THE 2020 WORLD MANUFACTURING REPORT

MANUFACTURING IN THE AGE OF ARTIFICIAL INTELLIGENCE

WORLD MANUFACTURING FOUNDATION

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2020 World Manufacturing Report: Manufacturing in the Age of Artificial Intelligence

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2020

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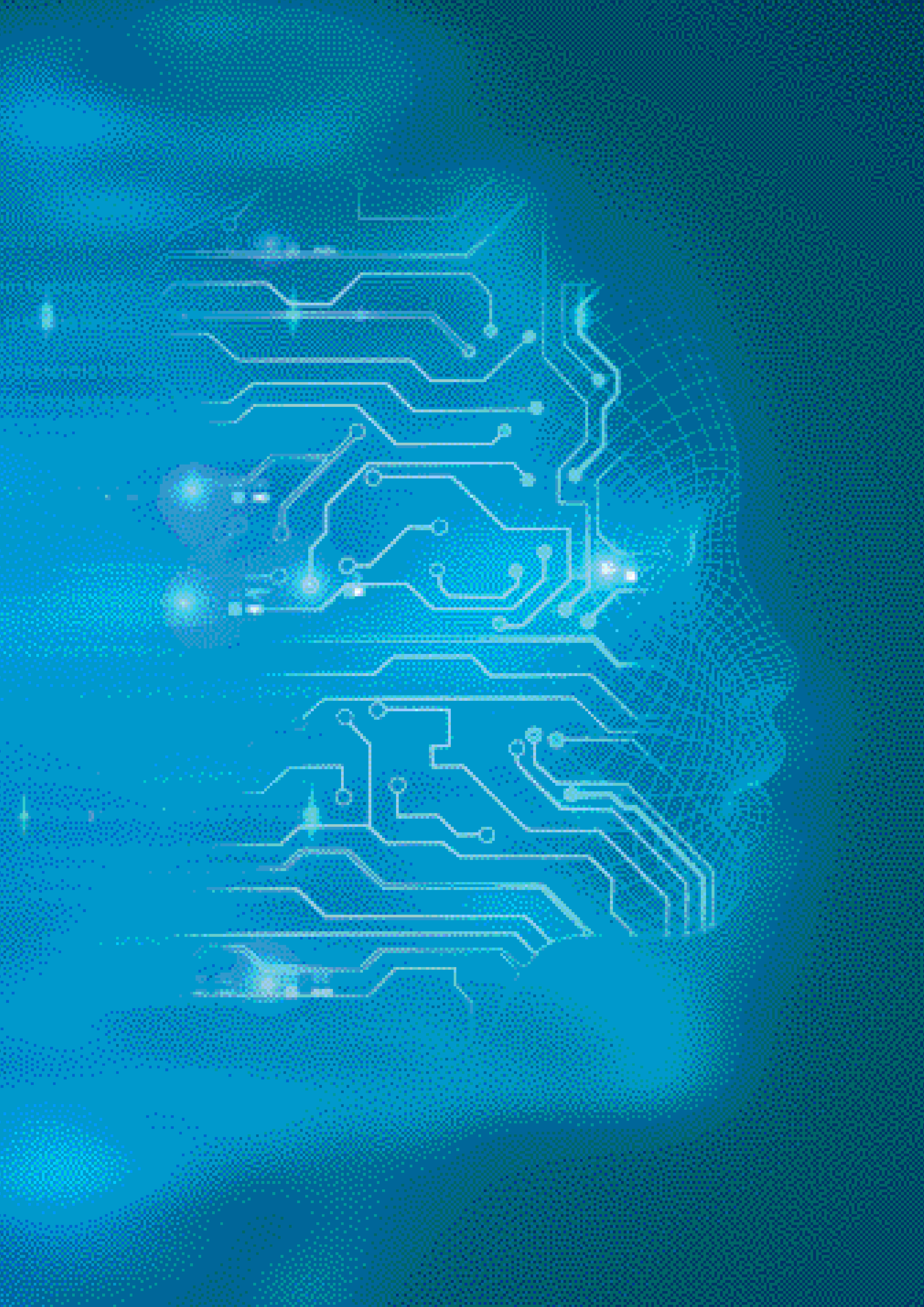

Foreword

Dear Readers,

In 2018, the World Manufacturing Foundation was formally established to undertake activities that promote industrial culture worldwide, enhancing manufacturing's role as a positive driver for sustainability and societal growth. Expanding knowledge, promoting innovation and fostering cooperation in the manufacturing sector have been our key strategic levers to advance our mission. The Foundation leverages on its experience of holding the annual World Manufacturing Forum which since 2011 has been an important platform bringing stakeholders together to discuss the most important trends in manufacturing.

The first *World Manufacturing Forum Report: Recommendations for the Future of Manufacturing*, published in 2018, analysed key trends in the sector and presented our vision for the future of manufacturing. In 2019, the *World Manufacturing Forum Report: Skills for the Future of Manufacturing* underlined the importance of a skilled and educated manufacturing workforce.

Continuing this tradition of outlining the most important trends in the sector, this whitepaper focuses on what artificial intelligence means for the manufacturing sector. It will analyse in detail the trends in AI adoption, applications of AI in manufacturing, implications of AI on human capital, and the ethical, legal, policy and societal perspectives of AI.

Through this report, we aim to add value by devising key recommendations, developed with a global group of experts, that could be adopted by stakeholders such as policymakers, companies, educators, and the society at large to promote a successful and trustworthy adoption of AI in manufacturing.

This whitepaper and its Key Recommendations were prominently discussed at the 2020 World Manufacturing Forum held in the 11th to 12th of November, 2020. The 2020 Forum entitled *Artificial Intelligence in the Manufacturing Renaissance* was participated by stakeholders from all over the world.

The World Manufacturing Foundation, through the rebranded World Manufacturing Report, commits to produce high quality and non-partisan research about timely and relevant themes in manufacturing. We hope that this whitepaper will encourage a lively societal debate about AI and promote a positive view of the future of manufacturing in the age of AI.

The World Manufacturing Report Editorial Team

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Executive Summary

The *2020 World Manufacturing Report: Manufacturing in the Age of Artificial Intelligence* presents the global AI state of play, outlines the various applications of AI in the manufacturing value chain, investigates how AI is transforming the workforce, explains key relevant ethical and policy themes of AI in manufacturing, and finally lists 10 Key Recommendations for a successful and trustworthy adoption of AI in manufacturing.

Artificial Intelligence is not novel in manufacturing. In the last decade however, thanks in part to advancements in AI algorithms, computational power, connectivity, and data science, it has gained more importance as companies increasingly see it as a driver for competitive advantage. This is evident in the projected increase in global revenues from AI for enterprise applications and a significant share of AI spending in manufacturing. However the lack of experienced talent to work with AI, lack of know-how, and the need for accurate data remain important challenges for organisations in adopting AI. Notwithstanding these, organisations are increasingly realising the potential of AI in bringing not only efficiencies in production but also new capabilities to stay competitive.

The impact of AI applications is significant across all levels of manufacturing activities and is expected to increase in the coming years. At the broadest Digital Supply Network (DSN) level, AI is has proved valuable in demand forecasts and the associated synchronized planning, automated warehouse management, automated design and development, and connected services. In the factory or shop floor level, AI applications are aimed at energy efficiency, product and process quality, scheduling optimisation, robotics, and enhancing the abilities of the human operator. At the most basic machine tool level where AI applications are most mature, automated quality inspection, monitoring, and control, data-driven tool wear models, and predictive maintenance stand to benefit from AI.

With regards to the manufacturing workforce, AI has significant implications on the future of work. Manufacturing stands to benefit from AI because of the sheer amount of tasks that can be automated. However, it could not replicate many human-centric tasks making the role of humans as important as ever. AI will augment many existing roles in the organisation and will also create completely new ones, not only in the area of research and technical development of AI related technologies but also in areas which are focused on business strategy, ethics and compliance, and human-AI interaction. The skills required to work with AI are also relevant, with workers expected to possess not only the more technical AI and manufacturing skills but also human-centric ones such as skills for ethical/trustworthy AI and transversal skills. This means that organisations should prioritise education and training among their workforce to make them successful in AI-centric manufacturing environments.

While AI is expected to have a positive impact on growth and productivity, it also raises ethical dilemmas and regulatory issues that risk to hold back its adoption. To this regard, many governments and organisations have put up ethical initiatives and frameworks that identify and try to address relevant ethical challenges. This report identifies key ethical challenges when deploying AI in the manufacturing sector: Transparency in AI Systems, Privacy and Data Protection, Technical Robustness and Safety, Human Agency, and Lawfulness and Compliance. Standards and Regulations which do not stifle innovation can support the deployment of AI and guide the development of trustworthy AI systems.

Finally, a set of 10 Key recommendations addressed to different stakeholders have been outlined to guide a sustainable adoption of AI in manufacturing. These recommendations focus on key topics from promoting social awareness about AI to implementing standards and regulations, and are aimed to help stakeholders address key issues and harness the potential of AI in manufacturing now and in the future.

Project Methodology

The World Manufacturing Report is a yearly whitepaper published by the World Manufacturing Foundation outlining key trends in the manufacturing sector. A relevant topic is chosen for every edition of the report.

In developing the report, the World Manufacturing Report Editorial Board worked alongside an Advisory Board, composed of senior individuals from academe and other organisations from ten countries. In developing the report, an extensive review of existing literature on the topic of artificial intelligence in manufacturing has been undertaken. The reports analysed include scientific journals, policy papers and publications published within the last five years.

To develop the Ten Key Recommendations outlined in this report, expert interviews were conducted. Experts come from multinational companies and SMEs, industry and trade associations, international organisations, governmental and non-governmental organisations.

Expert interviews were conducted in which experts were asked to provide their personal views on the main topics covered on the report. The main contribution of experts was to provide their key short and long term recommendations to promote successful adoption of AI in manufacturing.

For this year's edition, a selection of outstanding essays written by members of the Young Manufacturing Leaders network was also featured. Young Manufacturing Leaders is a European Commission-funded network, under the EIT Manufacturing initiative, which aims to create a global network of students and young workers interested in a career in the manufacturing sector. The YML Network held an essay contest calling for contributors to write an essay on defined topics related to AI in manufacturing. The outstanding essays were featured in this report.

1

AI State of Play

"Success in creating AI would be the biggest event in human history. Unfortunately, it might also be the last, unless we learn how to avoid the risks."

Stephen Hawking

AI State of Play

There is a lot of interest and excitement around Artificial Intelligence (AI) at the moment and the term AI seems to be mentioned a lot in everyday life. However, since the time the official idea and definition of AI were first coined by Jay McCartney in 1955 at the Dartmouth conference, the question remains: what is AI exactly? Artificial Intelligence, in its simplest definition, is the ability of a computer program or a machine to think and learn. Surprisingly, though, the lack of a precise, comprehensive, and universally accepted definition of AI probably has helped the field to grow, and advance at an ever-accelerating pace. Still, a definition remains important and on that regard, European Commission's High-Level Expert Group on Artificial Intelligence has recently provided a comprehensive and useful one:

"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions."[1]

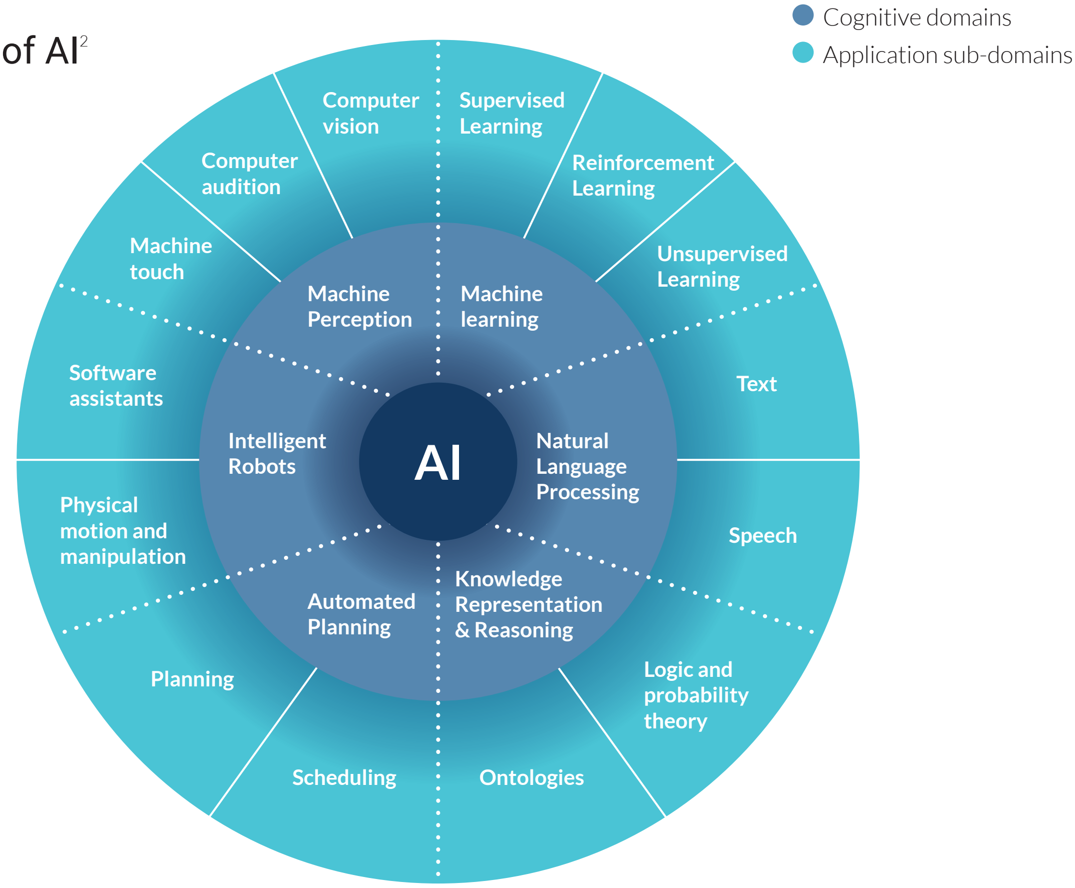
Nevertheless, this attempt to define AI might also have its shortcomings, considering that there might never be a perfect definition for AI, as technology continues to evolve faster and faster.

When it comes to classifying AI, functions, applications and techniques are often confusingly aggregated. To that end, Figure 1 provides a simple categorization of functions/domains and applications/sub-domains for an easier understanding. On that regard, AI can mimic six major cognitive functions, i.e. machine learning, knowledge representation and reasoning, automated planning, natural language processing, machine perception, and intelligent robots. Digging down deeper, the second layer illustrates corresponding sub-domains (however not exhaustive) as applications of the major six categories.

Figure 1

Classification of AI[2]

(Source: Appanion)



In today's business environment, companies using AI as integral part of their products and services become enormously successful. Therefore, in order to get down to the why, what and how of Artificial Intelligence, it is of paramount importance to understand the current industrial ecosystem, as well as key trends, main benefits, and challenges of AI's adoption and implementation in industry. For that purpose, this section will investigate the key figures of AI presented in the most recent and relevant published reports, and will extract key messages for providing clear insights to the international community of manufacturing and other sectors.

Global Perspective of AI

AI will have great impact in addressing many of the greatest societal challenges the world faces today, and will improve social welfare. Besides, it will significantly contribute to increasing industrial competitiveness across all sectors. It offers tremendous potential for industry, already fostering production efficiency, flexibility, and reliability.

Global revenues from AI for enterprise applications is projected to grow from $1.62B in 2018 to $31.2B in 2025 [3]

As the ways to use AI in industries grow, so do the number of companies implementing this cutting-edge technology to their business. According to Statista, the rate of adoption is quite high — global revenues from AI for enterprise applications is projected to grow from $1.62B in 2018 to $31.2B in 2025 (Figure 2).

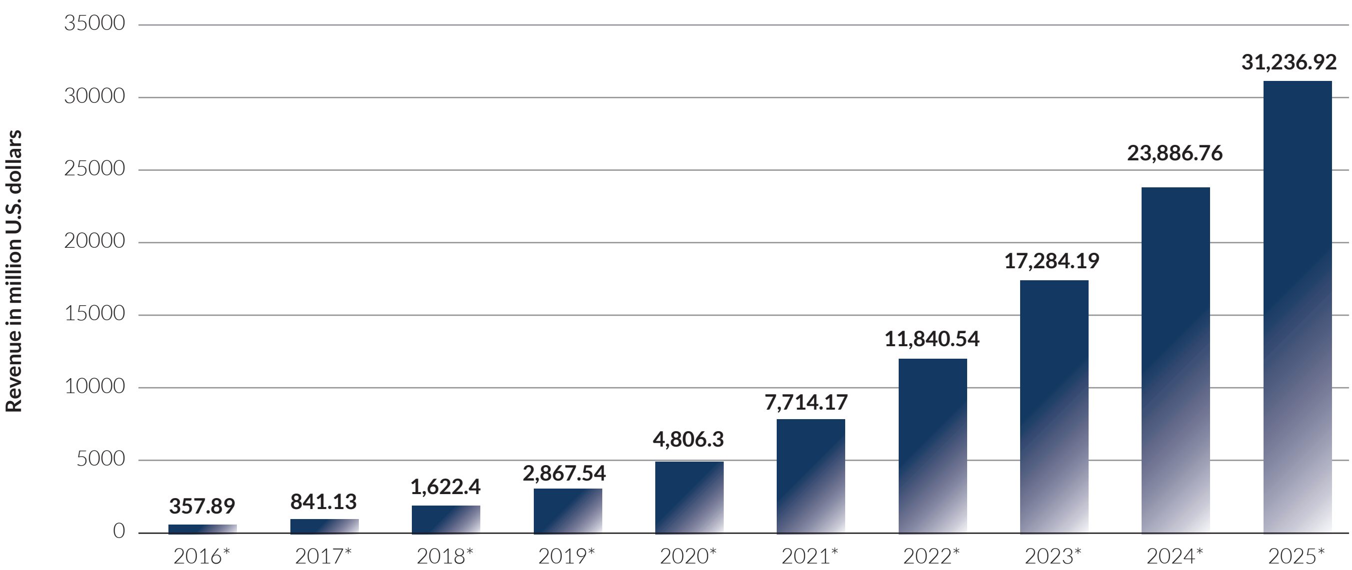
There is a growing realisation of AI's importance, including its ability to provide competitive advantage and change work for the better

A majority of global early adopters say that AI technologies are especially important to their business success today—a belief that is increasing. A majority also say they are using AI technologies to move ahead of their competition, and that AI empowers their workforce.[5]

Figure 2

Revenues from the AI for enterprise applications market worldwide[4]

(Source: Statista)



Machine Learning, Deep Learning, Natural Language Processing (NLP), and Computer Vision are the four most in-demand skills on job portals

One of the best ways to understand the growing trends and needs in the industry is through investigation of job market realities. Guided by this principle, the most in-demand skills on popular job portals like LinkedIn, Indeed, SimplyHired, Monster and AngelList relate to AI, Machine Learning, Deep Learning, Natural Language Processing (NLP), and Computer Vision being the first four respectively (e.g. Figure 3).

Emphasizing on the same aspect of growing trends in AI, a 2019 Statista report reveals that the NLP market will have a tremendous increase reaching to 43.9 billion dollars by 2025 (Figure 4).

For the successful adoption and implementation of AI, there are several market drivers, and some of the most significant among these are as follows:
- Significant improvements in machine learning algorithms
- Shift to enhanced profitability metrics
- Greater implementation of IoT sensors and networks
- Advances in hardware and software
- Demand for more granular control over processes and products
- Growth in cloud-based AI

Figure 3

Job Openings, Skills Breakdown

(Source: Monster.com)

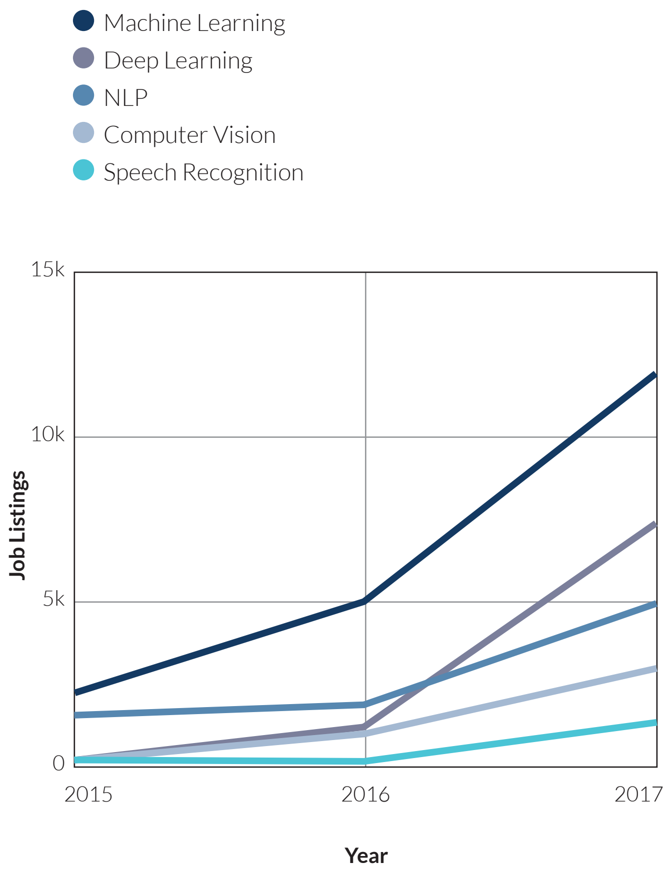
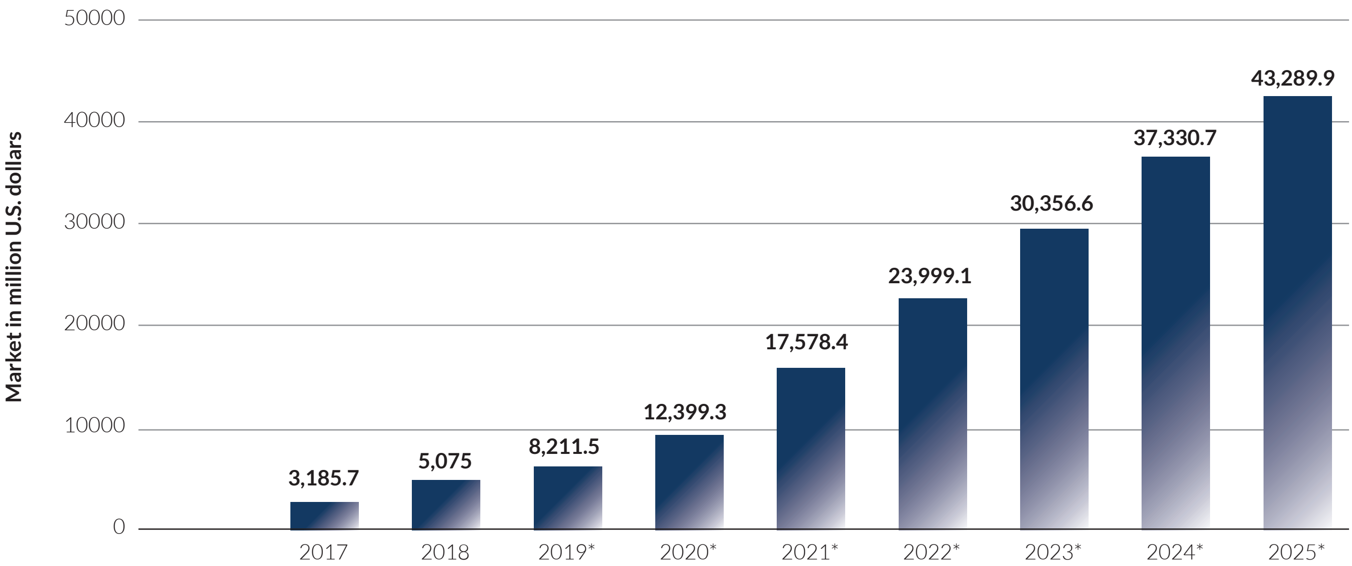


Figure 4

Revenues from the NLP market worldwide[6]

(Source: Statista)



Industrial AI Ecosystem

AI is gaining more and more importance in the manufacturing sector, with annual spending on AI software, hardware, and services to increase from $2.9 billion in 2018 to $13.2 billion by 2025

According to a new report from Tractica, annual worldwide manufacturing sector investment in AI software, hardware, and services will increase from $2.9 billion in 2018 to $13.2 billion by 2025 (Figure 5).[7] This shows that manufacturing companies are now incorporating AI technology within their environments at a modest, yet steady, pace. These AI technologies used in smart manufacturing applications include machine learning, deep learning, natural language processing, computer vision, machine reasoning[8], and strong AI (i.e. a theoretical form of machine intelligence that is equal to human intelligence).

Guided by these AI technologies, the top use cases for AI in smart manufacturing will be those that increase operational efficiencies and therefore reduce the cost of production processes. On that regard, such use cases like root cause analysis, yield improvement, quality monitoring, energy management, digital twins, and predictive maintenance are all driving increased investment.

As manufacturing becomes more cost-sensitive and customers demand quality, manufacturers are using AI to enhance the performance of equipment, reduce downtime, increase the quantity, and improve the quality of products. The overarching driver of AI technology is the ability to find insights in large data sources that would be too unwieldy for humans to analyse quickly.

AI has the potential to remarkably increase industry growth, and manufacturing sector will lead the way in the application of artificial intelligence technology

If we look at the projections for the manufacturing industry in particular, expected AI spending by 2021 will be $9.5 billion (Figure 6), making it one of the most invested sector related to AI technologies.[9] Thus, the manufacturing sector will lead the way in the application of artificial intelligence technology.

Figure 5

Total Manufacturing AI Revenue by Segment, World Markets: 2018-2015

(Source: Tractica)

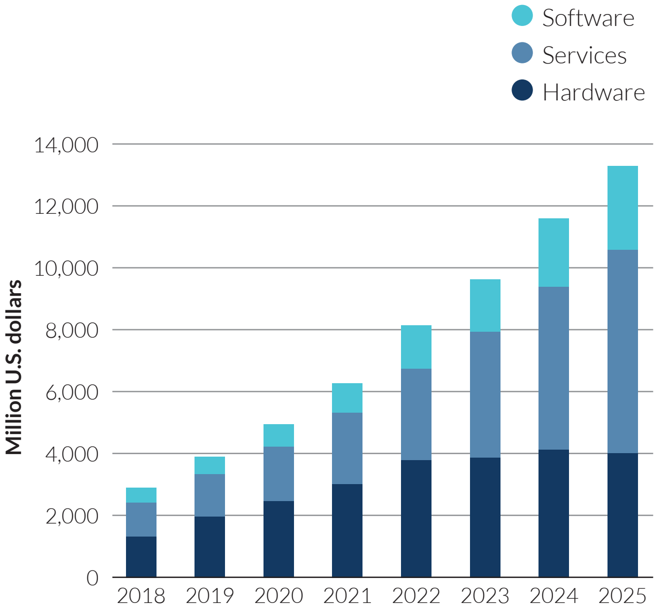


Figure 6

Projected AI spending by industry

(Source: Atos)

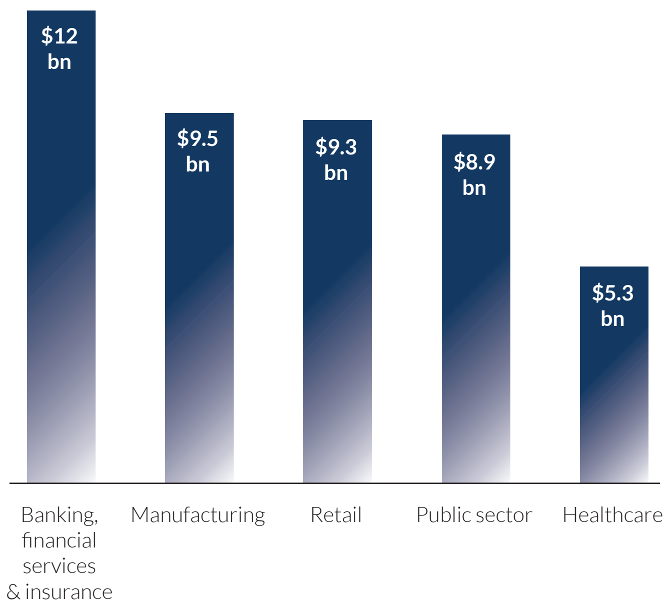
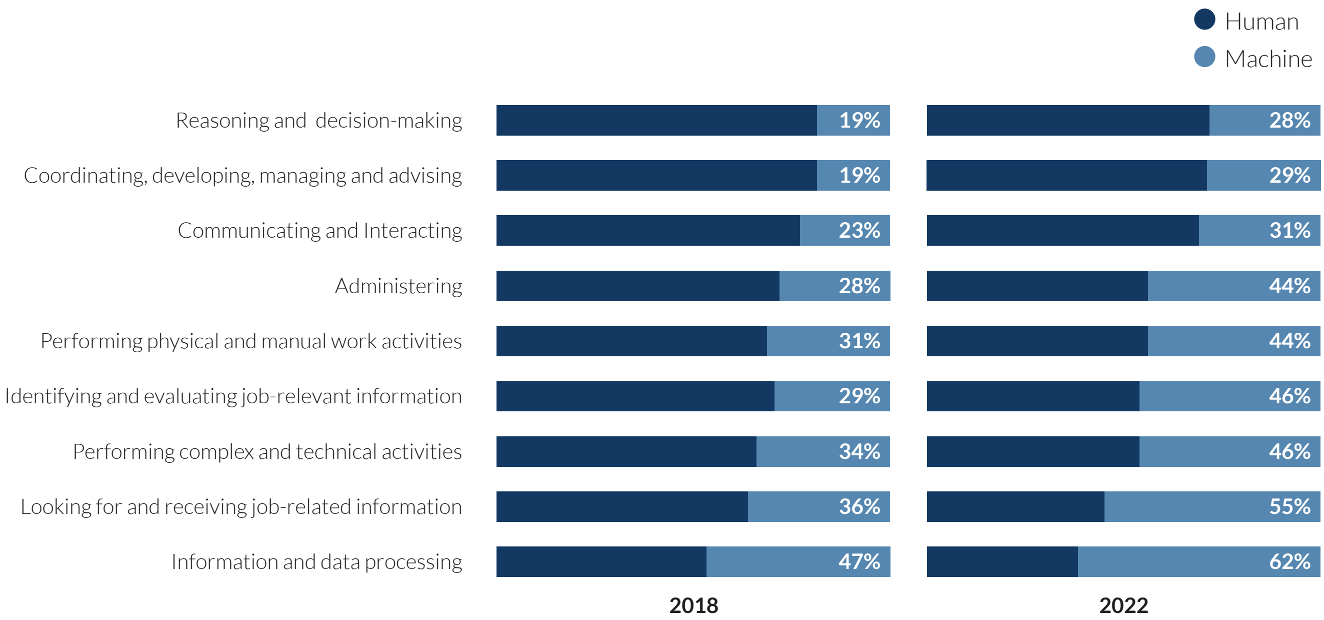


Figure 7

Ratio of human-machine working hours, 2018 vs. 2022 (projected)

(Source: Future of Jobs Survey 2018, World Economic Forum)



Challenges in Adopting AI Technologies

Job Displacement, Human Augmentation, and Transformation of Work

There will be a significant shift on the frontier between humans and machines when it comes to existing work tasks, and in organisations that are more mature in their use of AI, employee resources will be augmented rather than replaced

One of the biggest concerns around AI is that the human capital will lose value with the advancements in technology, as some believe the automation provided by AI will reduce the need for costly human labour. However, this argument is flawed as the majority of companies, with efficiency and services improved, will also have increase in job opportunities. In organisations that are more mature in their use of AI, employee resources will be augmented rather than replaced. Organisations that utilize this approach stand to benefit from employees' increased skills and greater motivation to help further explore what AI can bring to the table[11].

According to the World Economic Forum, more than 130 million new roles by 2022 will be the result of a new division of work between humans and machines. In fact, there will be a significant shift on the frontier between humans and machines when it comes to existing work tasks between 2018 and 2022 (Figure 7).[12]

Lack of Experienced Talent

Artificial Intelligence has a growing knowledge level that will require more skilled workers who need to be educated and trained to develop, maintain and troubleshoot systems

Today, manufacturing industry experiences ever-shorter cycles of technology advances which, in turn, leads to a rapid change in the very nature of the manufacturing jobs that need to be performed and hence in the skills set of the workers. It's a common complaint and worry among manufacturers today that they face a huge challenge in employing people with the required skills to apply and maintain these technologies as the current workforce training and experience will become obsolete over time with all these changes becoming faster than ever before.[13] New careers requiring advanced degrees and technical skills will then emerge to address the resulting skills gap.

Since workers will be managing computers and machines that are increasingly intelligent, employees must be trained to work at a similar level of new smart technologies. However, the industrial workforce is not the only group within society that must be trained to deal with new technologies. The general public must also be educated as advanced technology is becoming embedded in every facet of life. In order to avoid people becoming overwhelmed by machines, everyone needs to be more prepared for these new technologies and challenges. The need for more education across multiple domains is due to the fact that technology will be a vital part of daily life. Workers will not only compete among human talent but also with machines and AI algorithms. As a result, education is increasingly relevant compared to the past.[14]

As a matter of fact, the share of jobs requiring AI skills has grown significantly since 2013 (Figure 8), according to the identification of AI-related jobs using titles and keywords in descriptions of jobs on the Indeed.com platform.

Need for Accurate Data

AI systems are not limited to a single aspect of Data Management, but encompass the broad fields of data capture, data storage, data preparation, and advanced data analytics technologies.

Data Quality is one of the topmost challenges to successful implementation of AI systems in enterprises

A significant issue in Enterprise Data Management today is Data Quality, because business data requires thorough cleansing and preparation to be used as input to any Analytics or Business Intelligence system. There is an overwhelming effort needed in data preparation and exploration, largely due to data quality problems. On that regard, a recent survey of Price Waterhouse Coopers[15] survey highlights that most large businesses now realise that despite piling up business and customer data over the years, they are severely handicapped to leverage advanced data technologies due to poor Data Quality. Furthermore, generating meaningful insights from this pile of data requires convergence of both data science and domain expertise. However, there is a shortage of data scientists and domain specialists.

The main reasons provided by business executives in the PwC survey for failing to meet their data analytics targets were data silos, bad data, data compliance issues, lack of data experts, and inadequate systems (Figure 9).

Figure 8

Share of jobs requiring AI skills

(Source: Indeed.com)

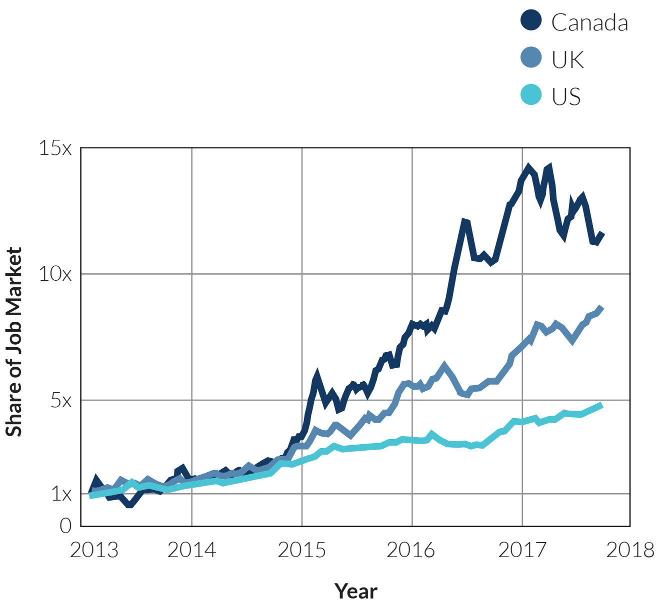


Figure 9

Data related challenges of AI[16]

(Source: PwC)

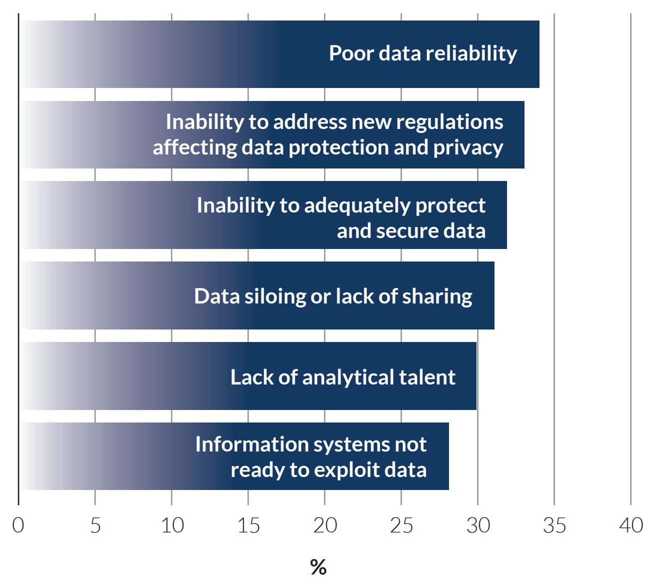
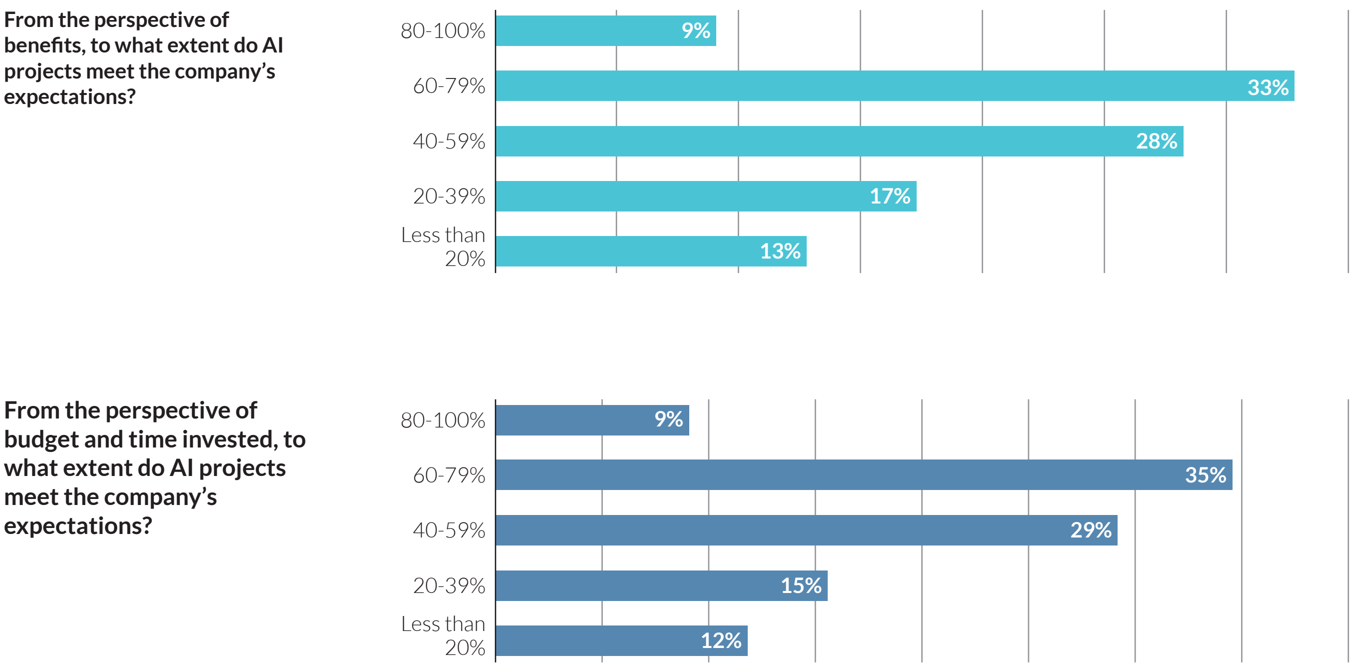


Figure 10

The gap between AI implementation and expectations

(Source: 2019 Deloitte survey on AI adoption in manufacturing)



The Lack of Explainability and Trust

The lack of explainability and trust hampers our ability to fully trust AI systems

Explainable AI is essential for detailing recommendations in a clear manner with transparent information, evidence, uncertainty, confidence and risk, which can be understood by people and interpreted by machines.[17] To that end, people want computer systems to work as expected and produce transparent explanations and reasons for decisions they make. However, there is a concern regarding the control and understanding of humans over the decisions taken by advanced artificial intelligence mechanisms. This issue poses a challenge to the implementation of AI systems for several tasks in industries.

Challenges with Stakeholder Buy-in

The foremost and the earliest challenge to AI adoption for any business is to get buy-in from stakeholders.

The foremost and the earliest challenge to AI adoption for any business, especially if it is a traditional, established organisation, is to get buy-in from stakeholders. These stakeholders include everyone involved in operating the business from the directors and investors all the way down to the last employee. It is vital to convince each of these stakeholders of the value of using AI applications not only to the organisation but also to them individually.[18]

Unrealistic Expectations around AI

It is quite common that gap exists between the effects and expectations in AI implementation

A recent survey of Deloitte[19] found out that almost 90 percent of AI projects failed to meet expectations of companies either from the perspective of benefits or the time and budget invested (Figure 10).

This gap could be explained by several reasons such as infrastructure limitations, data collection and quality, lack of engineering experience, excessively large scale and complexity, as well as obstacles from existing experience and organisational structure.

Barriers to and Drivers for AI adoption

Top Barriers to AI adoption focus on data, know-how, and talent

Analysis of the current industrial landscape shows us that significant barriers exist to AI adoption in manufacturing. According to the 2019 survey of the MAPI foundation[20], the most significant barrier to deployment of AI solutions pertains to a lack of data resources (58% of respondents), followed by the uncertainty about how to implement AI solutions to solve specific manufacturing challenges (52%). The next two major barriers with equal respondent rate of 47 percent include lack of sufficient workforce digital skills, and a lack of interoperability between equipment that precluded the data integration necessary to support AI applications (Figure 11).

Other significant barriers are as follows:
- Skepticism about achieving sufficient return on investment (ROI) from AI solutions (40% of respondents);
- Being unaware of how to define the AI skills needed (34%);
- Lack of financial resources to support requisite investments (31%);
- Lack of senior leadership buy-in (21%); and
- Concerns about cybersecurity risks (21%).

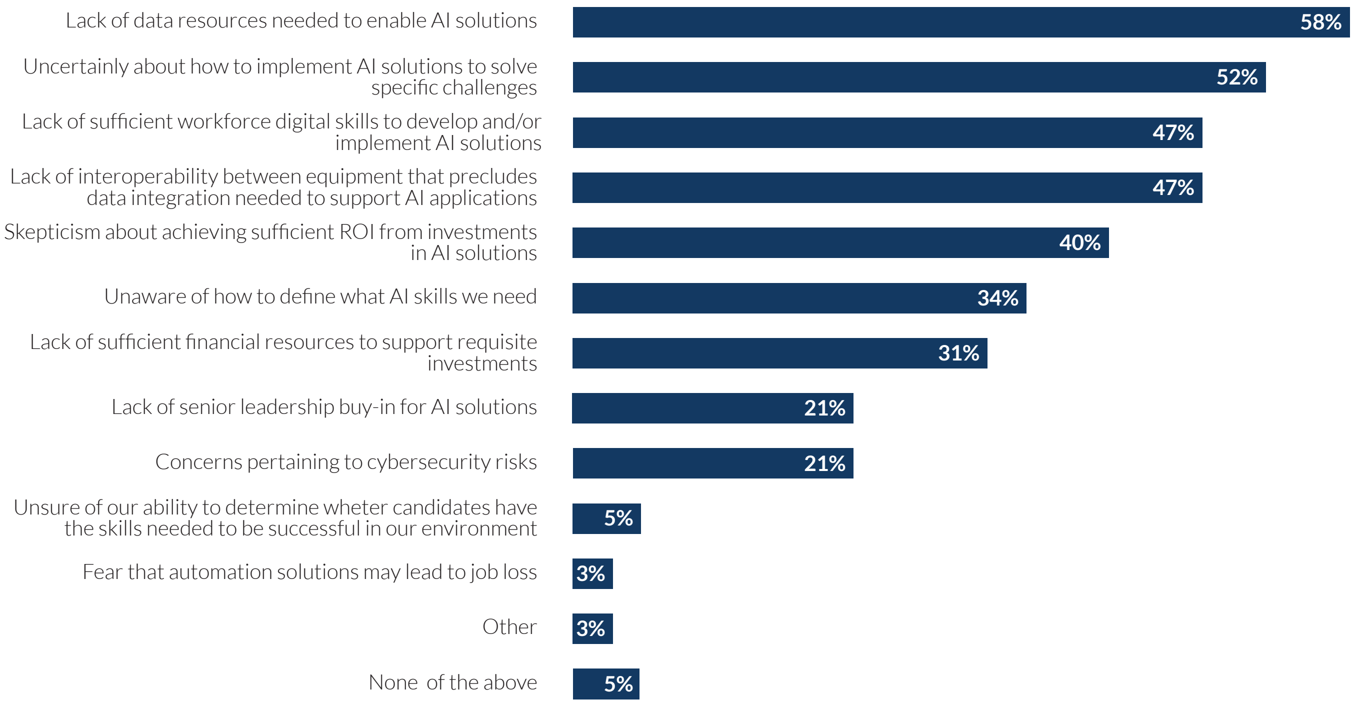
Major Drivers for AI adoption are related to advancements in AI algorithms, computational power, connectivity, and data science

There are many drivers for a successful AI adoption in manufacturing companies. The major drivers of such are as follows[21]:
- Dramatic increases in computing power;
- Data science advances, and development of more sophisticated algorithms;
- The continued extension of connectivity to smaller devices starting with mobile and now with the rise of the Internet of Things (IoT);
- Trusted standardized data sharing[22];
- The ability to collect more data and analyse information via Big Data platforms; and
- Growth in Cloud-Based AI services.

Figure 11

Barriers to AI adoption

(Source: MAPI Foundation)



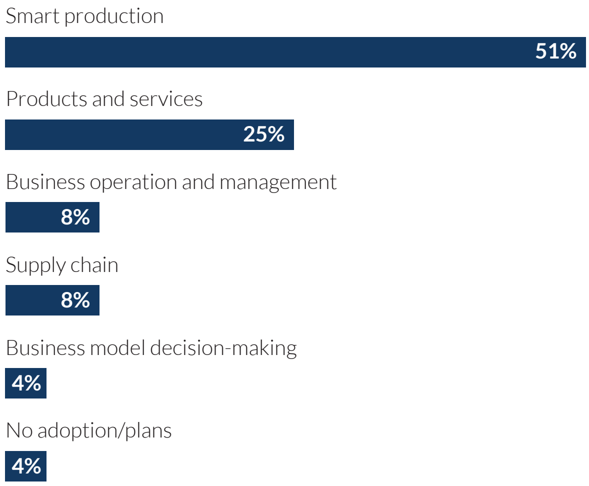
Key Fields of Application and Expected Benefits

According to the 2019 Deloitte survey on AI adoption in manufacturing[23] as illustrated in Figure 12, smart production is and will be the first choice deployment (51%) among manufacturing companies in the next two years, followed by products and services (25%).

Figure 12

Key fields for AI adoption

(Source: 2019 Deloitte survey on AI adoption in manufacturing)



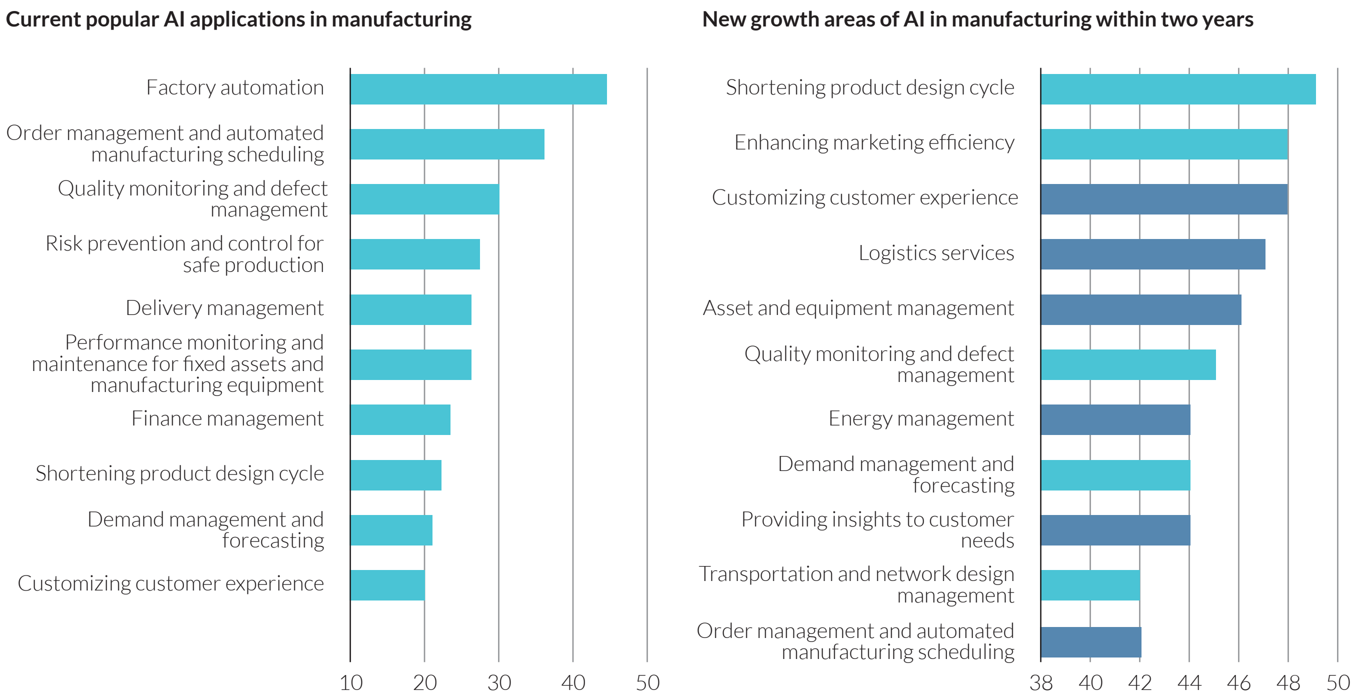
Popular applications of AI in industries will shift from smart production to products/ services and supply chain management

The above mentioned 2019 Deloitte survey highlights that popular applications of AI in industries will shift from smart production to products/services and supply chain management. Besides, there will be new growth areas within two years, and businesses will significantly increase investment for enhancing market efficiency, asset management, logistics, insights to customer demand, and energy management (Figure 13).

Figure 13

Changes in popular AI applications in manufacturing

(Source: 2019 Deloitte survey on AI adoption in manufacturing)



One of the main benefits that business organisations expect from adopting AI is to obtain or sustain a competitive advantage

According to a recent report and survey from Statista, the top reason for business organisations for adopting AI is linked to their aim of having a greater competitive advantage within their respective market (Figure 14).

This survey of Statista highlights that 84% of enterprises believe investing in AI will lead to greater competitive advantages. 75% think that AI will open up new businesses while also providing competitors new ways to gain access to their markets, whereas 63% of these responders believe the pressure to reduce costs will require the use of AI.

New capabilities, not cost savings, are biggest drivers of AI adoption

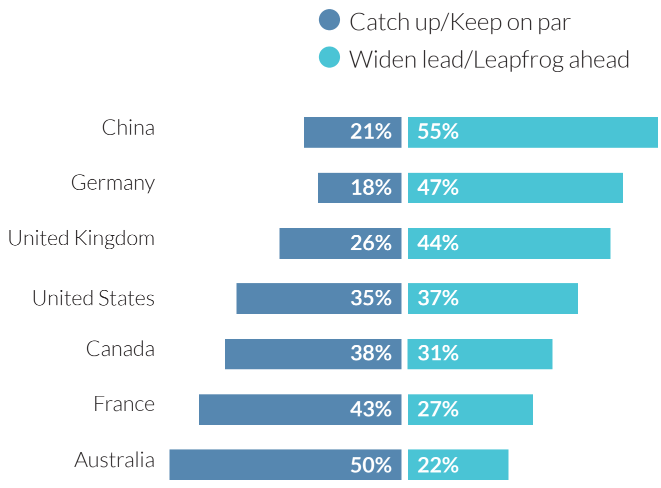
Businesses are looking at artificial intelligence (AI) as a truly disruptive technology, with the potential to change the way they run their organisations.[26] A recent Global Data survey[27] results highlight that companies have high expectations when it comes to AI, and 44% of the respondents that invested in AI indicated that they did so in order to gain new capabilities. 35% took the decision for improving customer experience.

In fact, another recent survey of Deloitte aimed at understanding whether early adopters use AI primarily to stay on par with peers or to create a competitive lead. Perspectives vary considerably. Thus, AI early adopters in some countries are more likely to use AI to create a strong competitive advantage (Figure 15).

Figure 15

AI early adopters and their expectations[28]

(Source: Deloitte Insights)



Note: Not shown - respondents who take the more neutral stance that they're "edging slightly ahead".

Figure 14

Business organisations' reasons for adopting AI worldwide[24]

(Source: Statista)

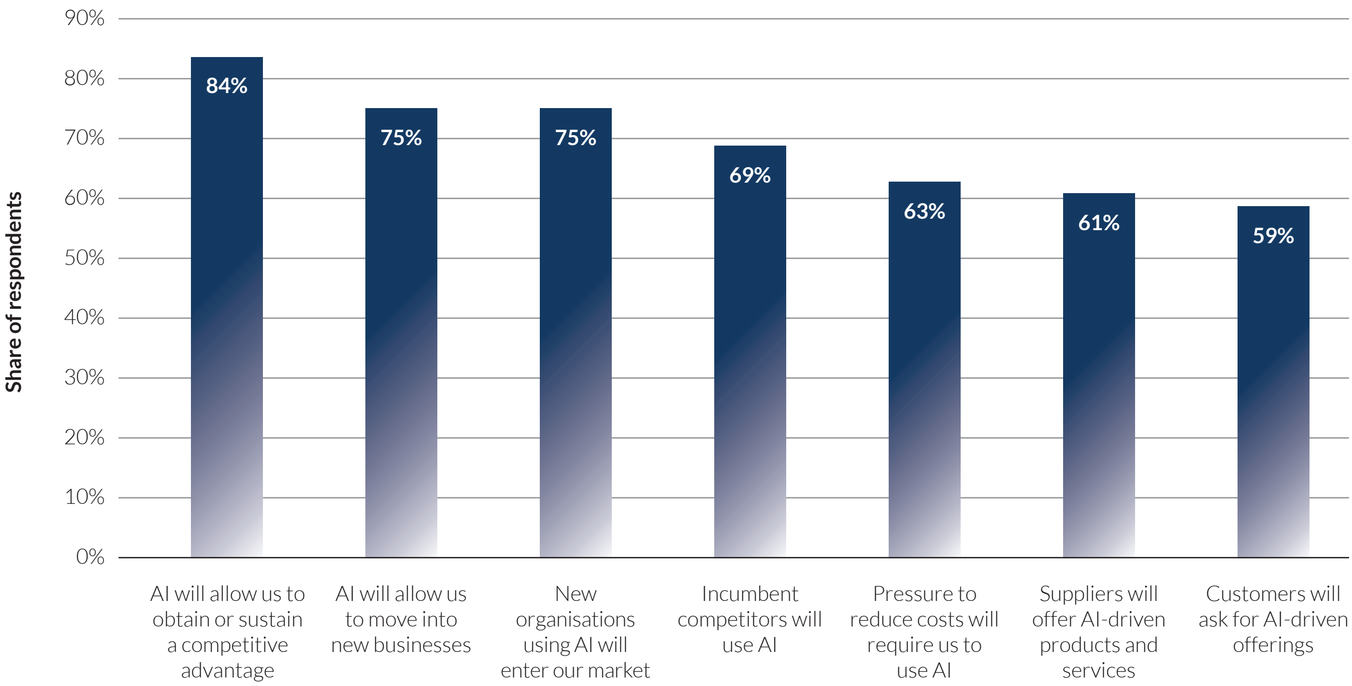
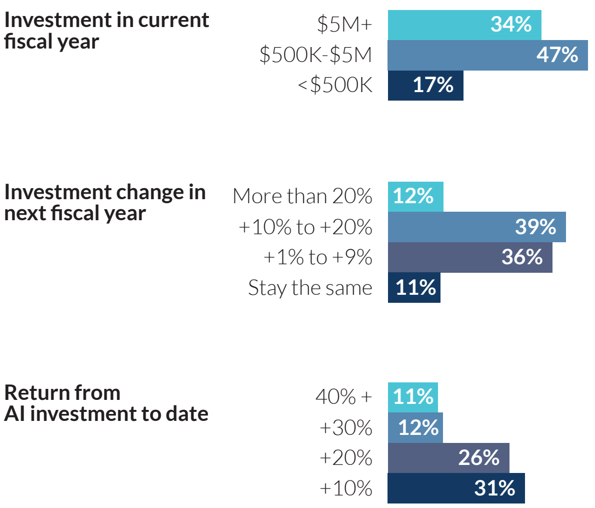


Figure 16

Return from AI investment to date[29]

(Source: Deloitte Insights)



Notes: Percentages may not total 100 percent due to not including all answer choices from all questions; all monetary amounts are given in US dollars.

Organisations are spending on AI technologies and seeing a return on their investment

Maximizing the potential of AI means maximizing Return on Investment. A recent survey carried out by Deloitte illustrates that organisations are now seeing a return on their investments (Figure 16).

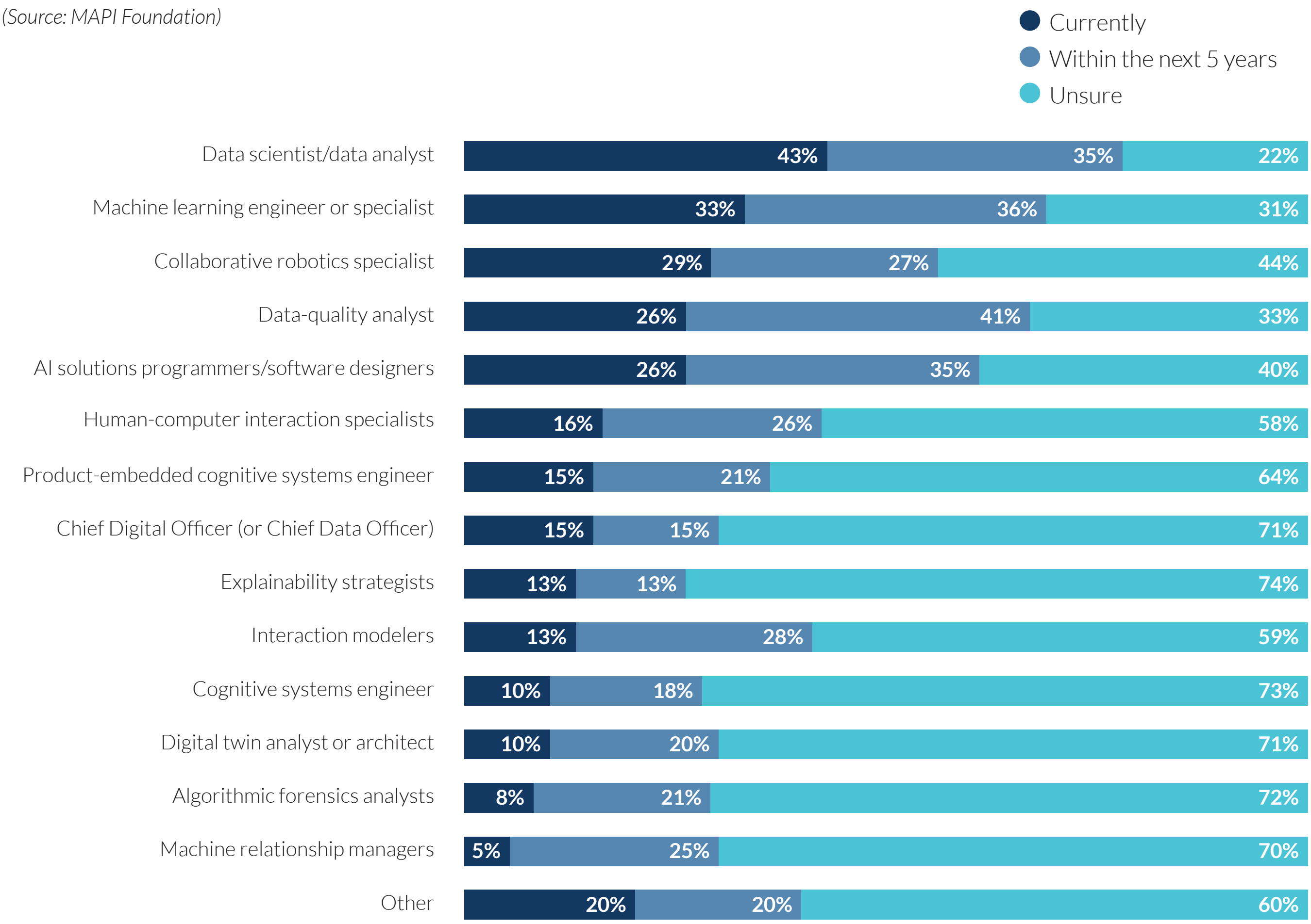
AI spurs introduction of multiple AI-related job titles

As highlighted in Figure 17, there are several AI-related jobs created due to advancements in AI. The top jobs in current situation are data scientists, machine learning engineers, and collaborative robotics specialists. However, within 5 years, jobs like data quality analysts, and AI solutions programmers will gain more and more importance. [30]

Figure 17

AI-related job titles

(Source: MAPI Foundation)



Boosting the introduction and uptake of AI technologies by manufacturing SMEs through hands-on workshops

Dr. Stefan Pauli
Swiss Smart Factory, Switzerland Innovation Park Biel/Bienne AG

Dr. Dominic Gorecky
Swiss Smart Factory, Switzerland Innovation Park Biel/Bienne AG

While the interest of industry in Artificial Intelligence (AI) technologies is constantly increasing, and more and more exciting AI use cases become public (the current World Manufacturing Report mentions some of them), the application of AI technologies in the manufacturing sector is still lagging behind its true potential, especially in manufacturing SMEs which lack the knowledge to start AI projects or are even not aware of the economic potential of AI technologies. The reluctance in the uptake of AI technology by manufacturing SMEs is often due to doubts about what is possible with AI technology and how to best deploy and use it. A major reason for these uncertainties is that personal touch points to AI technology are missing.

In order to reduce the existing barriers to AI and to get manufacturing SMEs and their employees excited about the topic of AI, a series of practical one-day workshops on AI where conducted by Swiss Smart Factory. The aim is to give a general overview about the topic of AI and also provide hands-on experience and inspirations in order to apply AI in the context of the own company. Therefore, the workshops consist of 3 parts: (i) theory of AI, (ii) practical implementation of AI and (iii) discussion of use cases.

Theory session

AI or Machine Learning algorithms are explained in a well understandable way. Covered are algorithms for clustering, classification and regression (e.g. k-means, Random Forest, Neural networks).

The session also looks at how algorithms can automatically identify the most important parameters from hundreds of parameters, how the prediction quality of the algorithms can be measured with test and training data and how they can be compared with each other – in short, a compact and easy to understand introduction to the AI and the respective Machine Learning (ML) algorithms.

Practical implementation session

In the practical part of the workshop, the participants apply the learned knowledge about the AI and ML algorithms on a simple but real industrial setup, which is accessed remotely via the web browser on the MyLiveZone training platform. On the example of the industrial setup in the included figure, which is equipped with IO-Link connected sensors, a PLC, an IoT Gateway, and a “smart light” as visualization solution. The participants start to collect sensor data and clean it in a professional AI software environment. Next, the collected and cleaned data is used by the participants to train the Machine Learning algorithms as learned in the theory part. Finally, the results of the Machine Learning algorithms are sent back to the industrial setup and will be displayed via the smart light. The practical implementation allows the participants to go through the entire process of AI-based data analysis on the example of a simple but realistic industrial setting.

Use Case Discussion

In this part of workshop, various industrial AI use cases are presented to the participants, many of which were implemented with an effort as low as 100 hours. The goal is to offer the participants a perspective on AI and to demonstrate that AI projects can start small and with low entrance barriers. Examples are quality prediction for film extrusion, predictive maintenance in compressors, optimized dosing in a pharmaceutical plant or efficiency gains in a test system.

In addition, the participants are asked to identify opportunities in their company and start drafting own ideas for AI use cases. The identified ideas are then discussed with the experts from Swiss Smart Factory and the other participants. In this way, the participants learn how to best start their own project and are better prepared to get active in their companies, whenever new opportunities arise.

Assessment of the impact of the workshops

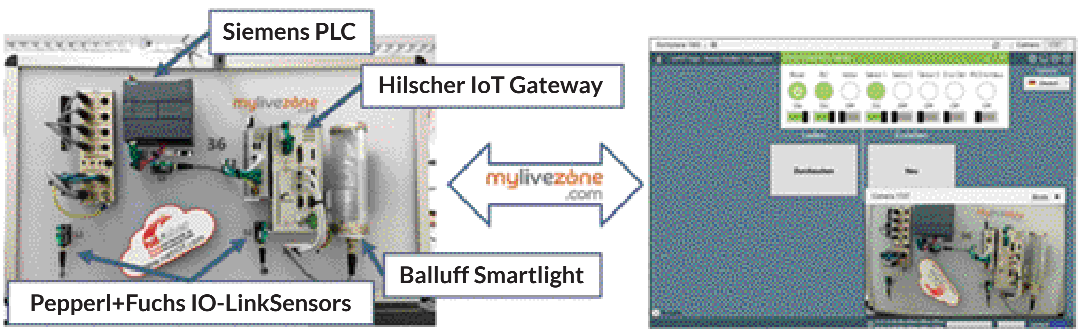
Since 2019, Swiss Smart Factory has held 9 workshop session in Switzerland and Germany with a total of 92 participants from 48 different companies. The workshops were highly appreciated by the participants, as participants could take the first step towards applying AI in their companies. The participants received a better understanding of how AI algorithms function; they learned about the practical steps to implement an AI project and how data analysis can be used specifically in their company. The statements of the participants testify to this:

"It takes away the fear of Big Data and shows useful applications of AI in industrial environments."

"The Machine Learning workshop was a great introduction to AI and modern data analysis."

"A very good, broad-spectrum introduction for industrial partners to systematic data analysis."

As a direct outcome of the workshops, many participants have started and successfully completed the first AI projects in their companies. For example, one participant has developed an AI application to analyse and optimise an air filter system in his company using ML algorithms, allowing the filters to be used much longer. Overall, the experience with the hands-on workshops on AI showed, that in addition to the many technical achievements, the involvement and training of the workforce is a crucial task in order to successfully deploy and use AI in manufacturing SMEs. The workshops have proven to be an efficient means to boost the uptake of AI technologies by inspiring and preparing the SMEs' workforce to design and implement own AI use cases in a bottom-up manner.



Real Industrial training system **Access via Browser**

2

Applications of AI in Manufacturing

AI already transforms manufacturing today - moving forward, the ability to embrace and integrate AI in the workflow will distinguish globally competitive manufacturers from the rest

Applications of AI in Manufacturing

The impact of AI applications is significant across all levels of manufacturing activities and expected to further increase over the next 5 years

This chapter focusses on current and future AI applications in smart manufacturing systems. First, we will briefly discuss the special circumstances put forth by the manufacturing domain with implications for AI applications and their value adding use. Then we will dive into specific AI applications at the Digital Supply Network (DSN) level, the factory/shop floor level , and the machine tool level. Each of these sub-sections is structured in the following order: objective, capabilities, key data sources, current and future applications supported by numbers and/or predictions, and concluded by a discussion of common challenges. It has to be noted, that the factory level includes also AI applications that enable the human operators (Operator 4.0). The more granular the area, the more technical the AI applications tend to be and the outcome (i.e. insights and provided value) tends to be more specific, applicable, and quantifiable. At a more abstract DSN level, the AI applications' results are often more in form of input for human decision makers, and thus less quantifiable and measurable in terms of value. This translates also directly in diversity, access, and quality of data that feeds in the AI algorithms. On a DSN level, data in various formats and semantics among other characteristics are sourced from different organisations and sources, while on a machine tool level, established industry standards and/or protocols (e.g., MTConnect) support the dedicated development of value adding applications. However, the impact of AI applications across all levels of manufacturing activities is significant and expected to further increase. AI applications at the various level address distinct capabilities of the system at each level. Figure 18 provides an overview of the core capabilities targeted at each level. However, this is an abstraction and cannot be generalised across all industries, systems, and applications. It should be seen as more of an indication and guidance rather than the true north.

While we decided to structure the different AI applications

Figure 18

Core capabilities targeted at each level

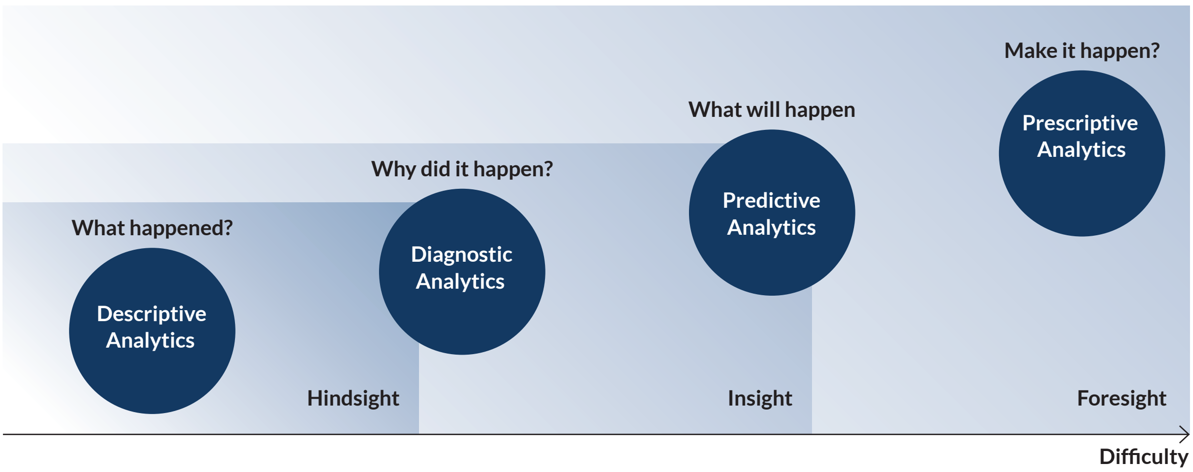
(Source: World Manufacturing Foundation)

	DSN	Factory	Machine
resilience	●		
agility	●	●	
risk	●		
flexibility	●	●	
quality		●	●
dynamics		●	
safety		●	●
efficiency			●
adaptability			●

Figure 19

Categories of analytics objectives of AI applications[31]

(Source: Gartner)

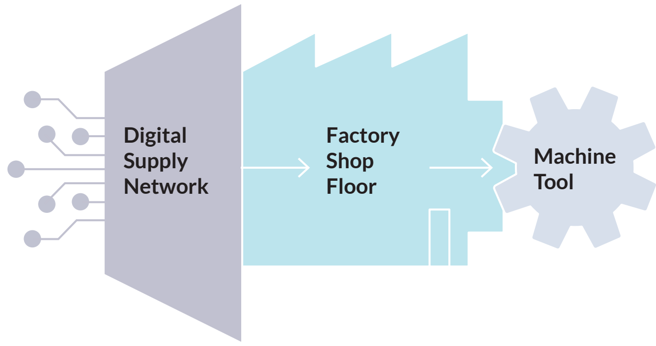


based on these three levels, there is another aspect that is relevant when discussing the topic in a manufacturing context. The different AI approaches and applications differ significantly in their complexity and difficulty of implementation, as well as their potential value-add for the business objective. As expected, the most challenging applications to implement provide the most value-add if applied expertly (see Figure 19). The three types of insights develop from hindsight, with predominantly descriptive analytics, to new insights (diagnostics and predictive analytics), to ultimately prescriptive analytics. Prescriptive analytics align closest to the visionary view of AI to understand novel problems and directly provide the 'best solution' for them. However, this vision is yet to be broadly established in the manufacturing space as we will see when discussing the current applications.

Figure 20

AI applications in manufacturing

(Source: World Manufacturing Foundation)



What make AI applications in manufacturing special

When talking about AI and AI applications, we always have to consider data as well. AI is a 'hot topic' across all nuances of today's global society including social media, ICT, and various industries just to name a few – and data is the key resource that enables all AI applications across all areas. However, this resource 'data' varies significantly between different application areas, for example in terms of quality, access, and granularity. Some of the most impressive progress in AI stems from areas where data is highly available, accessible, and contextualised. Examples include targeted marketing based on social media data by Facebook/Cambridge Analytics, making controversial headlines, or self-driving cars relying on a rapidly growing data pool filled by thousands of cars driving millions of miles. Many prominent AI algorithms, such as Deep Convolutional Neural Networks are optimised for (very) large data sets (big data), e.g., millions of pictures readily available through social media, biometrics, etc. A common misconception is that algorithms work equally well independent of the parameters of the data input. In reality, AI experts agree that the data input is actually the key determining factor for any successful AI application.

Manufacturing and manufacturing data differ from many areas where AI is applied prominently and successfully today

Therefore, before diving into specific AI applications in manufacturing, we need to first address the underlying reality of manufacturing data. Manufacturing and manufacturing data differs from areas where AI is applied prominently and successfully today. Manufacturing data sets are often smaller compared to large public data sets used to train facial recognition algorithms for example. Furthermore, they are often unbalanced, meaning that the data set has less 'problematic' (e.g., scrap parts or product quality issues) examples compared to the steady state. This underrepresentation can cause issues with supervised learning models[32]. However, this requirement for AI algorithms is in the end contradicting the objective of the manufacturing system to produce 'zero defect' quality and thus this unbalanced data set issue will persist in a manufacturing environment, and might require dedicated algorithms developed for manufacturing applications with limited transfer from advances in other domains. Furthermore, manufacturing data is often noisy and data quality, semantics, and integrity is crucial for successful applications. Another aspect where manufacturing differs from many other domains is the need for understanding causality. Manufacturing is set in the physical space and as such, the laws of physics apply. For (most) manufacturing processes and operations that are grounded in the physical world we have gathered extensive domain knowledge, e.g., tool wear models, that can be utilised together with data driven AI approaches to improve the predictions.

When discussing AI the notion of the generalised AI that trains itself and is applicable across domains, problem areas, and data sets persists. However, in reality we are not close to having such a general AI available today and that will not change for the foreseeable future. It is not helpful that the term AI is heavily overused and often understood as this nebulous, all-knowing system that magically learns itself and solves all kind of problems (aka. the 'terminator'). In reality, especially in manufacturing we see predominantly the applications of specific AI targeted to solve distinct problems applying data-driven methods (aka. machine learning).[33] This is important to consider when reading the specific applications of AI in a manufacturing environment at the digital supply networks level, factory/shop floor level, and the machine tool level in the following sections. While the following list is not exhaustive as there are thousands if not millions of different applications of AI in the wider manufacturing domain, it provides a representative and comprehensive overview of the most common and proven AI applications in manufacturing today. This supports the notion of 'tasks change with the introduction of robotics and AI, yet jobs remain' – effectively countering the widespread fear that AI and robotics/automation will lead to large scale unemployment by highlighting the many tasks for human operators in developing, training, and maintaining AI and robotic systems as well that there is an optimal degree of automation for most objectives.[34]

AI Applications on the Digital Supply Network (DSN) level

AI in Digital Supply Networks has the potential to reduce the administrative cost of operations by 25-40%

The Digital Supply Network (DSN) level covers all activities of manufacturing organisations beyond the factory boundaries. Every manufacturing company today is in some form, shape, or fashion part of a supply chain or supply network. Throwing digital transformation initiatives in the mix leads to the emergence of DSNs. However, the integration, scope, and size of the DSNs vary significantly by company, industry, and other factors. AI is an integral part of DSN and enables many of the core features such as synchronised planning, dynamic fulfillment, intelligent supply, and smart factories.[35] In the following we introduce specific AI applications at the DSN level supported by current industrial examples. It has to be noted that many of the different AI applications are used together to deliver full benefits. Besides targeted applications, a general benefit of AI in DSNs is also the potential to reduce the administrative cost of operations by 25-40%.[36] The core capabilities addressed by AI implementations at the DSN level are resilience, agility, reduced risk, and flexibility.

The first application of AI in DSNs that we will discuss is focused on ***demand forecasts and the associated synchronized planning*** within supply networks. Demand (and to some extent supply) forecasting is an essential task to enable reliable production planning that depends on a wealth of factors. AI applications focus on identifying patterns in these big data sets to predict demand more reliably. This can be changing preferences (e.g., seasonal products in fashion), weather (e.g., hurricane), unique events (e.g., Olympics, black swan events such as COVID-19), or policy impact (e.g., trade tariffs). Enabling the DSN to better predict the future demand of goods allows to better plan production, suppliers, and logistics – down to the daily stock levels of certain products in individual stores.[37] The predicted improvements are significant with McKinsey estimating a possible 50% reduction of supply chain forecasting errors through AI[38], which directly translates in better business outcomes.

Automated warehouse management is another aspect where AI applications are adding value to today's DSNs. Modern warehouses and logistics centres are highly automated and optimized. AI applications are used to identify the best place to store products for maximum responsiveness, efficiency, and safety depending on the optimization goal. Given the size and volume handled by modern warehouses, either for end products, parts, or consumables, human operators without AI support are not able to efficiently handle the operations any longer. The AI algorithms continue to learn and thus improve over time – creating a 'learning warehouse' – that is more dynamic, agile, and responsive than before.[39] Together with AI-enabled technologies such as Automated Guided Vehicles (AGVs), Augmented Reality (AR) solutions, and other Operator 4.0 technologies, AI has a tremendous effect on warehouse management and operations today. However, a word of caution is that a 100% AI-run warehouse is at least a decade away according to Amazon, one of the leading players in this space.[40]

The third area where AI applications make a mark at the DSN level is ***automated design and development*** of new products and/or services. Today's consumers in both the B2C and B2B space are increasingly demanding customised or even personalised products. This requires often a redesign, -development, and -planning of the product itself but also the manufacturing process(es). AI applications are providing the necessary capacity to scale such customisation by automating many tasks for companies, designers, and production planners. For instance, AI-powered generative design optimisation that is already included in many CAD platforms and creates optimised designs for load bearing parts. In this case, the AI algorithm supports the human designer from optimising the for the design objective to automatically design new products based on diverse inputs.[41] In the future, design variants can be automatically adapted based on the new requirements by AI-powered tools learning from historic design decisions of human designers.

Connected services are the last aspect where AI on a DSN level is crucial. AI applications are capable of automatically monitoring, clustering, and predicting the use of machinery and products. This capability is the foundation of offering Manufacturing as a Service (MaaS) and other related concepts (XaaS).[42] Product-Service Systems (PSS) are one example where AI is utilised to spec out the requirements and thus value of offering a PSS but also enable continues learning and improvement of the system. An example is KONE's '24/7 Connected Services' which utilise AI to improve the prediction of the likelihood of future breakdowns and/or service needs. Through these insights in future demand, their customers – in this case building and/or maintenance managers – are able to improve reliability and uptime of the KONE equipment (e.g., elevators and escalators) and thus deliver a significantly enhanced customer experience and satisfaction as well as optimise the efficiency and effectiveness of their own service operations.[43]

All these DSN level AI applications impact the resilience, efficiency, and scalability of manufacturing operations and is every more important as we learned through black swan events like the current COVID-19 pandemic.

AI Applications on the factory/shop floor level

In today's manufacturing facilities (aka. factories) and on the manufacturing shop floors, we see many AI applications provide value in different areas impacting energy efficiency, maintenance operations, and operational efficiency. This level is 'stuck in the middle' in terms of scope and challenges between the complex and diverse DSN level and the more targeted and defined machine tool level. Here we face both, clear standards and well curated data on the one side, together with more qualitative input and human interaction on the other. The core capabilities addressed by AI implementations at the factory level are quality, dynamics, agility, and flexibility. In the following, we highlight a selected few examples where AI applications impact manufacturing facilities today.

The first aspect that we will discuss are AI applications focused on energy. Energy and ***energy efficiency*** is one of the key drivers across manufacturing. AI is used in a variety of ways to monitor, assess, predict, and improve the energy efficiency on a plant or production line level. As mentioned before, the three levels we apply here are overlapping and energy is also a core objective on the machine tool level. On a production line and factory level, AI applications enable us to derive insights relevant for reducing the overall energy impact of the facility as a whole. Analyzing and predicting the energy use from data provided by a diverse set of manufacturing assets (e.g., milling centres), supporting equipment (e.g., AGVs), and others (e.g., heating/cooling). Another aspect is the estimated 30% reduction of scrap rates through use of AI that directly impacts the energy used in production.[44]

Another aspect where AI applications in manufacturing are impactful is ***product and process quality***. In multi-stage discrete manufacturing systems, the product quality state depends on deviations in previous processes, which are complex and little understood today. AI enables the production engineer to identify key drivers that impact the overall product quality at various stages throughout the process. Based on these insights provided by the AI application, either the operator can intervene in case of an event or the AI can automatically adapt the process parameters.[45] Another relevant AI application with quality implications is computer vision allowing for in-situ contactless automated quality monitoring. However, this overlaps with robotics below and section AI Applications on the machine tool level where more details are provided.

Today, scheduling is often task with limited AI support and relies human operators and complexity reduction

Another aspect where AI is crucial, and connected to demand forecasting on the DSN level, is ***scheduling optimisation***. AI enables production planners to merge historic data with real-time sensory input to predict the production time more precisely and update the schedule dynamically. This increases the dynamic of the manufacturing operations response and at the same time improves time-to-market, quality, and/or inventory cost.[46] AI applications in scheduling are most beneficial when it comes to complex and high-variety production where the algorithms can utilise the ability to integrate a variety of different data sources. Today, scheduling is still often handled by human operators with limited technology support and relies on complexity reduction.

An area that is continuously growing in importance when it comes to AI applications on the shopfloor is ***robotics.*** Robotics is a broad area and historically connected to AI. Without AI applications such as computer vision robotics applications as we know them today would not be possible. While listing all AI related activities in the industrial robotics space would go beyond the purpose of this section, we want to mention a selected few. Novel and exiting AI applications in the robotics field emerge daily. One of them is the ability of industrial robots to teach themselves how to assemble a part based on the CAD file of the parts and assembly[47]. This greatly reduces the time-consuming programming of robotic systems[48] and manages the skills gap in the field. Another aspect where AI is essential for current and future applications is human robot interaction, where AI enables the robot to work with humans without safety cages[49]. Forbes actually states that "smart robots equipped with advanced sensors that feed data to complex algorithms powering AI and machine learning will further improve work processes and the supply chain, so much so that collaborative robots (cobots) might represent the model application for AI and automation."[50]

The last area we will discuss on a factory level where AI applications are impacting manufacturing are the many applications of ***AI that enhance the abilities of the human operator*** - also called Operator 4.0[51]. AR and intelligent assistance systems have found their way on the shopfloor and recently matured from their early proof of concept stage to robust and valuable tools. We saw and are seeing more AI fueled applications utilising wearables, vision systems, AGVs, and AR with the emergence of the COVID-19 black swan event, enabling manufacturers to adhere to safety policies and guidelines.[52] AI powered Natural Language Processing (NLP), pattern recognition and vision systems enable manufacturers to keep production running while keeping their employees safe.

AI Applications on the machine tool level

The most developed area with the most mature AI applications is the machine tool level. A recent study found that 29% of AI implementations in manufacturing aim at maintaining machine tools and other production assets.[53] This does not come as a surprise as the system boundaries are more clearly defined, the data picture more homogeneous, and detailed expert knowledge build over decades readily available. Nevertheless, we can observe a continuous development of new and exciting AI tools on this level as well. The core capabilities addressed by AI implementations at the machine tools level are quality, efficiency, safety, and adaptability. Similar to the previous sections, the following application represent a snapshot of established and representative AI applications. There is again an overall in the different applications as their utilise similar techniques and serve the same overall manufacturing objectives.

Automated quality inspection, monitoring, and control is one of the key areas where AI provides tremendous value in this space. It has to be noted that this paragraph focusses on quality of manufactured products ('product quality') which reflects process quality as well. The (quality) monitoring of machine tools themselves is discussed in the following predictive maintenance and tool wear paragraphs respectively. When it comes to quality, among the many available AI applications, the use of computer vision for real-time in process quality inspection is especially intriguing. A recent example of this powerful AI application is the use of DCNNs on 100% inspection of micro-manufacturing using light-field cameras to incorporate depth-perception.[54] The next stage of vision based quality monitoring systems aims to move from predictive to prescriptive by earning from the defects and automatically adapting the process accordingly.[55]

Another application for AI-powered tools are ***data-driven tool wear*** models that enable the manufacturing system to adapt to different materials and cutting conditions. Modern CNC machine tools are equipped with a myriad of sensors that provide ample data to feed into AI learning algorithms to reliably predict the tool wear and performance to avoid product quality issues, high energy consumption, and catastrophic events such as tool breakage. Increasingly, data-driven models are merged with physics-based models to increase the prediction performance and leverage the wealth of existing knowledge in this area.

The savings from predictive maintenance applications are considered significant with some studies claim a 10% reduction in overall maintenance cost and a 25% reduction of annual inspection cost

The third core application for AI tools on the machine tool level are ***predictive maintenance*** applications. Predictive maintenance is highly sought after by industry as the value add and ROI is clearly quantifiable. According to a recent study, over 80% of the surveyed companies planned to engage in some form of predictive maintenance initiative.[56] The savings that can be realised depend on various factors but are considered significant with some studies claiming a 10% reduction in overall maintenance cost and a 25% reduction of annual inspection cost.[57] Initiatives like 'zero downtime' portrait a glorious vision for manufacturing that relies on powerful AI applications.

Last but not least, AI applications are impacting the ***Overall Equipment Effectiveness (OEE) and energy efficiency*** of machine tools. Utilising data driven AI to assess and optimise machine tools holistically has proven very effective, for example a 28% decrease in overall energy consumption through optimising the component level energy efficiency.[58]

Closing the Quality Control Gap with AI-powered Visual Inspection for Manufacturing

Daniel Bibireata
Principal Engineer, Landing AI

As more manufacturers strive to achieve the full potential of digitization and Industry 4.0, quality control continues to pose a major challenge. Inaccuracy is no surprise given the tedious and repetitive nature of inspectors' work, which involves examining hundreds of products for tiny defects along a fast-moving production line. It's cognitively taxing work that strains the eyes and invites human error.

The introduction of Automated Optical Inspection (AOI) streamlined inspections, but still falls short of the dream of a fully efficient, digitized quality control process. Traditional machine vision relies on rigid rules hard-coded by human operators, which makes it hard to adapt to changing environments, requirements or highly complex situations. This inflexibility leads to a rate of false positives (the proportion of parts marked defective that are actually acceptable) as high as 40% for many manufacturers, necessitating human inspection of rejected parts.

To reach the full potential of digitization and Industry 4.0, manufacturers must embrace AI-powered solutions that finally close the quality control gap. Unlike traditional machine vision, AI-powered visual inspection doesn't require hard-coding. It uses sophisticated AI techniques such as deep learning (DL) and machine learning (ML) to continuously learn and improve performance over time. These systems particularly excel at identifying cosmetic defects such as surface scratches as well as verifying proper assembly and part location. AI models can also be trained to tolerate variability and deviation, such as changing backgrounds, lighting or perspective. This dramatically improves accuracy: Compared to traditional machine vision solutions, AI can lower false positives by as much as 95%.

By making inspections more efficient, AI lowers costs and frees up human inspectors' time to search for the root causes of defects or perform other high value-add work. In the long term, AI visual inspection systems also collect rich data that can be used to generate actionable insights that further optimise manufacturers' operations.

Historically, it has been difficult for manufacturers to roll out AI visual inspection systems at scale. But technology can now solve most of the major barriers:

- **Small data:** Most big data solutions train on millions of data points. As manufacturing defects are relatively rare, there may only be a few dozen pictures of a given defect. Techniques such as transfer learning and the use of synthetic data (computer-generated photos of defects) can be used to fill gaps, making the application of AI to visual inspection possible.
- **Ambiguous defect requirements:** Inspectors' tired eyes aren't the only source of human error in the inspection process. It's not uncommon for two inspectors to deliver a different verdict on the same error — one thinks the error is worth rejecting a part, while the other thinks the error is small enough to be ignored. Inspectors can align on these issues by documenting defects in a digital "defect book" programmed to highlight any ambiguities. A defect book also makes it easier to adapt AI models as inspection requirements evolve over time.
- **Compounding complexities:** When a large manufacturer deploys AI models across many plants, product lines and defects, it could result in thousands or even millions of custom AI datasets and software components. It's more than any one person can track — and the complexity multiplies as scope grows. A software platform can unite AI models across multiple plants and product lines, showing manufacturers important trends (e.g., a defect becoming more frequent) at a glance. A platform can also reduce overall AI project development time by up to 67% and speed up the labeling process by as much as 50%.

AI is an important tool that powers the digital-first factory of the future. Since its inception, Landing AI, a Silicon Valley-based startup founded by AI pioneer Andrew Ng, has been working with leading global manufacturing companies to implement AI-powered visual inspection solutions into production. The work has led to the creation of an end-to-end platform that enables manufacturers to quickly create, deploy and manage their AI visual inspection projects, allowing manufacturers to build a more streamlined, cost-efficient and forward-thinking manufacturing process.

How AI can promote cybersecurity in manufacturing industries

Andrey Suvorov
Chief Executive Officer, Adaptive Production Technology (APROTECH)

Andrey Lavrentyev
Head of Machine Learning Anomaly Detection (MLAD), Kaspersky

Industrial data is in large part facilitating a change in approach and a new level of quality for modern digital services.

Consider the simple analogy of an oil refinery built a couple of centuries ago. With the advent of the first distillation and kerosene technologies, the world began to change and adapt towards the creation of new products. As a result, nowadays dozens of technologies are used and thousands of products are produced in this field, and the oil conversion ratio reaches up to 90% and higher.

A similar situation is now being observed with industrial data at the production facility level. If one considers, for example, any technological equipment or its separate element, it may be the case that only 10-15% of data could be transferred to the enterprise domain. For instance, a vibration or acoustic sensor connected to a drilling platform can generate valuable data. Data processing can prevent an accident or predict the failure of an element if it plans maintenance in advance, and orders a replacement element and specialist to do the job. Our experience shows that 50GB per minute can be generated in an industrial control system of a medium-sized enterprise.

But new value from industrial data can shift the focus to additional cyber-related topics.

Over the past five to seven years, cyberthreats have been the subject of discussions at board level. According to Allianz's annual Risk Barometer report, in 2013, cyberthreats ranked 13th in the list of risks for CEOs, and seven years later, they were already in first(!) place (https://www.agcs.allianz.com/news-and-insights/reports/allianz-risk-barometer.html).

The traditional approach in these matters is becoming less and less effective. The previous attack scenario is constantly being replaced by the next one that exploits a new vulnerability. In response, cybersecurity companies came up with the option of offering updates to the market, but this approach doesn't work in IIoT, where devices (a lot of devices) have limited power and computing capacity.

A cyber-immune approach will gradually replace traditional applied cybersecurity, particularly in IIoT and critical infrastructure. An IT system is cyber-immune if the overwhelming majority of different cyberattacks won't affect its critical functions in the usage scenarios described at the design stage. Creating such systems requires a certain methodology and trusted software, such as KasperskyOS. Among other solutions, we are now in the advanced stages of developing an IIoT gateway based on these principles.

With today's new level of industrial data processing and advanced cybersecurity, it is now possible to change the existing technological landscape of enterprises, as well as C-level attitudes.

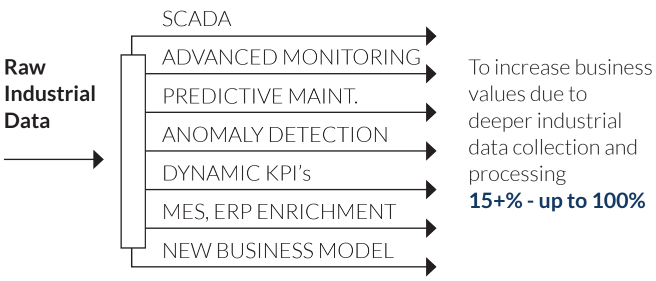
Our first projects show that this synergy can be achieved both in regards to existing applications and in the sphere of new digital services (see Figure 1). Anomaly Detection represents a new class of solutions that can provide business value from raw industrial data.

Rich and frequently sampled telemetry data capture the behavior of industrial assets in considerable detail. Assuming that the asset's machinery performs stationary or repetitive processes, we can speculate that every aspect of a machine's behavior can be accounted for in a sufficiently lengthy dataset. Therefore, from this dataset we can build a model imitating a normal asset's behavior. By comparing the model's output with a real-time data stream, we can detect the slightest anomalies in the asset's operation.

Anomaly detection helps reveal destructive disruptions, such as hacker attacks or impending equipment failures in the early phases of their development when the asset's operation still appears normal. Disruptive processes are detected long before the system's condition reaches the

Figure 1

'Raw' industrial data. Usage Value



critical threshold when conventional alarms start going off. This buys us valuable time to react before any real harm is done.

To build such an anomaly detector, we created a model powered by artificial intelligence that learns from telemetry data until it is able to accurately predict the current state of the asset from its recent behavior. The model needs approximately 100-500 thousand data points to be trained. In terms of time, this is about one week's worth of data if measurements are sent every second. When an anomaly is discovered, the detector outputs a list of affected signals for the operator to analyse and respond to.

Let's take a look at a few cases where the use of an anomaly detector resulted in clear savings.

At an oil refinery, expensive repairs on pumps were required so frequently that it hampered production. SCADA did not notice any trouble. However, the anomaly detector found unusual quick drops in pressure in the pump that correlated to the change of raw materials fed into the refinery. The issue was an incorrect temperature setting that was causing cavitation in a specific type of crude oil, and consequently, a plunge in pump pressure that was too short for a human to notice. The immediate damage to the pump was minor, but over time it caused a noticeable degradation of pump performance.

In another case, a hacker attacked a chemical plant by spoofing a feed flowmeter in a reactor. For short periods, the flow reading was repeatedly set to a fixed value that was inside the normal corridor, so no alarm was triggered. However, due to the dynamic nature of the reaction, the flow would normally have been increasing at this stage. After failing to observe the expected response from the flowmeter, SCADA continued to open the valve. The excessive amount of the reagent fed into the reactor considerably degraded the quality of the product. This attack was discovered by the anomaly detector because the behavior of the flowmeter did not match the expected pattern learned by the model.

Another skewed flowmeter, this time affected not by a hacker but by a coke deposit inside a furnace tube, would have caused a major fire. The problem was discovered in a time when a detector alerted plant staff about the unusual changes in temperature.

All the aforementioned cases have something in common: even though traditional surveillance measures, such as human operators or SCADA, failed to notice the issues, they still left traces in the telemetry data streams. With modern data processing tools, these traces can be detected and the issues identified. Using the same telemetry dataset, a model can be trained to predict the time left until a certain event. The application of this model is in predictive maintenance. For example, a bearing must be replaced when it reaches a certain level of vibration.

Soft sensors are another type of treasure that can be mined from data. If a certain important parameter is not contained directly in the telemetry or measured too seldom, we can use machine learning to restore the parameter from other data. This is made possible because the telemetry signals are correlated and the missing parameter leaves traces in other parameters that we can observe.

For example, this was achieved with measurements of product quality that were used to optimize a chemical process. The product was sampled only twice a day due to the technical limitations of the facility. Armed with these half-daily measurements as reference points, we were able to build a model that estimated the product quality metric from the plant telemetry that did not contain this metric at all. As a result, the plant was able to continuously optimize its process, which considerably improved the quality of the product.

Industrial data includes an abundance of actionable insights. Recent technological advancements, especially in machine learning and artificial intelligence, provide the means to uncover these insights, resulting in significant benefits for manufacturing industries. The economic advantages have been confirmed in a wide range of applications, from reducing downtime and repair costs, to improving product output.

Prysmian Group: manufacturing the future through predictive analytics

Antonio Adigrat
Plant Quality Manager

Carlotta Dainese
Head of Digital Innovation Lab

Giuseppe Pagnoni
Group Product Quality Director

Digital Ambition

Prysmian Group is a leading cable manufacturing company for energy and telecom infrastructures, with 106 production plants in the world, 29,000 employees and a turnover worth 11.5 billion euros in 2019.

Prysmian has a "digital ambition", enabling the transition from leading cable manufacturing company to solution provider for the energy and telecom sectors. The Group aims at optimising business performance through data leveraging digital tools and solutions, sustaining growth by integrating digital services in our products, and supporting collective intelligence by digitalizing the company's culture. The value proposition of this ambition is based on 3 pillars: efficiency through data, develop value adding digital products, diffuse digital practices in the organisation.

In this framework, data are at the core of the Company "digitalisation" process, in fact the Group believe that extracting value from them is the key to remain a leader in the current fast-changing market.

Because of this, last year Prysmian started a program to deliver value from the data collected in the plants to 1) prevent quality issues, 2) reduce cost and 3) improve efficiency through new enhanced tools based on advanced statistical algorithms and machine learning.

Different plants imply heterogeneous initial conditions. Because of this, Prysmian outlined a standard workflow to evaluate the specific barriers and the potential benefits for each single plant to replicate the implementation of data driven tools in different situations.

Strategic Approach to Predictive Quality

Prysmian Group's big database is currently exploited for different production line management activities, but there is still a large gap between the way in which data are currently used and the great opportunities enabled by state-of-the-art technologies and solutions. Because of the complexity of our production processes and the variety of information buried in large and fast data streams, it is difficult to make data a true asset for the Company with currently adopted solutions. Since Prysmian believes there is no plug-n-play recipe to apply new methodologies (as AI), the Company has figured out its own path.

In 2019, Prysmian launched the Predictive Quality project with a first pilot in a Fiber Optic plant in southern Italy. The huge amount of available data and the complexity of both operations and process interactions made this plant an optimal candidate for developing the new approach.

The project team includes people from Prysmian HQ Digital Innovation and Quality Departments, Operations and R&D. In this innovation project, Prysmian is supported by Mathematical Modeling and AI experts from Moxoff SpA, the spin-off of the Mathematical Engineering department of Politecnico di Milano.

The challenge was to detect process trends that may lead to failures or product quality issues and therefore trigger troubleshooting activities as prevention rather than correction countermeasures. The idea was to develop a "visualization tool" integrating advanced data analytics and modelling methods to reach these main results:

• Faster decision making and corrective actions, improving the process control procedures by relying on new anomaly detection capabilities and the analysis of interactions among different process phases. These methods are designed to make the root cause analysis easier, faster and more reliable.
• Operation management optimisation by implementing a global system view, with synthesized parameters and valuable information extracted at shop floor level.
• Scrap reduction by predicting the likelihood of non-conformity occurrence, with a consequent reduction of costs of poor quality and improvement of plant efficiency.

As a by-product, this approach also led to a more comprehensive understanding of the analysed production processes. The project started by mapping the whole production line and identifying the relevant data sources. The first milestone was the selection of the KPIs that would be used to monitor the effectiveness of the approach.

The key request was to identify the critical paths in the production flow which have a negative impact on some preselected KPIs. New algorithms, specifically designed and tailored for the application at hand by Moxoff's experts, enabled the investigation of new and complex relations between different stages of the production process and multiple variables at the same time. The identification of these relations allows to detect problematic nodes so that process experts can immediately focus the trouble shooting activities on a specific subset of production machines. These models, together with performance indicators based on the comparison of monitored variables patterns, are the underlying components that immediately point out to the operator the process steps and machines that need immediate attention, by means of easily understandable graphical representations. This tool is currently in use by the plant operations team and is delivering real time insights on process performances.

Next Challenges

The next challenge is to scale up the solution to other Prysmian plants and to include additional automated decisional support and Machine Learning layers to further enhance the efficiency and effectiveness of predictive-based actions.

The execution of the pilot project has already yielded tangible results. At the same time, Prysmian Group is already planning the extension of this approach to other plants in the Group, leveraging a change in the data analysis to catalyse a broader cultural evolution on the use of data for decision making.

Prysmian Group doesn't want to be just a market leader but also an innovation leader in pioneering these new approaches.

3

AI and Human Capital

A more positive view is when people work in harmony with AI, complementing each other's capabilities.

AI and Human Capital

Now that we have explored the background of AI through a statistical analysis as well as understanding its role in manufacturing, it is important to understand the intersection between people and AI. Currently and even more so in the future, people are consistently interacting with AI. As a result, this changes the nature of work and technological interaction. Particularly, the modern workplace will be affected by the implementation of more AI into processes. Tasks once solely performed by humans will begin to receive an AI component to varying degrees as technological process takes foot and begins to become more commonplace amongst businesses of varying sizes.

Undoubtedly, there is a great amount of scepticism and fear around the introduction and integration of AI into the manufacturing workplace. However, in this section we aim to showcase how utilising AI and incorporating it into existing factory infrastructure can be beneficial to both workers and processes.

Our goal is to be realistic yet clearly explain how AI does not have to mean displacement or replacement but rather new and improved opportunities for workers. The hope is that this chapter can allow for a more open-minded view of AI while encouraging organisations to prioritise the well-being and development of employees.

AI and Future Work

This subsection is meant to provide a positive but realistic view of how AI will change the landscape of manufacturing and ultimately affect workers.

It seems every day one can open an internet browser and find countless news articles about how "AI will take over manufacturing jobs," or "robots are replacing humans and taking their jobs!". It is no doubt that the manufacturing world is changing. That is an undeniable fact as all industries change, grow, and evolve over time. However, we want to dispel the myth that AI creates a bleak outlook for the future of manufacturing workers.

Increased automation provides a unique opportunity to streamline processes and upskill workers if handled correctly

Certainly, AI is changing how people work in manufacturing and that does have an impact on the labour market. According to many forecasting studies, manufacturing consistently ranks as the industry that has the highest potential to automate processes. These predictions are undeniably worrying for manufacturing workers and can create uncertainty. However, it is key to note that increased automation also provides a unique opportunity to streamline processes and upskill workers if handled correctly.

In a 2019 report, the Brookings Institution notes that while at first glance many may think that AI is detrimental to the average manufacturing workers, AI will rather change the role of workers and the tasks they perform.[59] AI can help to streamline processes to make manufacturing and other sectors more efficient, but also enable new product-services and business models. Workers are still certainly needed but perhaps in different roles. Instead of someone working on a production line and assembling one part of a vehicle, that person may be in charge of operating and maintain an AI-based system that is able to complete that task at twice the speed of a human.

Understanding that AI cannot replicate many of the human-centric actions and responsibilities can help us to maintain a positive view on future outlooks for workers

Moreover, when discussing how AI plays a role in how work will change and not necessarily be displaced, it is key to note that it is rare that entire jobs are automated. Jobs are made up of a set of tasks that an employee is supposed to complete. Tasks within jobs will be able to become automated allowing for a more streamlined and efficient approach. Understanding that AI cannot replicate many of the human-centric actions and responsibilities can help us to maintain a positive outlook. As seen in

Figure 21, there are many elements of human work that cannot be replicated by that of an AI machine. There is a unique human skill set that regardless of progress will not be able to be authentically replicated. As many companies have noted when discussing AI, utilising new technology is not about eliminating workers but augmenting their capabilities and creating collaborative teams where humans and machines can complement and extend the potential of one another.[60,61]

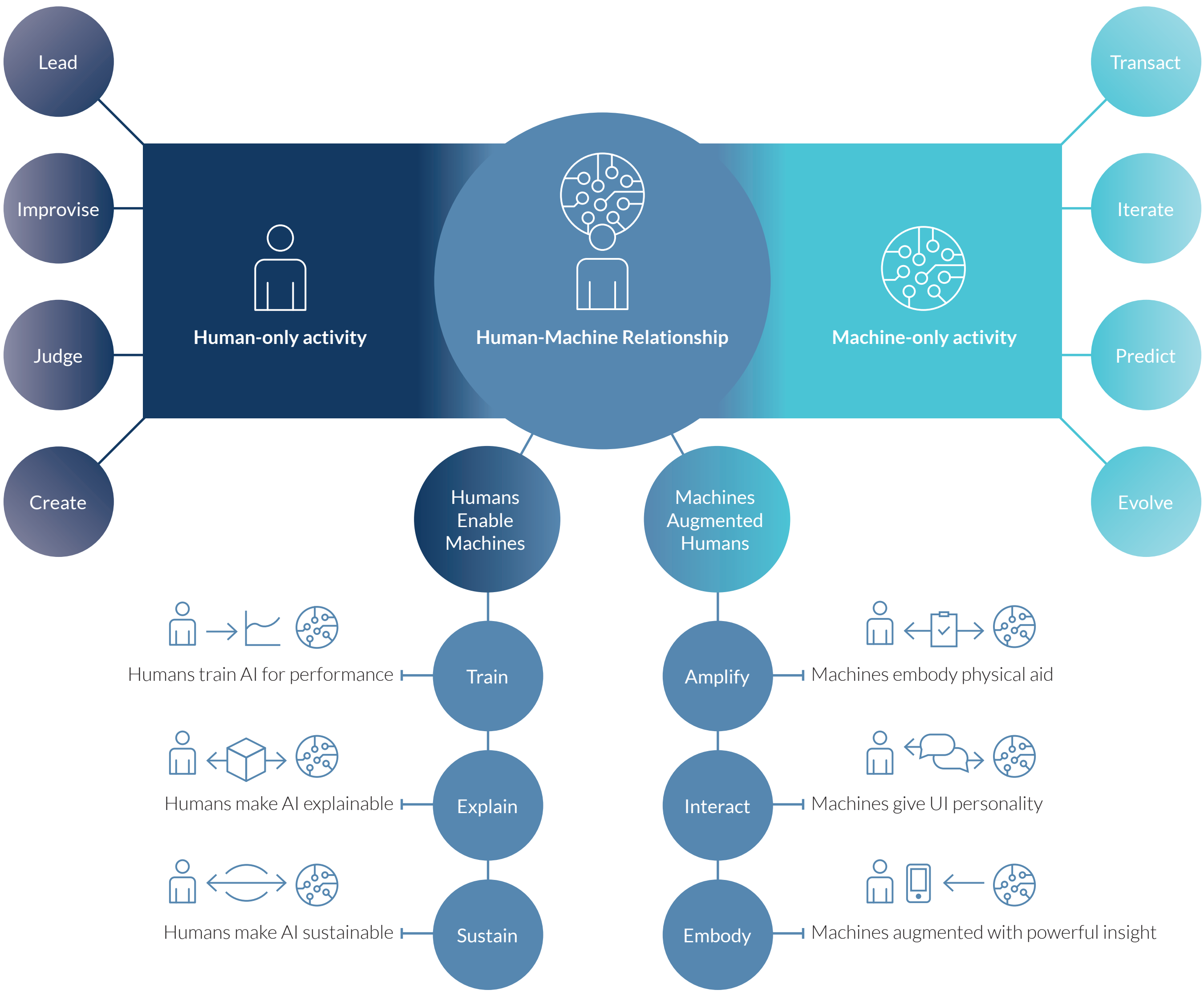
Moreover, manufacturing is not the only sector that will be affected. According to Harvard Business Review, less than 5% of occupations could be entirely automated, but about 60% of occupations in the U.S. have at least 30% of tasks that can be automated.[63] These figures illustrate that the implementation of AI is not an isolated manufacturing issue but rather one that we, as a society, must proactively engage to throughout time. Instead of fearing and resisting changes that will eventually come, we aim to educate and help provide resources on how to lead the transformation and exploit this technology in a socially sustainable way.

While this change is understandably challenging, we maintain an optimistic view. As we mentioned in the 2019 World Manufacturing Forum Report: Skills for the Future of Manufacturing, investing in workers through up-/re-skilling, life-long learning, and professional development is crucial to create a 21st century workforce that is equipped to handle the new challenges that technologies, such as AI, present.[64] If we are able to retrain and upskill workers, then we are able to make the transition without leaving manufacturing workers behind.

Figure 21

Human-AI collaboration[62]

(Source: Daugherty and Wilson)



AI and Existing Roles

It is undeniable that AI and new technologies will change manufacturing. In this sub-section, we will explore how current workers will need to learn and work with AI. We hope to make readers feel hopeful that incorporating AI into their current activities could help their work and therefore enable a more positive work experience.

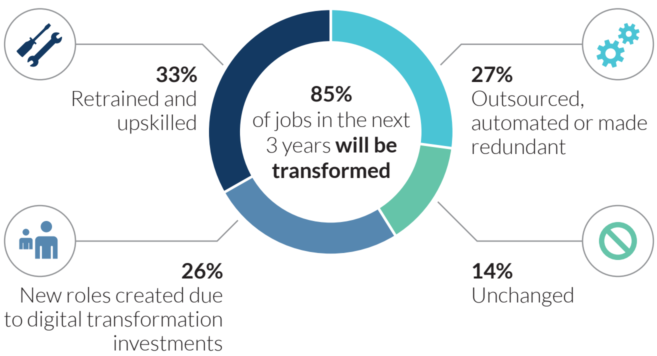
According to a recent study from Microsoft and IDC focused on the Asia Pacific region 85% of all jobs will be transformed in the next three years. This includes 33% of workers needing to be retrained or upskilled, 26% being new roles that are created due to digital transformation investments, 27% will be outsourced, automated or made redundant, and only 14% will remain unchanged.[65]

The skills that are needed for a 21st century manufacturing paradigm are ever changing and require agile and adept employees who engage in life-long learning. AI is a key technology that will require workers to engage in activities such as upskilling, reskilling and lifelong learning.[66] Instead of fighting the changes, the manufacturing sector can take this opportunity to work to implement new technologies in a social sustainable way and create a more positive work experience.

Figure 22

Transformation of Jobs

(Source: Microsoft/IDC)



AI and people working together harmoniously can improve efficiency and at the same time also allows for emotion and creativity throughout the process

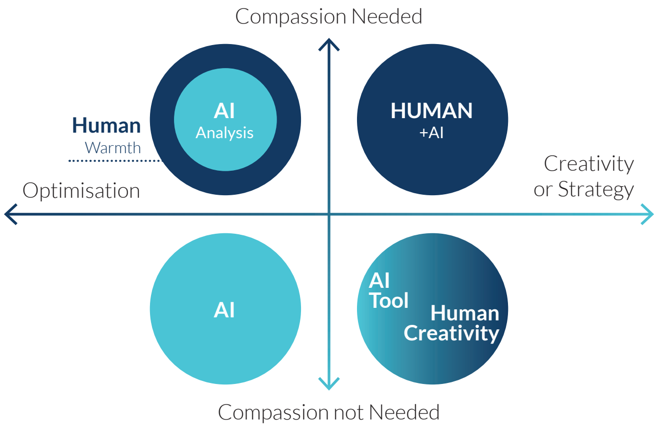
Another key element of how AI and existing roles will change is the increase of human to machine interaction. As displayed in Figure 23, it is key to note that when AI and humans can work together harmoniously, we cannot only achieve optimisation and efficiency but also allow for emotion and creativity throughout the process.

The nature of work for many roles may change as there will be increased human to machine interaction rather than human to human contact. While certainly this has some implications in workflow, it may have some benefits given the Covid-19 pandemic which has forced many people and many jobs to abide by physical distancing standards.

Figure 23

Combinations of AI and human capabilities[67]

(Source: BBVA OpenMind)



AI could enable inclusivity in the workplace

Additionally, AI may help to make work less strenuous and more inclusive for many groups. For example, instead of assembling parts the worker now controls the robot that assembles the part making it faster and less strenuous. This could open up that role to people who may not have had the physical capabilities to perform it earlier, meaning that we are tapping into a part of the workforce that may not have been heavily involved in traditional manufacturing roles. Symbiotic systems between workers and AI will allow them to work together to achieve optimal results that combine the best of both AI and human intelligence.

Emerging Roles in AI

As companies adopt AI technologies in their organisations, AI will augment many existing roles in the organisation and will also create completely new ones

Broadly speaking, there are three main categories of roles created by AI: **Trainers** teach AI systems how to perform from teaching language to coding human like behaviours. **Explainers** bridge the gap between technology and business leaders who can explain exactly how AI works. **Sustainers** keep AI systems working and providing maintenance and ensuring that quality results are met.[68]

The roles outlined in the section include already existing roles that the World Manufacturing Foundation thinks will increase in relevance in the near future, or roles that have only been recently introduced as organisations are increasingly transformed by AI.[69] The roles are grouped into four main categories, each with a differing objective: Strategy, Research and Technical Development, Ethics and Compliance and Human-AI Interaction. The list is not exhaustive, and we acknowledge that given the rapid pace of innovation on AI, new roles will continue to emerge.

Strategy

There is a need to align a company's strategic goals and objectives with its over-all AI strategy. Investing in AI is both a financial and business decision and hence managers must be able to take into consideration the economic and business use case of AI.

Within this group are **Business Leaders** who are able to articulate what type of AI solution can advance the company's strategic objectives and business models.[70] They have a clear understanding on what an AI solution means for the organisation in terms of its economic use case for different company stakeholders. They need a basic understanding of how AI roles work, and the data sets deployed with them. More importantly, business leaders should be able to think critically, and exhaust relevant data to help in decision making.

Research and Technical Development

Technical development refers to the actual coding, software development, and development of AI applications.

AI engineers develop products and production applications related to AI. AI engineers are able to develop models from scratch and (commercially) deploy those models into production. AI engineers are expected to possess not only AI specific knowledge but also programming, computing, and corporate IT/OT environments.[71]

Data engineers have an in-depth understanding on how data could be transformed or used to solve an AI related problem. In simple terms, Data engineers prepare the required data that is fed into the system. While data engineers are instrumental in data collection, the significant portion of their time is spent on assessing, cleaning, and treating data. Given that the success of AI applications depends on the quality of data utilised, data engineers have an increasingly instrumental role within organisations.

Ethics and Compliance

This aspect deals with ensuring that the ethical considerations revolving around AI are addressed in the organisation.

Ethicists will have an oversight role within organisations ensuring that activities related to the development and implementation of AI are within defined ethical boundaries. For instance, ethicists work alongside engineers in ensuring ethical considerations are embedded in AI algorithms. On a broader scale, the AI ethicists consult regularly with "users" throughout the organisation, and together with top management define a clear governance framework that specifies clear responsibilities and the boundaries for AI development.

Privacy Specialists have a strategic role within organisations ensuring that data from customers and other sources is protected and fairly used. AI has accelerated the way that organisations can collect and process data from different sources, and in some cases, without consent. In the EU, recent regulations such as the GDPR have set defined guidelines for collection and processing of personal information. Hence, privacy specialists have the potential to reduce compliance costs and risks for the organisation.

Human - AI Interaction

Undeniably, situations where people and machines work side by side is a core aspect of future manufacturing. This group ensures smooth interaction between people and machines that are increasingly driven by AI.

Collaborative Robots Expert 2.0 AI and machine learning will augment the existing capabilities of robots allowing them to decide on what action to take next depending on how they interpret the environment. The collaborative robot expert, in addition to the usual work to define, install, configure, and maintain "co-bots" integrated with factory/enterprise systems should be knowledgeable on how AI is transforming and could transform "co-bots" allowing them to operate in its fullest potential.

AI coaches (explainers) are able to respond in simple terms employee questions about AI. They are able to explain how AI works, what AI means for workers' roles, and more importantly how they complement their existing activities. AI coaches not only need to have a solid background on AI but also need to strong communication skills and possess empathy for others. AI coaches have the potential to increase awareness and transparency about AI throughout the organisation, allowing workers to increase trust on AI.

Skills needed to work with AI

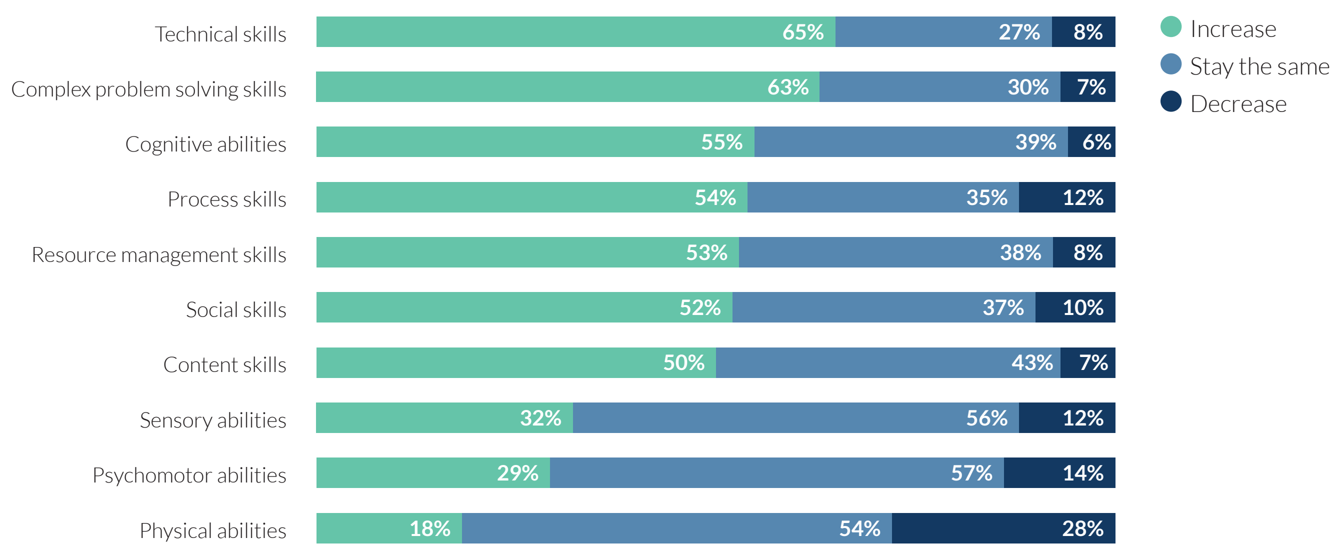
As discussed in the previous paragraphs, the transformation of manufacturing with the introduction of AI has important implications for roles and skills of people working in industry. First, the key role of people in re-defining the company's strategy has been highlighted. Once the strategy is outlined, other people are needed to plan and evaluate the interventions necessary for the transformation. The emergence of new roles and profiles specialised in design, implementation, operation, maintenance of new AI applications throughout their life cycle is envisioned. Finally, people will interpret deeply modified roles within a new organisation of human and artificial intelligences. Those roles will be characterised by an expansion of the traditional set of skills, which concerns both strengthening foundation skills and core competencies of the manufacturing domain, and the acquisition of new skills related to data and AI. It will also be increasingly necessary to master decision-making and management skills, as well as social skills.

The main categories of skills that we consider fundamental are summarised below.

Figure 24

What Skills are Needed to Use AI Effectively[72]

(Source: Deloitte)



Foundation skills

A first area covering basic skills will need to be strengthened, especially numeracy, STEM, digital and data skills. Data literacy and basic AI literacy will be more and more indispensable for work and daily life, and should be fostered across society.[73] Raising the level of foundation skills is, therefore, crucial to create a fertile ground for the development and continuous updating of technical-professional skills and transversal skills for the roles of the AI-enabled manufacturing of the future.

Core manufacturing skills

Manufacturing workers will always need strong skills related to the core activities that characterise the industry, such as how to design and produce the best product-service using advanced materials, innovative shapes and designs, and cutting-edge technologies. Besides, manufacturing will always need knowledge and skills related to manufacturing processes and systems, necessary to design, manage and innovate processes and systems from research and development, to production, from quality to maintenance, logistics and supply chain.

AI skills

New technical and managerial skills will be needed to fully grasp the potential offered by AI in manufacturing.

First, it will be crucial to understand how AI-based systems work, learn, and interact with users; to identify the possibilities and limits of AI and where AI could be used in the organisation in order to reimagine the company's existing processes and improve their outcomes.

Also, a fundamental skill will be the ability to create new AI-based business models rather than simply improving old processes. The skills to imagine innovative business solutions to complex problems leveraging AI and successfully manage innovation initiatives will have more and more value for workers and organisations alike.

Besides, the skills related to data modelling and evaluation, probability and statistics, applying algorithms or building new ones, programming languages, software engineering and system design will be critical for realising the potential of AI.

Furthermore, according to Daugherty and Wilson, manufacturing workers will need to develop the skills to collaborate with AI systems and to perform tasks alongside AI in an iterative, cyclical process in which machines learn from workers, and workers, in turn, learn again from machines.[75]

Finally, manufacturing workers will need the capability to recognise when the output of an AI system doesn't make sense and to develop the ability to determine the best course of action when the system is uncertain about how to proceed or when an error might occur.

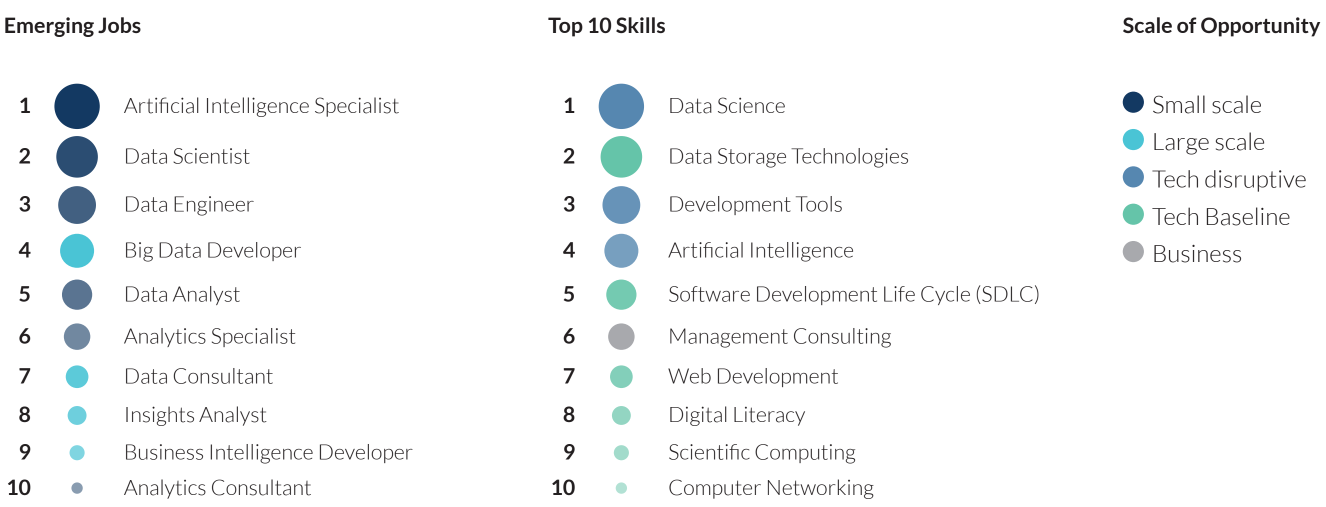
Skills for ethical/trustworthy AI

According to the EU, trustworthy AI should be : (1) lawful,

Figure 25

Emerging Jobs and Top 10 Skills[74]

(Source: World Economic Forum)



i.e., respecting all applicable laws and regulations; (2) ethical, i.e., respecting ethical principles and values; (3) robust, both from a technical perspective while considering its social environment.[76]

To responsibly shape the purpose of AI as it relates to individuals, businesses, and society and to achieve a tangible development, deployment and use of AI system that meet the requirements for Trustworthy AI, new skills will be essential. Those skills can be nurtured by creating specialised AI courses and/or integrating into existing technical AI courses concepts, methods and tools for addressing (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, non-discrimination and fairness, (6) environmental and societal well-being and (7) accountability.

It is also important to stress the growing importance of sustainable development, which will be increasingly integrated in all aspects of manufacturing. Accordingly, specific technical skills but also innovation and social skills will be required to maximise the benefits of AI and minimise its risks for the environment and society.

Transversal skills

Manufacturing workers will not only need new or advanced technical-professional skills, but these must be complemented by transversal skills - such as the purely human traits of creativity and entrepreneurship, personal and social skills - of which importance will increase in future as they cannot yet easily be reproduced by AI but can complement it .

First, the ability to collaborate will become increasingly necessary due to the integration of AI and other fields that are placed in different and rather specialised domains. Moreover, the integration of processes inside and outside the factory, will require an ever-greater collaboration between people who work in different groups, as well as external suppliers, customers and other stakeholders.

The ability to communicate effectively – also through different media - and teamwork will be essential, as individual professionals will contribute to several teams. Consequently personal, relational and social skills to operate in more diverse production contexts will be required and will play an essential role when developing AI systems.

Furthermore, imagination and creativity, the capacity for innovation and an entrepreneurial mindset will be fundamental. Strategic thinking, the ability to think outside the box, and proactivity in identifying, developing and implementing new ways to create value for the organisation, stakeholders and society as a whole, will be increasingly relevant.

Finally, the abilities to learn and change will be also central. As machine intelligence becomes more sophisticated, the life cycles of technology shrink, and change is fast and steady, it will be crucial to develop those skills to anticipate changes, to be able to seize opportunities, to pursue personal and professional skill development goals and continue to update them throughout life.

What can organisations do to prepare workers for AI?

Companies must invest in workers during the age of AI to help improve their organisations both productivity wise and socially

The implementation of AI in manufacturing has a significant 'people' element, not just for the workers who are seeing parts of their tasks become changed, but also across the workforce in terms of the skills and mindset required to make AI a success. Communication, change management, training and preparation for the transformation are therefore of crucial importance.

Keep clear communication with workers, HR, and business leaders in organisation to manage all needs. Manufacturers should start with developing a solid strategy and a roadmap defining where they want to go and what they need to add to the company to get there. Working with AI therefore requires keeping clear communication with business leaders, HR and workers, in order to guide the journey and manage all needs. Change can be successfully accomplished within the organisation only when both the organisation and workers see opportunities to realise their common aspirations.

Start small, gradually add AI into the workflow and get workers excited about AI rather than fearful of it

Manufacturers should implement proper change management. They should start with "quick wins" that are relevant and easy to grasp, gradually add AI into the manufacturing processes and get workers excited about AI rather than fearful of it. To learn and innovate, workers need to feel psychologically safe. Worker involvement is also important to boost commitment to change. They should be the starting point in the design process and agile development. All the results that come out should be measurable to easily show wins and celebrate achievements for both the company and workers alike.

Invest in skills development and create conditions to nourish lifelong learning

Embracing AI requires a continual reimagining of work and ongoing skills development. Manufacturers must assess which tasks will be needed and which skills will be required to fulfil those tasks. They also need to map internal competencies to new roles and then invest to develop (or hire) new skills to bridge gaps. This should not be an episodic quick fix but a continuous process of workers' and organisational learning. Besides, together with governments and social actors, support for workers at risks of being displaced should be provided, so that transitions to new roles can be managed whilst avoiding high social costs.

How can AI revolutionise learning?

AI has the potential to augment learning delivery to help upskill and reskill current workers and develop the next generation of manufacturing workers

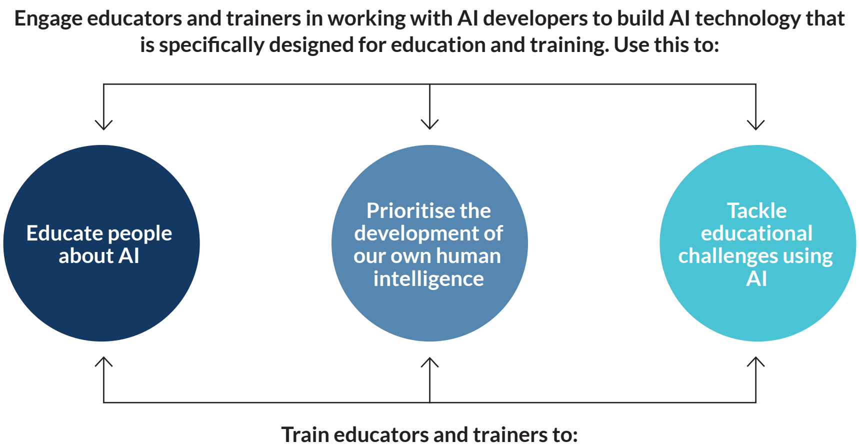
AI is set to change not only what people learn but how they learn and the opportunities for AI to support education and training are broad. It is therefore important to approach AI focusing on the creation of educational and training systems that use AI wisely to prepare people to work and live with AI[77] .

In this respect, it is of paramount importance to engage learners, teachers and education leaders, in working with AI developers to build AI systems that are specifically designed for education and training purposes. Besides, cutting edge AI education and training for present and future manufacturing workers cannot be achieved without taking into consideration the crucial role played by educators and trainers at every level and in every path.

Figure 26

Approach to AI for Education and Training[78]

(Source: OECD)



Educating people about AI in manufacturing

To develop the skills needed to work with AI, conceptual education on AI capabilities and potential for use in manufacturing must be complemented by experiential learning, including both experiences working side by side with AI systems and experience creating new AI solutions for manufacturing.

Moreover, to tackle the multi-dimensional aspects of AI and its effects on industry and society, it is crucial to foster more cross-disciplinary collaboration in education and training. Many providers around the world are already encouraging collaboration across faculties and with manufacturing players, and some of them are also responding with more structural solutions.[79]

In this respect, Testing and Experimentation Facilities for Smart Manufacturing can have a key role in facilitating knowledge transfer and training.[80] This can be done through open lab days, bootcamps, exploring pilots/ demonstrators and implementing innovation projects on AI applications in manufacturing processes.

Physical facilities can be also complemented by Virtual Labs, where “hand-on” activities can take advantage of open data, (anonymised) manufacturing repositories or data from physical laboratories, as well as open standards, open source algorithm platforms, etc.

On the job training and apprenticeship can enable participants to learn by doing on active company AI use cases and facilitate embedding AI into daily operations. Bootcamps and hackathons can also stimulate the emergence of new ideas from multi-disciplinary teams and boost the creation of AI-based innovative solutions to address company challenges.

Tackling education and training challenge using AI

AI can help learners, educators/trainers and providers achieve their goals. AI applications are often at an early stage, but there are many examples of promising uses that show how AI may support education and training[81]. According to recent reviews[82,83], these applications can be classified into three main categories:

Learner-facing AI solutions are software that allow learners to acquire knowledge and skills in a more personalised way, such as intelligent tutoring systems and adaptive learning management systems. Moreover, AI-enabled augmented/ virtual reality applications can support workers’ learning on the job. AI systems can also provide a range of interfaces to knowledge for people who have disabilities. For example, wearables using AI can help visually impaired people to read books and recognise faces, and thus to learn and socialise within their peer community.[84]

Educator/trainer-facing systems are used to support the instructor and reduce her workload by automating tasks such as administration, assessment, feedback. AI can free from repetitive and mundane tasks and allow to invest more of time and energy in creating richer learner experiences. Educational AI tools can also provide insights into students’ learning progress so that the educator/ trainer can proactively offer support and guidance when needed.

System-facing educational AI solutions provide information for administrators and managers at the institutional level. For instance, several education providers are using AI to monitor attrition patterns and enhance early identification of people who might be at risk of drop out.

The Democratisation of Computing and the Transformation of Manufacturing Education into the Era of AI/ML (The Purdue University Case Study)

Ragu Athinarayanan
PhD. Professor, Purdue University, West Lafayette, IN

Grant Richards
PhD, Professor of Practice, Purdue University, West Lafayette, IN

Three strategies are core foundations in the transition to Industry 4.0: "Making All Things Digital," "Making all Things Connected.," and "Making All Things Smart." Enabled by the Internet of Things (IoT), real-time data, Artificial Intelligence (AI)/Machine Learning (ML), and interconnectivity, these technologies, and capabilities are fundamentally transforming the manufacturing industry across the United States and globally.

A 2018 report by McKinsey Global Institute states that manufacturing is poised to see the most significant gains from IoT, with nearly 26 Billion IoT devices in service by 2020 driving data volume. The ability to generate and collect data no longer serves as the benchmark for progress and innovation; instead, it is now the ability to manage, analyse, summarise, visualise, and discover knowledge from the collected data promptly in a scalable fashion. Small and medium-sized enterprises (SME), including large corporations in the United States (US), accumulate vast amounts of data; however, data utilisation remains very low at less than 6% nationally. Reports point to a lack of proven strategy for purposeful collection and use of data, driven by a lack of expertise and access to tools for analysing the data they collect. The expansion of cloud platforms from providers such as Microsoft, Google, and Amazon have reduced the barrier to entry for manufacturers of all scales. It allows for more straightforward pathways to deploy high technology tools such as AI for developing functional solutions to everyday manufacturing challenges. McKinsey predicts that US manufacturing has the potential to see a 20-50% reduction in cost for inventory holding, a 10-20% reduction in costs due to quality issues, a 45-55% increase in productivity, and a 30–50% reduction in total machine downtime when using data-driven strategies such as AI in manufacturing. Accenture follows with estimates that AI will add $8.3 trillion of value to the US economy by 2035. Progress in the IR4 era, however, requires a skilled workforce knowledgeable of digital transformation strategies for manufacturing organisations to capitalise on these benefits and opportunities.

A 2019 study by the US Bureau of Labor Statistics (BLS), Deloitte, and the US Manufacturing Institute estimated that by 2028, skills shortages could lead to nearly 53% (2.4M) of US manufacturing positions remaining unfilled. If a qualified workforce is unavailable to fill the open jobs, they estimate a 17% impact on the forecasted US Manufacturing GDP equivalent to US$2.67 trillion. As one of the global manufacturing superpowers with 16.7% of total world manufacturing output, this is both a reason for concern and a call for action.

In March 2019, Purdue University formed a coalition with Microsoft Corp, Rockwell Automation, and PTC to address the imminent workforce challenge the US will be facing in the not so very distant future. Among its objectives is to fundamentally transform manufacturing higher education to facilitate the preparation of the next generation of manufacturing engineers who could democratise and aid the transformation of US manufacturing industries. Working collaboratively with its partners, Purdue University developed the framework for a curriculum to address manufacturing from the perspective of data-driven products, processes, and services for optimising critical systems through the use of IoT, AI/ML, Cloud/Edge computing, and integrated enterprise solutions. The cross-disciplinary framework focuses not only on the preparation of graduates in the core foundations of science and engineering but also on the application of data science and computing in the context of manufacturing. It focuses on developing capabilities supporting the Citizen Data Scientist role that is rapidly emerging among manufacturing engineers in the US. Gartner defines a Citizen Data Scientist as a person that creates or generates models that use advanced diagnostic analytics or predictive and prescriptive capabilities, but whose primary job function is outside the field of statistics and

Brian Evergreen
Artificial Intelligence Strategy Lead, Microsoft, Redmond, WA

Chris Bunio
Senior Director of Higher Education, Microsoft, Redmond, WA

analytics. This role addresses the critical shortage of graduates with data science skills necessary to meet the growing demands in a US economy rapidly undergoing digital transformation. Skyrocketing demand, increasing at upwards of 30% annually, for data science professionals has left many organisations, including manufacturing, with the challenge of attracting and retaining data science talent. The Citizen Data Scientist role empowers manufacturing engineers to perform routine data science tasks complementary to their job functions, allowing manufacturers to focus dedicated data scientists on the most complex data challenges.

The democratisation of computing and accessibility to infrastructure and resources offered through cloud computing platforms has reduced the barrier to presenting data science through on-demand scalable computing resources and prebuilt toolsets. These features allow for the selective presentation of data science concepts to support the preparation of graduates for the Citizen Data Scientist role. Purdue is working closely with its technology partners, namely Microsoft on the development of graduates to assume this role successfully. As manufacturing data scientists, these graduates will have a deeper understanding of manufacturing systems and processes where they can leverage their engineering skills to develop meaningful and actionable insights to manufacturing problems faster than a traditionally trained data scientist. Their cross-training in AI/ML and analytics will allow them to solve many manufacturing challenges and add value as engineers to manufacturing organisations. We don't foresee these Purdue graduates replacing the need for data scientists in manufacturing; in fact, they are essential for performing heavy-duty modeling and algorithm development work outside the scope of Citizen Data Scientists' preparation.

The structure and the financial model of US tertiary education impose unique constraints not present in higher education systems located in prominent manufacturing countries throughout the world. These conditions result in a higher percentage of skilled graduates who immediately enter the workforce and not graduate education. Consequently, this project is focused on the preparation of undergraduates to address the workforce skills challenge and to create change at an impactful scale. This new program will officially launch in August 2022 in the brand new $140M, IR4 themed, Gateway to Engineering complex currently under construction on the Purdue University campus. This facility will also be the home for an ecosystem of manufacturing laboratories to support the delivery of the program, comprising of the Intelligent Learning Factory, Industrial IoT Laboratory, Intelligent Process Manufacturing Laboratory, and the Smart Foundry 4.0. With assistance from experts at Microsoft, Rockwell Automation, and PTC, the infrastructure in these facilities will adhere to current and developing industry and digital reference architecture standards. Collectively these facilities serve as a horizontal/vertically integrated manufacturing value chain network providing student experiences with complex interdependencies and intelligent AI/ML-based manufacturing technologies in at-scale operation.

4

Ethical, Legal, Policy and other Societal Implications of AI

"'Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less."

Marie Curie

Ethical, Legal, Policy and other Societal Implications of AI

In previous chapters, we discussed how AI is transforming manufacturing, and what these changes mean for companies, industry roles, and the skill set required of workers.

While AI is expected to have a positive impact on growth and productivity, it also raises ethical dilemmas and regulatory issues that risk to hold back its adoption. For example, what values should underpin the development and deployment of AI? How can we address the risk that AI may further concentrate wealth and power, leave low-skilled workers behind, and exacerbate inequality? Who should have a stake in the new "data dividend" generated by the exploitation of large sets of personal data? How can we prevent AI from perpetuating existing biases? Should AI systems be given legal personhood, and what are the consequences for robot-human relationships? Who should be legally responsible for the decisions taken by algorithms?

Stimulating an informed public debate around these questions, gaining stakeholder buy-in on the core principles that should inform the deployment of AI systems, and translating them into regulatory requirements, are essential steps to build trust in AI and support its deployment.

Central to these goals is the promotion of a narrative that inspires confidence in the potential of AI without creating false expectations. Misconceptions about the potential of AI, as much as fears, can contribute to an ill-informed public debate, with potentially counterproductive consequences for AI research, funding, regulation, and reception.[85]

Against this background, this chapter deals with the societal implications of AI, and the central role of trust in harnessing its potential; ethical challenges in the field of AI, and key concerns raised by industry; the need for AI standards and regulation; and finally how governments around the world are grappling with these challenges, and their strategies.

Societal Implications of AI and the Role of Trust

According to estimates by Accenture and Frontier Economics, AI has the potential to boost economic growth rates by 1.7% points by 2035 across 16 industries, spanning from 0.7 in education to 2.3 in the manufacturing sector. In the latter, AI adoption could yield US$3.8 trillion in additional gross value added (GVA) by 2035, a value which is almost 45% higher compared to business-as-usual (US$8.4 trillion).[86]

Despite its potential benefits, AI raises concerns about job loss risks, security, privacy, and legal compliance

Despite the economic promise held by AI and other potential benefits discussed in chapter 1, according to an Ipsos Global Poll conducted for the World Economic Forum in Spring 2019, four in ten adults across the globe are concerned about the use of AI, with 48% supporting more regulation for businesses[87]. These results are consistent with the findings of a 2017 Special Eurobarometer survey gauging public opinion about digital technologies, in which only six in ten respondents claimed to have a positive view of robots and AI.[88]

According to data by Accenture Research, the most pressing concerns surrounding AI technology relate to its impact on jobs (38%), security threats (24%), data privacy (19%), and maintaining compliance with an evolving regulatory environment (17%) (Figure 27).[89]

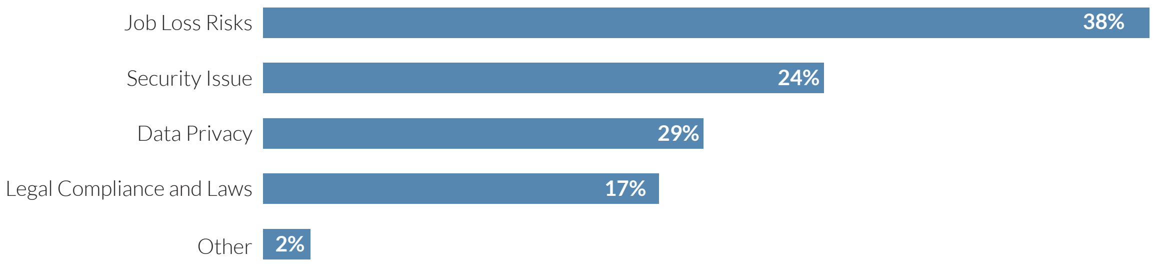
To some extent, these concerns are well-founded.

Existing research on past industrial revolutions suggests that in the short-run technical innovations tend to displace workers from tasks they were previously performing.[91]

Figure 27

The Principal Concerns Surrounding AI Technology[90]

(Source: Accenture)



Although it is difficult to forecast the interplay between task substitution and task complementarity, it is undisputed that some sectors, roles, and demographics will be more affected than others by the sizeable changes introduced by AI. Recent empirical evidence suggests that AI may primarily impinge on well-paid, white-collar workers in highly exposure sectors such as motor vehicle manufacturing and textile industries, likely reflecting the increasing adoption of emergent AI applications in industries firms controlling robotics, detecting anomalies, recognizing patterns, and more.[92,93]

Furthermore, recent headlines showcasing AI failures or abuses by large corporations (e.g., the pedestrian fatality involving a Uber test self-driving car in Arizona, the Facebook-Cambridge Analytica scandal, or the controversy about racially biased AI-based facial recognition tools sold to the police by IBM, Microsoft, and Amazon) have unveiled to the general public some of the dangers of "untamed AI" on responsibility, the delegation of decision making, privacy, democracy, human rights, transparency and bias (Coeckelbergh, 2020).

Concerns about AI are magnified by a polarized narrative that undermines trust in its applications, thus holding back meaningful progress

While most of the concerns surrounding AI are present and real, they are also magnified by an AI narrative that favours either hype or fear.

According to the Royal Society, overly negative or sensational depictions of AI that do not reflect its real capabilities risk creating a disconnect that can have several negative consequences. First, the prevalence of utopian depictions of AI can contribute to a hype bubble that, if it bursts, risks to undermine public confidence in the technology and its advocates. Second, false fears may divert the public debate away from the real challenges at stake, and lead to lost opportunities. Third, if the public debate is dominated by the fear of robots replacing humans, important conversations about the future of work, the distribution of wealth, and the direct impact of AI on specific tasks and roles may never take place. Fourth, distorted narratives could also result in bad regulation either by influencing policymakers directly or by inducing them to take ill-founded actions to appease the public. Finally, the disconnect can lead to a misdirection of research funding into fields which are prominent in certain narratives, at the expense of other fields of research.[94]

Trust in AI is essential for researchers to innovate, industry to invest in AI capabilities, workers to support change, and consumers to engage with products that embed AI technologies

The result is a trust deficit in AI, which risks holding back its deployment. Without trust, researchers will not be given sufficient leeway to innovate, the industry will not invest in AI capabilities, workers will oppose change, and consumers will not engage with products that embed AI.

As rapid advances in AI increase the scope and scale of its potential applications, it will be essential to promote a multi-stakeholder dialogue between policymakers, experts, and researchers in a variety of fields, private sector, and civil society on the values and public objectives that should guide the development and deployment of this new technology, and to reach a consensus on the necessary features of trustworthy AI systems.

Ethical Initiatives in the Field of AI - Key Challenges

Ethical initiatives and frameworks

The deployment of AI raises a broad variety of ethical dilemmas that, if not addressed, will undermine public trust in its uses, and violate fundamental human rights that we often take for granted. These range from the impact of AI on privacy and security, to the risk of reinforcing existing bias.

Over the last few years, a wide array of stakeholders has put a lot of effort in identifying ethical challenges raised by AI and the principles that should underpin its development

Acknowledging the need to foster confidence in trustworthy AI systems, in the last few years governments, think tanks, policy institutes, academia, companies, industry, consultancies, and associations in several countries have put a lot of effort in identifying the most relevant ethical challenges raised by AI, and the principles that should underpin its development.

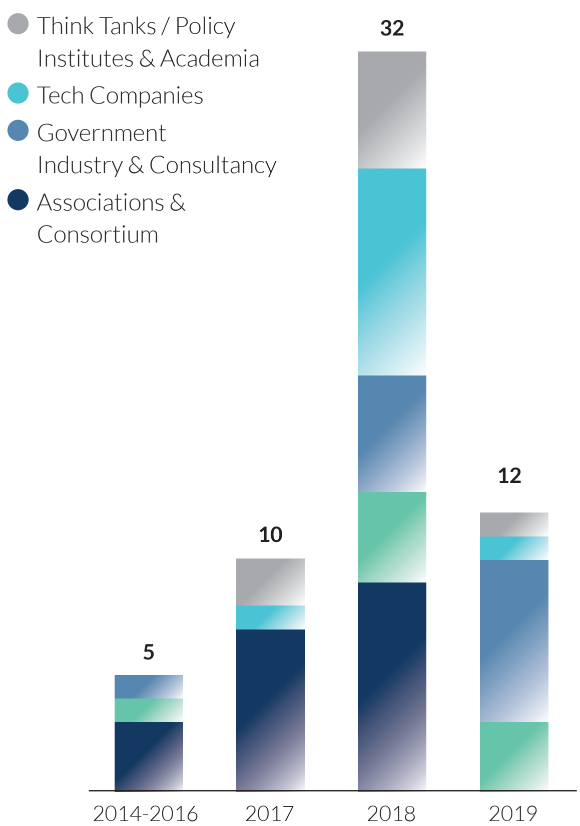
Based on a dataset of ethical challenges compiled by PricewaterhouseCoopers (PwC) by analyzing 59 documents on ethical AI principles, Stanford University's Human-Centred Artificial Intelligence Institute (HAI) offers a synthesis of these efforts by year and type of organisation. A first observation is that associations and consortium have been leading the way, followed by think tanks and academia. Tech companies that lead the research on AI (and have been the subject of several scandals), industry, consultancies, as well as a majority of governments, started to address the issue only later, starting 2018 (See Figure 28).[95]

While different stakeholders have an emphasis on different key concerns, for manufacturers the most relevant ethical challenges are going to be transparency, privacy and data governance, technical robustness and safety, human agency, lawfulness and compliance

Figure 28

Number of ethical AI frameworks produced 2016-2019, by type of organisations[96]

(Source: AI Index Annual Report, Stanford University)



Furthermore, the study conducted by HAI also spends time analyzing the top twelve ethical challenges which were consistently raised across these 59 documents. Although priorities vary across different stakeholders and countries, ethical challenges commonly covered include (in order of frequency): fairness, interpretability and explicability, transparency, accountability, data privacy, robustness and security, human control, safety, diversity and inclusion, lawfulness and compliance, multi-stakeholder engagement, and sustainability.[97]

Acknowledging these differences, supranational organisations and intergovernmental fora have tried to build consensus on the necessary features of trustworthy AI systems.

One outstanding example in this field is the “Ethics Guidelines for Trustworthy AI” developed by the High-Level Expert Group on Artificial Intelligence set up by the European Commission, and that tried to address all relevant stakeholders – i.e., companies, organisations, researchers, public services, government agencies, institutions, civil society organisations, individuals, workers and consumers (further details in the “In Focus: EU Ethics Guidelines for Trustworthy AI”).[98]

Other significant multilateral initiatives on the ethical implications of AI are the OECD Principles on Artificial Intelligence[100], which were adopted in May 2019 by OECD member countries along with Argentina, Brazil, Colombia, Costa Rica, Peru, and Romania (further details in the “In Focus: OECD Principles on Artificial Intelligence), as well as the G20 AI Principles that draw from them. Both sets of principles, which were endorsed by a majority of countries in all continents, except for Africa (Figure 29), support an AI centred on people, aligned with ethical and democratic values, transparent, safe, and accountable.

In Focus: EU Ethics Guidelines for Trustworthy AI[99]

Based on an approach grounded in fundamental human rights, the “Ethics Guidelines for Trustworthy AI” represent an expert consensus on how to promote an AI that is lawful, ethica, and robust.

Moving from four key ethical imperatives (i.e., respect for human autonomy, prevention of harm, fairness, and explicability), they specify the requirements that ought to be met by different stakeholders involved in AI systems’ life cycle to achieve trust:

1. Human agency and Oversight;
2. Technical Robustness and Safety;
3. Privacy and Data Governance;
4. Transparency;
5. Diversity, Non-Discrimination and Fairness;
6. Environmental and Societal Well-Being;
7. Accountability.

All principles and requirements are of equal importance, but some may be of lesser relevance for some applications.

Furthermore, they may sometimes conflict with each other, requiring AI stakeholders to identify and communicate existing trade-offs.

Finally, while some requirements are already reflected in existing laws, some others maybe not. Yet, as specified by the guidelines, adherence to ethical principles goes beyond formal compliance with existing laws, and may be achieved by employing both technical (e.g., quality of service indicators, explanation methods) and non-technical methods (e.g., regulations, codes of conduct, standards, certifications).

In Focus: 2 OECD Principles on Artificial Intelligence[101]

The OECD Principles on AI promote AI that is innovative and trustworthy and that respects human rights and democratic values. To this end, they identify five complementary value-based principles:

1. Inclusive growth, sustainable development, and well-being;
2. Human-centred values and fairness;
3. Transparency and explainability;
4. Robustness, security, and safety;
5. Accountability.

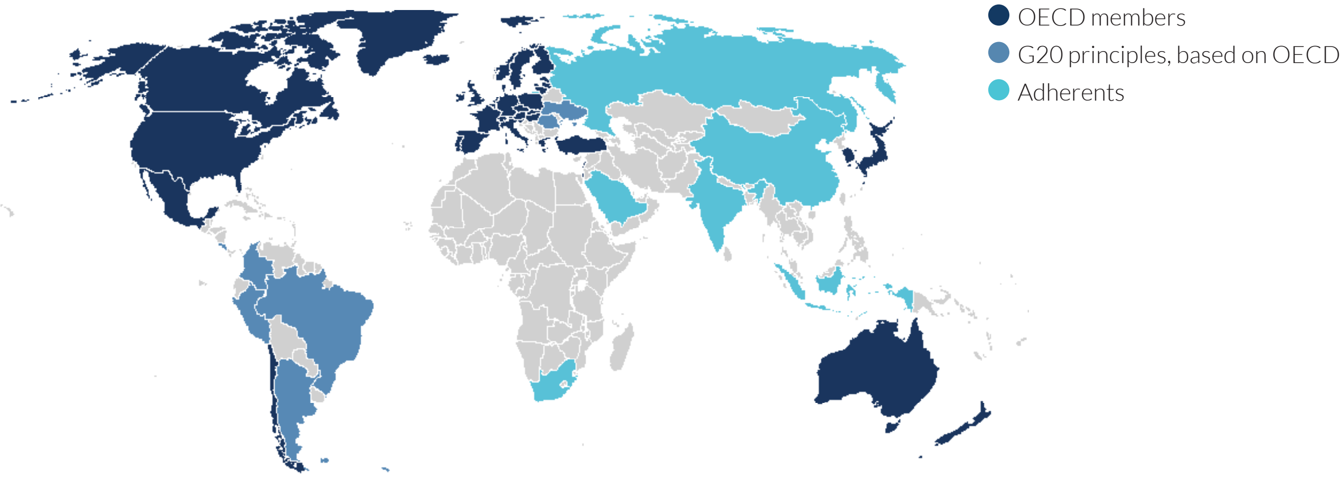
Consistent with these value-based principles, the OECD also provides five recommendations to governments: investing in AI research and development; fostering a digital ecosystem for AI; shaping an enabling policy environment for AI; building human capacity, and preparing for labor market transformation; international co-operation for trustworthy AI.

While these initiatives have the merit of identifying ethical principles and concrete requirements that ought to be upheld to build trust in AI, it is now up to lawmakers, in concert with relevant stakeholders, to identify the appropriate policy instruments to make them operational and to offer a compass to navigate existing trade-offs.

Figure 29

Countries which have committed to the AI Principles[102]

(Source: OECD)



Key ethical challenges when deploying AI in the manufacturing sector

Based on the interviews conducted and the inputs received when drafting this white paper, the most relevant ethical challenges that need to be addressed in a manufacturing context are transparency, privacy, and data governance, technical robustness and safety, human agency, lawfulness, and compliance.

a) Transparency

While increasing the transparency of data and business models can be relatively easy, transparency can be difficult to achieve in the case of modern AI systems

According to the EU Ethics Guidelines for Trustworthy AI", the transparency requirement needs to be fulfilled for each and every element relevant to an AI system: the data, the system, and the business model. In the case of data, transparency is achieved if it is possible to trace which data and processes were used to formulate a specific decision. In the case of an AI system, transparency is achieved if it is possible to explain the rationale underpinning a certain decision. Finally, humans have to be made cognizant of their interaction with an AI system, and its capabilities and limitations should be communicated.

While increasing the transparency of data and business models can be relatively easy, transparency can be difficult to achieve in the case of modern AI systems, especially those based on artificial neural networks (ANNs).[103]

The opacity of AI systems is extremely problematic in manufacturing, where both the cost of poor decisions taken by AI systems, and the degree of human involvement are usually high

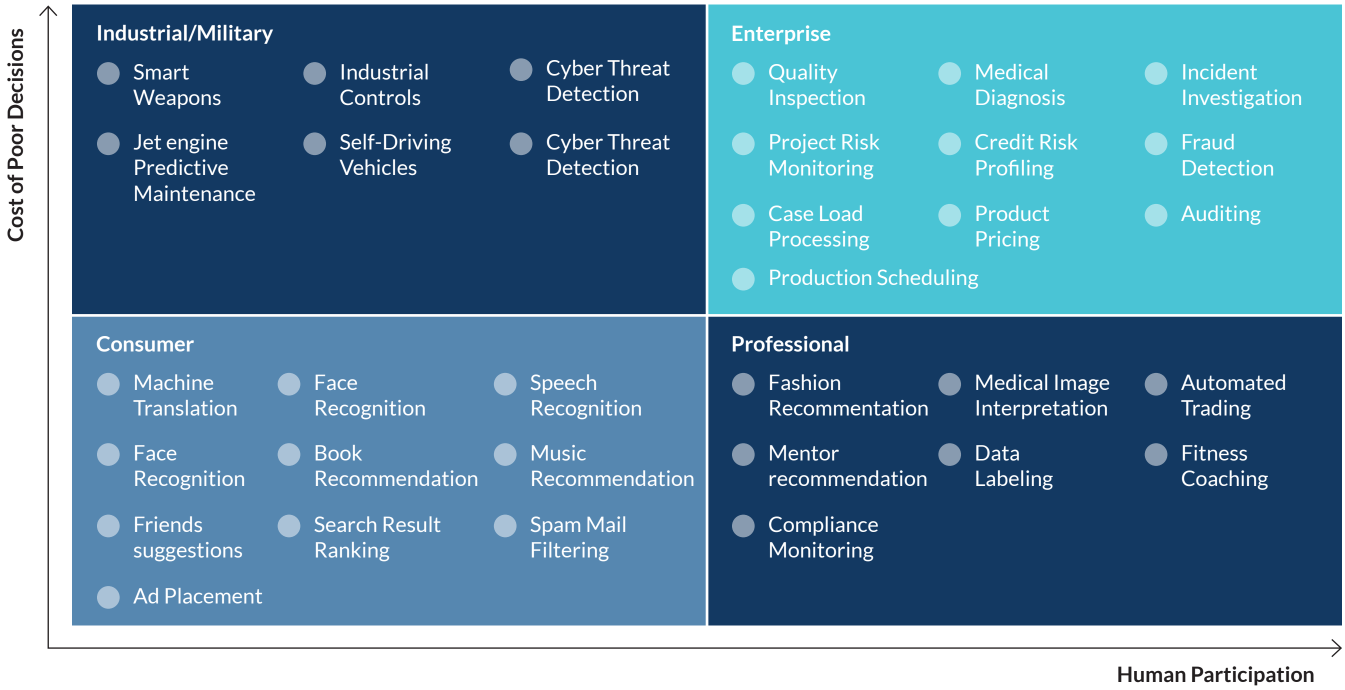
The opacity of AI systems is extremely problematic in manufacturing, where both the cost of poor decisions taken by AI systems, and the degree of human involvement are usually high. As explained by Accenture Labs, "the underlying dynamic is that as the human impacts and implications of AI decisions increase, so does the need to explain".[104]

This observation seems to be supported by current market trends. Figure 30 shows where different AI systems stand concerning these two variables, with the need for explainable AI increasing as we move towards the top-right quadrant. While most successful applications of AI to date are in the bottom-left quadrant, and mainly consist in online consumer-focused services (e.g., a personalised song recommendation or an advertising placement), AI systems used in the manufacturing value chain usually fall in the top two-quadrant (e.g., industrial controls, quality inspection, production scheduling, incident investigation,...), suggesting that the deployment of AI

Figure 30

The need for explainable AI rises with the cost of poor decisions[106]

(Source: Accenture)



in this sector crucially rely on ensuring an appropriate degree of transparency.[105]

From a manufacturer's perspective, simply receiving a notification about a predicted failure is not sufficient to take action. They also need to know "how" and "why" the AI system reached a specific conclusion. For example, "if an AI system corrects a machine that may be shifting and drifting, manufacturers should be able to look at the data and algorithm to determine in detail why and how the correction was made".[107] These considerations are even more relevant on the factory floor, where the cost of poor decisions can destroy equipment or injury.[108]

Ultimately, it is the manufacturer, not the machine, that is accountable for the implications of the actions taken by an AI system, and for the manufacturer to be accountable, they need to understand how the system works.

Transparency is also going to play a key role in the commercialization of products that embed AI capabilities

Transparency is also going to play a key role in the commercialization of products that embed AI capabilities.

It is important that autonomous systems are transparent to a wide range of stakeholders. In this sense, transparency can build public confidence in the technology, allow consumers to engage with the product, expose AI systems to regulatory scrutiny, and in case of an accident allow investigators to trace the internal process that led to it, lawyers or other expert witnesses to inform their evidence, require transparency to inform their evidence.

Finally, transparency can deepen humans' technical knowledge about manufacturing processes

Finally, transparency also has an epistemic value, as it can deepen humans' technical knowledge by improving their understanding of a process. "Garry Kasparov, for example, may find an explanation of a particular chess move made by an algorithm beneficial for his own ability to play chess."[109] This means that the interaction between humans and transparent AI machines can trigger a positive feedback loop that augments human abilities without replacing them.

Moving from the observation that "the effectiveness of (AI) systems is limited by the machines' current inability to explain their decisions and actions to human users"[110], in 2017 the U.S. Defense Advanced Research Projects Agency (DARPA) launched an international effort to produce explainable AI through several funded research initiatives (further details in the "In Focus: The U.S. DARPA's XAI Program").

In Focus: The U.S. DARPA's XAI Program

The program, which is called Explainable AI (XAI)[111], mobilizes $75 million and involves about 1200 researchers and more than 30 universities and private institutions.[112] After a first exploratory phase, each participating institution is now tackling one or more problems in two "challenge areas" that represent the intersection of two important machine learning approaches (i.e., classification and reinforcement learning) and two important operational problem areas for the U.S. Department of Defense (i.e., intelligence analysis and autonomous systems).

1. Using AI to classify events of interest in heterogeneous multimedia data;
2. Using AI to construct decision policies for an autonomous system to perform a variety of simulated missions

The final goal of the program is to create a suite of new machine learning techniques and user interfaces that government or commercial groups could use to build their own explainable AI systems.[113]

b) Privacy and Data Protection

Machine learning (ML), the subfield of AI which has seen the greatest advances in recent years, crucially relies on the collection, storage, and elaboration of data.

Its value chain consists of five steps, in each of which data is a core element (Figure 31). Firstly, raw data have to be collected from a variety of sources. Secondly, these data need to be securely stored in data centres. Thirdly, data need to be prepared before they can be used to train the AI algorithm. Finally, algorithms are ready to make predictions using new data, which are later translated into actionable insights via applications.[114]

When the data used by AI systems relate to humans, they can pose new privacy threats that need to be mitigated by putting in place appropriate data protection policies and procedures.

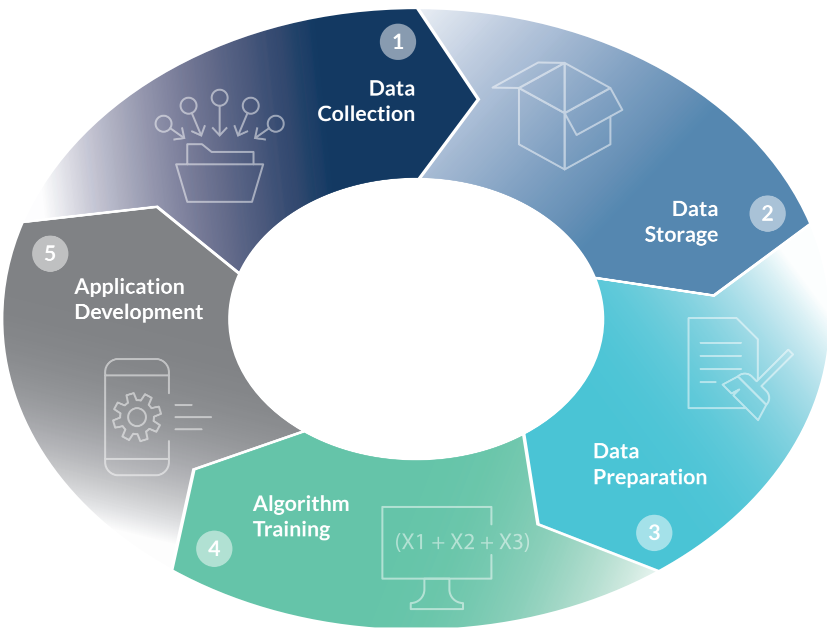
Manufacturers that want to adopt AI systems will have to comply with AI privacy laws but also start considering responsible data collection and management practices as a key driver of competitiveness

Privacy considerations are going to be especially relevant in the manufacturing sector, where humans play a key role at each and every stage of the value chain.[116] As a result, to perform their functions AI systems deployed on the factory floor will need to collect a tremendous amount of personal data via sensors (i.e., touchscreens, microphones, video cameras, wearable devices).

Figure 31

The Machine Learning Value Chains[115]

(Source: Carnegie Endowment for International Peace)



The first implication for manufacturing companies that want to adopt AI is that they will have to comply with existing privacy laws, such as the EU General Data Protection Regulation (GDPR), or the California Consumer Privacy Act (CCPA).

Furthermore, with data privacy being one of the most pressing concerns surrounding AI technologies , companies need to start considering responsible data collection and management practices as a key driver of competitiveness. This observation is supported by the unfolding of the Facebook-Cambridge Analytica scandal, where the resulting reputational damage of a privacy violation had more profound consequences than its legal implications.

While legal compliance may appear straightforward, it requires a dedicated effort to understanding regulatory requirements, their implications for the company's business model, and how they can be implemented without curtailing the efficiency of AI systems. These considerations are even more salient in the absence of a mature understanding of the potential privacy threats posed by AI systems and targeted legislation setting clear privacy requirements for AI technologies.

In a fluid legal and technical landscape, companies' best 'bet according to the Future of Privacy Forum is to be proactive and consider the privacy implications of AI technologies early in the design stage, and to run periodic monitoring and reviews of the risks involved.[117] For companies subject to the GDPR, these recommendations translate into ensuring that, by default, AI systems will collect only personal data which are necessary for relation to the purposes for which they are processed ('data minimisation')[118], and that the

In Focus: The EU General Data Protection Regulation (GDPR) and AI

The program, which is called Explainable AI The EU General Data Protection Regulation (GDPR), the world's first comprehensive approach to personal data protection effective May 2018, establishes how companies, government, and other entities can process the data belonging to EU citizens and residents.

The GDPR sets out seven principles for the lawful processing of personal data:1. lawfulness, fairness and transparency; 2. purpose limitation; 3. data minimization; 4. accuracy; 5. storage limitation; 6. integrity and confidentiality (security); 7. accountability.

Despite being the gold standard of privacy legislation, some of its principles are now challenged by the rise of AI systems. According to the Norwegian data protection authority, these are[119]:

Fairness and discrimination. Here, the main challenge is how to ensure that data protection authorities can access training data and AI algorithms to investigate if the principle of fairness has been safeguarded in the processing of personal data;

Purpose limitation. While this principle requires that the reason for processing the data should be clearly stated when data is collected, the development of AI technologies often relies on combining data originally collected for different purposes. The key question here is when the further processing of data can be considered compatible with the original purpose;

Data minimization. A challenge when developing AI is that it may be difficult to define the purpose of processing because it is not possible to predict what the algorithm will learn. This makes the data minimization principle a key obstacle to the development of AI;

Transparency and the right to information. The key challenges here relate to the complexity of AI systems and the risk that making information about the model fully transparent may expose commercial secrets and endanger intellectual property rights.

The need to reform the GDPR to untap the full potential of AI technologies has also been stressed by the Information Technology and Innovation Foundation (ITIF).[120] In particular, the ITIF has been calling for easing existing restrictions to data processing that require organisations to minimize the amount of data they collect and use it only for its original intended purpose, as they "significantly limit organisations' ability to innovate with data", and removing some of the obstacles that currently hold back the use of automated decisions.
Unless EU policymakers amend the GDPR, there is an actual risk that EU companies will be put at a competitive disadvantage compared to their Chinese and U.S. counterparts.

results of Data Protection Impact Assessments are brought to the attention of the executive board.

The deployment of AI raises new privacy challenges also for policymakers, that will need to find a balance between protecting consumers and supporting innovation

As AI technologies are applied across new and existing industries, platforms, and applications, policymakers will also have to deal with new challenges, such as: how to ensure the transparency of training data and AI algorithms; under which conditions AI developers can use personal data that were collected for different purposes; what are the implications of the data minimization principle for AI; how to balance the transparency requirement with the need to protect commercial secrets and property rights (further details in the "In Focus: The EU General Data Protection Regulation").

A promising approach to balance privacy-efficiency trade-offs is to create regulatory sandboxes that provide businesses with a testbed to try innovative AI applications in a controlled environment, and legislators with the ability to identify appropriate privacy protection safeguards that can be translated into legislation.

c) Technical robustness and safety

One key requirement to achieve trustworthy AI is technical robustness and safety, which "requires AI systems be developed with a preventive approach to risks and in a manner such that they reliably behave as intended while minimising unintentional and unexpected harm, and preventing unacceptable harm".[121]

Manufacturers that adopt AI systems will need to minimize both technical failures and cyberattacks. The first objective can be achieved by redirecting responsibility to humans whenever there is a problem or AI is not able to make an accurate prediction

In a manufacturing environment, achieving technical robustness and safety entails both putting in place safeguards that can prevent or minimize harm in case of technical failures, and protecting AI systems and their users against possible cyberattacks perpetrated by malicious actors trying to steal trade secret or cause material damage. In the case of technical failures, the prevention and minimization of harm are closely related to the concept of accuracy (i.e., "AI system's ability to make correct judgements, (...) predictions, recommendations or decisions based in data or models"[122]). As inaccurate predictions of an AI system used on the factory floor can result in the damage of expensive equipment and materials, and even in the injury or loss of human lives, manufacturers must devise measures that shift responsibility back to humans any time there is a problem or a machine is not able to predict with the desired confidence level.

Manufacturers that want to adopt AI systems should also get ready to face a growing number of cyber threats

Concerning cybersecurity, the integration of ML techniques in a broad array of manufacturing processes automatically expands the venues available to malicious actors to manipulate computer systems and networks. According to cybersecurity experts, the most realistic and present threat to machine learning systems are adversarial attacks (i.e., "adversarial machine learning") aimed at deceiving AI systems into making incorrect predictions on new data. This could happen either by training new algorithms with inaccurate or misrepresentative data or by introducing maliciously designed data into a trained algorithm with the intent of deceiving it into making errors.[123]

While these threats are relevant to any industry that wants to untap the potential of AI, the risk and implications are going to be even more serious in manufacturing, where AI systems are added to the Internet of Things, increasing the scope for attacks and the network links over which an attack can be launched. Furthermore, an attack perpetrated against an AI system used on the factory floor may result in the exposure of private or sensitive information or, in the worst case, in the loss of lives. Examples of cyberattacks to manufacturing firms include the deception of a facial recognition solution for monitoring employee access to sensitive areas or the manipulation of a turbine on a cooling system resulting in the overheating of the plant.[124]

A Recent study by Tuptuk and Hailes (2018) shows that from 2010 to 2015 there has been a significant increase in the number of manufacturing vulnerabilities reported and logged in ICS-CERT (Industrial Control Systems Cyber Emergency Response Team). These findings suggest that manufacturing systems are not ready to face new cybersecurity challenges, as they "have typically either been designed without security in mind or with the explicit presumption that the system is isolated and so not subject to (outsider) attack".[125]

Effective cybersecurity will require a three-pronged approach: embedding security

considerations early in the design stage, identify threats and capabilities, have measured in place to minimize harm once it occurs

For manufacturing firms, there are three priorities for action to reduce these vulnerabilities. First, security should be considered early in the design stage of AI systems. "Lessons from history suggest that where an attempt has been made to retrofit security on systems for which the primary driver was the development of functionality, there are inevitable and costly breaches".[126] Second, manufacturers should identify, analyse and evaluate potential threats and vulnerabilities about key assets owned, and choose controls which are appropriate to the risks faced by the organisation and the level of risk that can be tolerated. Third, manufacturers should have procedures in place to minimize the impact of attacks once they have occurred.

The promotion of standards, guidelines, and best practices by regulators can support companies' cybersecurity strategies.

In this new threat landscape, regulators can also play an important role by promoting standards, guidelines and best practices to help companies manage their cybersecurity risks. For example, in 2019 the UK National Cyber Security Centre (NCSC) released guidelines that can help small and medium-sized organisations, public sector, cybersecurity professionals, and large organisations to think through the cybersecurity risks they face concerning the use of AI systems (further details in the "In Focus: The UK National Cyber Security Centre's guidance on intelligent security tools").

d) Human Agency

The need for "human agency" should increase with the extent of possible harm caused by AI systems

There is almost unanimous consent across different stakeholders and geographies that AI systems should never replace human judgement, but they should help "individuals in making better, more informed choices in accordance with their goals".[128] In other words, "AI systems should empower human beings, allowing them to make informed decisions and fostering their fundamental rights".[129]

Ensuring human agency is particularly important in those contexts where AI systems can cause irreparable damage or undermine fundamental rights. For example, inaccurate predictions of AI systems used in factories or warehouses can result in physical destruction and injuries to workers and end-users. Similarly, AI systems used by manufacturers in their HR processes, if left unchecked, the risk to discriminate against candidates who do not fall into standardized categories, thus reinforcing historical biases.

In Focus: The UK National Cyber Security Centre (NCSC)'s guidance on intelligent security tools[127]

In April 2019, the UK National Cyber Security Centre (NCSC) released guidelines on what factors may affect an intelligent tool's ability to perform the task it was built for.

In particular, these guidelines provide a set of questions that can help small and medium-sized organisations, public sector, cybersecurity professionals and large organisations to think through the cybersecurity risks they face concerning the use of AI systems concerning three possible sources of vulnerability:

Reliability. This entails understanding how the intelligent tool makes decisions based on the rules it has learned from data and if it will do what is expected to do;

Resilience. While the guidelines recognise that it's not possible to identify all the potential vulnerabilities of an intelligent tool, organisations and cybersecurity professionals are invited to understand how the failure of an intelligent tool, either due to accident or attack, could impact the system;

Limitations. AI is not capable of solving every problem. Thus, the guideline stresses the importance of understanding that while there are many uses for AI, the promises of the tool need to line up with what is currently possible with AI techniques.

The lack of human oversight should be compensated with stricter testing and governance of AI systems

Nonetheless, it is important to recognise that in some cases human oversight of AI systems might not be technically feasible or efficient.

Whenever humans are not in the condition to monitor AI system to prevent or minimize harm, more extensive testing and stricter governance" should be required.[130]

The centrality of human agency in the realisation of trustworthy AI systems has been also sanctioned by the Institute of Electrical and Electronics Engineers (IEEE), which put human values and agency at the core of its "Ethically Aligned Design" crowd-sourced initiative (further details in the "In Focus: The IEEE "Ethically Aligned Design" crowd-sourced initiative).

e) Lawfulness and compliance

A final key requirement of trustworthy AI systems is their lawfulness and compliance with any applicable norm and requirements.

This requirement, which raises questions of both attribution and remedy, is particularly relevant when trying to address whether the existing legal frameworks apply to the decisions taken by AI, who or what should be liable for the harm caused by AI, how should a fault be identified and apportioned, what remedy should be imposed, and how the same harm could be prevented in the future.[133]

In the case of products incorporating AI, recent accidents involving autonomous vehicles have exposed the challenges of attributing liability when an AI system makes mistakes causing damage to or injury to property and human beings. In this case, failure may derive from issues related to the algorithm itself, inaccurate, biased, or wrongfully constructed training dataset, problems in the assembly process, the failure of the broadband system that is supposed to support the correct functioning of the vehicle, or the driver's carelessness and excessive reliance on AI.

Similar challenges are raised by the failure of AI systems which are used in the productive process, where it could be difficult to unbundle responsibility.

Uncertainties regarding the applicable legal framework and who should be liable for the harm caused by AI risk to hold back AI adoption

Under both scenarios, uncertainty regarding the applicable legal framework and the extent of manufacturers' liability risks to hold bank investment in AI systems and applications, cause workers' backlash, and scare away potential customers.

In Focus: The IEEE "Ethically Aligned Design" crowd-sourced initiative[131]

International standards organisations are developing various standards for how to guarantee human agency in autonomous robotic systems. One outstanding example is the "Ethically Aligned Design" launched by the Institute of Electrical and Electronics Engineers (IEEE).

The initiative, which is the most comprehensive, crowd-sourced global treatise regarding the Ethics of Autonomous and Intelligent Systems available today, resulted in some preliminary "pragmatic and directional insights and recommendations"[132] serving as a key reference for the work of technologists, educators, and policymakers in the coming years. The Pillars of the Ethically Aligned Design Conceptual Framework broadly fall into three areas, reflecting anthropological, political, and technical aspects:

1. **Universal Human Values:** Autonomous and Intelligent Systems should be designed to respect human rights, align with human values, and holistically increase well-being while empowering as many people as possible.

2. **Political Self-Determination and Data Agency:** People should have agency over their digital identity, meaning that they can access and control the data constituting and representing their identity.

3. **Technical Dependability:** Autonomous and Intelligent Systems should accomplish the objectives for which they were designed reliably, safely, and actively, while advancing the human-driven values they were intended to reflect. To this end, technologies should be transparent, understandable, and auditable, to ensure that their operation meets predetermined ethical objectives aligning with human values and respecting codified rights.

AI Standards & Regulations

Codes of conduct, standards, laws, and regulations may be needed to support the deployment of AI. But to be effective they need not stifle innovation

Identifying ethical principles and understanding their implications may not be sufficient to ensure the deployment of AI. The absence of clear rules and standards on how these principles should be operationalized may create uncertainty, which could, in turn, undermine the trust needed to support data sharing and cooperation between humans, AI tools, chatbots, etc.

In recognition that AI is a fast-moving technology still in its early stages, one of the biggest challenges will be to develop codes of conduct, standards, laws, and regulations that build trust in AI, without stifling innovation. This means making sure that requirements are not over-prescriptive, without being irrelevant.

Most governments are delaying the adoption of laws and regulations, preferring to wait and see how AI can be (mis)used

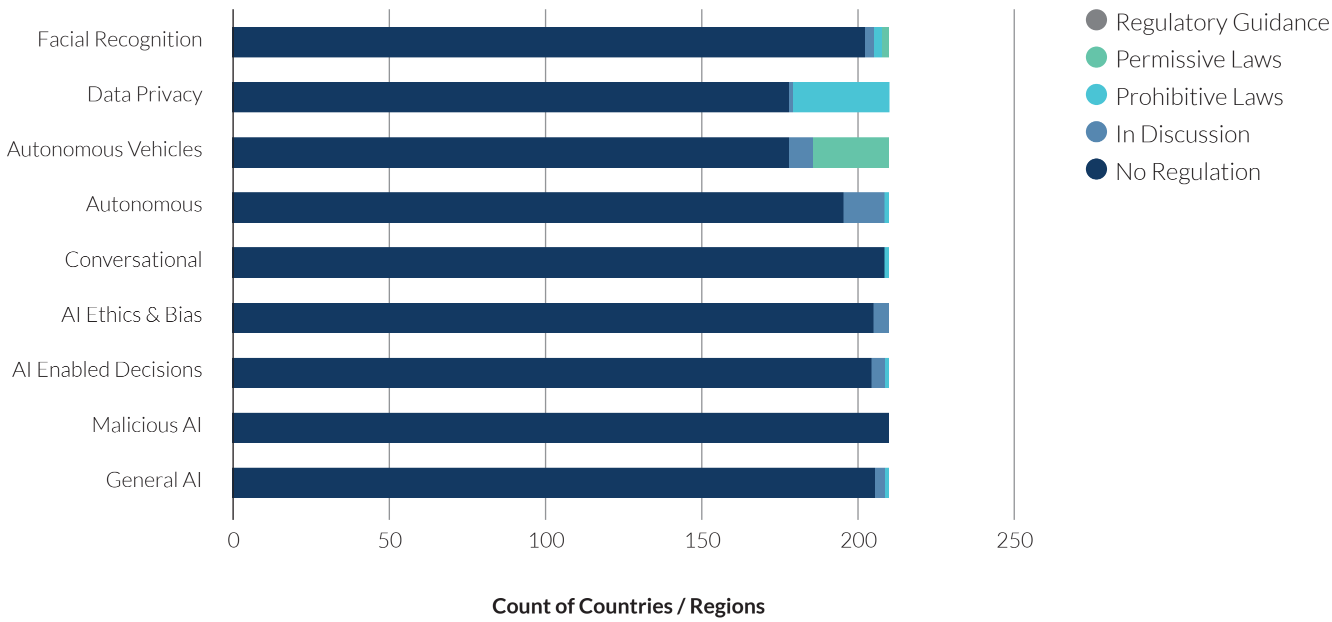
According to a study conducted by Cognilytica, most governments are delaying the adoption of laws and regulations in almost every category identified (i.e., facial recognition and computer vision, autonomous vehicles, data privacy, conversational systems and chatbots, lethal autonomous weapons systems, AI ethics and bias, AI-supported decision making, malicious use of AI, AI systems), with data privacy, autonomous vehicles and facial recognition being the only exceptions (Figure 32).

According to the research firm, the European Union is the most active regulator, with existing or proposed rules in seven categories, whereas the United States prefers a hands-off approach to regulation.[134]

Figure 32

Country and Regional AI Laws and Regulations[135]

(Source: Cognilytica)



While overly restrictive laws and regulations may harm the deployment of AI, a new generation of standards can be helpful, especially for manufacturing SMEs

While governments wait to see how AI can be (mis)used, the development of a new generation of standards that address the ethical concerns identified can be particularly helpful for manufacturing companies, especially SMEs. For these companies, standards can support AI adoption in at least four ways.

Standards can create a common language

First, standards can create a common language and facilitate communication between stakeholders with different technical backgrounds and priorities, such as regulators, AI developers, manufacturers, workers, and consumers. The lack of a common terminology not only can lead to counterproductive or ineffective policies, laws and regulations, but it can also generate misunderstandings and unrealistic expectations about the ease and speed of AI adoption, setting manufacturers up for failure. One effort in this field is the current work of ISO/IEC JTC1 on foundational standards (further info in the "In Focus: The role of ISO/IEC JTC1 in AI standards).

Standards can guide the development of trustworthy AI systems

Second, standards can guide AI development in a way that is consistent with commonly agreed on ethical principles and corresponding requirements, such as transparency, privacy, security, and reliability. One of the earliest examples in this category is BS 8611 Guide to the Ethical Design and Application of Robots and Robotic Systems (British Standard BS 8611, 2016), which guides how designers of robots and robotic systems "can identify potential ethical harm, undertake an ethical risk assessment of their robot or AI, and mitigate any ethical risks identified".[136]

Standards can provide a tool to assess AI systems for compliance

Third, standards can give manufacturers the tools to assess if the AI systems used or embedded into consumer products are compliant with ethical principles or applicable norms and guidelines. Falls into this category IEEE's proposal to "develop new standards that describe measurable, testable levels of transparency, so that systems can be objectively assessed, and levels of compliance determined" from the perspective of different stakeholders (i.e., users, agencies required to validate or certificate algorithms, accident investigators).[137]

Standards can promote interoperability, data sharing, and technology transfers.

Finally, the standardization of technical requirements can enable interoperability, data sharing and technology transfers, which are essential to foster AI adoption and allow new applications to emerge. Some standards that fall into this category are Linked Data (e.g., JSON), and for "Knowledge Graphs" (e.g., RDF, OWL).

As manufacturers start integrating AI technologies into their production lines, data scarcity is going to be a major bottleneck

As manufacturers start integrating AI technologies into their production lines, data scarcity is going to be a major bottleneck. Unlike software companies, which routinely collect an incredible amount of data that can be used to train their AI systems, the collection of sufficiently large training sets in a manufacturing setting is often not feasible.[138] For example, a manufacturing company would have a hard time training a visual inspection model using only proprietary data, as the rarity of equipment failures and defects makes it difficult to collect enough data points.[139] While AI researchers continue working on developing solutions to the "data scarcity problem" (e.g., generating synthetic data via software), technical standards - and particularly standards about "semantic interoperability" - can help develop the trust needed for data sharing.

According to the World Economic Forum, with AI applications becoming more mature and powerful, manufacturers will have increasing incentives to share their data. But at the same time, manufacturers might also start looking at their data as strategic assets to be protected by developing close ecosystems to lock others into their structure.[140]

Between these two extremes, governments and industry associations may want to step-in to help manufacturers realise the importance of secure data sharing, incentivize the use of common reference architectures and standards, and find new ways to securely aggregate manufacturing data in the public interest.[141] Additionally, they could also choose to support businesses, especially SMEs, by directly providing data solutions such as vouchers to buy AI technologies.[142]

In Focus: The role of ISO/IEC JTC1 in AI standards

Subcommittee SC 42, which is under joint technical committee JTC 1 of the International Organisation for Standardization (ISO) and the International Electrotechnical Commission (IEC), is currently looking at the entire AI ecosystem to develop a wide set of comprehensive standards. Its work, which sees the involvement of 30 participating members and 14 observing members, is articulated in five macro areas: foundational standards; computational approaches and algorithmic techniques; trustworthiness; use cases and applications; big data.

To date, the efforts of SC 42 have already resulted in:

- A document providing a set of terms and definitions needed to promote improved communication and understanding of this area;[143]

- A document providing examples of big data use cases with application domains and technical considerations;[144]

- A document specifying the big data reference architecture;[145]

- A document describing big data relevant standards, both in existence and under development, along with priorities for future big data standards development based on gap analysis.[146]

Furthermore, SC 42 is currently working on AI concepts and terminology; frameworks for AI and ML; AI risk management; bias in AI systems and AI aided decision making; trustworthiness in AI; robustness of neural networks; AI use case, ethical and societal concerns; computational approaches for AI systems, process management framework for AI analytics; governance implication of the use of AI by organisations.

National and International Strategies and Roadmaps

AI's expected contribution to economic growth also has important implications for geopolitics. For this reason, several countries across the globe have already committed substantial resources and political capital to support the development of AI.

The first AI strategy to be released by a country was the 2017 CIFAR Pan-Canadian AI Strategy[147], led by the Canadian Institute for Advanced Research in close partnership with the Canadian government, followed soon after by Japan's "Artificial Intelligence Technology Strategy" and China's "Next Generation Artificial Intelligence Development Plan".

To date, more than 50 governments around the world have devised AI strategies. While these strategies differ in terms of goals, investment levels, and commitment to ethical principles[148], many countries are investing considerable resources in AI research and development (R&D), infrastructure, human capital formation, and product development.[149] So far, China and the United States have been leading the AI race, pouring money to bolster R&D, and implementing protectionist measures to shelter their key players from foreign competition.[150]

China

China's ambition to become the world's "primary" AI innovation centre became apparent with the release by the State Council of the 'New Generation AI Development Plan' in July 2017. By implementing targeted initiatives and setting goals for R&D, industrialization, talent development, education and skills acquisition, standard-setting and regulations, ethical norms, and security, the Chinese government aims to nurture an AI industry worth 1 trillion RMB by 2030, with related industries worth 10 trillion RMB. As part of this comprehensive AI plan, the government is also supporting 'national champions' in the hardware department with substantial funding, encouraging domestic companies to acquire chip technology through overseas deals, and made long-term investments in supercomputing facilities[151]. Concerning data, China is both implementing policies that favour national AI companies in accessing data from the country's domestic market, and still favouring a lax privacy policy (although China's People's Congress announced that a privacy law is on the agenda)[152]. Finally, the Chinese government has started building a technology park in Beijing dedicated to AI development research, with the hope of producing $7.6 billion in annual output by 2023.[153]

United States

China's proactive approach is matched by the United States', whose AI strategy launched by President Trump with an executive order in February 2019 (i.e., the 'American AI Initiative') focuses on developing policies and implementing strategies for "promoting AI innovation in the U.S. for the benefit of the American people".[154] These activities align with several areas of emphasis: AI for American Innovation, AI for the American Worker, AI with American Values, and AI for American Industry. It is important to note that, when addressing industry's needs, the strategy emphasizes the need to remove regulatory and other barriers that can hamper AI innovation or drive it overseas, in favour of ten transparent regulatory principles that should guide the use of AI in the private sector: public trust in AI; public participation, scientific integrity and information quality, risk assessment and management, benefits and costs; flexibility; fairness and non-discrimination; disclosure and transparency; safety and security; interagency coordination.[155] Following the American AI Initiative, the U.S. also released the 'National Artificial Intelligence Research and Development Strategic Plan: 2019 Update', establishing a set of objectives for Federally-funded AI research based on eight strategic priorities: make long-term investments in AI research; develop effective methods for human-AI collaboration; understand and address ethical, legal and societal implications of AI; ensure the safety and security of AI systems; develop shared public datasets and environment for AI training and testing; measure and evaluate AI technologies through standards and benchmarks; better understand the national AI R&D workforce needs; expand public-private partnerships to accelerate advances in AI.[156]

European Union

Another key player in the race for AI dominance is the European Union. In December 2018, the European Commission released the first international strategy on AI, setting out seven key objectives: encourage the Member States to develop complementary national strategies; boost investments in AI through public-private partnership and more financing for startups and innovative SMEs; strengthen excellence in AI by investing EUR 1.5 billion in several large-scale test sites open to all actors across Europe; support talent, digital skills, and life-long learning; create European data ecosystems built on trust, data availability, and infrastructure; develop ethics guidelines with a global perspective and ensure an innovation-friendly legal framework; conduct further research on the security implications of AI.[157] On this basis, in February 2020 the Commission also published a white paper and a data strategy. While the first contains policy options on how to promote the uptake of AI while "addressing the risks associated with certain uses of this new technology"[158], the data strategy celebrates the EU's strong industrial base as an opportunity for leadership in AI but also acknowledges the block's delays in developing AI solutions and promoting their concepts of data access compared to competitors such as China and the U.S.[159]

India

Despite being a laggard, India is trying to pave the way for emerging and developing economies to use AI as a means to solve their societal challenges.

India's AI preliminary strategy, called #AIForAll, was developed by NITI Aayog (i.e., a policy think tank of the Government of India) in collaboration with various experts and stakeholders, following an explicit mandate by Hon'ble Finance Minister.

#AIForAll, which is outlined in the strategy paper "National Strategy for Artificial Intelligence", has three main goals: to ensure social and inclusive growth; to support the effective implementation of AI solutions that can be scaled and replicated in other emerging economies; and to tackle some of the global challenges raised by AI's (e.g., AI application, AI research, AI development, AI technology, or responsible AI).[160]

From an operational perspective, the strategy developed by NITI Aayog proposes to focus on those sectors that are expected to have the greatest positive externalities and solve societal needs (i.e., healthcare, agriculture, education, urban-/smart-city infrastructure, and transportation and mobility), and it assigns the government a leadership role in developing an implementation roadmap.

Furthermore, NITI Aayong puts forward a leapfrog pathway that would allow India to adopt existing AI technology and adapt it for India's unique needs while building foundational R&D capabilities that would ensure India's long-term competitiveness. First, India should promote the creation of academic research hubs (i.e., Centres of Research Excellence in AI), focused on understanding existing core research and pushing the technology frontier, and of International Centers of Transformational AI (ICTAI), entrusted with developing and deploying application-based research, in close cooperation with the private sector. Second, these research efforts should be guided by am umbrella organisation, responsible for analyzing of socio-economic trends related to AI, and promoting international cooperation. Finally, NITI Aayong suggests the Indian Government to pursue "moonshot research projects", develop a "CERN for AI", as well as computing capabilities and other related infrastructure for AI.[161]

These broad recommendations will now have to be further refined on the basis of the consensus that will emerged in a wider consultation.

South Korea

Like other governments in Asia, South Korea's government is also heavily investing in AI, with the ambition to position itself as a global contender by 2030. What makes South Korea a credible contestant is a strong semiconductor, automotive and electronic industry, and widespread use of industrial robotics. Furthermore, the country is home to tech companies that are aggressively investing in AI, such as Samsung, LG, and Hyunday.[162]

South Korea's strategy for AI, released in December 2019, focuses on maximizing the country's strengths, such as its ICT infrastructure and its dominance in the global supply of memory chips, while making AI work for the people. In order to achieve these overarching objectives, it identifies three areas of work (i.e., establishing a global-leading AI ecosystem, making the best use of AI, and realizing a people-centred AI) and a detailed list of tasks that the government will perform to achive nine strategic objectives: (1) enhancing AI infrastructure; (2) securing competitiveness in AI technology; (3) creating a "negative regulatory environment" based on the principle "Approval first and Regulate later", where companies and developers can innovate without limitations; (4) nurturing global AI start-ups, as well as (5) world's best AI talent; (6) promoting the uptake of AI technology across all industries; (7) building an efficient digital government that supports people in need and better serves citizens; (8) establishing an inclusive job safety network; and (9) creating an AI code of ethics to turn to when dealing with AI dysfunctions.

Some key actions to achieve these strategies include making data held by public institutions completely open to the public via data platforms, strengthening the linkage between public and private data maps, and introducing "AI voucher" to help companies use data to implement tailored AI solutions.

South Korea's AI strategy is part of the Moon administration's commitment to promoting science and technology, which led to the launch of its 5G commercial service in April 2019.[163]

Japan

Japan launched a national initiative on AI shortly after Canada, in 2017. Its "Artificial Intelligence Technology Strategy"[164], developed by "Artificial Intelligence Technology Strategy Council" (i.e., a body established by Prime Minister Shinzō Abe to ensure a coordinated approach across different ministries) outlined an "Industrialization Roadmap" andidentified three priority areas: productivity, health, and mobility.

This strategy was then updated in 2019, in order to integrate measures that the government should take to facilitate the effective future utilization of AI to realise the Fifth Societal Transformation, also called Society 5 or "super-smart society".[165] This is a new paradigm that goes beyond the Fourth Industrial Revolution, and which envisions inclusive and sustainable socio-economic systems powered by emerging technologies such as big data analytics, AI and the Internet of Things (IoT).[166]

As many other countries, Japan is struggling with the lack of an educated workforce able to handle AI technologies, and it is putting a lot of effort to facilitatate data sharing and to promote R&D by creating a network of centres of excellence.

Key Takeaways

While AI is expected to have a positive impact on growth and productivity, it also raises societal concerns that relate to its impact on jobs, civil liberties, growing inequality, and respect of the law. To some extent, these concerns are well-funded. But they are also magnified by a polarised narrative centred on hype or fear, and the lack of rules and standards that may guide the deployment of AI systems towards the achievement of clear public policy objectives. The result is a deficit of trust in AI applications that risks holding back their adoption.

The need to build trust in AI is especially relevant in the manufacturing sector, where the use of AI technologies raises ethical concerns such as transparency, privacy, safety, human agency, lawfulness and compliance. While business leaders need to embed ethical considerations early on in their AI strategies, each stakeholder needs to stand up to these challenges and take concrete actions which align with their role and capabilities:

- ***Policymakers*** should facilitate a multi-stakeholder dialogue on the values and public objectives that should guide the development and deployment of AI. In recognition that AI is a fast-moving technology in its early stages, policymakers should also: implement policies that reflect AI realities; strike a balance between protecting consumers and supporting innovation; promote industry guidelines and best practices that can facilitate companies' AI strategies; close legal gaps and remove regulatory bottlenecks that are holding back AI adoption;

- ***Supranational organisations and technical bodies*** should facilitate regulatory convergence and promote a new generation of standards. While regulatory convergence is needed to preserve a level playing field in global trade and protect consumers, the development of industry standards can help companies, especially manufacturing SMEs, to effectively communicate with other stakeholders (e.g., AI developers, lawmakers and workers), develop trustworthy AI systems and assess them for compliance, and enable interoperability, data sharing and technology transfers;

- ***Academia and AI software developers*** should educate the public about AI, counter misinformation, and create realistic expectations about what AI can do – and cannot do. Furthermore, they should work on developing AI systems that empower human beings, and redirect responsibility to humans whenever there is a problem or AI is not able to make an accurate prediction.

- ***Companies*** should develop framework and processes that ensure that their AI systems work as intended, in accordance to customer expectations, organisational goals and societal laws and norms.

Trusted data eco-system to foster data exchange between industrial partners

Dr.- Ing. Reinhold Achatz
Chairman of the Board and President, International Data Spaces Association

With the growing ability to evaluate data with mathematical algorithms and methods of analytics and artificial intelligence (AI), the value of data is dramatically increasing.

In manufacturing, the use of data analytics and AI allows to optimize production processes and systems as well as the design of products and solutions. For example to increase quality and output, to increase energy efficiency, to optimize logistics or to identify the most relevant customer data will play a major role. The conscious selection and use of data will optimize the results of analytics and AI applications.

In the real world, a big number of parties create data. That means to be able to make use of the data a data consumer needs access to date from different sources. On the other hand, data generators need an incentive to provide data to data-users and in this way become a data provider. One organisation or party can be a data generator or data provider and a data consumer at a time. The interplay between data generators and data consumers forms a data eco system. The interaction in a healthy data eco-system generates a win-win situation between data provider and data consumer.

In addition, the notion of trust is very relevant in a data eco system. Partners in the eco system need to be identifiable to avoid the risk of fraud. In addition, a data provider may want to define what a data consumer is allowed to do with the data provided.

To make data exchange efficient a data exchange standard for syntax and semantics needs to be established. To be able to provide an adequate incentive for the data provider a standardized way of describing mutually agreed software readable contracts needs to be defined.

Having that understanding in mind, a group of representatives of companies came together in January 2016 to form a non-profit organisation to define and promote such a standard development on basis of a proposal of a number of Fraunhofer Institutes, a German applied research organisation. In the group of companies where steel companies like thyssenkrupp and Salzgitter, the automotive company Volkswagen, the chemical and pharmaceutical companies Bayer HealthCare and Boehringer Ingelheim Pharma, the software company Atos and a number of smaller and medium size companies. It is remarkable that mainly users, who understood the need for a data exchange standard and not software companies, which want to generate a new market, started this initiative. The initial name of the non-profit organisation was "Industrial data spaces" (IDS), which was later changed into "International Data Spaces Association" (IDSA) with the understanding that standardisation is always global and the use of such a standard will support data exchange not only in the manufacturing and industrial world but also in many other industries. Currently initiatives and projects are under way in the medical, mobility and logistics domain, just to name some examples. The first manufacturing oriented use cases include a case, implemented by IBM, Fraunhofer and thyssenkrupp, addressing the challenge to design and optimize parts for additive manufacturing and print it at a print hub close to the customer. It was demonstrated at last year's Hanover Fair.

Today the International Data Spaces Association has more than 110 members from 18 countries, including a number of European countries, Japan, China and US.

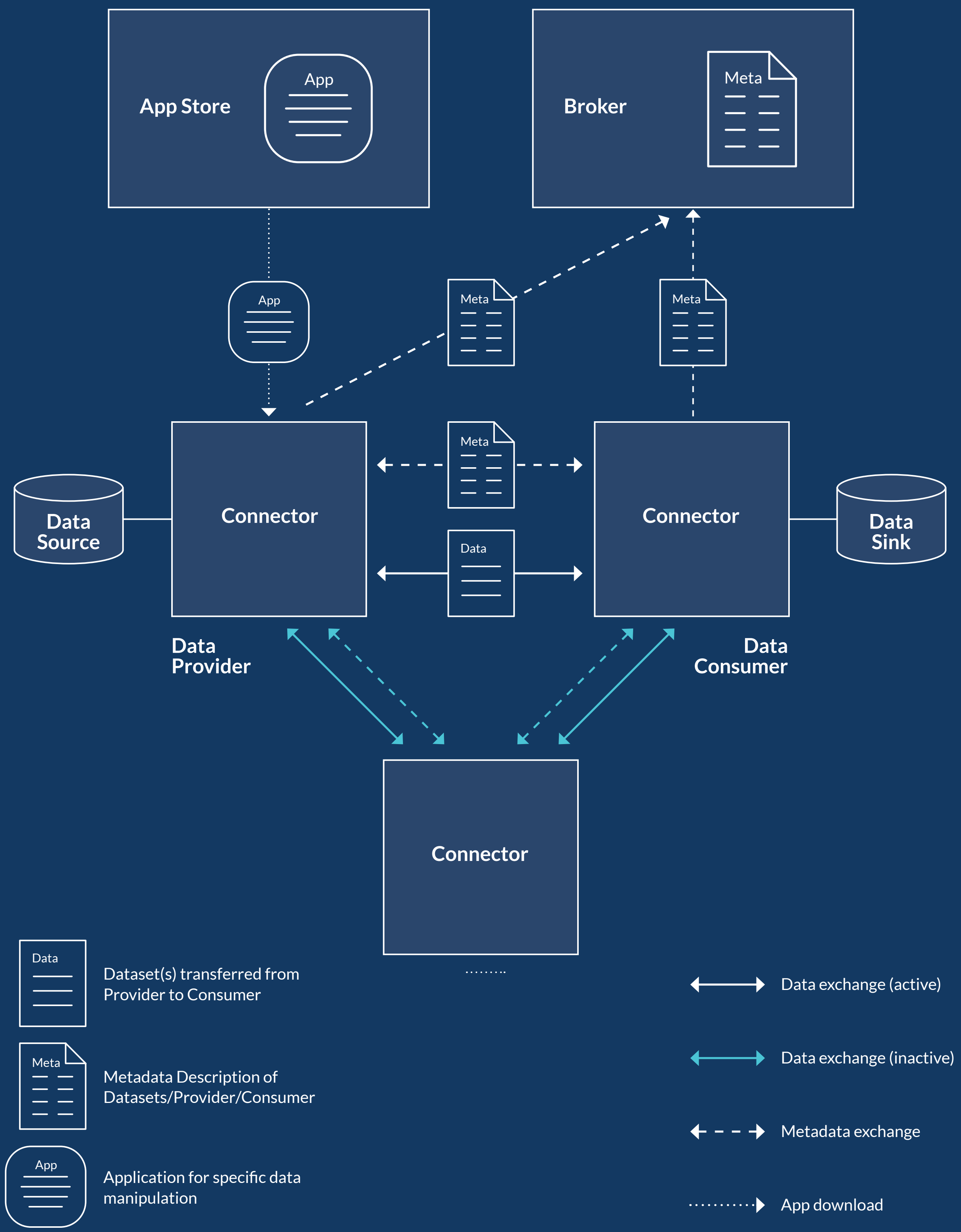
A key element of the implementation are connectors, which are integrated into every application program to ensure the standardized communication including software readable "contracts" which describe the agreed use of the data provided. Syntax and semantics of the exchange protocol are publishes as DIN 27070 standard (proposed to ISO). It is the intention of IDSA to publish an open source version soon.

Other elements of the eco-system are a broker with a meta data description of datasets, providers and consumer and an App store. An identity provider checks the identity of the communication collaborates (see basic architecture).

More information is available at the web site: https:/ www.internationaldataspaces.org/

International data spaces: Basic architecture

(Source: IDSA)



Case Study

AI in ABB Electrification Smart Power

Antonello Antoniazzi
Corporate Executive Engineer, Electrification - Smart Power

Giorgio Parente
Hub Europe Production Development Manager, Electrification - Smart Power

Federica Gallo
Hub Europe - Manufacturing Unit Italy Communications, Electrification - Smart Power

ABB is a leading global technology company that energises the transformation of society and industry to achieve a more productive, sustainable future. By connecting software to its electrification, robotics, automation and motion portfolio, ABB pushes the boundaries of technology to drive performance to new levels. With a history of excellence stretching back more than 130 years, ABB's success is driven by about 110,000 employees in over 100 countries. ABB's operations are organised into four global business areas, which in turn are made up of 18 divisions.

ABB Smart Power Division

ABB Smart Power Division builds on a strong product portfolio with innovative digitally connected low voltage products and solutions, that aim to become the cornerstone of smart electric distribution.

From fast-charging stations for electric vehicles and cloud-based energy management to predictive maintenance, innovations from ABB Smart Power equip utilities, industries, transport and infrastructure for the energy challenges. Its product portfolio provides the latest technologies in power conditioning, low-voltage circuit breakers, switches, chargers, motor protection and control, and safety products, and the ABB Ability™ tailored digital solutions for energy and asset management.

ABB Smart Power Division is active in 80 countries with 17 manufacturing facilities, 28 service locations and a global team of 13,500 employees.

The Italian operations is well rooted in the historical SACE, an electromechanical company founded in 1934 in Bergamo. Today, the R&D centre in Bergamo is the leading development centre for low voltage power distribution products, and factory in Frosinone is the centre of excellence for production of low-voltage molded-case and air circuit breakers.

The factory in Frosinone has been recently selected, together with those in Dalmine and Santa Palomba, by the Italian Technological Cluster Intelligent Factory (CFI) on behalf of the Ministry for Economic Development (MISE), as Lighthouse Plant (LHP) of the Italian Enterprise Plan 4.0: a model for companies aiming for Digital Transformation in accordance with Industry 4.0.

The reasons why Smart Power Division is looking to AI are based on ABB's three purposes.

ABB succeeds by creating superior value

Creating superior value means creating success for the customers, and ABB believes easing life and work for its customers and business partners along the value chain is a way of creating success.

To make that happen, the Division is developing a software tool, based on deep learning and computer vision, which enables panel builders to generate the Bill of Material of a plant directly from the schematics (Single Line Diagrams, in technical words), even when they are in paper version. This will slash the time spent in wandering catalogues and other low added-value tasks, and minimize the risk of mistakes.

A deep-learning image-recognition engine is also the core of augmented-reality apps intended to ease aftersales services. An app will help technicians to select and mount accessories in ABB Tmax XT and Emax 2 circuit breakers, by displaying where and how the accessory shall be installed. Another app will help maintenances and service engineers to identify the ordering code of spare parts, just by taking a snapshot with their mobile phone. Machine Learning really needs huge amount of data for training and testing, and ABB engineers learned that in such projects the toughest challenge is not the deep learning algorithms but building up the large datasets needed.

So, collecting the data and finding ways to reduce the cost of the data have been a key part of the projects. Sometimes, when the "real" data are not enough, synthetic data can to used instead. For instance, for the Single Line Diagrams a generator of synthetic diagrams was developed and used to build the training dataset, whereas real diagrams were used for testing. In a similar way, the image-recognition engines of the augmented-reality apps is trained using images generated from the 3D CAD models.

ABB energizes the transformation of society and industry to achieve a more productive, sustainable future

Going back to the purposes, the second one is about transforming industry to achieve a more productive future, and ABB believes the best way to do that is transforming its manufacturing first, also using AI. In this regard, the company is applying computer-vision visual inspection along assembling lines to trap defective parts and assembling mistakes as early as possible, in order to avoid expensive reworks and future malfunction in the use phase.

Another application ABB is working on is intended to streamline the cumbersome thermal calibration of thermomagnetic circuit breakers. Today this is a two-step process: first the relay is heated under the rated current (up to 1000A) till tripping, and the tripping time is adjusted by means of a screw. Then, after cooling, the calibration is verified with a testing current. In the future, an AI tool will be used for room temperature calibration, saving substantial time and energy, and improving first-pass yield. The AI tool is trained using geometrical and material data collected across all the manufacturing steps. Again, data are the key challenge. But this second purpose is also about achieving a more sustainable future, and this is probably the most important in this time of climate change. It is common understanding that the only socially and economically sustainable way to meet CO2 reduction targets is switching from fossil fuels to electric power generated from renewables in as many applications as possible. This is what the world is doing, even if probably not as fast as needed, but further increase of renewable generation is challenging.

Renewable generation is not dependable. A solar roof generates more power when solar irradiation is stronger, and a windmill when the wind is stronger, not when more power is needed. So continuous balancing of generation and demand in the grid is much more difficult than with conventional generation, which is more controllable. Switching off fossil fuels, then, requires massive in troduction of energy storage (e.g. batteries) but also a smarter grid and smarter electrical installations, e.g. in buildings and industrial plants, able to orchestrate the loads and the different energy resources to continuously balance the power demand with the power available in the grid. ABB is working hard on applying AI to such autonomous power systems.

ABB pushes the boundaries of technology to drive performance to new levels

This last but very important purpose is about pushing the boundaries of technology. For ABB, that means experiencing the latest technologies to stay ahead of competition and customers' expectations, even when technologies are not close to application yet.

Electronics embedded in Tmax XT and Emax2 low-voltage circuit breakers monitor Current and Voltage in the circuit to detect faults. ABB is considering AI and ML for this task, as the company thinks that could enable better protection and ease of use at the same time. For instance, such AI-enabled protections could detect the fault earlier and pinpoint its location in the circuit, and they would not need any complex set-up, as they would "learn" the circuit themselves. ABB engineers are investigating this application even if they think it is far away in the future. On one side fault data available are not enough for training, but another key issue is the lack of explainability. Deep-learning models are black-box, very difficult to explain and communicate, therefore very difficult to trust. For safety applications, like electrical fault protection, the company believes such models would be hardly accepted, unless they are the only viable technology, such as in self-driving cars.

To conclude, AI can strongly benefit the whole manufacturing value chain, from assembling to end use and the user experience, but its applicability is still limited or slowed by the lack of training data and the poor transparency. To exploit AI's full potentials, companies need to take on these issues.

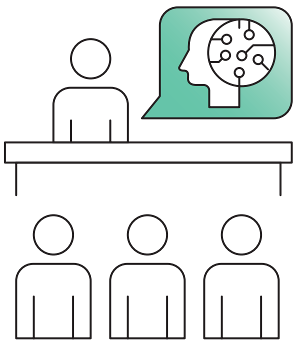
5

Key Recommendations

The World Manufacturing Foundation, in collaboration with experts globally, is pleased to present the Ten Key Recommendations for the 2020 World Manufacturing Report.

We hope our readers are able to embrace these recommendations and work towards a successful and trustworthy adoption of AI in manufacturing.

1. FOSTER PUBLIC CONVERSATIONS TO INCREASE UNDERSTANDING AND BUILD TRUST IN AI SYSTEMS



- **Educate the society on the importance and capabilities of AI**
- **Correct misconceptions about AI**
- **Discuss and address the socio-economic impacts of AI**

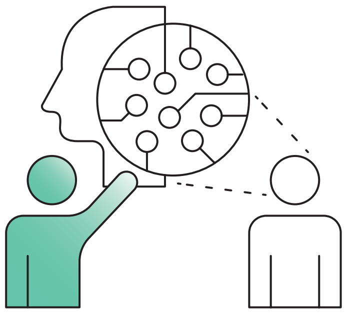
In order for artificial intelligence to continue to grow in the future, it will require a better understanding from the general public. When the general population discusses the future of AI, they often envision robots from science fiction that pose an inherent risk to society, rather than a computer reading data from sensors and choosing pre-programmed responses based on what information the sensors give. Consider the notion of self-driving cars. For the majority of the population, it is a terrifying thought that either a car is able to drive on its own or that a self-driving car may be next to you on the road with no individual guiding the car. The majority of people who may be afraid to have self-driving cars on the road may not understand that the majority of other transportation are almost completely autonomous. For example, the majority of airplanes fly on autopilot. Similarly, many doctors are now using AI to assist with surgery, where computers are able to be more precise than human doctors. With better education about artificial intelligence, we may be able to dismiss misconceptions about AI and foster understanding about its capabilities.

One issue to consider in AI systems that can affect public trust is how transparent each system is. There are many different forms of AI ranging from the most basic forms of AI such as simple machine learning models like ordinary least squares to complex deep learning neural network methods. When implementing an AI system, consider the goal the system is trying to accomplish. In the majority of cases where AI affects human life , it will be more beneficial to have explainable models to give reasons to the public as to why actions are taken, and to provide accountability and understanding of issues when problems occur.

It is also important to remember that AI is a community project, and that everyone should be learning about both the successes and failures of AI. It is critically important, however, that there is a place where individuals are able to come forward and discuss both these successes and failures. Doing this will ensure that communities, societies, and all individuals using AI remain at the forefront, and we can take advantage of its full potential to the society.

Finally, it is important to encourage discussion about the socio-economic impacts of AI on the company and on the broader society. Once these socio-economic impacts are understood, it is imperative to devise mechanisms that would help mitigate its impact on affected individuals (i.e. social benefit programs for displaced workers).

2. MANAGE MANUFACTURERS' EXPECTATIONS OF AI CAPABILITIES



- **Choose the optimal AI solution based on the company's needs, resources, and capabilities**
- **Understand the limitations of AI and act to address them**
- **Encourage sharing of best practices on AI use cases**

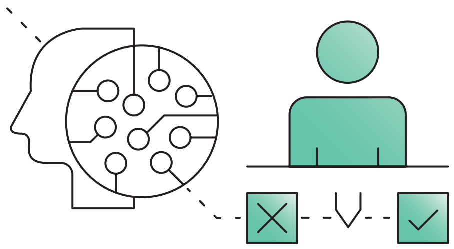
It is important for manufacturing executives to understand that artificial intelligence will not be a simple "one and done" solution. Although artificial intelligence is able to provide solutions to complex problems, it is often difficult to create these solutions, and they are often always different from each other. Additionally, the artificial intelligence field is constantly evolving. For example, the text analysis field has had an explosion of new modeling techniques. As each of these techniques comes to light, industry will need to research the costs and benefits of use before implementing. When taking a decision on AI, the company should critically analyse their organisation's readiness, by assessing their resources and capabilities. Although it is important to ensure time is taken to make these decisions, it is important to not take too much time, or be too cautious, to implement specific techniques.

This is where the distinction between artificial intelligence and automation is critical. Automation is a field that can often be viewed as a one and done solution. Once technology is in place to perform a certain process, it can be done over and over again. However, with artificial intelligence, there will always be new technologies, new ways of storing data, and new privacy risks that must be accounted for. Constantly reviewing these risks and issues is necessary in the use of artificial intelligence, unlike in the field of automation.

Additionally, workers who are artificial intelligence users should be constantly learning about artificial intelligence systems, and should constantly question these systems in order to avoid misuse. These users should follow the same protocols that we have previously discussed in the report including: understanding their companies core values in solving problems, understanding the flaws in the data, understanding the sensitivity of personal information, ensuring privacy protections are in place, ensuring that models can be easily understood, and that a system of accountability is in place.

It is important that companies are informed about how AI could positively transform production as well as understand its various limitations. This report has outlined how manufacturing could be valuable on the digital supply network, factory floor, and machine tool levels. In terms of the value provided by AI to the organisation, companies must understand not only the potential of AI in driving efficiencies in production but also leverage on the data and experience generated by AI to create new or transform business models in an organisation. These success stories should be shared to the manufacturing community. Governments and industrial associations for example could provide a framework that describe macro level processes and use cases of artificial intelligence that companies could read in order to understand how artificial intelligence could be used. This may also help manage expectations of manufacturers expectations of artificial intelligence and serve as an important tool for manufacturing policy.

3. IMPLEMENT ETHICAL CONSIDERATIONS THROUGHOUT THE AI LIFE CYCLE



- **Consider ethical implications in the ideation, development and implementation of AI projects**
- **Ensure that AI systems do not discriminate**
- **Promote interdisciplinary teams working in AI projects**

Acknowledging and addressing relevant ethical issues are key to building trust on AI technologies. In this regard, ethical issues should be considered in the ideation, development, implementation, and review of AI projects.

Even when data quality is perfect, artificial intelligence systems will most likely make mistakes just like humans do since it is impossible to have perfect accuracy. For example, there is a risk that AI systems may amplify existing biases in society especially when data fed into the system is not inclusive enough (i.e. when certain ethnic groups are historically under-represented in the data pool). In this regard, AI systems should be "trained" not to discriminate based on colour or ethnic background.

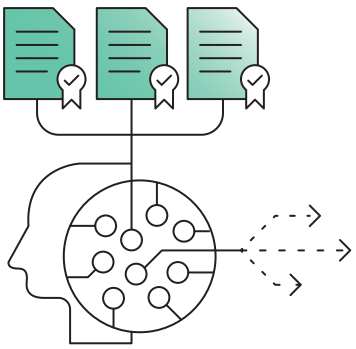
Furthermore, is important that AI systems have some form of accountability built into them. One way to have proper accountability measures are to favour AI systems as decisions support systems, rather than automated decision systems. This means a human is able to make a decision based upon a systems recommendation but is able to intervene when necessary.

Additionally, privacy and ethical considerations should be given to any AI system, but especially those that deal with sensitive data. It is indispensable to have guidelines on how data is collected and used in different contexts. For instance, workers in the shop floor should clearly understand how data from their usage and operation of machines are used. In the same way, data pertaining to customers' purchase and use of products should be used sensibly and not be shared without their consent.

In many situations, it helps to engage people from diverse backgrounds such as psychology and humanities in the development and implementation of AI projects. As mentioned in Chapter 3 of this report, ethics officers are instrumental in ensuring that teams consider the ethical dimension in every AI project.

Finally, to many companies who use AI, ethical and privacy considerations maybe viewed as an obstacle that prevents research, rather than an important tool in keeping individuals' privacy safe. Companies should put extreme importance on privacy and ethical use of data, as failures of doing so have cost companies both large sums of financial consequences, as well as damage to their own reputations.

4. ENSURE DATA QUALITY, PRIVACY, AND AVAILABILITY



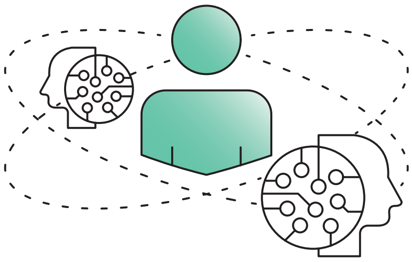
- **Ensure data accuracy and completeness**
- **Promote responsible data collection and management practices**
- **Explore new ways of trusted data sharing**

One of the most important facts about artificial intelligence is that the systems are only as effective as the data they are given. If the data is incomplete or filled with inaccuracies, an AI system would not be able to deliver the expected outcomes. In this case, the model will have the same quality as the data it was given: flawed and inaccurate. This highlights how data is critically important to artificial intelligence systems. Inaccurate data will result in biased systems. Missing data will result in model gaps. Additionally, users of AI systems should be aware about what kind of data is collected, how is it collected, and how it is used in models to formulate a specific decision.

Data privacy is another fundamental issue especially when data collected relates to humans. The increasing cost of compliance to data privacy laws means companies must consider responsible data collection and management practices. In addition, as outlined in Chapter 4 of this report, policymakers need to find a balance between protecting consumers data and supporting innovation. More proactive approaches should be promoted such as regulatory sandboxes where companies could test AI applications in controlled environments, allowing them to interact with regulators early in the development cycle. Doing so could speed up the development of new AI applications spurring innovation and at the same time allowing policymakers to identify potential risks, and react accordingly.

In addition, data is often difficult to share based on the financial importance it brings companies who own it. When data provides so much financial benefit, or more importantly, that the possibility of sharing data could result in financial loss or loss of competitive advantage, companies are not incentivized to share data. When moving into the future, it is important to understand different options to incentivise data sharing. For example, trusted data sharing frameworks facilitates sharing of data among actors in an efficient and transparent manner. Such framework could help companies identify the optimal mechanism to share data and decide whether and which data can be shared while respecting legal and regulatory requirements. In the future as AI technologies evolves, novel ways of sharing data would be needed to support innovation and competitiveness in the manufacturing community.

5. PUT HUMANS AT THE CENTRE OF AI WORK ENVIRONMENTS



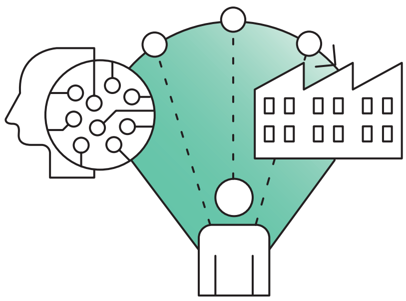
- **Prepare workers psychologically for a future with AI**
- **Empower humans to enhance AI capabilities and vice versa**
- **Increase acceptance by making AI explainable and transparent to workers**

It is critical that humans are at the centre of any artificial intelligence system. Companies should always consider how jobs are impacted by the use of AI. More concretely, it is important to let workers know about their value and how their job is expected to change and support them in the process. This includes helping them to prepare "psychologically" for a future with AI. Companies should help workers acknowledge that there will be many instances of AI creating decisions in the manufacturing workplace, and that they may feel that they are losing some control in certain tasks. However, this does not necessarily make them inferior to AI. In fact it has been shown that workers can work in harmony with AI, making the best use of their time and talents on tasks that involve critical thinking and judgement, and delegating manually tedious and time consuming tasks to AI systems.

To increase acceptance among workers, it is important to ensure the transparency and explainability of AI systems. It must be clear that AI does not downgrade the role of the operator but rather enhance it. It is important that workers understand that AI could provide them with valuable support but at the same time workers must feel that they are in control. To increase acceptance for AI projects within the company, it is important that workers have a say and that their voices are heard especially when AI has important implications on their jobs.

Will individuals need to acquire a new set of skills in order to be successful in the workforce? Does the implementation of artificial intelligence allow for a growing or shrinking workforce within the company? These questions are important because they impact the individuals who are working at each company, and will subsequently impact how each individual views the company. Similar to how a worker would rather work at a company that has strict safety measures, workers will choose to work at manufacturing companies that put humans at the forefront of AI.

6. ENSURE AI STRATEGIC ALIGNMENT ACROSS THE ENTIRE ORGANISATION



- **Perform strategic exercise when making decisions related to AI**
- **Ensure that voices from across the organisation are heard in AI projects**
- **Devise an AI change management strategy for the entire organisation**

Whenever a company chooses to implement an artificial intelligence system, they should first perform a strategic exercise and ask internal questions. These questions may include: what is the issue they are trying to solve, how does this fit into their core missions, what data do they have to analyse, can their workforce support the project, etc. After performing this evaluation, the company should next ask itself what are the ethical and privacy implications of using AI. Additionally, it should be determined how the AI system will be held accountable for any problems that may arise from its use. Only after all of these strategic alignment questions are answered should an organisation consider using AI. Additionally, often times executive leadership in a company will not have as much of a technical understanding of artificial intelligence as the data users in a company will. For this reason, it is crucial that anyone who uses data or is implementing the artificial intelligence speak up when they see possible issues in the artificial intelligence system. Additionally, there should be constant reviews of AI systems to try to determine any possible flaws. In addition, while companies could start initially with projects focused on a specific application of AI, companies should not lose sight of the bigger picture on how AI could be beneficial for the entire organisation.

Additionally, AI should be viewed as company-wide issue. Each project should be approached strategically by the entire organisation. Doing this will ensure that all voices are heard and everyone discusses possible issues during development and implementation to avoid ethical, privacy, or practical issues.

A clear change management strategy should also be in place to prepare the entire organisation for a future with AI. Top management should also come up with a compelling story on how AI could transform the organisation. They should also exhibit leadership for sustainable AI practices. The creation of new roles such as Chief Data, AI, and Ethics officers could also be instrumental to drive this organisation-wide change and build a company culture that is more receptive to AI.

7. SUPPORT MANUFACTURING SMES IN THEIR JOURNEY TOWARDS AI

- **Provide incentives to encourage uptake of AI in SMEs**
- **Support SMEs in building a skilled workforce**
- **Promote alliances and platforms to share data and other valuable resources**

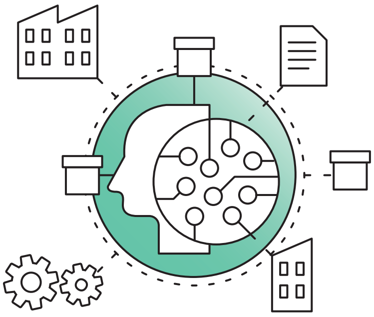
Throughout this report, we have discussed the benefits of artificial intelligence. What is less apparent, however, are the problems that will be caused to those organisations who will be unable to use artificial intelligence in the future. SMEs stands to benefit from AI, potentially transforming different aspects of their operations. To start with, many SMEs are already struggling with digital transformation. In addition, because artificial intelligence relies so much upon data and require specialised skills, small and medium-sized enterprises face more risk now than ever before.

The cost of adopting AI can often be quite high, which can serve as a barrier to small and medium-sized enterprises. Financial incentives (i.e. provided by the government) could help lessen the impact of initial capital outlays related to AI. Access to data is another important aspect. It is important to remember that small and medium-sized business will not have the resources to be part of many data sharing groups, or have the financial resources to purchase data (if possible) from other companies. Additionally, a skilled workforce is needed by SMEs to successfully implement AI projects. However, skill resources will most likely not be readily available to these companies based on costs of both skill and training materials.

Finally, there is also a large cost of compliance regarding artificial intelligence. Throughout the previous recommendations, there has been a lot of discussion based on the risks of AI to a company that uses it, from accidentally releasing sensitive data to risk of bias. For many larger organisations, although privacy concerns are always to be avoided, they usually have financial resources to pay any fines or repay customers for errors if they occur. For small and medium-sized businesses, however, one privacy risk could lead to such a large fine or loss of customer base, that it could be very dangerous for the company. Thus, the cost of compliance is even larger for small and medium-size enterprises than for larger-sized enterprises.

To begin, we would recommend that readers interested in this recommendation refer back to the previous World Manufacturing Forum Reports, where there is talk about how to can best help small and medium sized enterprises. The information from those reports remain relevant currently and also applies to artificial intelligence. Additionally, it would be very beneficial for small and medium-sized companies to create partnerships with other similarly sized organisations. Through this, it may be possible to pool and share resources so that small and medium-sized businesses are also able to help each other.

8. PROMOTE AI TO SUPPORT RESILIENT SUPPLY NETWORKS



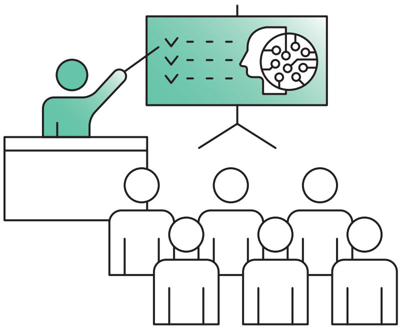
- **Leverage on AI to detect and respond to disruptions in supply networks**
- **Exploit AI capabilities to optimise day to day operations**
- **Use AI to develop new approaches to solving problems and create new business models**

Artificial intelligence will be important for partnerships and networks of organisations. Although we have previously discussed how companies may be unwilling to share data, there will be partnerships or organisations that work in supply networks or often work together that may try to organise and align in terms of AI. For example, a metal supply company may align AI technology with a metal production company in order to minimize production delays and maximize purchase order efficiency.

AI could also help supply networks deal with global disasters. Although it should be noted that we should approach these situations carefully as AI may not be the most effective approach, it may help supply chains facing disruptions such as those caused by the 2019 coronavirus pandemic. Although once again we stress the care that should be taken before implementation, AI holds promise to create resilient supply networks for those situations.

In addition to wide-scale disruptions, AI can also help organisations on a much smaller scale in their day to day operations. AI holds promise in enabling quicker analysis of supply chains, demand-side chains, operations, processes, and procedures. For example, AI systems can analyse data in order to create process flow maps that identify areas where improvement and automation are possible, in addition to looking at the largest bottlenecks in process are, as well as recommending alternatives when breaks in processes occur. In addition to all the built-in functionality, AI technologies can most importantly assist companies in thinking of existing problems in new ways, which can help the companies in more ways than simply focusing on cost and efficiency. In addition, companies could look into AI-based business models to speed up product and service development and predict consumer demand. Through the use of AI technologies, supply chains can become stronger and more resilient to major disruptions in addition to day to day uses.

9. EDUCATE AND TRAIN THE CURRENT AND FUTURE WORKFORCE TO BE PREPARED TO WORK WITH AI



- **Teach both technical and human-centric skills needed to work with AI**
- **Integrate AI education in different academic disciplines**
- **Leverage on AI to make learning more effective and inclusive**

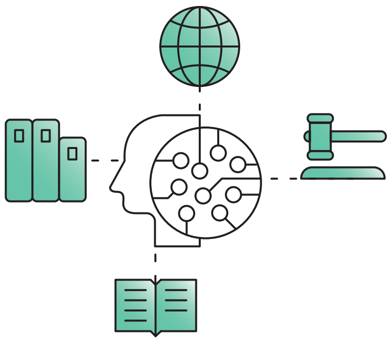
Workers must be prepared for a future of manufacturing. As extensively discussed in the *2019 World Manufacturing Forum Report: Skills for the Future of Manufacturing*, the digitisation of manufacturing will fundamentally change the required skills sets among workers. This heightens the need to train and reskill the current and future workforce equipping them the required skills and encourage a culture of lifelong learning.

As the world learns how to navigate artificial intelligence in the future, it will be critically important that the population is able to continue to adapt to understand how to work with AI. Although AI systems can give us programmed results, it is up to workers to interoperate results and ensure that the model is sound. Working with and generating value out of data and an understanding of ethics and privacy will all be essential skills in working with AI.

It is also important to understand how education in general is shifted by artificial intelligence in today's world. Education will be different from individuals who will need to learn to adapt and understand how to work with AI compared to children in schools, who will most likely need to learn how algorithms and technology will work in the new world. Developing AI literacy at an early age must be prioritized to prepare future workers. Additionally, AI should be thought not only in computer science programs but also in other disciplines such as engineering, business and humanities. Although many individuals may think of the need to have more hard skills to bridge this gap, soft skills might be more important in learning how to deal with AI. This is because as we have discussed in Chapters 3 and 4, and in Recommendation 5, people will be at the forefront of AI and AI will involve many decisions that affect people.

Finally, educators must apply AI in ways that make the future of work more inclusive, especially in aging populations and individuals with disabilities. More specifically, AI could enable (re)skilling and training tailored to the cognitive and physical attributes, needs, and skills of diverse individuals. For example, AI could enhance and augment an individual's skills through AI-enabled assistive hardware and software.

10. IMPLEMENT STANDARDS, POLICIES, AND REGULATIONS TO GUIDE A SUSTAINABLE AI ADOPTION



- **Evolve standards, policies and regulations to fast-changing developments in AI**
- **Develop over-arching principles or guidelines that can be adopted in policy formulation globally**
- **Establish standards to guide the development of trustworthy AI systems**

Standards and regulations will be important to contribute to growth and innovation in the artificial intelligence field. As described above, AI is a very dynamic field. New technological breakthroughs are continuously occurring. Standards and regulations must reflect this in that they should be dynamic as well. One of the best ways to ensure that standards and regulations are dynamic is to have government craft them as a set of general guidelines or best practices rather than a set of strict laws. This could also help in the harmonisation of AI standards and regulations globally. Understandably, there will be some areas where laws will need to apply to ensure that artificial intelligence follows certain privacy thresholds and does not adversely impact any particular group of individuals. However, a strict set of laws can often stifle innovation, and reduce the ability for AI to have meaningful impact in society.

One key area where standards and regulations could be useful is to discuss how much transparency is necessary in creating and maintaining models. Experts often warn that both too much and too little transparency can hinder the uses of AI and pose risks to individuals. On the other side, a lack of transparency also is not a good option. With model transparency, we may be able to avoid this if others were to review models and point out where error and unfairness occur. When considering the issue of transparency, standards and regulations can help to create guidelines or committees that help review models, thus providing a safe form of transparency for AI users.

Additionally, standards can be used to create data standards for acceptable use. As described in previous recommendations, data quality is important in creating efficient and impactful artificial intelligence systems. Standards that ensure proper use of data will be meaningful in the future. Additionally, standards can also help ensure that data is able to be easily harmonized with other data sources. In this, we need to ensure that data is properly cleaned, formatted, and machine readable so that users begin from the same position and do not clean data in different ways, thus resulting in different outcomes. Additionally, defining schema to ensure that common data sources can be housed in similar places and easily combined together will be important in future standards and regulations. In summary, regulations and policies should enable , not hinder AI innovation and growth.

Conclusion

The *2020 World Manufacturing Report: Manufacturing in the Age of Artificial Intelligence* provided a holistic discussion of AI in manufacturing by incorporating the technical, social, and ethical dimensions of AI. It then outlined 10 Key Recommendations to successful adoption of trustworthy AI in manufacturing.

Throughout the document, the concept of trustworthy AI has been emphasised. After all, in order to truly harness the potential of AI in manufacturing, society must first learn to trust and embrace it. A precursor to this is to have a realistic understanding of the capabilities of AI, as well as the possible challenges associated to its use. This document highlighted how AI can positively transform the manufacturing value chain, and how it could be a source of competitive advantage for companies. However, companies must have in place a well-thought strategy in choosing, implementing, and evaluating AI projects to unlock the value of AI for their organisations.

The implications for workers are also profound. Given the pace of innovation in this field, workers must be continuously trained to equip them with the right mindset and skills to work with AI. This holds true for current and future manufacturing workers. It is essential to highlight that AI is not meant to replace workers but it exists to empower them. Human-centric skills such as critical thinking, decision making, and openness to change will be more important than ever. It has been shown that AI systems are not perfect, and only when acting in concert with humans can it truly provide immense value for organisations. It Is therefore important that in any circumstance, workers do not feel left out and that they feel supported and empowered in the company's AI journey.

Key ethical issues concerning the use of AI such as transparency and privacy are of particular concern. For this reason, it is important to have appropriate safeguards within organisations and in the broader policy and regulatory environment. Policymakers have an important role to play in ensuring that regulations are in place to address these challenges. Regulations and standards should support and not stifle AI innovation.

Finally, cooperation among all stakeholders is necessary to ensure the successful adoption of AI in manufacturing. Stakeholders can cooperate in different ways ranging from agreeing to harmonise standards, industry-academe collaboration to increase uptake of AI innovation in industries, and sharing of best practices to spur innovation. Each one of us is responsible in ensuring that AI innovation not only benefits the manufacturing community but also ultimately contributes to the greater societal good.

Young Manufacturing Leaders

Essay Contest

Young Manufacturing Leaders is an open initiative for **students, young workers and professionals** interested in a career in the manufacturing sector.

The YML network is strongly committed to raise awareness about the possibilities in manufacturing, and to spread knowledge of the skills needed in this sector. It supports members with different activities such as peer-to-peer seminars, mentorship with professionals and entrepreneurs, and participation to the activities of the World Manufacturing Foundation.

From June to September 2020, the YML Essay Contest was held inviting young leaders from all over Europe to submit their essays on topics related to Artificial Intelligence in Manufacturing. The submissions were evaluated by the World Manufacturing Report Editorial Board and the winning and outsanding essays are included in this section.

The Young Manufacturing Leaders network initiative was launched in 2020 by six partners: Politecnico di Milano, Chalmers University of Technology, Czech Technical University in Prague, Tecnalia, Technische Universität Braunschweig, and the World Manufacturing Foundation. The inititative is funded by the European Commission, within the framework of the EIT Manufacturing programme.

For more information visit youngmanufacturingleaders.org

This activity has received funding from the European Institute of Innovation and Technology (EIT), a body of the European Union, under the Horizon 2020, the EU Framework Programme for Research and Innovation.

:YML

Help me to help you
The role of AI in supporting manufacturing workers

Rafael Lorenz
City Hub: Milan

Thomas Gittler
City Hub: Milan

Put the lights out – let AI do the job. This is how we sometimes imagine the future of manufacturing. But will AI really take over the work of the employees in manufacturing firms? Or will in contrast, AI remain another hype cycle that workers in the future will be reminiscing about, after working a late night shift down at the shop floor? We believe the truth lies somewhere in between.

Artificial Intelligence, or short "AI", is certainly one of the most hyped topics in manufacturing[1]: it fills academic conferences, agendas of C-suite meetings within companies, and marketing brochures of every manufacturing- related consultancy. The definition of AI by the European Commission's Communication as "systems that display intelligent behaviour [...] to achieve specific goals"[2] refers to the narrow definition of AI. In this definition, AI is given a certain goal, which it tries to achieve with the highest accuracy. In contrast, general AI would refer to AI that is able to cope with any task and can learn it itself without providing a certain goal. Much like a worker on the shop floor can be given a task to assemble a product in the morning, drive a pallet truck after lunch or prepare a presentation for the next shop floor management meeting – this form of AI could solve all generalized tasks. Even though this singularity might become reality somewhen in the far future, let us stick to the narrow definition of AI for now. As even this form is still far away from being a standard in industry[3]. Hence, to cut the whole fuzz, if anything, we will in the near future only be able to use AI to solve specific tasks – and not replace all tasks of an employee by one AI. Or in other words: there will be no one AI to rule them all.

Yet, if AI can be used to solve specific tasks, will we just have plenty of algorithms that will solve all our tasks in manufacturing? Yes and no. Yes, as there are certain use cases for which AI will replace the work of an employee[4]. Let's take the visual inspector for instance: AI is already capable of spotting mistakes on parts with a higher accuracy than the human eye ever could – and without ever getting tired. Or that production planner, who used to estimate the demand and schedule the jobs on the machines in sequence? Or that process analyst in that chemical plant evaluating the one-on-one correlations from the thousands of variables from their sensors? Yes, AI is on the way to, and has sometimes already managed to replace their tasks[5]. For those repetitive jobs, or tasks requiring a razor sharp focus, AI outperforms the worker.

But let us get back to the reality of the manufacturing shop floor in a plant far away from the big tech buzz vibes of Berlin, Stockholm or Milan. To your next-door manufacturing plant, where machinery equipment was bought long ago – and shall last for even longer. Here, where every worker has a machine she knows in and out, with all its little flaws. Here, where production data is scarce, unstructured and distributed over dozens of different excel sheets. Applying predictive maintenance using time series data to autonomously send a service request to the equipment supplier? Machine parameter optimization based on historic quality data to produce each single part with the optimal setting and prevent any defects? No, at such plants these tasks are and will still be performed in the near future by those employees calling their machines by names. Certainly, there are more and more plants that have made their homework to enable such solutions. But those are the exception, not the norm. To come to that level, these next-door manufacturing plants need to retrofit their equipment to get the required data – and this takes time and resources.

But what is the role of AI in this case, if it is not replacing the human worker? We believe, it is in supporting their decision making. AI will thereby not purely replace the tasks of the workers, but suggest the best solutions based on probabilistic estimates. It will work side by side with the workers, monitoring their tasks and suggesting improvements. The focus of AI will be the use of available and incomplete data in a manner to provide predictions with best possible accuracy. But to be able to be trusted by its colleague, the human worker, accuracy is not enough. AI needs to be explainable as well so that the workers can understand why a certain decision was taken. Why is this part potentially defect? Why will the machine soon break

YML

Winner

down? Why should this job be preferred over the other one? AI needs to indicate answers for these questions – and yet, it hardly ever does in this regard. All too often black box models are implemented on the shop floor. Even though such models like deep neural nets have a high accuracy, they lack the ability to explain the underlying reasons for their decision[6]. This hinders the trust between the worker and the AI enabled decision support system. Explainability is key here to create this trust[7]. Certainly, AI can be incredibly hard to create, train and to deploy. With all development efforts invested to get an AI solution off the ground, risks are high to overlook the role of the worker as the pilot in command. This is like building a plane and leaving the pilot with no cockpit or instruments: crash landing inevitable. Hence, it is the task of the developers to ensure that AI is explainable and trustworthy, thereby fulfilling its part of the homework.

However, the workers have their share of the homework too. They need to learn to understand and adapt to the new tasks. For the first part of the homework, the worker needs to upskill their analytics capabilities to understand the fundamental mechanisms on how AI solves problems. They need to acknowledge and appreciate what AI is capable of – and what not. This leads also to the latter challenge of adapting to new tasks. The worker will not be the sole problem solver anymore as it has been for many years. Instead, the worker will more and more get into the role of a problem identifier. This means, they spot processes that do not run well and can be supported by or even replaced through AI. This task not only requires certain knowledge about the mechanism of AI, it also requires a certain creativity from the worker. Opening up and obtaining this creativity is the second part of the homework for the worker.

If all parties, the plant, the AI developers, and the workers, do their homework, workers can expect a continuous reduction of tiring and repetitive processes in their day-to-day work. Cumbersome tasks, requiring merely a small share of the human cognition can be assigned to an AI solution, while problem identification and solution verification remain in the hands of the workers. Gone are the days of meticulously examining surfaces for small defects or dents. Gone are the days of endless glaring at multi-variate control charts of multi-stage processes to anticipate or spot minor process irregularities. And gone are the days of contemplating an optimal solution, just to realise it cannot be executed due to numerous hard and soft constraints. Oh, and who appreciates discovering at the very last step of a manufacturing process that the machine, tool or even raw material were faulty and should not have been used in the first place? Exploiting the full potential of any manufacturing systems starts with taking the right decisions – at any time, based on distributed information streams, towards a global optimum – in real time. Which is, after all, a very imprecise problem. Therefore, AI needs to support workers in specific questions, problems or tasks to provide decision support with the highest possible accuracy.

Consequently, in the future AI will be able to successfully support the worker in the decision making. Workers can expect AI to be their best support, their apprentice and instructor at once, collaborating on a constant and mutual exchange of information. We believe it is still a long way to go on this route. However, we will walk it with the lights on.

:YML

The WHY beyond the WHAT: People and Jobs in the Fourth Industrial Revolution

Andrea Tanzini
City Hub: Milan

"In order to keep everything the same, everything must change." The central point around which the book The Leopard orbits should also be taken as a reference to navigate through the Fourth Industrial Revolution, where changes are so substantial and rapid that detecting and understanding them in time becomes very hard. Robotics, artificial intelligence, 3D printing, big data (and many other enabling technologies), when individually considered, are already changing the world. As their paths increasingly cross, the spread of one accelerates the development of the others, inevitably twisting the world with their entanglements. The ecosystem that arises from combining robotics with artificial intelligence could be the most interesting to be studied, as it involves humans both on physical and intellectual level. Although roles will certainly be disrupted, people are not in danger of becoming obsolete, on the contrary, they will become more important than ever. Without people a process will never be upgraded or innovated: striving towards improvement is purely human.

The late 1800s and 1900s were marked by the introduction of the assembly line and consequently by the unraveling of the most distinctive methodological revolution at a manufacturing level, with the exclusion of the Fourth, that is only now consolidating. The assembly line generally consisted of a main conveyor belt that slid through, carrying the different objects to be assembled and delivering the finished product at the end of the process. Each worker could thus assemble a single piece through repetitive movements, allowing a considerable saving in production and training time. The adoption of this type of process was what made mass production possible, shifting the know-how from the operator to the tool in use.

The expertise of people working the assembly line often resulted in alienating movements and tasks, with very low safety requirements and near-zero human added value. The first side effect of the 20th century assembly line was, as a matter of fact, the lack of attention paid to workers' condition, caused by their high interchangeability: anyone could easily fill any role on the line. The second was a total alienation of the human being. People were being so often used only for their physical strength instead of their intellect, that they themselves became a replaceable tool.

The type of process just described allowed for decades the production of objects that were acceptable to everyone, but perfect for no one. The high standardization, in fact, was necessary to allow the factory to be developed with a starting point and a final one, without too many branches of the pathways depending on the variation of products. The current trend, however, is the extreme opposite. From mass production, the market is shifting towards mass customisation. An increasing number of users claim to be 100% satisfied with the product used, without making any compromise. This trend directly affects the production units of companies: being able to manufacture hundreds of different set-ups for the same type of car, for example, can push the possibilities of a production plant to the edge (while being a nightmare for all involved departments). From cars to computers, from bicycles to shoes, most manufacturers are raising the degree of customisation, thereby shattering the assembly line and mass production paradigm as it has been known to date.

Thus, since manufacturers have to produce customised products in a mass-production context, the scenario that is emerging shifts from complicated to complex: from a difficult single process with a beginning and an end that follows a well-defined linear course, to multiple processes characterised linked together by high non-linearities and strong couplings in various production levels.

Among this trend, the increasingly demanding standards of quality, safety (related to both product and production) and the more and more important efforts to reduce wastage are also contributing to elevate the global manufacturing sector to a whole new level of complexity. Quality, safety and waste reduction are by definition in antithesis with human manual production (especially at a mass-production level), because humans have little repeatability in their movements, do not have the dosing ability of a precision device and most importantly, unlike machines, humans can get hurt and fall ill when operating in (sometimes inevitably) unhealthy conditions. This is leading to the ongoing need to exploit new technologies: to date, fewer and fewer operators are being replaced by machines to reduce the impact of the labor cost. The technical feasibility required to produce a car, a drug, or a telephone, would be missing if the production had to be carried out manually (and this risk is increasing because of the always shorter lead time available). In addition, thanks to increasingly high-performance computers, applications with artificial intelligence are already meeting mankind's needs to cope with complexity. From vision systems and production scheduling algorithms to real-time tools to analyse plant performance, production processes are increasingly exploiting data, pointing out the higher reliability of results if it's a computer, instead of a human, handling huge amounts of data and repeating specific tasks.

Therefore, humanity faces an unprecedented challenge, having to compete with robots on the physical side and with super-computers on the intellectual side: people's skills risk limiting the productive context, which should itself improve people's quality of life. Surprisingly, if people may be the problem, they are also the solution. The human contribution to production, especially in the mass production scenario, is expected to move away from the final end of the process: within the manufacturing company, it will tend to move to the early stages, in the design and analysis departments. Outside the company, on the other hand, it will concentrate on service and plant suppliers: the higher the degree of customisation of the final product, the more unique its production plant needs to be. This means that the expertise of designers, programmers and the human capital of machinery suppliers will be little replaceable by automatic processes.

Artificial intelligence encapsulates all the mathematical techniques allowing a computer to predict the probability that a certain event will happen again in the future, based on the re-occurrence of certain conditions. Computers therefore learn from the past and the data that represent it. This technology allows the realisation of a wide variety of models: from simulating the wear of a gearbox to prevent a machine stoppage, to calculating the best trajectory of a robot to maximize a given cost function, as well as signaling the early warning of emergency-risk. The data is the fundamental lymph of this learning process and, if roughly collected, could steer a whole production process wrong, leading to incorrect solutions. But data, as it's often repeated, is the new Oil: just as Oil, data requires extraction, refining and distribution in order to achieve real usability and bring added value. The human being becomes indispensable in each one of these phases: in understanding what data to collect so as not to deceive computers; in deciding what kind of sensors to use; in interpreting them, and in discerning good quality data from poor data. Even the interpretation of the result is, and will remain for a long time to come, linked to human analysis. Artificial intelligence is extremely good in predicting WHAT happens when certain conditions occur, but it's not able to understand WHY. However, in a complex scenario such as the one related to production lines, WHAT is only the starting point of a deeper analysis based on experience and knowledge: in a world where the framework is always rapidly changing, understanding WHY is the only way to achieve a better, sustainable and fruitful future for manufacturing. This flexibility and heterogeneity of ideas and intuitions is something

Balancing the role of domain experts and data scientists in an AI-powered factory

Mukund Subramaniyan
City Hub: Gothenburg

Artificial intelligence (AI) is starting to make an impact on factories. AI brings a variety of capabilities to a factory: machine learning (ML), computer vision, natural language processing, and robotics. To successfully adopt AI technologies, manufacturing companies are increasingly recruiting data scientists (who have expertise in computer science and AI). On the other hand, this creates confusion on the role of domain experts (who have deep expertise in manufacturing). Some scholars argue that domain experts' role will soon become irrelevant, and they are at risk of being replaced by data scientists in AI-powered factories. Data scientists often demonstrate that they can build AI solutions with little to no domain expertise in data science competitions (e.g., hosted in conferences, Kaggle), and their skills are transferable to multiple problems across different domains. These skills make data scientists look attractive to companies. On the flip side, these raise domain experts' anxiety and fear about the relevance of their manufacturing skills and the prospects of employment in an AI-powered factory. Dealing with this type of situation is a consequential matter of ethical responsibility. Manufacturing companies with ambitions to deploy AI systems must find a solution to balance the role of domain experts and data scientists.

Scholars argue for a solution in which domain experts should get new expertise in AI and match the skill level of data scientists. However, this can make domain experts feel pressured to specialise beyond their core manufacturing expertise, which they have gained through years of education and experience. I argue for a solution that encourages active collaboration between data scientists and domain experts for the development of reliable AI systems. I present a real-world example that shows the impact of this collaboration. A real-world manufacturing company wanted an ML algorithm that can predict bottlenecks in the factory. Bottlenecks constrain the factory throughput and, when eliminated, increases the throughput. The company collaborated on a research project to develop an ML algorithm. Me and two of my colleagues acted as data scientists as we had expertise in developing ML algorithms. The factory engineers, who had years of experience in the factory flows are the domain experts.

The project started with the engineers giving us a batch of factory data and a brief explanation about the production flow. We were confident at the start of the project that we will not require any additional information, and we can develop the ML algorithm quickly. When we started to explore the data, it was a complete mess. The files had several features, and we were not sure which ones can best describe bottleneck phenomena. We turned to academic literature to learn about the features. However, this was a complicated task because we found many features for the same purpose. We then decided to seek help from engineers. To our surprise, engineers recommended features were different from the academic literature and were unique to the type of production flow they have in their factory. *Here we understood the importance of domain experts' tacit knowledge in defining the features.* We then started to clean the data. With our expertise, we could do simple cleaning tasks such as removing duplicates and weekends. But we could not do complicated tasks such as outlier identification and deducing the reasons for those. We decided to take help from engineers again. *We then realised that domain experts' inputs are critical to identify the outliers and explain possible reasons (which usually is not directly evident from data).*

Once we prepared the final data set, we started to develop ML algorithms that can predict the bottlenecks. We wrangled the data and experimented with the most sophisticated ML algorithms. However, we could not achieve even achieve 50% accuracy. To improve accuracy, we thought more data sets were necessary. We presented the results and our action list to engineers. Though they accepted the low accuracy, they were skeptical by our proposal of using additional data sets. They argued that existing data had sufficient information to be able to predict the bottlenecks. During the discussion, much to our surprise, they gave one critical information that toppled our entire approach. They said that there was a significant improvement in the production flow and recommended to consider the recent 100 production shifts data. We failed to notice this change in production flow from the data set, even with sophisticated ML algorithms. With the new information, we improved the accuracy to 80%. Subsequently, we presented the instances where the ML algorithm was not confident in predicting the bottlenecks to engineers for interpretation. This interpretative analysis further improved our understanding of the domain that helped to fine-tune the ML algorithm. Due to this feedback loop, we achieved 86% accuracy. *Usually, data scientists think that ML algorithm development is a pure algorithmic challenge and does not involve domain experts and, so was our thought process. But in the end, we understood that domain experts' knowledge is indispensable during the ML algorithm development phase.*

When we presented the results to engineers, they raised one critical question: does the proposed ML algorithm performance surpasses our existing prediction method? This way of benchmarking with already existing real-world practices is not a standard procedure among data scientists. They usually compare the performance between different ML algorithms and argue for the results. In the factory, engineers followed a naive approach to predict the bottlenecks, meaning that the bottlenecks of the previous production run will continue to stay as bottlenecks for the upcoming production run. They developed this approach based on their shop floor experience. We then incorporated this logic into the data. The results were astonishing. This simple prediction method already yielded 70% accuracy. We then benchmarked the ML algorithm performance with the naive approach and presented the results to the engineers. This style of communication convinced the engineers to understand the added value of using an ML algorithm towards bottleneck prediction. *By this exercise, we understood the importance of domain expert's tacit knowledge in the evaluation phase that helped to quantify the impact of the results compared to existing practice.*

Overall, we learned two important lessons. First, for ML algorithms are to become embedded in manufacturing, they must work, be useful, and should be trustable by domain experts. For this, domain experts need to be engaged when designing the ML algorithm. They are people with a profound understanding of the factory dynamics, assess the usability of the ML algorithms, and ultimately utilize them in day to day operations. Second, we figured out that most domain experts who participated in the project can understand simple statistics. But ML algorithms were beyond for most domain experts. Similarly, we did not fully understand the factory dynamics to the required degree. When we co-worked with domain experts and enriched each step of the ML algorithm with domain information, it not only gave us and domain experts new knowledge but also strengthened our partnership.

To summarise, I posit that developing AI solutions for manufacturing should be a team sport. AI and manufacturing are two parallel fields. Advancements are happening in these fields at an unprecedented pace. In the AI field, for example, new algorithms are introduced almost every day. Data scientists are already better positioned to grasp these advancements. Likewise, domain experts can better understand the technological advancements happening in the manufacturing field and implement them in the factories. In such a fast-paced scenario, domain experts should continue developing their skills in manufacturing. Data scientists should continue honing their AI skills. A strong collaboration between these two experts is the way forward. Domain experts can help data scientists in a range of activities. For example, to identify the right shop floor problems that may benefit from having an AI system and support with their expertise from data collection to results and interpretation. I believe encouraging an active collaboration is an ethical and sustainable solution for domain experts and data scientists to be relevant in the era of AI-powered factories.

How can generative design support human creativity?

Lukáš Pelikán
City Hub: Prague

Can AI replace the work of designers? Will AI overcome human creativity? These are questions that cannot be answered unequivocally at the moment. In terms of the development of mechanical engineering, generative design technologies are at the very beginning. It is a method of creating design using software based on the principle of machine learning when program generating a number of outputs to meet specified criteria, which must be input form designers. From the principle of Artificial Intelligence, the results are constantly improving on the basis of new input data and already completed projects. The quality of the proposed design can be assessed according to several criteria, such as aesthetics, mechanical properties, manufacturing suitability, economic aspect, very often a combination of these requirements together.

It's unbelievable that humans have created AI that can create on such a wide range of fields. But how could man-made and programmed intelligence overcome human creativity itself?

Many designers claim that in the history of product design, all possible shapes have been drafted and in new designs you can always find a similarity with the previously introduced design, whether it is an overall proportional concept of the product or the implementation of specific details. This statement is supported by the great popularity of the so-called retro design, i.e. the repetition of successful shapes from history while adapting to current requirements and available production technologies. On the other hand, one of the greatest designers in the history of the Czech Republic, Václav Král, presented a very deep thought: "The fact that so many different designs have already been created is proof that many times more can be created." He built this statement on the uniqueness of each of us. On individuality and creativity.

But isn't our creativity limited by our own capacity? Can't brutal computing power overcome the uniqueness of human creative thinking when it receives a large amount of data about more or less successful designs? Such a question was asked by the Nissan development centre and they created a prototype AI that can recognise images and based on them it attempts to design cars. Four years ago, the company has been in the testing phase. The company says that the AI has already managed to design a car which no one has ever seen before. „This design may not be perfect but it is a strong start. "- However, 4 years after the launch of this project, no one but Nissan has ever seen designs made by this software.

Even the most creative designers are using inspiration to create their designs. Inspired by nature, from various industry, fashion, physical phenomena and countless other different sources. Only by combining individual creativity, inspiration and knowledge of technical and technological possibilities do the best designs emerge. And there is an extreme potential of Generative design as a way to explore ideas that could not be explored in any different way. Just think about how much time it would take a real person to come up with a hundred different ways to design a simple object. Artificial intelligence can do it in no time, letting the human choose from a wide range of options.

Apart from the aesthetic point of view, there is a great power of generative design in the field of design to achieve maximum mechanical properties according to the specified load, the topological optimization. Here, AI far exceeds human capabilities today. However, Autodesk, for example, is working with GM in a project called Dreamcatcher to improve the capabilities of this type of design creating. It is software that creates optimized structures based on a variety of input parameters and constraints. Using AI, the output is formed into an additive manufacturing (AM) friendly design because the Dreamcatcher project is aimed just at AM. Engineers are still trained to design according to conventional manufacturing method. With its predictive design, Dreamcatcher tries to help designers open their eyes and show possible AM-friendly shapes that engineers might not even be able to imagine.

Evaluating the contribution of AI to design is highly dependent on how we evaluate design. It will always be a largely subjective matter. If we define ourselves only to

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industrial design, it is a generally recognised and very well-accepted orientation when design follow the function. Thanks to very precise designs from the point of view of mechanical properties, generative design can create an inexhaustible number of ideas for combining a technically advanced design with an aesthetic value enriched by human creativity. If in the future we could combine the worlds of aesthetic generative design and technically oriented software for the clever creation of topologically optimized structures, we would have an extremely powerful tool for very fast and diverse development of new products. But we must still not forget that it is the human who sets all the criteria, constraints and requirements. And it should still be a human who forms something new, innovative and useful with his requirements.

Final thought? AI in generative design is like a fire. It is a good servant but a bad master. For people with strong creativity, it can be a source of thousands of new ideas and inspiration that can be transformed into more new and creative designs than ever before. However, very easily computer-designed drafts can limit the uniqueness of our thinking and take us to the easiest way, i.e. following artificially created designs without adding our own invention. This could become a very limiting factor, because AI would still learn only with its own designs, and it would not be possible to create completely new and unique concepts, as the human brain has been showing for millennia.

Artificial Intelligence applied to the manufacturing of the future

Naia Aurrekoetxea Palacios
City Hub: Bilbao

Artificial Intelligence (AI) has been an important topic of discussion for the last decade, but it is interesting to consider that in fact, this term was invented in 1956 by John McCarthy, Marvin Minsky and Claude Shannon in the Conference of Dartmouth. They were visionary people, far ahead of their time, who made very ambitious statements. Due to the lack of success at that time, AI was largely forgotten.

Many years later AI has come to the forefront of our conversations with the invention of the internet and development of computers' with greater capacity, faster speeds, and more refined software. All these contributions slowly improved the user interface and overall experience and helped to satisfy the industry's needs.

AI is often defined as "systems that display intelligent behaviour by analysing their environment and taking actions, with some degree of autonomy, to achieve specific goals". In this regard, experts have identified four different types of Artificial Intelligence: Reactive machines, Limited memory, Theory of mind and Self-awareness.

Reactive machines, which are the most basic type of AI system, cannot form memories or use past experiences to influence their present-made decisions. Therefore, they can only react to currently existing situations. While Limited memory consists of machine learning models that derive knowledge from previously learned information, stored data and/or events. This type of AI learns from the past by observing actions or data fed to it, to build experiential knowledge.

Theory of mind is characterised by a decision-making ability similar to a human being's mind but made by machines. This type of AI has to identify, understand, retain, and remember emotional output and behaviours while knowing how to respond to them. Finally, Self-awareness does not exist yet, but would be considered the most advanced form of Artificial Intelligence. Machines with self-awareness will have human-level consciousness, not only recognizing and replicating humanlike actions, but also thinking for themselves, have desires and understand their own feelings. Nowadays, great efforts are made to create such self-aware machines.

Artificial Intelligence and programming are very different concepts that sometimes get mistaken. The main difference between them is the ability to learn. Programs execute a code that humans have created, on the contrary, AI must be trained and taught for a system to be able to make decisions.

The process of learning is similar to the one followed when teaching children. Therefore, machine learning (ML) engineers have to present samples or observations to be learned by artificial systems. For instance, we could teach a system to distinguish a hexagonal screw from other kinds of screws. For doing so, a human being will give the artificial learning system a compiled number of photos of hexagonal screws and it will start to distinguish characteristic aspects (also called features) from the samples. Once the initial training is done, a human will start to mix hexagonal screws with other very different looking tools to improve the knowledge of the machine. The aim is to explain to the machine which photos contain a hexagonal screw and for it to find the differentiating aspects and store such information for future needs. Finally, the human will show very similar screws, to complete the characterisation of the hexagonal screw. This last time, the human must also let the machine know which are the right answers.

It is understandable that all this training is expensive due to the time and data required to be taught. Therefore, multinational companies have created challenges like the "Facebook 10 year challenge", where people were suggested to upload a 10 year old photo of themselves and place it next to their most recent photo to make their AI learn without having to pay billions for all the information.

Moreover, nowadays, companies are gaining awareness of the potential of teaching AI systems with data related to their clients' behaviours and choices. Thanks to AI, companies can provide more customisation options and understand consumer preferences and habits better, and

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as a result, they can deliver solutions that completely fit their individual needs. AI can be used in computer vision, natural language processing and optimisation processes.

Thanks to computer vision, all the manufacturing processes can be monitored and analysed in real time leading to the early detection of defects in manufactured products. This form of AI saves time and raw materials to create final products, which is a competitive advantage for businesses. Moreover, not only is this type of AI beneficial to the company, but also for customers since all products will have the quality desired without any superficial defect.

Natural language processor analyses texts such as letters to the director of a company automatically and can detect emotions based on the specific words used by the writer. This kind of AI is used to classify those texts and can help to provide more customised answers, which indeed will increase customer satisfaction.

Voice recognition feature recognise the orders given and translates them into text to subsequently look up the demanded information or follow the suggested actions. Not only its simplicity and intuitiveness can be beneficial, but it will be especially important for disabled people that have challenges writing.

Nowadays engineers look for a way to make AI recognise human voice and immediately do what is asked, for instance turning the voice into a text before following the orders. This change could save a lot of time in the processing of the data, but it would also allow companies to store the information obtained by the tone of the voice.

Another interesting application is the optimization of production processes, where the Artificial Intelligence analyses all the possible manufacturing options and makes a recommendation of which one to follow based on the amount of material used, the total production time needed, and so on. The ability to find the optimum levels will benefit customers due to the reduction of manufacturing prices and ecological impact.

Machine learning is a very broad term, but the recommendation systems are a very important quality for the customisation of the customer's experience. These recommendation systems classify each client based on their research history, time spent looking at different products or purchased products, services or activities. This classification leads to a variety of suggestions for the client on what to do or to buy next. This feature adjusts and narrows the client's profile and even tells what other "same type clients" have bought in their situation. For instance, Artificial Intelligence could analyse all the data given of a product or service and suggest the consumer buying it. Even though, just by looking at the summarised information, the client would have never bought that product/ service, due to the AI's recommendation, the customer looks at the detailed information and realises he/ she likes the proposed product/ service. In this sense, AI could create new necessities in the customer's mind that he/ she did not even realise he/ she had. As it may be seen, there are several benefits of applying Artificial Intelligence into the manufacturing system and client customisation process.

Last but not least, it is important to mention that companies have to be careful when managing the data used to train their AI-based systems since most of the times these datasets contain personal information about customers or citizens. Privacy concerns are seriously taken in mind by the European Commission that has provided a strict regulation known as GPDR (General Data Protection Regulation). This new law contemplates the risks of storing and managing personal data and how they should be addressed.

In conclusion, people may not realise how integrated Artificial Intelligence already is in their daily lives. This new technology is especially beneficial to customise the client's likes and improve the customer experience.

A powerful cooperation or a disastrous substitution

Alessio Fino
City Hub: Milan

Since the 1940s, when the first, rough concepts about Artificial Intelligence (AI) were formulated, there has been a pervasive fear in the public regarding innovations in this field, despite the fact that engineers were nowhere near developing a system to transform this concept into reality. The 21st century has seen some enormous steps ahead regarding the development of this technology, but the public still sees AI as a menace rather than the innovative tool it was supposed to be to the eyes of the world. The greatest fear people have is probably the one that AI-controlled systems will take over most of the jobs available with an efficiency several times greater than the one of a human.

The key piece of this profound fear is that people think they will have to compete with AI, which in some fields performs several times better than humans. It is not common to think about AI as a powerful tool we can interact with to extend our capabilities. It is important to point out that the interaction between humans and AI has already started: When a person opens Google and types something in the search bar, Google algorithms are capable of getting you to the websites you need to view based on what you typed in the search bar. Not only that, Google learns from each time we surf the internet and is able to adapt the search to our preferences. AI already helps us in several everyday tasks in which it performs better than humans do, and this allows a productive interaction, with the AI handling basic tasks while humans can focus on complex ones. So, where is the boundary between a productive interaction and an unproductive one?

Many business owners, even of very important firms, found breath-taking the idea of replacing employees that require a salary, an insurance, have to pay taxes and cannot work too many hours a day with programmes and machines that only concern the electric bill and some maintenance technicians. Some firms tried to do exactly that with terrible results. The act of replacing humans with machines makes sense on the balance sheet, however, there is one key piece of information most people working with AI miss: AI was never meant to replace humans, its purpose is to make humans more productive.

"Collaborative Intelligence: Humans and AI Are Joining Forces", an article published in July of 2018 by Harvard Business review, examines this aspect thoroughly, and outlines three ways AI can expand human capabilities: Amplify our cognitive strengths; interact with customers and employees to free us for higher-level tasks; and embody human skills to extend our physical capabilities.

Amplifying consist in providing humans with the right information at the right time without people having to search through archives and databases by themselves.

Interacting has a lot to do with virtual assistants, which have seen a huge leap forward in handling basic requests from customers and answering Frequently Asked Questions (FAQs), while humans can handle more complex requests while training AI to deal with them in the process through a process called Machine Learning.

Embodying human skills leads to the implementation of robots for repetitive tasks that require heavy lifting, while leaving to humans other tasks in which human judgment is fundamental.

The need for AI to interact with humans is determined by the fact that some activities that are vital to our society need human interaction, it specifically needs humans interacting with each other. We are social animals and the need of interacting with other individuals is crucial to our society, human relations are present everywhere, even in workplaces and there are some environments where human interaction is part of the equation to provide a good service to the customer. A voice assistant can be useful to handle repetitive requests and to elaborate responses through a rational thinking pattern, but what happens when it has to deal with another person's emotions? Humans have a big part of the brain dedicated just to our emotions and the understanding of other's ones, and the way it works is still an unsolved mystery for us, but we can feel the same emotions other humans do, and that's

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fundamental in human interaction, thus a human is needed for every task that goes through emotional thinking.

The 28th of August 2020, Elon Musk, CEO of Neuralink, presented in live stream an update about the progress of his company, Neuralink, whose objective is to merge AI with human intelligence, and the plan to do so implements that one or many microchips will be implanted in the human brain through surgery. Those microchips will be able to interact with the brain's neurons, receiving and analysing signals from the brain and sending their own signals back to the brain. This is supposed to act as a shortcut for us to get and process information quickly directly from the internet. Neuralink microchips thus will virtually build a connection between the internet and our mind, and all this has the potential to magnify our capabilities.

All this however, sparks fear in the public, but this time it's not based on sci-fi movies culture, while the technology has the potential to make a huge difference in people's lives, it also exposes people who use it to enormous risks, what if a hacker breaches the security system that controls a microchip implanted in your brain which has the power to send any type of signal to your body? In this case consequences can be catastrophic if proper counter measures aren't developed.

Neuralink was founded because of another pervasive fear towards AI: It may become an enemy to us. But while it has been proved that AI and humans can cooperate instead of competing, there is no study that certifies that it is impossible for AI to become hostile to us and since AI is able to outperform humans at an impressive high number of tasks, the fear instilled in each person is magnified. However, in this particular field nothing is certain, because there are no practical experiments, AI and humans can cooperate with outstanding results, but anything beyond that awaits a practical confirmation.

It is worth to make a point about the ethics of implanting a computer in our body, we can just imagine what could happen by doing so, maybe it would push the interaction between humans and IA too far, but we would know only when it becomes a reality. What we know for sure is that so far AI interaction with humans has produced positive and sometimes incredible results, improving productivity where cooperation was correctly established, while disasters when AI tried to replace humans completely. It is common to have fear of what we don't have an explanation backed by practical application, it is the field where our mind is free to make any assumption, because there is nothing that can be taken for certain. The fear of innovations that promise to be so game changing is part of the fact that we are human, our common sense tells us that we should survive as a species, and tries to keep us away from every way we could destroy ourselves, but it's also true that we are designed to evolve, and evolving means also innovating, it's our enthusiasm that drives us to make new discoveries, and one thing that we can learn from the course of history is that human curiosity can never be stopped, even if it threatens to make us extinct.

Do human workers still make sense in the AI era? Collaborative Robotics has the answer

Alessandro Fumi
City Hub: Milan

Dino Galassi
City Hub: Milan

Many wonder whether Artificial Intelligence and workers will coexist in a recent future or will clash. Indeed, AI has dramatically impacted the way we think about robots.
Companies - like ABB, KUKA, Fetch and Boston Dynamics - have demonstrated how sophisticated and smart robots can be, leading to questioning if robots will coexist with humans in workplaces.
Human-Robot Collaboration (HRC) in manufacturing was born in the mid-2000: it investigates collaborative processes where human and robot agents work closely to achieve shared goals (Hoffman and Breazeal, 2004). But with the surge of state-of-the-art artificial intelligence algorithms, collaboration with robots has become paramount.

In order to deepen our understanding of such a complex topic, we interviewed one of the most prominent experts of collaborative robotics, Dr. Federico Vicentini, former Researcher with the Italian National Research Council (CNR) and member of working groups on robot safety at ISO and UNI, now with Boston Dynamics Inc. (USA).
According to him, collaborative robotics has the goal to be complementary to conventional robotics, where robots and humans are conceived as two different systems: the core idea of HRC is to support and empower operators in performing actions that cannot be accomplished by more well-established solutions (Vicentini, 2019), with AI allowing solutions with physical contact between the human and the robot, and contact-less ones (Vicentini, 2019).

But when does this collaboration make sense with respect to its fully automated and AI-driven alternative? If on the one hand, many fear that AI will become better than human beings in performing a variety of "human" tasks, it is very unlikely the AI will fully replace human workers. A scenario in which human workers and robots operate together is very likely.

Accordingly, there are multiple premises to set the ground for the correct implementation of collaborative robotics systems. First, it is core to provide the appropriate reskilling pathways towards new employment opportunities enhanced by new technologies belonging to the Industry 4.0 paradigm (WMF Report, 2019); likewise, it must be stressed that most of the technologies, in particular in the field of the HRC, are very user-friendly and, beyond a simple plan of reskilling, it is fundamental to re-engineer the new organisational flow of tasks in the factory.

Second, the boundaries of even the most sophisticated collaborative robots must be defined.
According to the International Federation of Robotics[1], such collaborative robots can be used:

- **for tedious, repetitive and unergonomic tasks:**
  collaborative robots improve the performances in as reported by Dr. Vicentini, the choice of a collaborative approach for this kind of tasks is a matter of efficiency, while it is very difficult to always automate tasks for all types of robots, in particular close to the performance boundaries of the robot. Collaborative solutions could be smart if they are meant to bypass the hard-to-automate tasks;

- **in production lines that include workers:**
  production lines with the simultaneous presence of operators and robots are the most productive, because the collaboration leads operators and robots to perform the tasks they are best at: according to Dr. Vicentini, the testing (in general) is a good example of parallel execution of human and robotic tasks;

- **in short or variable production runs:**
  programming robots easily and reducing down-time is core for all the types of robots; anyway, collaborative solutions make the robots do simpler tasks with simpler tools; therefore, this means that collaborative robots can represent a viable solution for manufacturers with short or variable production runs as the robot can be quickly re-tasked to the new run.

Thirdly, the results must be measured in terms of enhanced productivity, scalability, personalisation and impact on

1 *https://ifr.org/post/international-federation-of-robotics-publishes-collaborative-industrial-rob*

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workers' well-being (Wilson and Daugherty, 2018): theoretically, HRC brings benefits in terms of productivity, decreasing unit production cost and upholding quality for critical production steps, scalability and personalisation for the flexibility with respect to the changeover of production equipment and limiting investments (Thomas, Matthias and Kuhlenkötter, 2016). Indeed, many scholars have demonstrated, at least from a theoretical point of view, the improved performances related to collaborative robotics (Wilson and Daugherty, 2018).

Given these premises, collaborative robotics is likely to be a very rewarding solution for manufacturers. However, if on the paper this has been proved, there is still a lack of evidence of this. The lack of reported quantitative evidence about benefits has been a long-standing pain point in collaborative robotics. This is even more severe in the case of broader AI. According to our interview with Dr. Vicentini, the limited availability of extensive records of field data of quantitative indicators supporting AI benefits and costs, translated into an absence of a benchmark of useful data, could be a major factor for the manufacturers - in particular if SMEs - to be very skeptical in purchasing these solutions.

The proof of the efficacy and efficiency, driven by AI, is a topic still rather unexplored in data-oriented, sample experiments on the factory floor; without indicators certifying the benefits of the solution, it is really difficult that a manufacturer, which theoretically may need an increase in the computational power for improving its performances, will spend money for AI.

For instance, taking into account the example of the manipulators, stating that they can relieve workload and reduce stress by compensating gravity in material handling, preventing operator's musculoskeletal disorders, is not enough: quantitatively, what does it mean? Which is the increase in productivity on manufacturers' performances? Which is the pay-off of such a solution? Manufacturers still struggle in back proofing with their products with data regarding their impact.

In conclusion, while there are many applications of collaborative robotics that are extremely effective, many other applications could have had valid technological alternatives if evidence about the benefits related to its adoption were sufficient. Nevertheless, research strongly suggests that, by balancing the multiple factors that contribute to HRC (including AI algorithms development, sensors' implementation as well as the essential reskilling of the workforce), workers and AI-driven robots will form a strong collaboration in the future. We, therefore, suggest to OEM using robots to strive to measure and clearly communicate the impact on the workplace, both in cost-saving terms as well as on other areas (for instance, the health conditions of workers).

Even looking at the distant future, AI-driven robots and human workers will likely work together by leveraging the concept of collaborative intelligence, merging human leadership, creativity and social skills with speed, scalability and quantitative skills of AI. In such a way, humans will have the role of assisting machines and vice versa. Indeed, humans need to train the algorithms, explain the results to those that are not experts in AI, and define a sustainable usage of AI systems, ensuring that algorithms are functioning safely and responsibly. Conversely, machines must assist humans, amplifying decision-making abilities, allowing a better interaction between employees and companies and embodying humans (Wilson and Daugherty, 2018).

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AI: Challenge for the New Generation?

Lůdmila Ružicková
City Hub: Prague

Companies are experiencing extreme competition, mainly due to increasing pressures from global and technological challenges. These pressures result in the globalisation of manufacturing, characterised by faster transfers of materials, complex payment systems and the compression of product lifecycle, which drive the need for the superior integration of technologies with increasingly sophisticated customer needs. (Caputo, Marzi and Pellegrini 2016).
The available literature indicates that the research about the impact of AI on technological innovation is still in its infancy with theoretical focus mainly on defining relevant concepts. (Liu, Chang, Forrest and Yang 2020).

Among existing challenges and complexities, the following ones are of higher importance and priority. Machine-to-machine interactions - it needs to ensure that individual AI solutions do not interfere/conflict with the working of other systems further down the line. Data quality - AI algorithms require massive and clean data sets with minimum biases, by learning from inaccurate or inadequate data sets, the downstream results can be flawed. Cybersecurity - the increasing use of connected technologies makes the smart manufacturing system vulnerable to cyber risks and the industry is not prepared for the security threats that exist. (Lee, Davari, Singh and Pandhare 2018).

Liu et al. further describe, based on their research, that AI significantly promotes technological innovation by certain mechanisms which are quickening knowledge creation, accelerating the capability of learning and absorption and increasing investment in R&D and talents. They also highlight that compared with high-tech sectors, AI has a more significant role in promoting technological innovation in low-tech industries and sectors with higher level of AI have a greater role in promoting technological innovation. In other words, AI improves technological innovation more significantly in low-tech sectors and the higher the level of AI, the more significant the impact of AI on technological innovation. Therefore, for countries with a relatively low level of technological development, strategies for the development and application of AI should be formulated to promote knowledge creation and technology spillover effects in order to enhance the level and magnitude of national technological innovation.

As an example, how does AI support innovation and knowledge creation in manufacturing, stands research from Japan by companies Fujitsu and RIKEN which shows AI's utility in material design. Success in materials development has until now relied on the years of experience and keen insights of researchers and technicians. AI and it's calculation can predict the characteristics of a specified material based in quantum mechanics, so it can predict optimal composition of a new high-functional material in advance of any experiments. (Fujitsu 2018).

The aim of their work was to predict the composition of a solid-state electrolyte for a use in all-solid-state lithium-ion rechargeable batteries that would provide high ionic conductivity, which was successfully achieved.

The expectations from Industrial AI are versatile and enormous and even a partial fulfilment of these expectations would represent unique and real challenges of applying AI to industries. It is clear, that AI is a fast-growing field with a great potential for application in manufacturing. AI can be applied in warehouses and their management, in production processes, as well as in the development of new materials, as has been shown in the research mentioned above.

Machine learning and the ability to analyse huge amounts of data allows to search for the best and the most efficient solution in a short time, which saves money and time. Fast and accurate diagnostics of machines based on data directly from the production process can detect defects in the process in real time but also in the machine itself. AI in industry could become a self-governing and controlling entity that, with the right algorithms and settings, will lead to the utility and efficiency of the production process.

Benefits that knowledge creation could bring can be divided into several areas. However, it is still usable in very

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specific tasks, where a certain amount of input data needs to be supplied - narrow AI.

In the project phase improvement of the product design, its yield and efficiency can be achieved, as well as the assessment of the most suitable supplier. The production phase can be improved by automation of assembly lines, prediction of maintenance service intervals, reducing errors, limiting product reprocessing and reducing material delivery time. In the promotion phase to predict sales, optimize pricing and refine sales-leads prioritization.

From the mapping of the potential market through the process of product design to its production and distribution, thanks to AI, these processes could become comprehensive and interconnected.

As already mentioned, AI can solve specific tasks based on the supplied data and a specific functional solution for the task. The artificial general intelligence (AGI), which could think for itself and create new ideas, in the field of manufacturing, is still a question of the future. General folk creativity is therefore still in demand, and the role of an engineer as a person who can come up with a new idea based on creative thinking is therefore irreplaceable. However, AI can be beneficial in the development of new products, but it is not able to invent a new product itself, only to optimize it based on the supplied data.

Another issue is security standards such as ISO standards. These are still in the preparation phase, even though the AI itself is already in the application and use phase. We cannot predict the behaviour of AI with certainty, especially if we move to the area of AGI, so it is essential that rules are established on how to create individual AI tools. At this point, safety regulations are far behind the development of AI. Another issue is the use of AI in innovations such as drones for military purposes. AI should not be used in the military sphere and yet it is used there. We have to be very careful how the rules are set and it is also always a question of what kind of people and with what intentions create the AI.

AI really is the challenge for the new generation. New generation of young people, who will lead the transformation on the threshold we stand and their approach to AI will determine the future shape of the industry.

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The World Manufacturing Foundation

Vision

"We strive to enhance manufacturing's role as a dynamic and positive driver for economic, social, and environmental growth and sustainability"

Mission

The World Manufacturing Foundation is an open platform spreading industrial culture worldwide. We promote innovation and development in the manufacturing sector, with the fundamental goal of improving societal well-being and inclusive growth in all nations through dialogue and cooperation among the manufacturing sector's key players.

We will pursue our goals by:

- **Supporting** and **shaping** local and international industrial agendas
- **Providing** a framework through which companies, governments, academic institutions and social organisations can interact or collaborate, acting as a catalyst for finding innovative solutions to major global challenges
- **Creating** and **disseminating knowledge** in both policy and technology through local and international meetings and publications

Triple-Helix Model

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

Spreading Industrial Culture Worldwide

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

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

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

Founding Partners

Thanks to

2020 KEY RECOMMENDATIONS BY THE WORLD MANUFACTURING FOUNDATION

1. FOSTER PUBLIC CONVERSATIONS TO INCREASE UNDERSTANDING AND BUILD TRUST IN AI SYSTEMS
2. MANAGE MANUFACTURERS' EXPECTATIONS OF AI CAPABILITIES
3. IMPLEMENT ETHICAL CONSIDERATIONS THROUGHOUT THE AI LIFE CYCLE
4. ENSURE DATA QUALITY, PRIVACY, AND AVAILABILITY
5. PUT HUMANS AT THE CENTRE OF AI WORK ENVIRONMENTS
6. ENSURE AI STRATEGIC ALIGNMENT ACROSS THE ENTIRE ORGANISATION
7. SUPPORT MANUFACTURING SMES IN THEIR JOURNEY TOWARDS AI
8. PROMOTE AI TO SUPPORT RESILIENT SUPPLY NETWORKS
9. EDUCATE AND TRAIN THE CURRENT AND FUTURE WORKFORCE TO BE PREPARED TO WORK WITH AI
10. IMPLEMENT STANDARDS, POLICIES, AND REGULATIONS TO GUIDE A SUSTAINABLE AI ADOPTION

WORLD MANUFACTURING FOUNDATION

World Manufacturing Foundation
Global Headquarters:
Via Pantano, 9 - 20122 Milano, Italy
Via Lambruschini, 4/b - 20156 Milano, Italy

worldmanufacturing.org