Plattform Industrie 4.0

中德智能制造联盟
Alliance for Sino-German Intelligent Manufacturing

AI Application Guide

Sino-German Company Working Group on Industrie 4.0 and Intelligent Manufacturing (AGU)
Expert Group Artificial Intelligence

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This publication is a result of close cooperation between multiple entities in Germany and China including the Sino-German Company Working Group on Industrie 4.0 and Intelligent Manufacturing (AGU) Expert Group Artificial Intelligence in support of the MoU signed in 2015 between BMWi and MIIT following the 2014 joint action plan "Shaping Innovation Together."

Since 2016, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH, commissioned by BMWi, and the China Center for Information Industry Development (CCID) are the implementing bodies for the cooperation on the German and the Chinese side, respectively.

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Executive Summary

Artificial Intelligence (AI) is a dynamic field with a wide array of applications and expands rapidly into many industries including all areas of manufacturing, hence, relevant planners, policymakers and engineers now face new challenges vis-à-vis AI and its technologies. Therefore, there is an urgent need to develop a common understanding among experts to meet these challenges. Working in the industry and on expert level, the Sino-German Company Working Group on Industrie 4.0 and Intelligent Manufacturing (AGU) Expert Group Artificial Intelligence (EG AI) aims to increase awareness of recent technological developments of AI. Furthermore, the EG AI fosters AI technological exchanges between German and Chinese companies and identifies opportunities and challenges for continued AI development.

This guide aims to describe the application of AI in manufacturing in Germany and China and is primarily targeted at individuals and units of manufacturing companies as well as third-party consulting or service companies that continue to face challenges in leveraging AI technologies and systems to improve production processes and support services. The practical case studies provide inspiration and concrete guidance for the selection and application of AI technology. To harness the potential of AI in manufacturing for both countries, this guide identifies solutions and policy recommendations for Sino-German cooperation on AI applications in Intelligent Manufacturing.

Chapter 1 describes the framework conditions of both countries as well as the objective, structure and research methodology of this guide. Chapter 2 introduces 10 use cases from German and Chinese companies, focusing on the main segments in the production and manufacturing processes. These use cases cover key applications of AI in the German and Chinese manufacturing industry and are grouped into four areas: design, manufacturing, supply chain management and operations. Further, the use cases are analysed based on a unified structure. First, the business background and possible challenges are described, then solutions and benefits for stakeholders are outlined. Finally, suggestions to German and Chinese enterprises are given for each use case.

After analysing the use cases, Chapter 3 summarises the main challenges faced by applying AI in the field of manufacturing, addresses future development prospects, and puts forward practical suggestions for German and Chinese enterprises and the governments. The main challenges identified in this guide include the readiness of AI technology for commercial usage, the social and ethical impact, the missing regulatory framework and the consequences on employment as well as the necessity of upskilling the workforce. In terms of future prospects, this guide describes the shaping force of AI, four future trends of AI in manufacturing as well as consumers'expectations and concerns. This Chapter also recommends that the Sino-German dialogue establishes tangible projects, raises awareness, optimises the development environment, improves capacity, deepens international cooperation and research on AI ethics, and improves governance and public acceptance. In addition, Chapter 3 also provides practical recommendations to the German and Chinese enterprises in terms of industry impact, organisational strategy, technological changes, risk assessment, AI ecosystems and talents.

1. Introduction

1.1 Background of the Development of Artificial Intelligence in China and Germany

1.1.1 China and Germany Attach Great Importance to the Development of Artificial Intelligence and Manufacturing

Economic innovation, industrial transformation and upgrading manufacturing processes are common goals of all countries in the world today. The manufacturing industry is the foundation of the real economy, the driving core of economic and social development, and inarguably plays a leading role in the development of national economies. Promoting a high-quality development of the manufacturing industry plays an important role in raising the overall level of development of national economies. China has proposed to build a modern economic system and has determined that the focus of economic development should be placed on the real economy, with improving the quality of the supply system, accelerating the construction of a strong manufacturing power and the development of an advanced manufacturing industry as its main direction. Germany is also eager to upgrade its manufacturing sector, maintain a stable development of the country and continue strengthening its central role in the EU economic system.

To this end, China and Germany have put forward a strategy on Intelligent Manufacturing and Industrie 4.0, both of which hope to promote the transformation and upgrading of the manufacturing industry by deepening the integration of information technology and manufacturing.

Artificial Intelligence (AI) is a rapidly developing new generation of information technology that has been recognised as an important technology for widespread application, innovation and technological progress. The World Economic Forum[1] describes AI as the engine of Intelligent Manufacturing and Industrie 4.0. It fosters new economic growth and brings direct contribution to economic and social development. It also stimulates a wide range of complementary innovation through spill-over effects, brings greater economic benefits and, thus, affects the entire economic system and all aspects of society. The integrated application of AI in the manufacturing industry is the key leap to promote the digitisation, networking and intelligent transformation of the manufacturing industry. Furthermore, the manufacturing industry is currently the area with most potential and most diversity for AI applications. Deloitte[2] believes that manufacturing will become the key to open new markets for AI applications. The global market for AI applications in manufacturing was estimated at about $120 billion in 2016 and is expected to exceed $720 billion in 2025 with a compound annual growth rate of more than 25%. In order to realise the aforementioned advantages, it is necessary to deepen the integration of AI and manufacturing. For this purpose, the world's major countries, regions and industries, including China and Germany, have attached great importance to this in recent years and taken action to change the traditional manufacturing development model and production paradigm.

1.1.2 China's Strategy for Promoting the Integration of Artificial Intelligence and the Manufacturing Industry

In the "New Generation Artificial Intelligence Development Plan"[3], issued by the State Council of the People's Republic of China in 2017, it was proposed to accelerate the upgrading of Intelligent Manufacturing and vigorously develop intelligent enterprises. Four specific aspects were identified:

1) Promote the integration of AI and innovation in various industries to carry out pilot projects of AI applications in manufacturing and other key industries. Promote the large-scale application of AI, and comprehensively enhance the level of intelligent development of the industry.

[1] Madzou, L. & Shukla, 2019, p. 4.
[2] Deloitte China, 2019, p. 100.
[3] State Council of the People's Republic of China, 2017.

2) Research and develop intelligent products and intelligent interconnected products, Intelligent Manufacturing enabling tools and systems as well as cloud service platforms. Promote new manufacturing modes such as intelligent process manufacturing, intelligent discrete manufacturing, networked collaborative manufacturing, remote diagnosis, cloud operation and maintenance services. Establish an Intelligent Manufacturing standards system and promote the upgrade of all manufacturing lifecycle activities.

3) Promote the intelligent upgrading of enterprises on a large scale. Support and guide enterprises in core businesses to apply new AI technologies such as design, production, management, logistics, marketing and others. Build a new type of enterprise organisational structure and operation mode, form a business model by intelligently integrating manufacturing with services and finances. Develop personalised customisation methods and expand the supply of intelligent products. Encourage large internet enterprises to build cloud manufacturing and service platforms, provide key industrial software and model libraries online for manufacturing enterprises, carry out manufacturing capacity outsourcing services, and promote the intelligent development of small- and medium-sized enterprises (SMEs).

4) Promote the implementation of smart factories. Strengthen the application demonstration of key technologies and system methods of intelligent factories, focus on promoting technologies such as production line reconstruction and dynamic intelligent scheduling, intelligent connection of production equipment, cloud-based data collection, multi-dimensional human-machine coordination and interoperability. Encourage and guide enterprises to build Big Data systems in factories and network-distributed production facilities. Realise the networking of production equipment, production data visualisation, production process transparency, unmanned production sites, and improve the level of intelligent operation and management of the factory.

As the competent authority in the field of industrial and information technology in China, the Ministry of Industry and Information Technology (MIIT) has released the "Three-Year Action Plan for Promoting the Development of a New Generation of Artificial Intelligence Industry (2018-2020)"[4]. This document proposes to implement Intelligent Manufacturing in depth and encourage the explorative application of a new generation of AI in every stage of the manufacturing industry. Research breakthroughs in the fields of algorithm and application innovation shall be supported in key areas, and the intelligence level of manufacturing equipment, processes and industry applications shall be systematically upgraded.

1.1.3 Germany's Strategy for Promoting the Integration of Artificial Intelligence and the Manufacturing Industry

As a traditional manufacturing powerhouse, the German Federal Government officially launched its AI strategy "AI Made in Germany"[5] in November 2018 to raise the importance of AI to a national level. It is a broad strategy with the overarching goals of fostering competiveness, ensuring a responsible and human-centric R&D and deployment of AI, as well as engaging in a social dialogue on ethical, legal and cultural terms for AI. The strategy contains an overview of 12 fields of action and 14 action targets. Important aspects of the strategy can be summarised by the following aspects:

1) Vigorously invest in the research, development and deployment of AI technology. The German government has invested heavily in the field of AI research and established 12 research centres for AI and a national innovation network. At the same time, more than 100 professorships shall be added to the academic field to ensure that AI plays an important role in higher education. In addition, Germany and France jointly built a virtual network for AI research and development (R&D) and established a European innovation cluster to provide joint research project funds within the next five years.

2) Comprehensively ensure the development and deployment of AI and its benefits for society. As part of a national training strategy, the Federal Government will develop a complete set of tools to promote the skills of employees. At the same time, training results are monitored to gauge and develop proficiency in new technology areas. Germany also provides a test platform for AI applications for different enterprises. Criteria for assessment will be developed to support AI applications that benefit the environment and the climate. At the core of the strategic objectives is the launch of 50 "lighthouse application" demonstration projects in related fields.

[4] Ministry of Industry and Information Technology (MIIT), 2017.
[5] Die Bundesregierung, 2018.

3) Establish a comprehensive social intelligence collaborative framework for AI development. These include data protection guidelines, AI learning systems, AI ethics guidelines, social communication mechanisms as well as national and international cooperation networks. Further develop an AI learning system platform that can establish a dialogue between the government, science, business and civil society. On the governmental level, continue promoting international bilateral and multilateral cooperation in the field of AI. At the same time, actively promote data protection related institutions and business associations by holding roundtable meetings to ensure compliance in the field of data protection. Furthermore, set up incentives for everyone to voluntarily share data in compliance with data protection rules.

4) Increase the commercial benefits of AI applications in Intelligent Manufacturing. Germany continues to strengthen its role in the field of Industrie 4.0 and is a catalyst for AI applications in this area. The German government offers various initiatives to effectively translate AI applications into commercial strength. At the same time, support new industries to develop specific incentives for relevant investors, and encourage and promote the creation of more derivatives from research.

5) For SMEs, Germany plans to provide comprehensive support in digital technology and business models through 25 SME 4.0 Competence Centres across the country. Furthermore, SMEs should also be supported through the program "KI in KMU" with the integration of AI-coaches in the SME 4.0 Competence Centres.

6) Germany plans to improve and simplify the framework conditions for the promotion of AI. Existing funding processes should be checked for their application for research on AI. The development of faster or new funding formats should be initiated. In order to make research funding overall more efficient and attractive for start-ups and innovative SMEs the Federal Government plans to make better use of the existing budgetary and subsidy law options. This also helps to make the results more easily accessible. Innovation competitions are another element of funding research, development and innovation. A variety of competitions have already been established, particularly for data-driven AI software applications that are based on machine learning. These can serve as benchmark tests and provide an incentive to find new and better solutions. Last but not least, a large number of start-up companies in the field of artificial intelligence also benefit from this type of competitions.

1.2 Background of Cooperation Framework of Sino-German Intelligent Manufacturing

In July 2015, the German Federal Ministry for Economic Affairs and Energy (BMWi) and the Chinese Ministry of Industry and Information Technology (MIIT) signed a Memorandum of Understanding (MoU) with the objective of supporting German and Chinese enterprises in creating a favourable business environment for Intelligent Manufacturing and Industrie 4.0. This MoU emphasises the importance of industry cooperation and highlights the shared interest in facilitating further dialogue at all levels between representatives from government, industry and academia. BMWi and MIIT commissioned the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH and the China Center for Information Industry Development (CCID) to support the implementation of the MoU. Under the direction of BMWi and MIIT, GIZ and CCID jointly established the Sino-German Company Working Group on Industrie 4.0 and Intelligent Manufacturing (AGU)[6]. The AGU was implemented as a platform for German and Chinese experts to discuss challenges and opportunities of Industrie 4.0 and Intelligent Manufacturing. The goal is to better understand the relevant business environment and policies, to exchange about best practices and develop joint policy recommendations. These discussions directly shape the bilateral political dialogue.

The AGU expert groups focus on four Industrie 4.0 areas. These include:

- Digital Business Models
- Training 4.0
- Industrial Internet
- Artificial Intelligence (AI)

[6] Deutsch-Chinesische Arbeitsgruppe Unternehmen Industrie 4.0 und Intelligente Fertigung (AGU)

Specifically, the Expert Group Artificial Intelligence develops guidelines on harnessing the potential of AI for policymakers and industry actors in both Germany and China. Through its work, the Expert Group increases awareness of recent relevant technological AI developments, fosters AI technological exchanges between German and Chinese companies and identifies opportunities and challenges for continued AI development.

1.3 Scope and Objective of this Guide

AI is a dynamic field with a wide array of applications and expands rapidly into many industries including all areas of manufacturing, hence, relevant planners, policymakers and engineers now face new challenges vis-à-vis AI and its technologies. Therefore, there is an urgent need to develop a common understanding among experts to meet these challenges.

AI is a big topic with long history. It originates back to the 1950s when AI was defined to broadly simulate human intelligence. Strelkova points out there are three levels of AI[7]:

- ANI (Artificial Narrow Intelligence): the first level that beat the world chess and Go champion, but with clear limitation.
- AGI (Artificial General Intelligence): AI that reaches and then exceeds the human intelligence level. AGI has the ability to "reason, plan, solve problems, think abstractly, […] and learn from experience."[8]
- ASI (Artificial Super Intelligence): AI "that is much smarter than the best human brain in practically every field, including scientific creativity, general wisdom and social skills."[9]

As an important part of the work of the Expert Group Artificial Intelligence, experts from China and Germany co-authored this guide. The guide aims to clearly describe the application of AI in manufacturing in China and Germany and is primarily targeted at individuals and units of manufacturing companies as well as third-party consulting or service companies that continue to face challenges in leveraging AI technologies and systems to improve production processes and support services. The practical case studies provide concrete inspiration and guidance for the selection and application of AI technology. For both countries to better realise and harness the potential of AI in manufacturing, this guide identifies solutions and policy recommendations for Sino-German cooperation in AI applications in Intelligent Manufacturing. This should enable affected companies to improve the AI application environment.

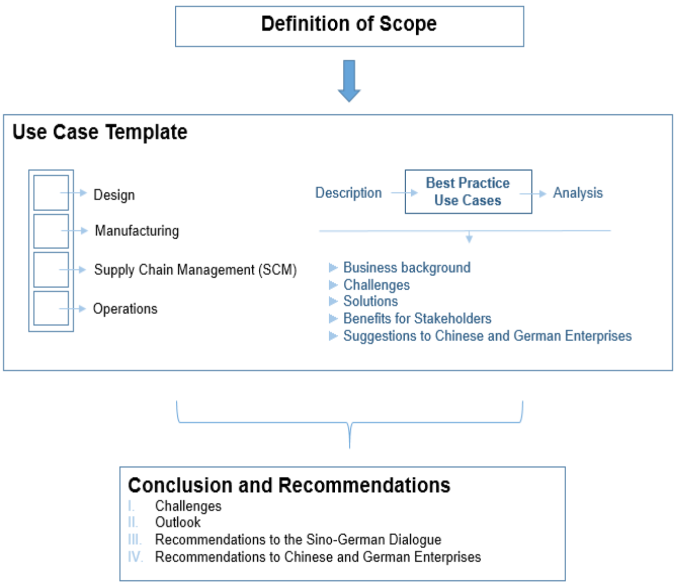

Figure 1 provides an overview of the structure of this guide.

[7] Strelkova & Pasichnyk, "Three Types of Artificial Intelligence.", p. 1.

[8] Gottfredson, Mainstream Science on Intelligence, p. 13.

[9] Bostrom, "How Long before Superintelligence?", p. 1.

1.4 Structure and Research Methodology

This guide focuses on the following issues:
- What are the key applications of AI in the German and Chinese manufacturing industry?
- How does the applied AI technology work in a specific environment and how is it implemented?
- What are practical suggestions for the Sino-German dialogue, Chinese and German companies and the objective to harness the potential of AI in Intelligent Manufacturing?

The guide contains the following sections:
- Practice case studies: By focusing on the main segments in the production and manufacturing processes, ten practical use cases were selected to provide guidance and suggestions on the application of AI technologies.
- Challenges, outlook and recommendations: This section analyses the main hurdles faced by AI in the field of manufacturing, addresses future development prospects, and puts forward practical suggestions for the Chinese and German governments and enterprises.

2. Analysis of Use Cases

AI has a wide range of applications in the manufacturing industry, which can cover all segments and all levels of the manufacturing industry as well as the entire lifecycle of manufacturing. At present, some enterprises in China and Germany have already carried out practical explorations in this respect and achieved remarkable results. Analysis of the application value of AI, coupled with specific practical cases, has significant value for understanding the integration path, content and mode of AI and manufacturing.

2.1 Design

In the research and development (R&D) design process, AI can be used to develop automatic R&D systems and even generate production-based R&D design systems. As a result, R&D efficiency can be greatly improved while significantly reducing its uncertainty. This implies that the transformation of a high-risk and high-cost physical R&D design towards a low-cost, high-efficiency intelligent R&D design should be promoted.

2.1.1 Case 1: Intelligent Product Design

Use Case Provided by SAP

- Business Background:
  Individualisation, digitisation and the Internet of Things (IoT) are forcing companies to innovate faster and more intelligently. With increasingly complex internal and external stakeholder collaboration, each asset's unique digital twin requires a consistent product definition to be embedded across the complex value chain. Intelligent product design is a must to ensure future product profit and reduce time-to-market.

  Intelligent product design can help companies to accelerate smarter product innovation with multi-discipline collaboration, requirement-driven development of intelligent products, and live product intelligence across the value chain.

- Challenges:
  Collaboration: It is crucial that a seamless data integration between product development partners takes place. When data cannot be easily adapted, the risk of mistakes increases, resulting in poorer product quality.
  Integration: A seamless end-to-end integration of the customers' requirements towards the product's features needs to answer two questions: 1) Which product features were built-in due to customer demand? 2) Due to which requirements were certain characteristics implemented? Failing to answer either of these questions will cause problems such as missing customers' requirements, leading to expensive re-work or unnecessary implementation efforts and costs.
  Practical insights: Easily accessing the relevant information in real time helps understanding potential issues as early as possible and,

therefore, avoiding problems as soon as they could potentially occur. This early identification of arising issues can help reduce costs required to fix them.

- Solutions:
  The collaboration option provides the possibility to define collaborations based on Document Center folders. It is easy to involve participants and has an easy-to-include task list, which is based on the workflow engine. This allows tasks to be handled upon the collaboration and a comprehensive integration, managed via the integration in the Document Center.

  The engineering option provides requirements management, the requirements interchange format (ReqIF) for requirement exchange with third party tools as well as block definition diagrams (for the systems engineering approach) within the enterprise architecture designer. Additionally, it includes the live product cockpit for overview on product data - especially IPD-related data - and constraint management to handle version restrictions between hardware and software.

- Benefits for Stakeholders:
  Speed: expedited introduction of new products to the market
  Accuracy: greater accuracy and transparency within the global product development process
  Profitability: lower costs on research and development
  Optimisation: increased development efficiency and an optimised operating environment for product development

- Suggestions to Chinese and German Enterprises:
  For the manufacturing industry, intelligent product design is the key to enhancing the company's product innovation capabilities and market competitiveness.

  On the one hand, intelligent product design requires product innovation, which will stimulate new R&D models and complex product design processes. On the other hand, letting end users participate in the innovative design process of products can help companies understand and control market demand. Thus, intelligent product design and development is powered by the users' demands. At the same time, a demand-oriented research and development (R&D) direction and a diversified system design can continuously optimise the company's R&D processes.

2.2 Manufacturing

In the production and manufacturing sector, AI technologies can be used to analyse, optimise and re-engineer the production processes of enterprises, to create a customised production process, to enhance the flexible production capacity, to increase the flexibility of production lines, and to improve the ability of manufacturing enterprises to respond to changes in market demand. At the same time, computer vision and other AI technologies can be utilised to carry out rapid quality inspection and quality assurance of the manufacturing sub-sectors with large output, complex components and high process requirements, and build an automatic quality inspection system for the whole production process.

2.2.1 Case 2: Adaptive Modular Intelligent Manufacturing Solution

Use Case Provided by SIACAS

- Business Background:
  The mechanical structure, industrial network and IT management software of the current high-volume, rigid production system are all deployed for an established product design. When the product design changes, the existing production system cannot respond quickly to the change. The mechanical structure, network and software changes of the production line in the workshop require huge costs, personnel and off-line downtime cycles. The existing rigid production lines cannot support the growing demand for high-volume customisation. Therefore, it is necessary to build an intelligent "Material Source" platform in the modular production mode to achieve flexible manufacturing and to obtain a greatly improved production efficiency quality.

- Challenges:
  Intelligent production process: Capture process knowledge through configurable process planning and AI training to achieve a

knowledge-based reconstruction and a rapid response to product change needs.
Manufacturing process intelligence: Improve the robustness of industrial equipment and processing accuracy through vision, sense of touch and other environmental awareness means, thus, improving production efficiency and quality.
Intelligent fault diagnosis: AI solves the problem of acquiring fault diagnosis knowledge, realises fault diagnosis technology based on human expert experience knowledge, and reduces the probability of fault occurrence and equipment operation costs.

- Solutions:
The solution uses wireless networks for industrial automation (WIA) industrial wireless technology and industrial software definition network (SDN) technology to transform the control system from traditionally wired deployment to wireless and flexible deployment to facilitate the decoupling of mechanical structures. Through the edge controller of the "Material Source" platform and the integrated AI algorithm, the autonomous intelligent operation of robots and other equipment as well as the virtual fusion and linkage of the equipment in the factory digital twin is realised. Then, the integrated flexible control software of the "Material Source" platform will automatically reorganise the process step, drive the adaptive reconstruction of the modular production unit, and greatly compress the transformation costs. Thus, the adjustment cycle is significantly shortened.

In order to realise the dynamic configurability within the production unit, a new structure of edge coordination control, formed by a self-developed edge controller and the edge gateway, is adopted. The robot motion control technology, visual image processing technology, AI technology and digital twin technology are combined to dissolve the coupling of the model within the working unit. Finally, it will add more flexibility through the characteristics of internal re-configurability.

At the same time, through periodic or continuous monitoring of the device's status, the condition of the equipment is analysed and evaluated based on machine learning algorithms and models. This way, it is possible to predict when the next failure will occur and when maintenance should be carried out. Based on the status of the equipment, its status monitoring and troubleshooting is realised.

- Benefits for Stakeholders:
Personalisation: Achieve a small batch customisation production mode.
Self-adaptability: Speed up product iteration cycles, respond faster to market changes.
Efficiency: Reduce the probability of failure and equipment operating costs.

- Suggestions to Chinese and German Enterprises:
Strong manufacturing needs to rely on industrial intelligence. This case takes the source platform as the core and the modular movable production organisation as the basis. Through the software definition of industrial network architecture, the traditional production line is decoupled into a modular production unit; thus, better solving the problem of lacking flexibility which the traditional rigid production system faces when design and production demand change.

The source platform should have the characteristics of a semantic fusion of data, edge computing and vertical distribution:
  - Data semantic fusion supports heterogeneous database unified indexing, user agent (UA), REST, WebSocket, message queuing telemetry transport (MQTT) multi-interface access, and semantic-based data association visualisation modelling.
  - Edge computing supports the resolution capabilities of more than 20 mainstream industrial protocols, SpringBoot, ServiceMesh microservice interfaces, Kubernate container management, visual processing, logic control, and motion control.
  - Vertically distributed support for lightweight micro services, system functions plug-and-play, support device model standard library and support integrated programming development.

2.2.2 Case 3: Visual Inspection

Use Case Provided by REHAU Corp.

- Business Background:
The important expectations on quality control (QC) are to lower quality issues, increase overall equipment effectiveness (OEE) and lower production costs through:
  - Releasing human workers from repetitive work and digitising QC experience.

- Increasing the accuracy of QC work.
- Building up end-to-end processes within QC and other departments such as product design, production, customer service, sales and finance.

In order to approach this vision, there are two important aspects which need to be considered:
- Digitise the staff's knowledge and experience.
- Implement robotic modules which can adapt the digitised knowledge.

The visual quality inspection of end products is an important procedure for quality assurance (QA) by the manufacturer. Some of the repetitive visual inspection work could be carried out by robot-like integrated solutions from image-taking to issue identification through machine learning.

- Challenges:

  In different industries, the QC staff is facing different challenges, for example, in make-to-order companies such as in the textile or furniture industry, the QC staff is more focused on colours and patterns. The QC process is very subjective and is likely to be influenced by the lighting conditions. In the make-to-stock industries such as process manufacturing or the food and beverage industry, QC is more focused on product and packaging defects.

  The QA routing work is complex and important and will normally not only cover the raw material goods received but also the control of semi-finished and finished goods. In some industries, the quality of packaging is also one of the most important process steps to be monitored. However, it is very challenging to cover all those work segments, ensure the quality throughout the whole process and fully understand the dependency between one another.

  Currently, the inspection of product quality is performed by QA staff in a predefined frequency (e.g. every hour). The potential quality issue during the inspection gap cannot be identified. Additionally, the quality control outcome depends strongly on the experience of the QA staff and other factors (e.g. lighting conditions). By increasing the capacity of production, new staff needs to be hired and their qualification cannot be ensured.

- Solutions:

  Although implementing image capture devices in the production line has become more and more popular, it is hard for the equipment or software system to distinguish new types of flaws. The following steps might provide support and be considered for enterprises aiming to introduce this technology:
  - Review the current QA process and identify the stages where to collect the structured data.
  - Implement a qualified image capturing device on the shop-floor.
  - Connect the devices with software servers.
  - Build up a machine learning mode and train it with your own quality standard as the initial step.
  - Continue to improve your machine's learning mode with more data input.

- Benefits for Stakeholders:

  A good QA result could help the manufacturing company not only reduce quality issues but also improve the EBIT with following benefits:
  - Reduce the gap between inspections. Real-time inspection on the production line can be realised.
  - Independent of human errors.
  - Digitise features of products and QC experience.
  - Digitise and automate the quality inspection.
  - Increase overall quality by inspecting on the production line.
  - Reduce the effort and costs for quality inspection.
  - Scalable with increased production capacity and overall equipment efficiency.

- Suggestions to Chinese and German Enterprises:

  Introducing machine learning to the QA process depends on the data quality of the enterprise. There are two different models to be recommended: data-driven and model-driven[10]. Considering many enterprises have very unstructured data, the model-driven mode should be recommended with lower initial investment. Besides, complex or live image data processing requires high-performance computing, thus, the cloud solution will be better compared to the on premise solution. Lastly, it is important to consider the integration of your machines and image capture devices and try to use it together with a standard or common communication protocol.

2.2.3 Case 4: Defect Detection in Flat-Panel Manufacturing

Use Case Provided by Shenzhen China Star Optoelectronics Technology Co., Ltd. (CSOT)

- Business Background:
  In order to efficiently detect defects in a flat-panel production line, self-learning and intelligent image classification technology are applied to the manufacturing of latest generation display panels. By introducing computer vision recognition technology, factories are able to establish self-learning abilities and apply uninterrupted and high-precision intelligent code technologies to their production lines. So far, the quality inspection time of the flat-panel production lines have been reduced by 50%. Meanwhile, the product defection rates have been reduced by 5% and the yield rates increased by 1.5%. Moreover, factory labour costs have been saved.

- Challenges:
  Intelligent defect detection is available for all industrial companies. Defect detection is the most important quality control link in all manufacturing industries. Even if the less frequently occurring defects are deducted, there are still hundreds of defect categories in panel products and dozens of them are common quality defects. Due to these, it is important to distribute multiple inspections through the front and back of the production line. However, the efficiency of detecting defects while using a large amount of manpower is relatively low, especially for the ultra-large size of the G11 high-generation production lines in Shenzhen. For display panels, the manual inspection is extremely difficult and has a serious effect on the production efficiency and the yield rate. Additionally, it is difficult to effectively reduce the production costs. Manpower consumed by the defect inspection process accounts for almost 30% of the entire production line. Furthermore, when human eyes observe a lighting screen for a long time, the error rate will likely be relatively high. As a result, the loss rate among the inspection personnel is the highest among all processes.

- Solutions:
  - By constructing an AI algorithm model, the captured images are analysed and innovative algorithms are used to find the defects in the image. Meanwhile, the overall scheme continuously optimises the defect detection algorithm, which makes sure that the accuracy rate and speed performance is optimal and the improvement of the comprehensive performance is balanced.
  - By applying computer vision methods (image segmentation technique in particular), the defect map of the products is firstly divided into backgrounds. The component diagrams are divided to perform various types of component cuttings and defect cuttings to form multiple sets of layers. Then the input design model is used for image pre-processing and defect positioning. After that, the defect layer is put into the AI classification model and the specifically trained deep convolutional neural network carries out the defect classification. Finally, the defect position as well as the position and type of the component layer are analysed to determine the condition of intersection disconnection. Eventually, the technical requirements for classification are achieved.

- Benefits for Stakeholders:
  - For equipment operators and data statisticians: Through the implementation of the project, the automation of the equipment can be further improved. Pictures and related data can be automatically collected.
  - For equipment manufacturing service providers: The equipment failure caused by human operation and the maintenance costs can be reduced.
  - For photo defect inspectors: The manpower consumed by the defect inspection process accounts for almost 30% of the entire production line. In addition, when the human eye observes the lighting picture for a longer time, the fatigue is high, thus, the error rate is relatively high, too. The loss rate among the inspection personnel is also the highest in all processes. The implementation of the project solves a common problem in the industry.

[10] Data-driven and model-driven refer to two different approaches where training and calculation take place. The data-driven model emphasizes that training as well as calculation take place where data resides. Whereas, the model-driven approach refers to the approach of bringing data to where the model resides.

- Suggestions to Chinese and German Enterprises:
  The implementation of various AI technologies is based on enterprise operational data such as a large number of equipment operational data, a large number of defect picture libraries and production data of production lines. Based on this data, machine self-learning, pattern analysis and computer vision analysis are realised.

2.2.4 Case 5: Product Quality Prediction

Use Case Provided by Siemens Ltd. China

- Business Background:
  Predicting manufacturing quality is one of the key measures for quality management. The manufacturing industry currently faces challenges, such as unexpected variations in product quality and quantity and the inability to rapidly scale and manage capacity. Before the products leave the production line, they must be inspected in order to ensure they have met the quality and safety standards. Currently, the inspection work usually requires intensive human labour in order to examine objects and identify problems. Automatic Optical Inspection (AOI) machines are widely used for quality inspection, but their costs, efficiency and reliability are big issues.

- Challenges:
  AOI systems are a powerful method for defect inspection, but they are relatively expensive, time-inefficient and not accurate enough. Sometimes, AOI systems act as a bottleneck.

- Solutions:
  The product quality is determined by the comprehensive analysis of both the process data and results data. Quality prediction focuses on the process while quality inspection focuses on the results, thus, they complement each other.

  Quality prediction uses industrial process data analysis: multiple parameters from multi-stage manufacturing processes are collected and analysed. With the combination of machine learning and deep learning technologies, the information representation is delivered from lower levels to higher levels, therefore, becoming more abstract and non-linear. Through representations in hierarchical levels, the “deeper” feature of multi-parameter manufacturing quality can be fitted into a regression model sufficiently.

  The trained machine learning model is deployed to an edge device for analysing high volumes of data and making low-latency decisions.

- Benefits for Stakeholders:
  - Efficiency and speed are improved.
  - Costs of procuring expensive machines are saved.
  - Labour effort on quality inspection and re-judgement is saved.
  - Flexibility is increased.

- Suggestions to Chinese and German Enterprises:
  - AI enables the prediction of product defects and can be a supplement to the conventional approach, such as AOI. Seamless integration with a conventional approach might be much easier to achieve with an old production line.
  - The availability of reference in edge devices is recommended.
  - Data scientist should work closely with the domain expert to transfer their knowledge into features and patterns. Feature learning is important.

2.3 Supply Chain Management

To grasp the changes in supply and demand in supply chain management (SCM), the application of AI will have very beneficial results. Through the establishment of real-time, accurate matching of supply and demand, the efficiency of supply chains, characterised by big fluctuations in market demand and complexity, can be upgraded.

2.3.1 Case 6: Supply Chain Segmentation Analytics

Use Case Provided by Accenture China

- Business Background:
  Future supply chains will intelligently configure a global network to respond to micro-segments providing multiple service choices adding to product value. Future supply chains will dynamically share assets and manage the ecosystem to efficiently support micro-segments. Becoming customer-centric requires the supply chain to operate and govern in a customer-focused, agile manner.

  Supply chain segmentation analytics tailor the supply chain to fulfil unique demand profiles with the aim of overcoming trade-offs between serviceability and costs. Tomorrow's segments will be defined based on combinations of different dimensions (e.g. customer, market, product, lifecycle) and then grouped by their supply chain requirements.

  Most companies seek to optimise their supply chain to overcome serviceability and cost trade-offs. Each demand-segmented group will have a unique supply chain model (e.g. agile, efficient, cost-conscious). This model contributes to realising the overall value proposition of each segmented market as well as contributing to supply chains, adapting to a designated purpose. While simultaneously improving serviceability and optimising costs, deliver a specific strategy for segmented markets, differentiated service and integrated regional operational model.

- Challenges:
  To stay competitive, a company's supply chain must keep up with changing and varied business needs while enabling lower costs at higher service levels as well as coping with ever-increasing consumer expectations and technological innovation.

  The key challenges faced were a one-size-fits-all supply chain, low serviceability at a high cost, limited product customer channel differentiation and siloed operational models.

  Architecting the right supply chain for the right customer is imperative. Evolving into a growth enabler requires transformations to supply chains, including:
  - Connecting with partners and customers through an intelligent platform, providing end-to-end visibility.
  - Optimising operations by applying analytical insights to monitor performance and drive continuous innovation.
  - Configuring the supply chain into an asset-light ecosystem that serves the needs of customer micro-segments.
  - Operating with a service-oriented approach, leveraging a flexible and data-driven workforce.

- Solutions:
  Solutions aim to tailor companies' supply chains to meet the needs of different customer value propositions:
  - Gather Data: Collect and validate customer needs and attributes for regions, products, channels, and customers.
  - Define Segments: Identify product channel customer segments on basis of qualitative and advanced analytics.
  - Set Decoupling Points: Establish push-pull boundaries for each segment to align business risks and cost service needs.
  - Define Supply Chain Strategy: Align manufacturing, network, inventory, and fulfilment strategies for each segment.
  - Align Network, Inventory and Transit Mode: Develop cost-to-serve and inventory models to align flow paths, stock levels and modes.
  - Develop Capability: Develop playbooks and configurable prototype tools covering segmentation, network, and inventory.

  Advanced analytics and machine learning address the complexity of evaluating a multitude of attributes to achieve cluster results. Once segments are defined, supply chain strategies must be revisited and tailored to each segment's unique needs. Understand the impact of the market group differentiation on the current supply chain operation mode and bring about all changes required for the transformation plan. Design the organisation, operating model and governance framework to enable efficient delivery of analytical capabilities and business insights.

- Benefits for Stakeholders:
  Potential benefits estimated based on prior experience including manufacturer, retailer, engineer, can be as follows:
  - Tailoring the supply chain strategy, improving inventory placement and optimising the transit mode reduce order-to-delivery cycle time. Order-to-delivery cycle time reduced by 20-30%.

- Tailoring the supply chain strategy and improving parts and product placement yield higher product availability. Product availability improved by 20-35%.
- Reducing order–to-delivery cycle time and improving parts and products availability, improving on-time delivery and reducing lost sales. Revenue uplift improved by 5-10%.
- Tailoring inventory strategy and optimising inventory placement reduce overall working capital and holding costs. Inventory costs reduced by 10-15%.
- Tailoring fulfilment strategy, reducing expediting, and translating transit mode optimisation to overall lower transportation costs by 10-20%.
- Tailoring manufacturing strategy, manufacturing economies of scale, and reducing expediting lowers manufacturing costs by 5-15%.

- Suggestions to Chinese and German Enterprises:
Accenture recently conducted research to understand future trends and their implications across six industries, six countries and markets, 200 supply chain professionals and 30+ Accenture supply chain professionals. The evolution to an intelligent and customer-centric supply chain has begun. Customer centricity is a direct result of changing customer expectations. According to its internal research, 76% want faster fulfilment, 71% want a wider range of choices, 76% want more customisation, 69% want sustainable products, 73% want more reliability and 65% want cheaper delivery. Expectations are becoming differentiated with unique needs and value propositions. Future supply chains must be able to service micro-segments and provide customised solutions that offer value to every customer. Companies must become customer-centric to remain competitive, growing to serve each and every micro-segment uniquely.

2.3.2 Case 7: Network & Flow Path Optimisation

Use Case Provided by Accenture China

- Business Background:
Future supply chains will significantly automate and add intelligence to supply chain decision-making in order to manage the new complexity at speed and scale. Network and flow path optimisation are leveraging digital technologies and advanced analytics to increase automation and inventory accuracy, reduce out-of-stocks and replenishment errors. Determine optimal combination of demands, routes and vehicles in order to minimise fuel transportation costs and maximise customer satisfaction. Consider all existing business constraints.

  Flow path optimisation is the tactical level within network optimisation and allows, given a certain demand, to optimise costs within all of the supply chain network. In order to save costs, it allows to make the decision of the product flow path within a distribution centre and warehouses. It allows a full end-to-end vision on the cost to serve.

  Routing optimisation is the operational level within network optimisation. Given certain parameters such as warehouse location, set of nodes, demand, set of vehicles and capacity, it determines the set of nodes to be visited by a vehicle as well as its order and initial load. Last-mile and real-time routing delivery optimisation is also key to meeting the expectations of the customers for faster and more flexible delivery.

- Challenges:
Within a traditional supply chain, most activities are performed manually and with minimal scientific techniques and the use of non-intelligent equipment. Minimal analytic techniques were deployed. Now, most clients want to undertake a complete supply chain revamping exercise with network planning at its heart, taking into account a set of restrictions related to resources, zones and type of incidences, for instance. Arrival time directly depends on the resource's location and vehicular traffic. To meet the exceptional features which surround the allocation of resources, a custom-made solution is proposed.
  - How to optimise resource allocation? How to recommend the ideal flow of each product group from a distribution centre to specific stores to improve service and reduce the cross regional shipment?
  - How to determine optimal combination of demands, routes and vehicles in order to minimise costs and maximise customer satisfaction?
  - What should the optimal configuration of the product flows be? (Cross dock, direct to customer, etc.)
  - Real-time scheduling is also a key challenge for some clients where tasks arrive at any time and need to be assigned to a resource as soon as possible.

- **Solutions**:
  The solution uses data and analytics to address key execution issues such as slotting, picking and inefficient planning, and tracks multiple key performance indicators (KPIs) using advanced algorithms, tools and techniques. Several execution analytics are conducted in real time using advanced models and optimisation algorithms that minimise allocation costs and arrival time, increase productivity, and translate business requirements to automatised processes.

  Novel mathematical formulations enable problems to be solved more easily. Implement a linear programming algorithm to concurrently optimise all costs. Leverage data from inventory levels, weather prediction, emissions and pollution as well as real time data feeds from inventory levels, traffic and others.

  The aim of the solution to be developed is to minimise allocation costs and arrival time, increase productivity, and translate business requirements to automated processes. Identify four essential capabilities required to cost-effectively meet consumer demand for a faster and more flexible delivery over the last mile:
  - Advanced analytics capabilities to predict collection and delivery locations, carrier capacity, product availability and the optimal fulfilment locations to increase route density, optimise inventory and reduce transportation costs.
  - Optimised delivery routes, turn-by-turn directions, workflow visibility, delivery details by order and delivery confirmation capabilities to increase route density and delivery efficiency.
  - Real-time track and trace capabilities, delivery notifications, flexible delivery windows and instant communication with the delivery driver or customer care operator to provide consumers with increased control across the delivery experience.
  - Machine learning and advanced analytics capabilities to measure delivery performance and identify opportunities to increase route density and delivery efficiency.

  Follow an agile methodology in order to see prompt results and have a continuous scope management.

- **Benefits for Stakeholders**:
  The potential benefit is estimated based on prior experience of manufacturers, retailers, engineers and others. Improve decision making and business benefits through stress analysis for current and future demand (new markets), flexibility to choose suppliers and shift manufacturing locations, and simulating probable scenarios with cost benefit analysis.
  - Total annual savings of 9%. Better understanding of cost-to-serve at product level. Trade-off between all costs and ability to perform what-if analysis on them.
  - Estimated service level improvement up to 8%.
  - Estimated storage cost reduction by 10%.
  - An average cost reduction target of 4% per year, including: reduction of transportation costs and maximisation of margins, improvement of fleet utilisation and delay reduction.

  A greater visualisation helps the company raise its network performance and better manage costs of transportation. After each optimisation cycle, the following suggestions are made at a product-customer level balancing customer service and net landed cost trade-offs:
  - Selection of best purchasing option (supplier and source)
  - Selection of best transportation modes
  - Optimal allocation of customers to distribution centres
  - Inventory levels (days)

- **Suggestions to Chinese and German Enterprises**:
  Accenture has conducted over 850 global supply chain transformation and post-merger integration projects in the last five years. Companies continuously strive to ensure that their supply chain network can reduce total delivery costs, improve customer service levels, and increase supply chain responsiveness and flexibility. According to long-standing expertise in both strategy and implementation and in order to unlock the value of network and flow path optimisation, we suggest Chief Supply Chain Officers to tackle three top priorities:
  - Align with leadership and lead with value. All investments should be driven by a clear value proposition and be anchored to the business strategy. The supply chain's role in delivering on that strategy should be clear and the Chief Finance Officer and Chief Operating Officer should be engaged in reaching meaningful decisions.

- Build the workforce of the future. New technology will not drive value if the organisation is unable to adopt and use it. The C-level must support a re-skilling strategy founded on continuous learning.
- Decouple data. Legacy systems can create a roadblock to the adoption. Decoupling data from legacy IT systems and moving it to broadly accessible cloud-based data lakes can help ensure that the right data is fuelling the use of network and flow path optimisation.

2.4 Operations

In the operation and maintenance process, an operational model of technical equipment and products based on AI algorithms can be established in order to monitor changes in operational status indicators, thus, predicting and solving failure risks of equipment, products and production lines in advance.

2.4.1 Case 8: Asset Intelligence Network

Use Case Provided by SAP

- Business Background:
  Capital intensive companies that deploy a variety of complex assets throughout their business value chain need to ensure that these assets have the best performance and availability. This results in the need to closely collaborate with vendors and other stakeholders on asset information as well as to leverage the sensor and condition data of connected assets to optimise maintenance service strategies. Based on asset collaboration and connectivity, companies will then be able to optimise their asset utilisation, providing them with a better return on their assets.

- Challenges:
  - Lack of cooperation
  - Outdated job descriptions
  - Asset information quality
  - No universal definition
  - No standardised data model
  - Information silos

- Solutions:
  <u>Secure Network:</u> A secure, cloud-based business network for assets.
  <u>Provider and Operator Network:</u> Connect multiple business partners for inter- and intra-company information exchange and collaboration.
  <u>Global Equipment Registry:</u> Standardised content that defines document models and equipment to be shared and stored for a consistent definition between business partners.
  <u>Shared Model Database:</u> Applications for collaborative processing of asset information such as equipment lookup, announcement processing like managing service bulletins and recall notices, performance improvement, spare parts management and managing obsolescence of equipment.

- Benefits for Stakeholders:
  <u>Reduction in safety and compliance incidents:</u> Ensure that asset information like as-built drawings is up-to-date and reliable.
  <u>Increase "wrench time":</u> Find documents and asset information more quickly, locate spare parts and up-to-date job instructions more quickly.
  <u>Reduction in effort to manage master data:</u> Manufacturers, service providers and third-party content providers are providing up-to-date asset information in a digital format ready to be used in systems of execution such as in computerised maintenance management systems (CMMS).

- Suggestions to Chinese and German Enterprises:
  To effectively manage the entire process of equipment like planning, designing, manufacturing, selecting, purchasing, installing and maintaining, high-level technology as well as economic and organisational support is needed. There could be maintenance, operation

and repair service requests when the equipment is in use. It could have information like technical data, maintenance records and technical parameters, which could then be used for analysing the entire lifecycle. For example, the data history of equipment could be used to contribute to management and decision making, thus, helping to optimise the lifecycle and the equipment management.

The management team could keep track of the equipment's status, improve the productivity, save costs and create more revenues for the enterprise with the foundation of asset lifecycle management platforms. Digitisation, intelligent transformation and visualisation should be the key elements of future asset management platforms.

2.4.2 Case 9: Intelligent Manufacturing - Predictive Maintenance

Use Case Provided by SAP

- Business Background:
  For businesses that rely on complex and costly machines as well as other physical assets to serve customers, the value of these assets can far exceed yearly revenue. Therefore, it is critical to keep them in excellent operational condition and prevent unplanned downtime. This requires proper maintenance – which is faster and more cost-efficient when using machine-to-machine connectivity and sensors that collect information about assets' statuses, analyse and predict failures, and make timely, data-driven decisions that dramatically optimise costs.

  Nowadays, the world is more connected. The prices of sensors, micro-processors, and wireless technologies drop dramatically. The rise of the Internet of Things (IoT) has made digitisation of businesses a mainstream phenomenon. New technologies such as machine learning and Big Data allow the capture, preparation and analysis of massive volumes of data in real time.

- Challenges:
  - High service and maintenance costs
  - Lack of visibility in asset condition
  - Inability to predict future failures leading to unnecessary unplanned downtimes

- Solutions:
  - Predictive maintenance and service collects sensor data, merges it with business information (like past maintenance records) and other data such as weather or text information.
  - Analyse data to find conditions or patterns for failures.
  - The solution then applies rules to current data to predict when an asset will fail and applies preventive countermeasures that will trigger maintenance orders in service or plant maintenance systems.
  - At any point in time, the solution provides full visibility into current asset condition and asset condition predictions by monitoring and analysing Big Data.

- Benefits for Stakeholders:
  Provides asset operators with higher overall equipment effectiveness, improved maintenance efficiency and lower maintenance costs as well as faster reaction to alarms and failures and higher mean-time between failure and lower mean-time between repairs.

  Provides equipment manufactures with improved service profitability while having lower service costs and new revenue streams. Higher percentage of calls resolved without technician dispatch. Higher first-visit-fix rate and higher service contract renewal rates. Enables manufacturers to offer new innovative business models.

- Suggestions to Chinese and German Enterprises:
  How to correctly read machine operation data is one of the most complicated parts of predictive maintenance, which involves converting data into actual customer benefits. At present, many companies still lack the awareness and knowledge of information digitisation. They are still performing predictive maintenance under the original framework. KPIs, pricing, sales, control and vertical integration have not been greatly improved yet.

  Therefore, only the independent digital organisation structure can realise the value of predictive maintenance. It can integrate product and service strategies, and, at the same time, transform data into effective information that can be analysed for enterprise decision-making. Only when technology and operation are combined, can it be changed. This way, an enterprise can survive in a fierce market.

2.4.3 Case 10: Predictive Maintenance for Auto Production Line

Use Case Provided by Manulism Technology Co., Ltd.

- Business Background:
  The first batch of large-scale automobile automation production lines in China took place in 2007-2009. The equipment has been in use for ten years, and most of it is in a period of performance decline. Innovative maintenance methods are needed to ensure a smooth operation and extend the equipment lifecycle. Moreover, the automobile production line has a mature automation base and a high degree of standardisation. It has the prerequisites for implementing predictive maintenance of equipment. Based on that, a new generation of information technology including the Internet of Things (IoT), edge computing, AI and other technologies, can be used to evolve the manufacturing process.

  The business objective is to realise the collection and storage of device status data, real-time monitoring, historical review, information summaries and report statistics. Meanwhile, the automobile manufacturers establish predictive maintenance models for the failure mode and monitor the equipment for operational status and fault warning.

- Challenges:
  It is common for automobile production lines to experience equipment anomalies and accidental downtimes, which produce a lot of maintenance and operating costs.

  In the period of the new technological revolution, new automobile technologies are emerging one after another. The technologies of mobile internet and intelligent predictive maintenance are developing rapidly. The automobile industry will usher a new round of industrial upgrading. This is both an opportunity and a challenge for automobile companies. Traditional automobile companies face the challenge of using Industrial Internet platforms to apply new technologies, solve corporate pain points and optimise business operations.

- Solutions:
  Investigate and analyse the actual working conditions and failure modes of the equipment. For predictive maintenance applications to be grounded, it is necessary to analyse the actual operating conditions of the equipment and combine the equipment maintenance and maintenance history to propose a feasible implementation plan.

  Develop a data collection plan to complete the collection and storage of equipment status data (including data cleaning and data quality verification). Then, develop the information that needs to be collected and use the data acquisition equipment to obtain the required data from the equipment controller or the programmable logic controller (PLC).

  Establish models to achieve lifecycle predictions for equipment and critical components as well as early warning of equipment failures. Models are built using various AI algorithms and acquired data. The model is run and adjusted after being deployed, so that the model can be consistent with the actual working conditions and accurately predicted.

- Benefits for Stakeholders:
  - For equipment maintenance and repair personnel: Reduce routine maintenance time and the cost loss caused by unplanned downtime.
  - For equipment service providers: Ability to monitor the current and historical status of the equipment to optimise it and provide better service to customers.

- Suggestions to Chinese and German Enterprises:
  Utilising the systemic predictive maintenance system of the high-tech system, the maintenance mode can be changed from traditional preventive maintenance to the predictive maintenance mode. Through real-time data monitoring, manufacturers are aware of the actual running status of the current device in real time. The predictive maintenance model powered by AI algorithms is used to monitor the status of the device, and the maintenance action is carried out according to the output of the model to the status.

However, the prerequisite for deploying the above technology on the production line is that the equipment has the ability to output data. At the same time, in the process of predictive maintenance of the equipment, it is necessary to combine the working conditions of the equipment with an established suitable model. Consequently, effects of the model can reach the optimum and the application can be implemented.

3. Conclusion and Recommendations

3.1 Challenges

3.1.1 Readiness of AI technology for Commercial Usage

Concerning the different stages of AI outlined in the second chapter, we are now at the level of AI-ANI[11]. AI gained attraction in recent years due to the advancement of machine learning and particularly its sub-domain deep learning in the 2000s. Deep learning and machines learning are both focusing on the capability of learning from data without being explicitly programmed. They are also called data science. AI is already able to generate a lot of impact, but it is still limited in making revolutionary impact. Noticeable areas of AI development are computer vision, voice recognition, natural language processing, robotics and autonomous driving.

The application of AI in the manufacturing industry is still in its infancy. Although some results have already been achieved, problems and challenges remain. In order to make AI better and more applicable in manufacturing in the future, we must identify the problems first. This mainly includes two aspects:

- In terms of supply capacity, the unavailability is still evident. Currently, research on AI application scenarios in manufacturing is still relatively small, AI products and system solutions that can be provided to manufacturing enterprises as well as case libraries, standard libraries, and databases are still deficient. Various manufacturing related data still faces great problems in areas such as collection, aggregation, organisation, and sharing. This results in AI being unable to sufficiently display its functions.

- In terms of enterprise capacity, the phenomenon of not utilising AI is very common. The application of AI is still in its infancy; deep application paths are not clear. Most manufacturers do not know how to apply AI or apply it better and more efficiently, especially if they do not know how to combine AI with core elements such as manufacturing processes. In particular, the AI application cases in small- and medium-sized micro-enterprises are even more lacking. Therefore, small- and medium-sized micro-enterprises urgently need to enhance their awareness and ability.

3.1.2 Social and Ethical Impact

The development of AI has the potential to improve human welfare by improving manufacturing, health care, education and many more. It also blurs the boundary between physical, digital and personal areas and raises complex social and ethical questions. Concerns about artificial intelligence often stem from unanswered questions and uncertainty about whether autonomous systems can be used fairly, responsibly, transparently, and in compliance with data protection regulations. AI allows computer programs and autonomous systems to make a wide variety of decisions that previously could only be made by humans. However, it also poses a range of socio-economic challenges including potentially dramatic changes to the future of work.

[11] Strelkova, "Three Types of Artificial Intelligence"

3.1.3 Missing Regulatory Framework

The application of AI can do incredible good for societies. It can optimise city systems, study employment patterns to give insights to policymakers, and revolutionise biotechnology. Technology in general can be used to make human life easier but only if it is subjected to informed policymaking and good governance. However, the EU's and China's regulatory development on AI is not extensive enough as of now. There is an urgent need for practical guidance and enforceable regulation on the issues of privacy protection, algorithm transparency and data bias in particular. Identifying and embedding authoritative ethical principles and issuing accessible guidance on AI governance to those using it in the public sector are necessary. Government and regulators must also establish a coherent regulatory framework that sets clear legal boundaries on how AI should be used in the public sector.

3.1.4 AI Skills and Employment

An increase in automation and productivity improvements by using AI will benefit both individuals, businesses and the entire economy. However, the development of AI will also involve replacing people with intelligent machines, therefore, potentially resulting in unemployment of low- and medium-skilled workers. Especially heavy manual labour jobs such as cargo handling, repetitive labour positions like manufacturing product assembly, high-risk industry positions such as in the mineral, chemical or firework industry, or light technical service positions like cashiers or customer service staff will be affected. This imposes two questions to both businesses and policymakers. One, how does a business find talents with the necessary AI skills? Two, how can the potential unemployment as a result of a growing scale of AI adoption be prevented? McKinsey estimates that three categories of work have a higher potential to be replaced by AI: repetitive physical work, data processing and data collection. These are representing 51% of the total workforce, and worth 2.7 trillion USD in wages.[12]

3.2 Outlook

3.2.1 AI shapes future

As the core driving force of a new round of technological revolution and industrial change, AI is currently releasing an enormous energy accumulated by the successive science and technological revolutions and the industrial transformation. In recent years, algorithm innovation, increasing calculation and computing power in the field of AI have not only promoted the innovation of AI technology but also made the application of AI, especially industrial applications, quite feasible. As the most important component of the real economy, AI applications in the manufacturing sector will be the first to be affected.

In our research conducted for this guide, we have seen that many companies are already experimenting with AI to drive new growth. Regardless of breadth or depth, the penetration of AI technology into the manufacturing field is advancing rapidly and the supporting effect on the overall development of the manufacturing industry is initially apparent.

Similar findings have been made by some international research consulting firms. In 2018, McKinsey conducted research on the embedded intelligence of global enterprises and found that different AI technologies were widely used in different parts of the world and in different industries with about half of the companies embedding AI into their business processes.[13] Accenture's research found that as many as three-quarters of executives said their organisation would "actively deploy" some kind of AI over the next three years.[14]

From a historical perspective, the development of technology applications such as the steam engine, electric power or the internet as well as the integration and penetration of general technologies is a long process. This means that the penetration of AI in various industries will also be an ongoing process. As McKinsey discovered in its research, AI applications are still in their early stages and most companies have yet to take steps to extract value from AI on a large scale. The integration of AI into manufacturing is still in the initial stage of exploration, the promotion path and the value-added model are still to be explored and perfected. Most enterprises are in a wait-and-see state and there is still a long way to go for the industry towards popularisation and application.[15]

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[12] McKinsey, "A Future that Works: Automation, Employment, and Productivity", p.6.

[13] Chui, M. & Malhotra, 2018.

[14] Shook, E. & Knickrehm, M., 2018, p. 8.

[15] Chui, M. & Malhotra, 2018.

Therefore, we must objectively study the development situation and current trends, find the right path and determine the model in order to seize the historical opportunity of developing AI, to accelerate the deep integration of AI and the manufacturing industry, and to inject new momentum into the transformation and upgrading of the manufacturing industry.

3.2.2 AI on Industry

In a recent research of Accenture on selected economies, it was estimated that AI could double the annual growth rate in those markets by 2035. It is partly based on the potential boost in productivity of up to 40% that AI can generate as well as partly on the creation of new products and services which will create new revenue streams and new markets[16]. While the benefit of adopting AI will occur in almost all industries, it has been observed that automobiles, financial services, high-tech telecom and manufacturing are leading industries in adopting AI.

In the manufacturing sector, we expect the following four major trends in the application of AI:

- The integration of AI will be a priority in the manufacturing sector due to its rich data sources and high acceptance level of new technologies.

- The deep integration of AI and manufacturing will be replicated and deepened in more areas and at more levels.

- Smart robots will play an integral role in many areas and sectors of manufacturing. Utilising intelligent robots not only saves time and increases productivity but also frees up the workforce and allows it to focus on more creative and value-added work.

- The application of AI technology in manufacturing must fall on specific industrial intelligence products or industry-specific system solutions. Compared with non-essential industrial intelligence products, the technology necessary for the production process is more easily accepted by the manufacturing industry.

3.2.3 AI on Consumer

AI can be used to provide intelligent, convenient and informed customer experience at any point along the customer journey. Consumers are becoming more used to interacting with chatbots, voice and facial recognition, autonomous cars and more – take the global adoption of Apple's iPhone and Amazon's Alexa. Servion predicts that AI will power 95% of all customer interactions within five years[17]. In the meantime, while enjoying the convenience and superior experience brought by AI, there has been a growing concern from consumers over how technology businesses use their consumption data and how to protect their privacy. In this context, we expect the debate on the balance between benefits from technologies and responsible use of technology consumer data. This is the place where policymakers can play a bigger role.

3.3 Recommendations to the Sino-German Dialogue

3.3.1 Establish close Sino-German collaborations with tangible projects

- The EU Commission published its latest AI white paper in Feb 2020[18]. The white paper introduced a coordinated European approach to the human and ethical implications of AI with support of a regulatory and investment approach. All those regulatory requirements will be further specified through standards. The same situation is applicable for the Chinese regulatory environment.

- In the recent AI Readiness Index published by McKinsey[19], a set of eight indicators are aggregated to measure countries' AI readiness. Germany is within the top 25% in the categories of automation, digital readiness, innovation and human skills; while China stands in the top 25% in AI start-up, investment capacity and ICT connectedness. This clearly shows great potential for Germany and China to collaborate on AI topics for mutual benefit.

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[16] Accenture, "Embracing Artificial Intelligence - Enabling Storing and Inclusive AI Driven Economic Growth", p.3.
[17] Servion, "What Makes Emerging Technologies The Future Of Customer Experience?"
[18] European Commission, "On Artificial Intelligence -A European Approach to Excellence and Trust."
[19] Bughin et al., "Notes from the AI Frontier: Tackling Europe's Gap in Digital and AI", p. 40.

- Projects on mutual interests such as research on the influence of AI on the society, layout of the regulatory legal framework, ethical use of AI, and governance of AI shall be set up.

- Take the lead in establishing norms for appropriate AI application. The EU's and China's regulatory development on AI have unparalleled influence and authority on the global stage and is in a unique position to set an example for the world on how AI should and should not be used. We suggest a collaboration on norms for AI application in the Sino-German Dialogue.

3.3.2 Guide the improvement and raise awareness

Guide and help manufacturing companies to enhance their cognitive level and application ability of AI and promote application practice from shallow to deep. Collect, summarise and publish typical cases of AI and real economy integration. Analyse and summarise those experiences and pathways from the aspects of technology, methods and models, then compile and form application guides for different industries and different businesses.

3.3.3 Optimise the development environment

- Build a competent AI technology and application detection platform and an AI application effect evaluation mechanism in order to provide technical support for the application. Establish an industrial intelligence public evaluation service platform and strengthen the safety testing service for industrial intelligent systems. Formulate and improve the safety operation code of AI equipment and systems in industrial production application scenarios.

- Eliminate industry barriers, build public databases, test standards and service platforms for AI. Promote open source and openness of all kinds of general software and technology platforms and form a positive environment for the industrial ecosystem.

- Accelerate the improvement of various inspection and evaluation standards and safety evaluation systems for industry-oriented AI applications. Eliminate entry barriers such as qualifications, data interfaces, and evaluation standards when AI is applied to various industries. Strengthen transparency, guidance and policy norms in order to avoid creating new barriers.

3.3.4 Create a smart carrier and improve supply capacity

- During the working group's research process, unique assets were produced such as Intelligent Manufacturing solutions, practical cases, AI training materials, and technology platforms from different companies. If different Sino-German enterprises could be brought together to form a Sino-German Intelligent Manufacturing innovation centre and realise a carrier pooling effect, Chinese and German enterprises will effectively gather to continuously deposit assets and form an industrial clustering effect.

- Select "Smart cities/enterprises" cases in China and Germany and summarise their experience for other cities and enterprises for case-study purposes. The cases could provide AI application solutions for manufacturing industries worldwide.

- Support the creation of AI application support platforms for the common needs for manufacturing industry and reduce the application threshold. Meanwhile, both governments should more strongly promote industrial data normalisation and create Industrial Internet of Things (IIoT) in a more intelligent way.

3.3.5 Deepen international cooperation

Beyond that, the cooperation between China, Germany and other countries and regions around the world could be further expanded. Both countries together can actively participate in and guide the formation of a new international division of labour and cooperation network. Together, they can encourage enterprises and research institutions of both countries to carry out exchanges and cooperation in AI technology and promote industrial cooperation through academic seminars. Therefore,

- Establish a framework to enable further policy exchange between German and Chinese think-tanks and policymakers to facilitate further collaboration between academia and businesses from both countries.

- Establish an industrial AI Technical Steering Committee of selected leading researchers from national academia (Chinese Academy of Sciences / Chinese Academy of Engineering, acatech / Fraunhofer) in both AI and Industrie 4.0.

- Establish an industrial AI community as a bigger platform for academia and businesses from both countries to share and exchange information between demand and supply.

3.3.6 Strengthen the ethical research of AI

Ensure that human interaction and values, including competencies, disabilities and diversity, are considered in AI data collection, model development, testing, and deployment. Unify and use clear language to define terms and concepts related to AI, promote interoperability and the overall harmonisation of vocabulary and terminology. Identify and screen technical issues involving ethics and incorporate them into privacy-protected and widely accepted terms.

3.3.7 Improve AI governance

Carry out research on AI governance in China and Germany, aiming to use AI in a safe, controllable, credible and practical way. The joint development of a safe and controllable governance system standard for the development of responsible AI provides a model and basis for the healthy and rapid development of the AI industry.

3.3.8 Improve AI public acceptance

It has been increasingly common in our daily life to come into contact with AI in various situations (home, retail store, hospital) and forms (hardware robots, software applications). AI has great impact on people's lives with its capability of prediction, providing recommendations or decision-making. Due to its lack of explainability, evolving nature and repeatability, AI, particularly machine learning, is a 'blackbox' which cannot gain sufficient trust. While businesses are promoting the ethical and responsible use of AI, technological advancements to make AI explainable will help provide the needed transparency and help gain social acceptance.

3.4 Recommendations to Chinese and German Enterprises

3.4.1 Impact of AI on Industry

Companies understand that hyperconnectivity and big data are the keys to value creation. Based on our collaboration with thousands of businesses worldwide, winning companies are moving quickly in three strategic areas.

- <u>Re-define the business model:</u> Most companies will only change their business models if a competitor or new entrant changes the rules of the game.
  - Outcome-based business models focus on the outcome, not the product. This change has implications from product design to profitability and services.
  - Data-driven business models turn data into insights. By applying AI, businesses have the capability to predict future developments based on past data. This creates new possibilities to use data to gain new insights and create competitive advantages.

- <u>Re-define the business processes:</u> When analytics and transactions are combined in real time on the same platform, business processes will never look the same.
  - Optimise the supply chain in real time based on demand signals. Today, it takes hours, even days, to send a demand change; with AI and big data, it could be in real-time.
  - Predictive software and machine connectivity will transform how we manage and maintain assets.
  - Detail-driven customer engagement and segmentation will transform marketing, personalisation, and customer loyalty, thereby improving people's lives.
  - Structured and unstructured data analytics will significantly improve how products are designed and marketed.

- Re-define work: Employer of choice status goes beyond recruitment and retention to fundamentally revolutionising the way people engage.
  - Accelerating processes by digitising manual steps (e.g., invoice and payment processing).
  - Improve productivity and profitability by enabling users to access the right information at the right time on any device.
  - Use predictive and self-learning software to improve machine-to-machine collaboration and optimise business decisions.
  - Use interactive technology to improve user experiences, including voice recognition, visualisation, and gaming.
  - Establish an employer/employee contract for the digital economy to invigorate and stimulate the changing workforce with the best technology and access to information.

3.4.2 Organisational Recommendations

Recognising AI is an important topic for businesses' digital transformation, assigning a Chief Digital Officer (CDO) is an effective way of having a dedicated executive with the mandate to drive business transformation.

The CDO oversees the development of the digital strategy, derived from the corporate strategy, and then ensures its implementation. When developing new business models, the CDO is responsible for the digitalisation and simplification of business processes to improve their efficiency and agility. In short, the CDO is set to connect the digital and the analog world to achieve a seamless customer experience.

3.4.3 Develop an AI strategy

AI is a technology that has the potential to transform businesses and improve productivity and create new innovations. To define the value of adopting AI and how to achieve it, businesses need to develop AI strategies.

- Business position in context to AI: To most effectively make use of AI, businesses need to have a clear understanding of their current position, their objectives of applying AI as well as the availability of the required data.

- AI transformation blueprint: With a clear understanding of the businesses' objectives in adopting AI, they then need to identify how AI can be implemented step by step. By identifying the types, conditions and attributes of collected data, companies are able to improve their performance when moving to further application scenarios.

3.4.4 Adapt to rapid technological changes

Insist on technology and application innovation to achieve maximum flexibility, and technology and platform neutrality. Focus on performance-based (as opposed to prescriptive) requirements to accommodate different approaches in meeting standards. Leverage AI infrastructure to access AI computation power and provide manufacturing businesses with the benefits of starting AI projects without sunk cost of investing in AI computation and of being able to always have access to up-to-date AI technology.

3.4.5 Conduct a risk assessment

Clearly define the scope and intended use of AI, allowing users to determine whether an application's AI standard is appropriate for another application based on the data or algorithm used or the level of risk it contains. At the same time, we have to learn from success stories of Sino-German Intelligent Manufacturing and increase the confidence in the application of AI in manufacturing.

3.4.6 Stick to the scene-oriented advance

Taking the project as the starting point, deepen the integration level of product design, manufacturing, sales services and other scenarios. Accelerate the promotion of AI and the manufacturing industry's in-depth integration of innovative projects. Realistically promote the development of AI in a series of initiatives in the manufacturing sector and support technology iterative upgrading. Establish a centre for AI and Intelligent Manufacturing innovation at the enterprise level. Focus on promoting research and development and the popularisation of AI applications in the manufacturing industry.

3.4.7 Build an AI ecosystem to collaborate

The integration of AI into the manufacturing industry is an interdisciplinary, multi-profession and cross-disciplinary work area that combines knowledge of many related fields. If one just relies on one certain kind of knowledge or ability alone, it will not be able to satisfy demand very well. To this end, we should strengthen the cooperation between manufacturing enterprises and AI enterprises, jointly promote the construction and open sharing of resources such as tool and model libraries and databases in the manufacturing sector as well as promote the agglomeration and efficient utilisation of cross-border innovation resources in order to enhance the efficiency and level of research and development.

3.4.8 Bring together high-quality talents

Increase the recruitment of high-level, professional and technical talents in areas such as AI application research, model promotion, and operation and maintenance of AI in the manufacturing industry. Accurately meet the needs of manufacturing companies, enhance the AI skill sets of existing personnel, and enable employees to actively grasp the important human abilities of judgement, communication, imagination and creativity. Both China and Germany should be more prepared for the potential impact of AI and develop strategies to help people facing higher unemployment risks as well as creating an inclusive and diverse culture that helps employees recognise and embrace AI.

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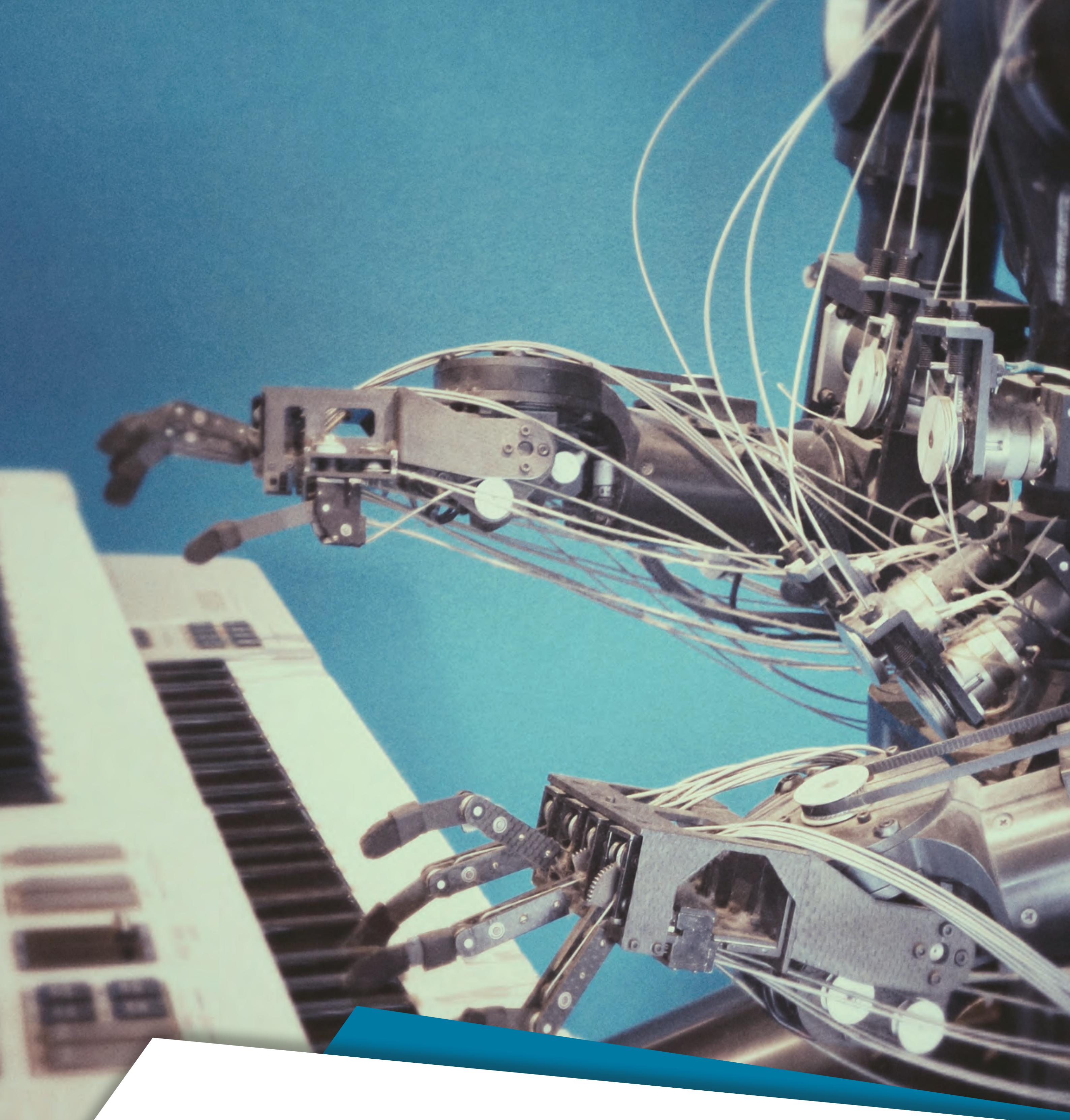

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