the pulling force is applied. 3B used AI to gain insight into what was causing the breakages and to act on the results.

When a single fiber breaks, it triggers a domino effect in which all the fibers going through the bushing knit together and the entire flow stops. The quicker an operator can repair this situation, the easier it is to fix and efficiency losses are minimised.

A set-up was created in which a camera constantly monitored the flow of the fibers as they left a bushing. A deep-learning 'computer vision' network then analysed the data.

In the first phase of the analysis the goal was for the AI to identify a break, which alerted an operator that a problem had occurred on a particular bushing.

In the second phase, the system had to predict that a break was about to happen, on average 75 seconds in advance (ranging between 65 and 85 seconds). The system also indicated where the problem occurred, allowing further investigations into the root cause.

Better visibility into the manufacturing process

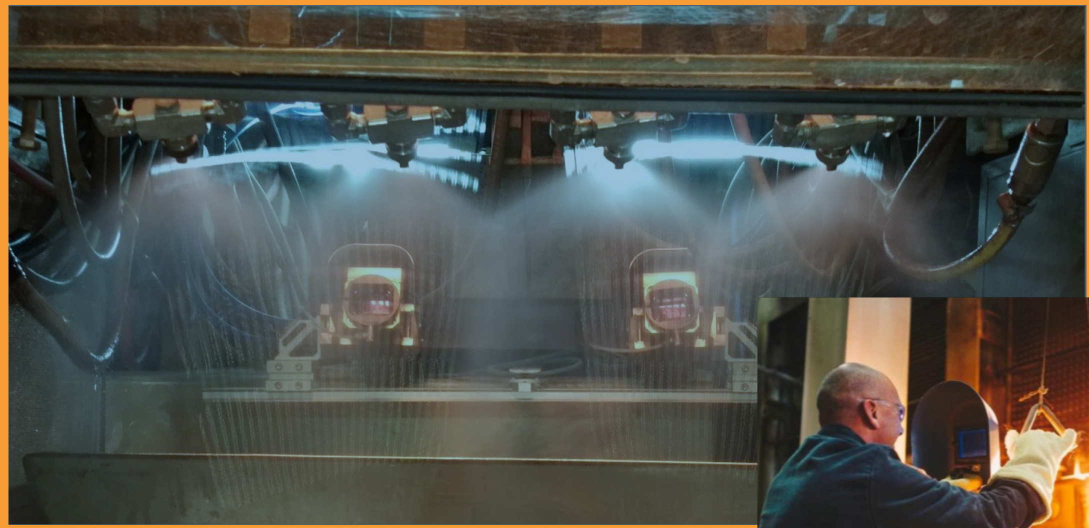
Improved overall efficiency & Overall Equipment Effectiveness (OEE)

Root-cause analysis: Initial investigations indicated that the system knew that a break was going to happen. Using sensors (mainly monitoring thermocouples, electrical currents and gas flow), 3B collected process information from within the furnace, channels and close to the bushings, which could be used to help explain what triggered breaks. Three years of data was analysed from hundreds of sensors, trying to make a link. Upon using a wide range of techniques, it appeared that:

- There was a common cause behind the breaks which was anything that influenced the structure of the glass.
- Time-series analysis indicated that break behavior was strongly auto-correlated - that is to say, a high break level in one time slot was likely to result in high break levels in the subsequent time slots. Autoregressive Integrated Moving Average Models (ARIMA) appeared to perform very well on the timeline.
- However, adding exogenous information from the sensors did not improve the forecast quality, nor did it entirely explain the observed patterns.

3B's experience proves that AI can add significant value in a manufacturing setting. It also proves that results do not always come easily: in this case, the computer-vision analysis was very successful, illustrating the power of deep-learning algorithms capable of making predictions that a human cannot. However, the root-cause analysis was more limited in its achievement.

One reason for this is that AI teams can only draw conclusions when the right data is included in the dataset. At 3B, very often the data was initially generated for overall process monitoring, not to have machine-learning algorithms applied to it.



Case Study 2:
ZF Friedrichshafen

ZF Friedrichshafen AG (ZF) is a leading supplier to the automotive industry worldwide, with more than 230 locations and almost 150,000 employees. ZF recently enhanced its AI activities by establishing its own technology center for AI[9] and expanding its partnership with Microsoft to establish one of the most comprehensive digital cloud platforms in the automotive industry[10]. These strategic initiatives are helping ZF to achieve 'Vision Zero', a future for mobility with zero accidents and emissions.

ZF is using AI in manufacturing to automate and optimise processes, in order to improve its production output and quality. These are two examples of how the company is using AI to improve gearbox production at its plant in Saarbrücken, Germany.

Predictive maintenance for gear-part production machines

- Improved Overall Equipment Effectiveness (OEE)
- Better understanding of the production process and equipment performance

Example 1: Predictive maintenance for gear-part production machines

Honing is a process that finishes an automotive gear's surface to specific dimensions. A honed gear produces minimal noise in a transmission, provides a high threshold for wear and tear and operates smoothly. In the ZF facility, honing gears is an essential process in the production of quality gear parts.

In a honing machine, the honing ring experiences wear and tear and is eventually replaced just before the end of its lifetime, to prevent it fracturing during operations. If the honing ring fractures earlier than expected, it not only damages gear parts severely, but also results in unplanned production downtime that impacts the level of overall equipment effectiveness (OEE). OEE measures how close factories are to perfect production – i.e. manufacturing only good-quality products, as fast as possible, with no stoppages.
For the company, a negative impact on OEE means availability loss, performance loss and quality loss. To tackle such negative impacts, ZF aimed to predict the fracture of the honing ring using data from vibration sensors. However, gathering, storing and analysing data were bigger challenges than anticipated because:

- Data had to be collected from multiple honing machines
- Sensors had a wide range of frequencies creating a lot of values for each measurement. This kind of dataset is hard to analyse using traditional methods
- There were significant data-storage requirements because sensors measure in milliseconds

ZF employed preliminary data-preparation steps before applying AI algorithms to predict the probability of the honing ring failing, in order to improve data quality and usability. As typically seen in the field of data science, data preparation was the most time-consuming part of the project, but paid off later when applying predictive algorithms. The time-series data first needed to be prepared by using missing value imputation, applying a rolling window, labeling each time window into 'fracture' and 'no fracture' and then extracting meaningful features from the prepared time series. In the next feature engineering step, individual attributes were analysed for anomalies. For attributes with high variance in the measurements, trends over time were computed using linear regression models and the number and level of top and bottom outliers were analysed using density-based models such as DBSCAN. Finally, attributes with very low variance were discarded in order to reduce data dimensionality.

Next, the data was transformed using the fast-fourrier method to analyse measurements across the entire frequency spectrum, with additional statistical features examined based on the fourrier-transformed data. On the basis of all these extracted features, supervised machine-learning algorithms could be applied for binary classification, i.e. to predict probabilities for 'fracture' and 'no fracture'. Various algorithms such as support vector machines, random forest decision trees and artificial neural networks, were applied to train prediction models based on historical data and to test their accuracy based on cross-validation methods. A random forest model showed the best predictive performance, with the strongest single predictor being the kurtosis of the fourrier-transformed data. The AI solution that was developed was capable of accurately detecting 99% of tool fractures.

Example 2: Smart end-of-line testing in gearbox production

At ZF, end-of-line (EoL) testing is a process that ensures the highest quality gearboxes are produced. The EoL testbench measures the gearbox's behavior using different sensors, including pressure, temperature, vibration and sound, for which EoL experts have defined thresholds using a complex manual process. The EoL testbench operator was notified that a threshold had been exceeded in a failed test run and then addressed the problem based on his or her personal experience. However AI-enabled assistance systems that support the decisions of testbench operators and rework personnel can significantly improve the efficiency of machine hours, working time and material consumption.

ZF sought to improve its EoL process with a Big Data approach, i.e. using all available measurement data instead of only the first exceeded threshold. This was complemented by automating the process using AI to reduce human misjudgment.

To identify patterns for rejected gearboxes using AI solutions the following steps were taken:

- Aggregating millions of measurement points from the EoL testbench to relevant features
- Reducing the number of features using dimensionality reduction methods like PCA and tSNE
- Analysing the data using machine-learning clustering algorithms such as DBSCAN or k-Means

The results from the algorithms were presented to EoL experts, combined with historical data on rework actions taken and their results. This allowed the EoL experts to assess the consistency of each cluster, based on error profiles and rework actions. For every consistent cluster, a label was applied so that supervised machine-learning algorithms can be trained to predict the specific label class.

Afterwards, using an automated hyperparameter tuning process, a variety of multiclass-classification models with optimised parameters were trained to find the best configuration for accurately predicting error classes and related rework actions. The best-performing model was both accurate and fast enough to allow real-time predictions for rework recommendations on the testbenches. The model was embedded into an end-to-end IT solution that enabled reliable daily operations with the AI solution on the shop floor. This augmented-intelligence solution enabled ZF to significantly enhance the EoL process, with potentially millions of euros saved per year.

Today, ZF still wants the EoL expert to be in the loop and manually validate whether clusters are consistent and rework recommendations are correct. In the future, this process can be fully automated, with the AI automatically and autonomously learning new patterns and connections between error profiles and rework recommendations.

The foundations of scalable AI

These examples are just two of many AI use cases that exist across ZF's multiple plants and divisions. However, in line with the main challenges for implementing AI at scale (Figure 5), ZF has realised it needs to put in place the foundations for scalable technology and a skilled workforce for AI.

The company is currently building a central 'data lake' and an enterprise platform for advanced analytics and AI, to solve the increasing challenges of Big Data and enable various AI use cases. To allow fast and scalable data processing, as well as the integration of the latest innovative AI algorithms, AI solutions are being developed based on open-source Big Data management technology and machine-learning libraries.

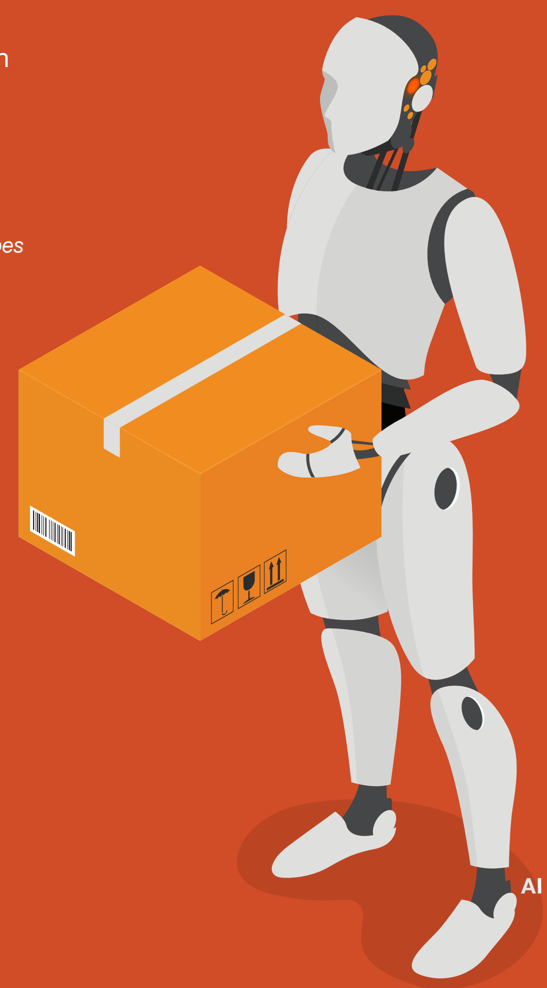
Today, most of ZF's manufacturing data and systems reside on-premises. Over the coming years, most of them are expected to move into cloud-based systems. To prepare for this future scenario and cover the current needs of AI use cases in manufacturing, ZF is implementing a hybrid platform with some systems stored on-premises and others in the cloud. This is built on a similar technology and architecture for smooth transition between both worlds.

In addition, ZF is also enhancing its workforce with the right analytics talent. It started by setting up a central analytics lab within its IT innovation department, to provide guidance around data-science topics and accelerate the development of analytics and AI use cases across ZF. The central analytics lab followed a clear prioritisation process to focus on high-impact business problems.
After conducting the first pilot projects in the central analytics lab, ZF realised that it had to add decentralised analytics teams to be closer to the business domains and better address their specific needs. The company set up multiple analytics teams for specific domains, including one focused on manufacturing. This team now works hand-in-hand with production and quality experts and receives support from the central analytics team where needed - for example, providing guidance on how to use specific components of the new platform. In addition to the central and decentralised analytics teams, executive support and external partners providing their outside-in perspective were critical success factors for ZF.

— Based on information from ZF Friedrichshafen AG, which does not necessarily reflect PwC's opinion.

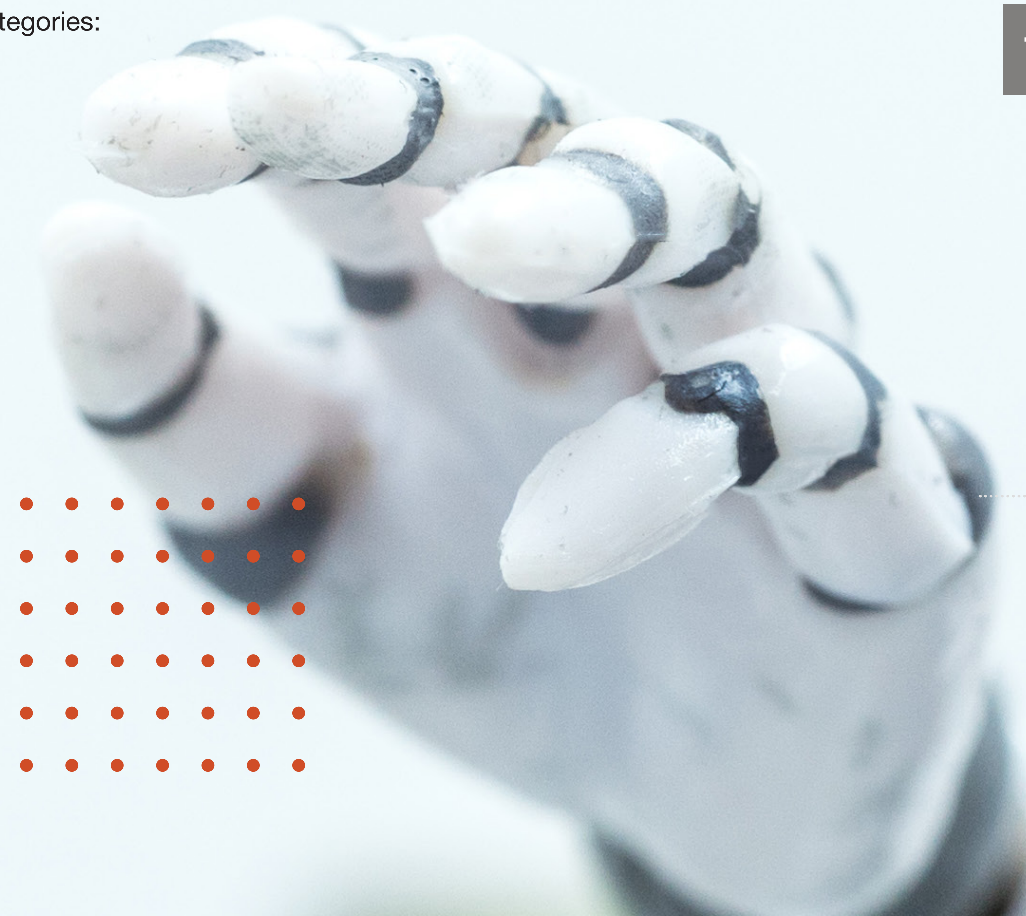
Smart end-of-line testing in gearbox production

- Higher efficiencies in rework
- Reduced costs
- Better understanding of product failures



Six building blocks for successfully implementing AI

Manufacturing companies such as ZF show that to take a lead in using AI solutions at scale, specific technological investments and organisational decisions are required. In this section, we look at the necessary business, technical and organisational changes that will form the basis of successful AI implementation. These fall into six categories:



Business Applications

What are you using analytics for?

- Identification and prioritisation of the core business use cases
- Multi-departmental lenses
- Make use of available data

Talent and organisation

Do you have the right skills and structure?

- Data scientists
- IT specialists
- Business analytics translators
- UX designers
- Center of competence / shared services
- Chief Data Officer
- Advisors & start-ups

Data

Do you have access to the right data?

- Single source of truth
- Data quality handling
- External data sources and services
- Unstructured data extraction
- Real-time data processing
- Data dictionatries

Process

Are your business processes optimal?

- Data democratisation
- Data governance (security, privacy etc.)
- Knowledge exchange
- Collaboration
- Agile development

Technology

Do you have the systems and tools?

- Central data platforms
- Cloud services
- Big Data architecture
- Open source tools
- IoT connectivity
- Machine Learning (ML) / AI
- User Interface (UI)

Culture

How can you build a data-driven culture?

- Experimentation mind-set
- Data-driven decision-making
- Adoption of analytics tools
- Trust in data and algorithms

- Business
- Technical
- Organisational

1. Business applications

Business applications must be the starting point for an AI strategy. Manufacturers need to ask themselves where they want to use AI in the near, mid and long term, and gather all the use cases across their operations in a structured way, grouping them together by function and prioritising projects based on expected business outcomes and effort of implementation. This helps to identify potential pilot and 'lighthouse' use cases to lead the way in the company's AI plans. Such early and high-profile use cases are a key success factor, because they help to drive adoption of AI across the business. Once the overall vision and specific use cases have been established, the technology and organisational requirements will follow on.

Insights from the field

> To create value with AI, 3B is not only aiming for the low-hanging fruit, but also the problems with larger value potential. Addressing these helps to convince leaders about the value of AI.
>
> Dimitri Laurent, Global Operations Director and Glass Science and Technology leader at 3B

> Think big but start small. You have to think about what it means to scale and adopt something across the entire enterprise. Building showcases helps to create awareness and prove the value, to get more people on board.
>
> Georg Gabelmann, Data Science Manager, IT Innovation at ZF

2. Data

Data is the foundation of any AI endeavor. As a result, reliable and accurate data acquisition, management and governance are key to effectively applying AI algorithms to the company's processes. Sensor data from connected factory equipment is a key data source in the manufacturing sector, so the production line and factories play a critical role in the data-acquisition process. Many enterprises are building 'data lakes' to collect raw data from sensors, Manufacturing Execution Systems (MES), maintenance processes and quality checks in one central place. They are also enriching it with external data to get a 360° view of both their production process and the product.

These large data-management systems require proper data cataloging and data lineage to keep track of all available information and flows, and to make the data easily accessible to a large number of users. Manufacturers should start by mapping their main data objects, such as production facilities, machinery and products, and the associated data sources to understand the data volumes, velocities and varieties they will be dealing with. Furthermore, they need to define data quality metrics and systematically monitor these to create awareness of their importance, which is often a major challenge for implementing AI.

Insights from the field

> AI isn't a kind of magic that works by throwing data into algorithms. You need to get your data right; the amount and quality of data is key, so companies must keep track of all the details when collecting and aggregating it.
>
> Dimitri Laurent, 3B

3. Technology

Technology for Big Data, Analytics and AI is still rapidly evolving, often causing uncertainty for companies around what their future IT architecture should look like, and which tools and vendors they should choose. Manufacturers should start using a 'functional reference architecture', which maps which tools the company needs to gather, store, manage and process data, as well as the necessary analytics and visualisation tools. Based on this functional architecture, they can define their requirements for an evaluation of the most suitable technologies available in the market and also set out the technical and infrastructure set-up they want to use.

Some open-source technologies have become the de-facto standards for Big Data management (these include HDFS[11] and Spark) and AI (for example, TensorFlow in Python), and have been integrated into most commercial Big Data and AI platform services (for example on Microsoft's Azure cloud-computing service or Amazon Web Services). These technologies allow for scalable distributed data processing and the training of sophisticated machine-learning models. These machine-learning models enable machines to detect complex patterns and anomalies.

Manufacturers should give special focus to 'time series' data processing and analytics capabilities to best handle data streams from sensors in a production environment.

Insights from the field

> AI is often misunderstood. Applied machine learning is AI, and data science is the key. ZF's first step towards AI is machine learning.
>
> Georg Gabelmann, ZF

4. Talent and organisation

More data and new technologies also require people with specific analytical skills in the manufacturing field. Companies have started to hire data scientists over the past few years, but are still struggling to find the right organisational set-up to make effective use of these new skills alongside those of traditional engineers.

We typically see manufacturers on a transformational journey, starting with fragmented and uncoordinated use of data and AI experts, moving on to a more centralised organisational model (for example, an AI center of excellence or lab, as described at ZF), which drives the AI maturity level of the organisation. In the final stage, AI capabilities may become decentralised again, as a fully integrated part of the organisation.

A central AI team should be comprised not only of data scientists, but should also include data engineers, data stewards, solution architects and analytics translators. These central resources then collaborate with teams from the various manufacturing functions to jointly develop and put into practice AI solutions for specific use cases. Often, the central team also drives the development of a central AI platform, based on the technologies described above, and this means hiring platform architects and DevOps staff.

Insights from the field

> Process engineers are smart, but they speak a different language than data scientists. They often express requests rather than specific needs, which makes it hard for data scientists to really understand the problem and come up with the best solution.
>
> Dimitri Laurent, 3B

5. Processes

To operate efficiently, enterprises need to define a minimum level of AI governance and processes. An example of such a process is AI use-case pipeline management, to identify and evaluate new use cases in the business on an ongoing basis, plan their agile development and ensure a smooth transition into operations. Another example is a defined development process for AI solutions. These typically build on the cross-industry standard process for data mining (CRISP-DM) and define the phases of data analysis and AI solution development.

Data and analytical model governance is a key capability for effectively operating AI solutions in manufacturing. Enterprises need properly to define data ownership, access and security along with AI model performance criteria. Furthermore, they need to assure AI model fairness, explainability and robustness, as well as consider ethics and regulation, as outlined in PwC's Responsible AI Toolkit[12].

Insights from the field

> At ZF, we are managing use cases in a structured process, from first ideas through demand clarification, use-case evaluation and prioritisation, to the planning of concrete implementation projects. This structured approach assures the best use of available resources for business value.
>
> Georg Gabelmann, ZF

6. Culture

Finally, manufacturers need to enable a data and AI-driven culture. To meet this objective, they must build trust in data and algorithms by not only educating the workforce about AI and its capabilities and value, but also its risks and limitations. At the same time, they need to manage the concerns of their workforce and create a compelling vision of effective human-machine collaboration to counter fears of AI replacing thousands of jobs in manufacturing.

Senior executives need to drive the change by showing commitment and 'connecting' with AI methods and technologies. They can also foster innovation by supporting a fail-fast experimentation approach for AI use cases. And while failure is condoned, success should be duly celebrated and communicated to drive adoption of AI across the organisation.

Insights from the field

> In the process engineering department, 3B is already seeing a change in culture towards strongly leveraging data and AI. Three years ago it was still hard to get people excited about these topics, but now they are coming up with ideas for using AI by themselves.
>
> Dimitri Laurent, 3B

Summary

AI is both a powerful source of **disruption** and a tool to gain **competitive advantage**. Manufacturing firms that fail to recognise the importance of AI are likely to lose their competitive edge.

While manufacturers have started to implement AI across the value chain, companies are most commonly using it in **core functions** such as assembly and quality testing, product development and engineering.

Manufacturers are implementing AI primarily to:

1. **Automate** manual and cognitive tasks
2. **Assist** in making decisions or taking action
3. **Augment** decision-making through continuous machine learning

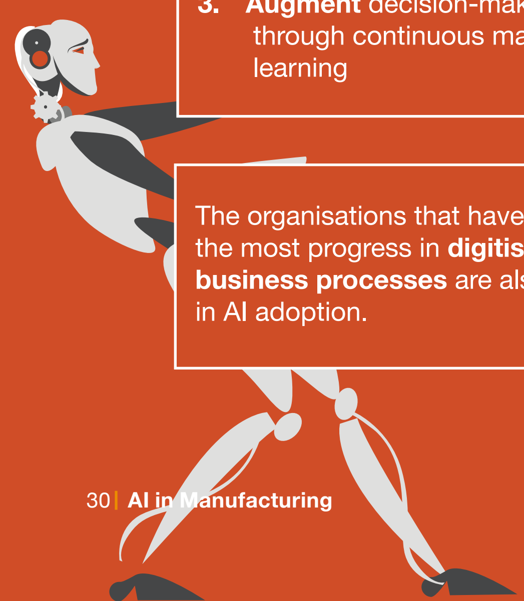
The organisations that have made the most progress in **digitising core business processes** are also **leading** in AI adoption.

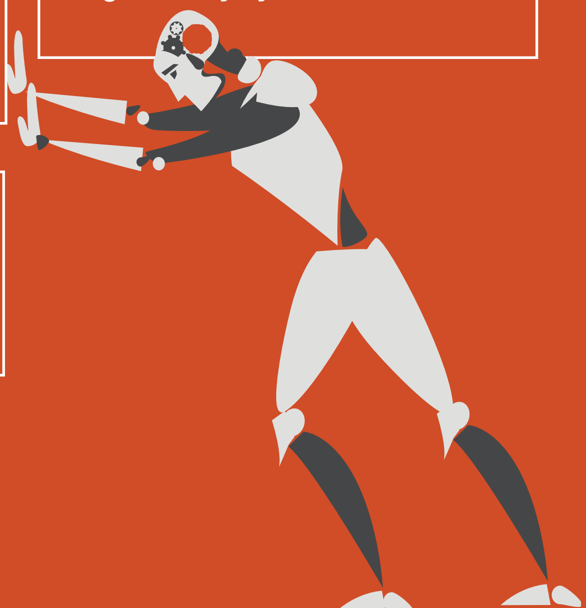
Companies such as ZF have shown that to take a lead in using AI solutions at scale, specific **technological investments** and **organisational changes** are required.

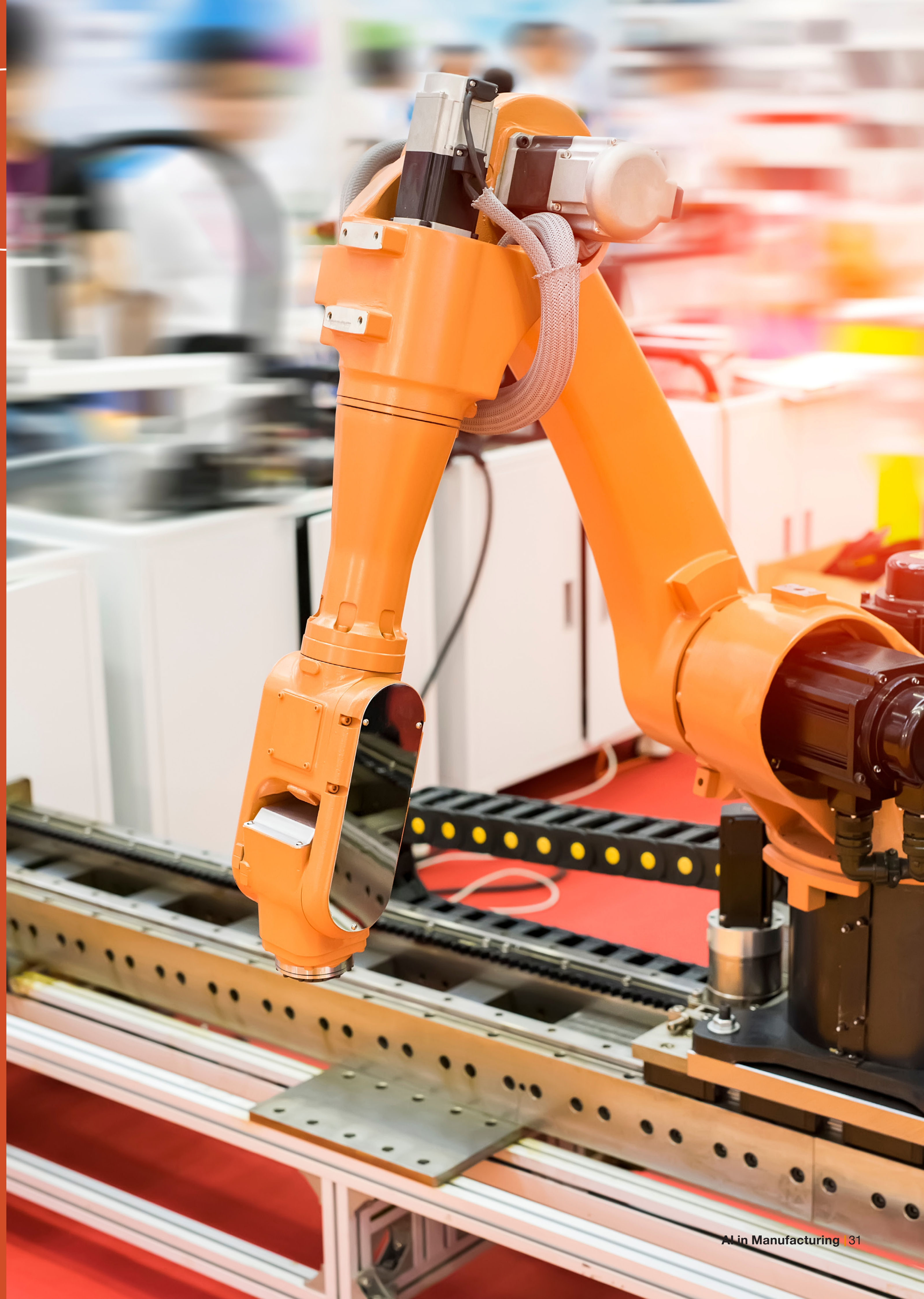
The **six building blocks** for successful AI implementation span **business, technical** and **organisational** factors:

1. Business application
2. Data
3. Technology
4. Talent and organisation
5. Process
6. Culture

While the current adoption rate in manufacturing is low, the prevalence of AI is expected to **increase significantly by 2030.**







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Koen Cobbaert is a director in the Management Consulting practice of PwC Belgium. His focus has always been on optimising the supply chain, with a strong focus on the tactical and strategic level. Over the years, Koen has built expertise in the application of analytics and machine learning in supply chain and operations management. Koen holds a Master degree in Industrial Management from KULeuven.

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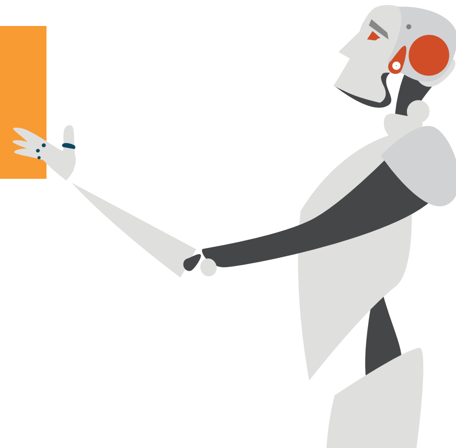

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[11] HDFS is the primary data storage **system** used by **Hadoop** applications. It employs a NameNode and DataNode architecture to implement **a distributed file system** that provides high-performance access to data across highly scalable **Hadoop** clusters.

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About the Global Manufacturing and Industrialisation Summit (GMIS)

The Global Manufacturing and Industrialisation Summit (GMIS) was established in 2015 to build bridges between manufacturers, governments and NGOs, technologists, and investors so that they can harness the transformative power of the Fourth Industrial Revolution. A joint initiative by the United Arab Emirates and the United Nations Industrial Development Organization (UNIDO), GMIS is a global platform that presents stakeholders with an opportunity to shape the future of the manufacturing sector and contribute towards global good by advancing some of the Sustainable Development Goals.

The first two editions of the Global Manufacturing and Industrialisation Summit were held in Abu Dhabi, United Arab Emirates, in March 2017, and Yekaterinburg, Russia, in July 2019, respectively, with each edition welcoming more than 3,000 high-level delegates from more than 40 countries.

GMIS 2020, the third edition of the Global Manufacturing and Industrialisation Summit, will be held alongside Hannover Messe, the world's largest industrial trade fair, between 20 and 21 April 2020 in Hannover, Germany, and will focus on glocalisation in pursuit of inclusive and sustainable global value chains.

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