POTENTIAL OF ARTIFICIAL INTELLIGENCE IN GERMANY'S PRODUCING SECTOR

Study on Behalf of the Federal Ministry for Economic Affairs and Energy (BMWi) within the Scope of Scientific Assistance on the "PAiCE – Platforms | Additive Manufacturing | Imaging | Communication | Engineering" Technology Programme

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Management Summary

Artificial intelligence (AI) is generally considered to be a future key technology and as such offers considerable economic potential. Different studies are already working to identify this potential. However, none of these studies has yet explicitly focused on the manufacturing sector in Germany despite this being one of the most important pillars of the German economy. The aim of this study is therefore to identify the potential of AI for Germany's manufacturing sector by compiling and comparing the assessments made by AI providers, potential AI users[1] (large corporations and SMEs in the manufacturing sector) as well as AI researchers. Unlike earlier studies, this study distinguishes between basic AI technologies, concrete AI applications and the value-added stages of the manufacturing sector. This study thus provides the baseline of the current state of AI implementation and enables relevant system requirements to be identified along with the most important value creation potential over the next five years. Finally, an analysis of the strengths, weaknesses, opportunities and threats for the manufacturing sector in Germany will summarise the results and combine these in the form of recommendations for future action.

The central results of the study are as follows:

- AI offers high potential for future value creation in the manufacturing industry. Over the next five years, the use of AI in the manufacturing sector in Germany will generate additional gross added value of around EUR 31.8 billion. This corresponds to around one third of the total growth of the manufacturing sector in Germany over this period.

- Research and development (R&D), service/after-sales service, production, marketing/sales and planning are the most important future areas of application within the value chain of the manufacturing sector.

- The greatest potential is offered by AI applications for predictive analytics, smart assistance systems, robotics, smart automation and smart sensor technology.

- Computer vision, machine learning as well as action planning and optimisation are cross-cutting technologies of particular importance. Machine learning, in particular, plays a key role in all AI applications.

- An average of 25% of large enterprises, but a mere 15% of SMEs state that they are already using AI technologies at the respective stages of their value chains. The majority of companies in the manufacturing sector expect the use of AI technologies to increase strongly in all stages of the value chain over the next five years.

- Although the degree of automation by AI-based autonomously deciding systems for controlling processes is still extremely low, it will increase significantly across all stages of the value chain.

- Especially large corporation rely on external AI providers for production and logistics as well as R&D. SMEs are even more reluctant in this respect.

1 The terms provider and user are used in this study in order to identify and differentiate companies rather than individuals. This means that only the masculine form will be used In the following text.

- Central system requirements for the use of AI in the manufacturing industry are robust algorithms, data quality, data sovereignty and access, security as well as the use of sensors and cloud computing. Users also stress other aspects, such as security and interoperability. One central obstacle to the use of AI is the lack of qualified staff and in-house skills.

- Companies in the manufacturing industry are therefore expecting to see a sharp increase in co-operation with external AI providers. SMEs, in particular, want European technological sovereignty and clearly prefer co-operation with suppliers and providers based in Germany or Europe, but only very few providers are aware of this geographical advantage.

- A survey among stakeholders suggests that Germany is the leader in the international comparison of AI applications in terms of quality control, smart automation and smart sensor technology, whilst the US is considered to play a leading role specifically in AI applications, such as predictive analytics, smart assistance systems, knowledge management as well as autonomous driving and flying.

- The US is very well positioned in almost all areas of AI technology research, with researchers considering Germany to lead the field only in natural language processing and cognitive modelling. This makes the US the main competitor with regard to the range of AI products and services. However, suppliers and providers from China are expected to be the main drivers of future competition.

- The study highlights strengths in the area of basic research in Germany, especially in natural language processing and cognitive modelling, whilst the transfer of research results to industry is sometimes still insufficient. One key flaw point is the very small number of spin-offs from within academia. This weakness is particularly evident in an international comparison.

- Germany's AI publications currently lag slightly behind in the international comparison. Other countries currently seem to be stepping up their R&D efforts in the field of AI more than Germany.

This means that there is a need for action as follows:

- In order to ensure the continued international competitiveness of Germany's innovation system, research activities in Germany must also be intensified further. Targeted support will be required for AI technologies with a cross-cutting character (computer vision, machine learning, action planning and optimisation).

- The specific needs of SMEs should be addressed in a targeted manner, such as the AI applications of specific relevance, e.g. knowledge management and quality control.

- In order to strengthen the supplier side, it is particularly important to support start-ups working on AI.

- Furthermore, it is also necessary to specifically improve the information situation regarding providers, service providers and R&D co-operation partners and to provide bundled information on use cases and best practices.

- Plans for political programmes and initiatives must focus on reducing existing obstacles to implementation. Specific attention should then be paid to topics such as data access, data quality, IT security and interoperability as key system requirements.

- Another key topic should be the swift development and expansion of vocational and academic education as well as further professional development and training programmes for AI-related topics.

- German AI providers should be increasingly involved in integrated, government-supported and lighthouse projects in order to guarantee technological sovereignty in the field of AI.

Parameter	Value
Average AI-induced annual growth in Germany's manufacturing sector until 2023	0.69%
Additional gross value added due to use of AI in Germany's manufacturing sector (cumulated until 2023)	EUR 31.8bn
Share of companies surveyed in Germany's manufacturing sector already using AI technologies today in the respective stages of the value chain	8% (finance/tax/law) to 36% (R&D)
Share of companies planning to use AI technologies in the respective stages of the value chain by 2023	40% finance/tax/law) to 69%(service/after-sales service, R&D)
Share of companies currently working with external AI service providers in the respective stages of the value chain, in as far as they use AI technologies	19% (human resources) to 40% (marketing/sales)
Share of all companies planning to work with external AI service providers in the individual stages of the value chain by 2023	53% (planning, finance/tax/law) to 68% (service/after-sales service)

Table 1: Key indicators regarding the use of AI in Germany's manufacturing sector

1 Introduction

The use of artificial intelligence (AI) in the manufacturing industry, as one of Germany's leading economic sectors, offers considerable growth potential. One major reason for this is the digitisation of industrial production that was massively pushed in recent years by industry, politics and science under the motto of Industry 4.0. An important characteristic of the advancing digitalisation of industrial production is horizontal and vertical interconnection of production and usage processes even across company boundaries. A centralised planning control system is replaced by a system where every component in a smart factory has a product memory that enables an enormous degree of flexibility thanks to dynamic, decentralised optimisation of the various production and usage processes. This basically enables companies to respond better to market changes and customer demand.

The result is a considerable amount of data that provides substantial added value for the processes at the company, the development of new products and/or new business models.[2] Due to the vast amount of data and greater complexity of processes, it is no longer possible to use conventional analysis and optimisation methods for evaluations. The central characteristics of AI systems, such as learning and adaptation ability, are required in order to exploit this innovation potential.

Systems with artificial intelligence are generally expected to behave in a way that up to now was primarily characteristic of beings with natural intelligence and, in particular, of humans. The crucial ability is to successfully handle new situations, to process new data or new information, to draw conclusions from available knowledge and to generate new knowledge on this basis, to master new tasks or to act independently in new, previously unknown environments. It is precisely this capability that distinguishes AI systems from conventional rule-based IT systems which have to be reprogrammed whenever tasks change, no matter how small the change.[3]

But what is the real potential of AI for the manufacturing sector, beyond any lofty visions of the future? Although several studies were recently published on the use of artificial intelligence in the economy, analysing the impact on individual sectors and addressing the potential in various fields of application, including those by Sopra Steria Consulting (2017), Purdy and Daugherty (2017) and Chen et al. (2017), an in-depth analysis of the manufacturing sector is still lacking. This is where this study comes into play and focuses on the use of AI by manufacturing companies.

The ability to master key technologies, such as artificial intelligence, is also essential for an economy in order to avoid or at least mitigate dependencies. The study therefore also addresses the role of German AI providers for the manufacturing sector in international competition. In order to pick up on the current discussion of technological performance for AI, the final part of this study will broaden the perspective somewhat and ask about the special features of the transfer of this technology from research to industry in Germany.

2 This is, in particular, so-called machine data, which is continuously generated by production and usage processes.

3 The appendix contains differentiated explanations of the approaches in AI research, specifically with a view to their scope and limitations.

The central questions of the study are thus:

- Which AI applications and technologies are already in use in Germany's manufacturing sector today and how will this picture change in the future?
- What are the prerequisites for the broad use of AI by companies in the manufacturing sector to actually take place?
- How is the role of German AI technology providers perceived in this field of application?
- From an international perspective, does Germany have special features where the transfer of AI technology from research to industry is concerned?

The core of the study is a systematic mapping of AI technologies and AI applications to the different stages of the value chain in manufacturing. These questions were the conceptual and methodological basis for interviewing manufacturing companies, technology providers and scientists with regard to their assessments in an online survey that was conducted in December 2017 and January 2018.

The study does not claim to provide an all-encompassing analysis and presentation of the potential of AI. Certain topics, such as the impact of AI on the labour market, or ethical questions regarding the use of AI, the transparency of AI procedures for machine learning and related issues of legal liability, are already being discussed in literature and in public discourse. Due to the diversity of topics, these and other aspects, such as AI-specific business models (such as machine learning as a service), are not considered in this study. However, one chapter addresses AI in China. China is transforming into a modern industrial nation and also making massive use of artificial intelligence in this context. This development, which is sometimes not sufficiently considered in the public debate, is of great interest, especially for Germany.

The following chapter 2 first introduces the design of the study and its analytical framework. Chapter 3 presents the findings of earlier studies on the use of AI in business and on the resulting value creation potential. This is used as a basis in order to extrapolate the AI-induced growth potential in the manufacturing industry in Germany for the next five years. Chapter 4 presents the results of the online survey. Chapter 5 examines the transfer of artificial intelligence technology from research to industry in Germany. Chapter 6 examines recent AI developments in China. Chapter 7 concludes with a summary in the form of a SWOT analysis and provides recommendations for action.

The authors would like to thank all the participants in the online surveys and the experts who provided valuable feedback in telephone interviews and validation workshops.

2 Study design

2.1 Analytic approach

In order to achieve the goals defined for the study, different methods were used based on a hierarchical concept as shown in Fig. 1. As a first step, relevant economic studies and AI publications were evaluated as part of a context analysis. Central databases, such as Web of Science, the federal government's funding catalogue and the database of the German Research Foundation (DFG, Deutsche Forschungsgemeinschaft) as well as the Crunchbase start-up database proved to be important sources for the analysis of the AI research and start-up landscape in Germany. This was supplemented in September and October 2017 by standardised telephone interviews with a total of 22 representatives from AI research, the manufacturing industry, AI technology providers and relevant multipliers.

The context analysis was helpful when defining the terminology relevant for the further study. At the beginning, stakeholders of the AI innovation system in Germany as well as important system requirements for the use of AI in the manufacturing industry were identified. Furthermore, the central examination levels were determined for the subsequent online survey. These are the value-added stages of the manufacturing industry, the AI applications which are or can be used there, as well as the AI technologies on which these applications are based.

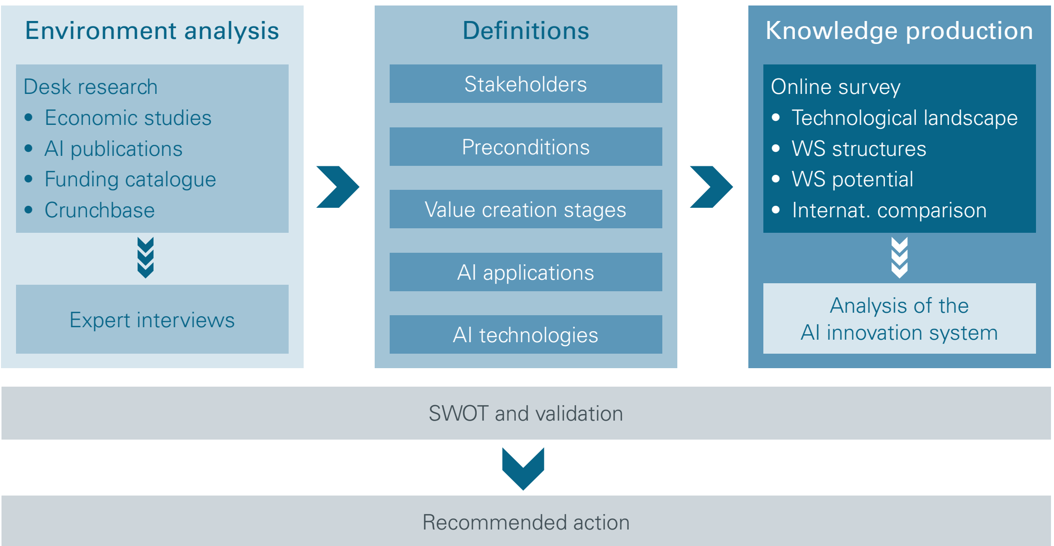


Fig. 1: Procedure for the preparation of the study

The actual online survey was then conducted from December 2017 until the end of January 2018. A representative sample of 230 people were interviewed, 90 of whom were users from the manufacturing industry, 63 providers of AI technologies and 77 representatives from academia. The identification of the respective target group was based on filter questions at the beginning of the questionnaire. Three sources were used to recruit the survey participants:

- the 'Markus' database of Creditreform[4] for company contact information,
- mailing lists of trade and/or the technical-scientific associations, i.e. Bitkom (Federal Association for Information Technology, Telecommunications and New Media), VDI (Association of German Engineers), VDE (Association of Electrical, Electronic & Information Technologies) and ZVEI (German Electrical and Electronic Manufacturers' Association) as well as
- a mailing list of participants in the PAiCE, Smart Service Welt and AUTONOMIK für Industrie 4.0[5] technology programmes funded by BMWi.

In addition, several research-orientated institutions from the iit environment, such as acatech (National Academy of Science and Engineering) and the members of various clusters of excellence, were won over to disseminate the online questionnaire.

Drawing on the findings of the online survey and the previous environmental analysis, an analysis of the AI innovation system in Germany was ultimately carried out, although this analysis did not claim to fully cover and map this innovation system. Instead, this analysis focused on the transfer of technology from academia to industry.

In February 2018, the results were presented to selected experts from academia and industry at a workshop and validated in discourse. Concrete recommendations for action were then derived from the results of all sub-steps.

2.2 Dimensions of the analysis

The use of AI in industry is characterised by a high degree of complexity since AI is a cross-cutting technology that can be used in very different areas of business. The degrees of application can also differ considerably from each other. In order to be able to map the use of AI in manufacturing despite this complexity, a step model was developed within the scope of this study (see Fig. 2). This step model is the starting point for structuring the online questionnaire and differentiates between three AI and/or company-related levels, i.e. value creation stages, AI applications and AI technologies. This distinction enables a more in-depth analysis of the use of AI in the manufacturing sector. The following sub-chapters will elaborate in more detail on the levels discussed here.

4 https://www.creditreform.de/leistungen/marketing-services/neukundengewinnung/markus.html
5 Some of the participants in the technology programmes can be considered to be early adopters, which does lead to a certain bias. However, it can be assumed that these companies will act as trendsetters and set a course that other companies will also follow in future.

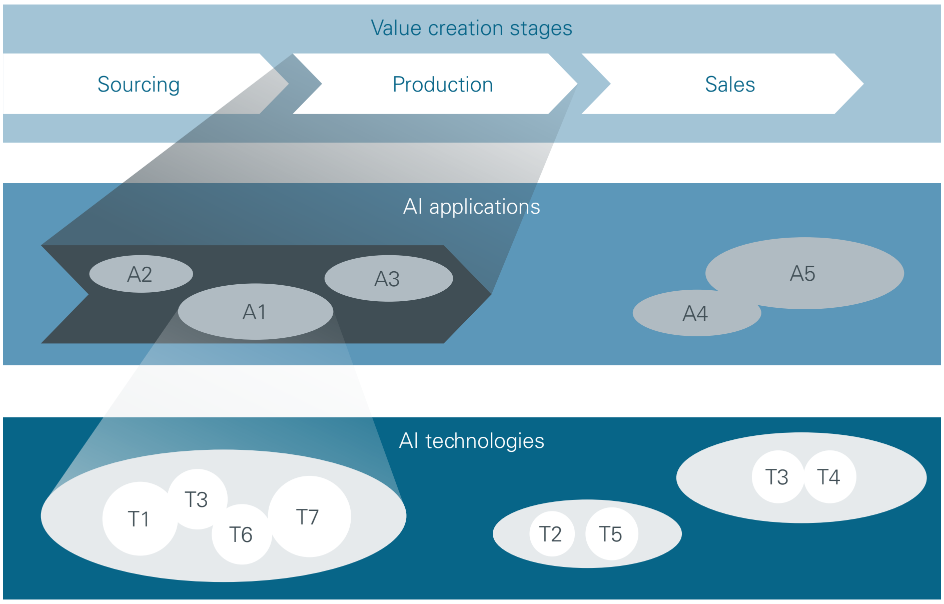


Fig. 2: Step model of the use of AI in the manufacturing sector (source: iit)

2.2.1 Value-added stages of the manufacturing sector

In order to identify the potential of AI with regard to the different value creation stages of companies, a value chain was defined in analogy to Porter (1985) which distinguishes between cross-cutting and core activities. Cross-cutting activities are activities that are relevant to all areas of the enterprise (such as research and development). Core activities, on the other hand, are activities that map the production process in an iterative manner (such as sourcing/procurement, production, etc.). The diagram in Fig. 3 illustrates the value chain.[6]

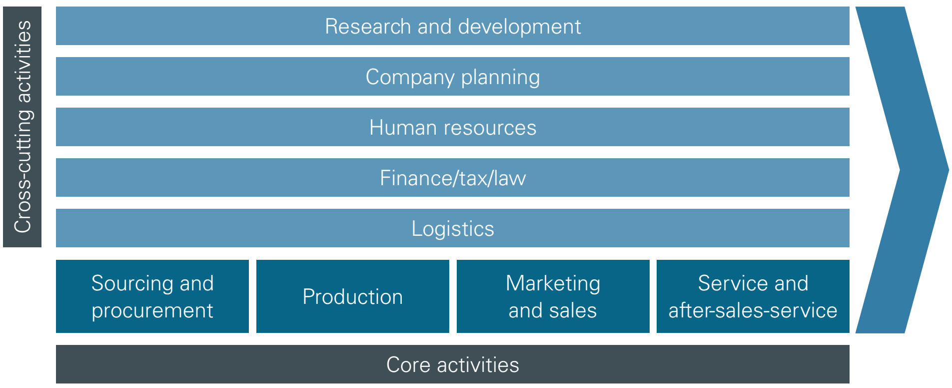


Fig. 3: Stages of the value chain of the manufacturing sector (source: iit, based on Porter 1985)

6 Unlike Porter (1985), this study does not subdivide logistics into inbound and outbound logistics, but rather into interlogistics and intralogistics in the sense of a cross-cutting activity. Since the AI systems used for operational and strategic planning may differ from those used in the areas of finance, tax and law, the latter were also defined as separate cross-cutting activities. Another difference when compared to Porter is the definition of sourcing and procurement as a core activity of the company. This allows the production process to be interpreted as a chronological sequence of core activities.

2.2.2 AI applications

AI applications are the second relevant level for mapping the potential of AI. Since the terms 'applications' and 'technologies' are often used synonymously in literature, AI applications were defined as follows for the purposes of this study:

> AI applications are artificial intelligence applications which are relevant for the value chain of the manufacturing sector and which are based on at least one AI technology.

Nine relevant AI applications were identified on the basis of this definition.[7] This definition was deliberately carried out across all stages of the value chain. Predictive analytics can be used not only for maintenance (predictive maintenance), but also for sourcing or production planning purposes. These overlaps allow the potential of AI applications to be assessed specifically with a view to their role in the value chain. Table 2 lists the AI applications relevant for the study and shows the further sub-applications into which they were broken down.

7 The AI applications were identified on the basis of the analysis of relevant specialist publications and expert interviews.

AI applications	Application examples
Predictive analytics	• Monitoring and maintenance of production equipment in order to draw conclusions from sensor data reading critical conditions, such as overheating of a production system and to enable a proactive response to possible problems • Sourcing planning taking sales fluctuations into account
Optimised resource management	• Optimisation of production and manufacturing plans • Personnel planning • Optimisation of processes in inbound and outbound logistics
Quality control	• Inspection of the condition of components or other production materials • Verification of the correctness of assembly processes using video, image or sensor data
Smart assistance systems	• Integration into administrative processes • Installation instructions • Support for manufacturing processes • Support for further qualification
Knowledge management	• Management of internal company information and processes • Data models for complex engineering processes • Product configurations and description of interfaces between different components and products
Robotics	• Adaptive, learning industrial robot systems in production and manufacturing • Adaptive service robots • Learning, self-regulating gripping systems and assembly robots
Autonomous driving and flying	• Driverless transport systems, such as cleaning robots or autonomous drones for filling shelves in warehouses
Smart automation	• Automation of routine processes in production and assembly through self-regulating adjustment of control parameters • Automation of work steps in IT-supported business processes (robotic process automation) including decisions that were previously only made by humans, such as reply e-mails to customer enquiries
Smart sensor systems	• Environmental perception (image, laser scan) and pre-processing of data in order to avoid collision of driverless transport systems • Pre-processing of data during monitoring of production plants

Table 2: AI applications and examples (Source: iit)

2.2.3 AI technologies

The AI applications described above are based on individual AI technologies which form the third central level of this study. AI technologies are defined as follows for the further course of the study:

> AI technologies are methods and procedures that enable technical systems to perceive their environment, to process the perceived, and to solve problems independently, to make decisions, to act and to learn from the consequences of these decisions and actions. (Russell and Norvig 1995)

This definition served as a basis for identifying seven AI technologies (Table 3).[8] AI technologies can be divided into behaviour-orientated and rationally inspired technologies. Behaviour-orientated AI technologies try to reproduce human behaviour with its strengths and weaknesses. They are often used where machines interact with humans or are otherwise exposed to variable demands which are difficult to measure and unforeseeable. Semantic technologies, natural language processing and cognitive modelling are based on behaviour-orientated approaches. Rational AI technologies, on the other hand, are developed with the goal of optimising a cost function and are preferably used where a measurable, objective criterion for successful behaviour or information processing can be formally defined. Computer vision, machine learning and action planning and optimisation are AI technologies which are typically developed along the lines of the rational approach.

	AI technologies	Associated procedures and methods
Behaviour-orientated approach	Cognitive modelling	• Simulation of human attention and decision making; capture, interpretation and generation of emotional expression; simulation of human problem solving and estimation of cognitive load
	Natural language processing	• Question-and-answer and dialogue systems, conversion of text into audio output (text-to-speech), comprehension of text and queries in natural language, machine translation
	Semantic technologies	• Ontologies, semantic web (e.g. Linked Open Data), knowledge representation (e.g. knowledge graphs)
Rational approach	Computer vision	• Object recognition in images, detection of actions in videos, environment recognition
	Machine learning	• Monitored and unmonitored learning, encouraged learning, artificial neural networks, deep learning, statistical models, ML ensembles
	Action planning and optimisation	• Motion planning and motor control, self-orientation and mapping of environments (e.g. simultaneous localisation and mapping), navigation, route planning, process optimisation
	Neuromorphic computing[a]	• Hardware architectures modelled according to the brain or neural networks

Table 3: Presentation of the relevant AI technologies[b] (source: iit)

8 A clear distinction between the individual technologies is often not possible. Statistical methods for analysing the meaning of texts, for instance, include aspects of natural language processing, semantic technologies as well as machine learning. The technologies therefore merge with each other and explicitly overlap. Table 4 in the appendix on pp. 63 eq seqq. gives a more detailed description of the respective technologies.

a Biologically inspired approach.

b The AI technologies were identified on the basis of the analysis of relevant specialist publications and expert interviews.

3 Studies on the economic potential of AI

The increasing importance of AI is reflected by the growing number of studies dealing with its potential for companies and the economy. This chapter summarises the key statements from these studies and bundles them in an extrapolation of the AI-induced growth potential.

3.1 Use of AI in the economy

The first question concerns possible fields of application of AI as well as its current use in the economy. Individual studies have already provided first results in this respect.

3.1.1 Central fields of AI application

The economic fields of application for AI are extremely diverse. On the one hand, AI is found in the form of components in end products and services, for instance, in autonomous driving applications, but also in an area offering substantial automation potential, i.e. in productive core and support processes at companies. In the production process, potential exists particularly in the area of systems for plant and machine maintenance, as well as in production whenever collaborative and context-sensitive robotics is used. Furthermore, AI can support process optimisation, for instance, in production and capacity planning as well as in quality control. Considerable potential also exists in operational support processes, primarily in value chain management, research and development as well as in administrative processes.

McKinsey (2017) identifies four core areas within production processes where the future use of AI will exceed traditional dimensions:

- AI-based predictive maintenance systems: Maintenance improved by AI-enhanced predictive maintenance enables better prediction and prevention of machine failures by combining data from sensors and maintenance logs with external data sources.
- Collaborative and context-sensitive robotics: Collaborative and context-dependent robots will significantly improve production output in labour-intensive areas. This increases productivity, even if full automation is not possible.
- Increased efficiency and earnings: The combination and evaluation of large amounts of data across machine groups and production systems leads to a reduction in scrap rates and inspection costs.
- AI-based quality control: Improved and especially more efficient, more reliable and integrated data processing (especially machine learning) ensures continuously improved product and service quality. Improved manufacturing leads to a reduction in scrap rates and inspection costs.

In the area of autonomous driving, considerable potential also exists for the manufacturing sector, especially with regard to the impact on goods and passenger logistics. Current expectations are that freight traffic can be widely automated first, followed by passenger traffic at a later point in time. But even beyond autonomous driving, the use of AI technologies offers considerable potential for logistics, especially in the area of supply chain management.

3.1.2 Current use of AI technologies in central AI applications

According to a recent survey among business decision-makers conducted by Sopra Steria Consulting (2017), every second German company (46%) already uses AI technologies and four out of ten are planning to do so.

The current focus is on AI applications, such as robotic process automation (i.e. automation of IT-supported work processes, such as after-sales service, accounting, etc.). However, smart automation (i.e. automation of routine processes in production and assembly) and digital assistants (such as Siri, Cortana or Alexa) are also being increasingly used. The range of applications for AI technologies varies between the different sectors of industry. The manufacturing sector is generally the area with the highest application density for AI applications.

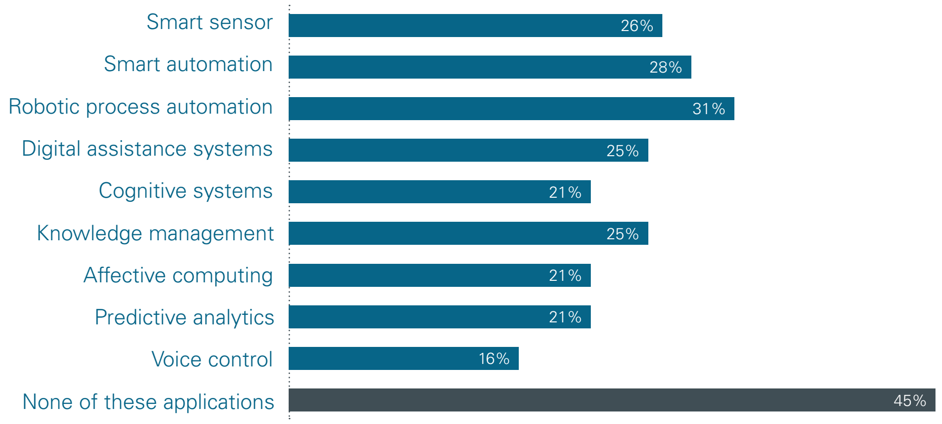


Fig. 4: AI applications used at German companies in the manufacturing sector (source: iit based on Sopra Steria Consulting 2017)

According to the results of Sopra Steria Consulting (2017), applications for smart automation in general and robotic process automation are currently the most relevant. According to the study, smart sensor technology used in the manufacturing industry is also already widely used. Smart pre-processing of measured values, for example, in equipment controllers or when measuring values in realtime are the key factors here. Digital assistance systems and cognitive systems (which, according to Sopra Steria, are systems that learn from interaction with humans) are also becoming increasingly important, and so too are affective computing systems (i.e. systems that recognise human emotion) as well as predictive analytics (i.e. predictive models) (see Fig. 4).

According to Sopra Steria Consulting (2017), digital assistants and knowledge management systems promise the greatest technological potential, followed again by robotic process automation for IT-supported work processes at companies as well as smart sensor technology (Fig. 5).

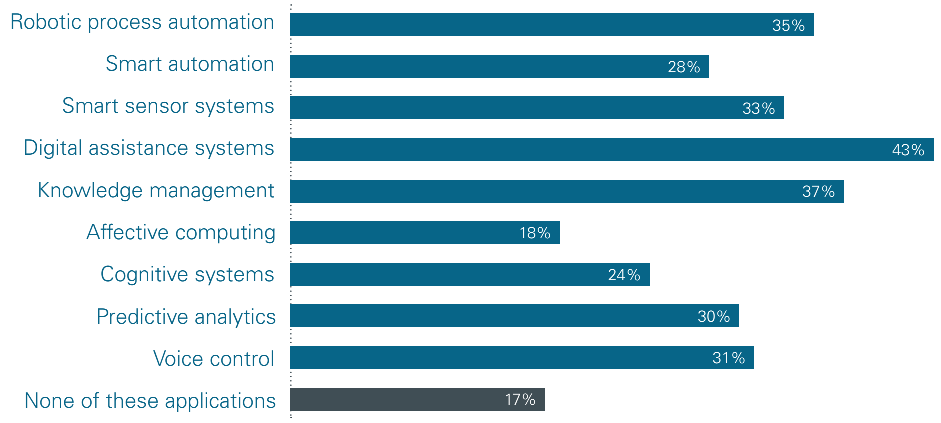


Fig. 5: AI applications with the greatest technological potential at German companies (in percent) (source: iit, based on Sopra Steria Consulting 2017)

3.2 Potential of artificial intelligence for value creation and productivity

While studies from 2009 do not yet provide uniform estimates of the overall economic potential of digitalisation (see, for instance, Qiang and Rosotto 2009 and Koutroumpis 2009), more recent studies assume increasingly high growth effects. The key driver for this is the use of AI in industry. Particularly strong growth momentum can be expected from the use of AI in mature, high-tech economies.

A study by Purdy and Daugherty (2017) assumes that the use of AI can trigger up to 2% additional annual growth in gross added value by 2035. The authors identify automation as the most important growth driver with the potential to enable productivity increases of up to 37%. For Germany, the study mentions possible additional growth of 1.6% p.a. and an increase in labour productivity by 29% (Fig. 6).

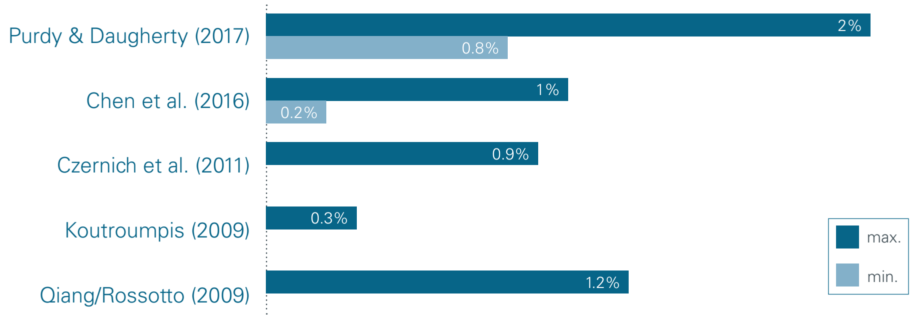


Fig. 6: AI-induced growth (in percent) (source: iit based on Qiang and Rossotto 2009, Koutroumpis 2009, Czernich et al. 2011, Chen et al. 2016, Purdy and Daugherty 2017)

The high expectations sometimes result from the fact that AI is relevant for almost all sectors of the economy (see Fig. 7). However, the strongest momentum is expected to come from the manufacturing sector.

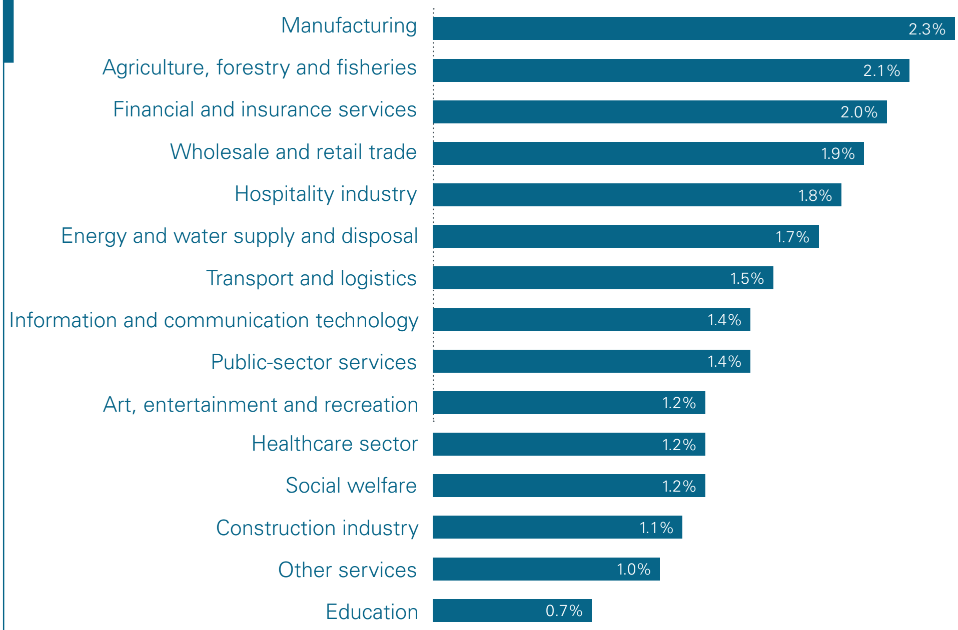


Fig. 7: AI-induced growth p.a. of gross added value in selected sectors of mature economies (in percent) (Source: iit, based on Purdy and Daugherty 2017).

3.3 Extrapolation of AI-induced growth potential

The studies by Purdy and Daugherty (2017) as well as Chen et al. (2016) serve as a starting point for a summary estimate of the additional AI-induced added value over the next five years. Although both studies use very different approaches, they nevertheless produce comparable results.

Chen et al. (2016) combine two approaches. On the one hand, the authors use AI investments (private sector and venture capital investments) for their estimates. On the other hand, the calculation also uses historical data which serves as a basis for assessing the impact of previous technologies (such as mobile phones, broadband Internet and industrial robots) on economic growth. Depending on the method, the authors thus calculate additional annual AI-induced growth of between 0.2% and 1.0% of gross domestic product (GDP) by 2025.

Purdy and Daugherty (2017), on the other hand, use a macroeconomic model capable of mapping 12 countries and 16 economic sectors in order to calculate AI-induced growth. The authors calculate additional 1.6% annual gross added value due to AI for the German economy as a whole and 2.3% for the global manufacturing industry in 2035. The relatively long time horizon of the study is due to the authors' expectation that the technology will require such a long phase to unfold its full potential.

Our own calculations suggest that linear interpolation of the growth rates calculated by Purdy and Daugherty (2017) up until 2023 will result in average AI-induced annual growth in the manufacturing industry in Germany of 0.69%.[9] Assuming a moderate annual growth rate of 1.5% independent of AI, this leads to additional gross added value in the manufacturing sector in Germany of EUR 31.8 billion during the period from 2019 to 2023 which is relevant for this study. This corresponds to around one third of total future growth (see Fig. 8).

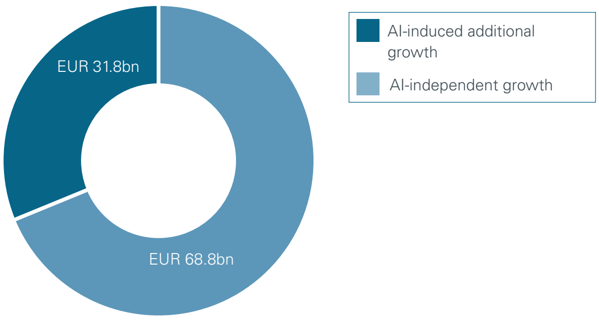


Fig. 8: Estimation of the additional AI-induced growth from 2019-2023 in the manufacturing sector (source: iit)

9 Regarding the plausibility of this value, it should be noted that it is contained in the interval calculated by Chen et al. (2016).

4 Assessments and expectations of AI providers and users in the manufacturing sector

The step model described in section 2.2 forms the framework for the online survey presented here. Providers of AI technologies as well as users from the manufacturing sector and scientists working on AI were interviewed as part of this survey. The key assumption is that each of these groups surveyed has different areas of core competence. Users, for instance, are primarily familiar with the value chain and application levels, whilst the expertise of AI providers additionally includes the technology level since they use AI technologies in order to develop applications for very specific stages of their customers' value chains. The scientists' view differs from that of the users and providers in that the competence of the latter groups primarily concerns the application and technology level. Different questionnaires were therefore developed for the different groups surveyed.

4.1 Potential of AI applications and technologies

This section first analyses the future potential of the individual AI applications. An additional aspect of the analysis addresses the question as to which AI technologies are used in which AI applications. This in turn allows conclusions to be drawn regarding the strategic importance of individual AI technologies.

4.1.1 Potential of AI applications

As part of the online survey, providers and potential users were first asked about the disruptive potential[10] of individual AI applications over a time horizon of five years. Fig. 9 compares the percentages of providers and users who consider the respective applications to present high to very high potential. Both groups consider predictive analytics, smart assistance systems, smart automation, robotics and smart sensor technology to be the most relevant AI applications.

The illustration also shows that the assessments of users and providers are very homogeneous. Accordingly, the data points line up along the 45° diagonal which marks the area in which the same number of users and providers attribute high to very high potential to the respective AI application.

One striking result of Fig. 9 is that just around half of the providers and users surveyed consider the application of autonomous driving and flying to have high to very high potential in the manufacturing sector. The same applies to optimised resource management. The quality control application came last in the survey. Just around 40% of providers and 45% of users consider this to have particularly high potential.

10 The disruptive potential is here understood to be the potential to change existing structures, processes and business models. This definition was also given to the participants of the survey.

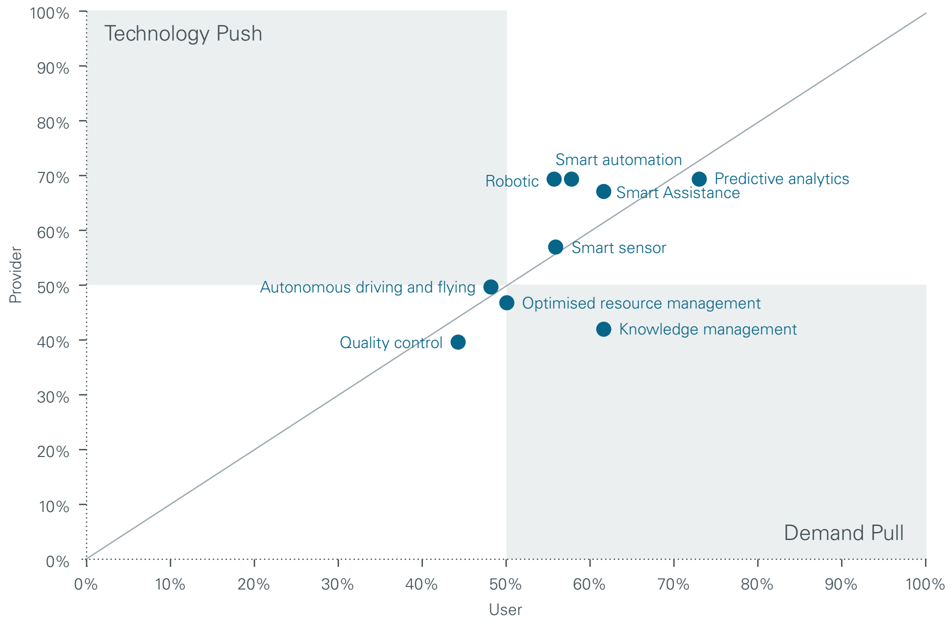


Fig. 9: Share of users and providers surveyed who attribute high to very high disruptive potential to the respective AI applications in five years (source: iit)

Small and medium-sized enterprises (SMEs) and large corporations also report different assessments of the future application potential of AI in certain areas. Differences can be found in robotics and optimised resource management where large corporations see greater potential whilst SMEs put a stronger focus on knowledge management and quality control (see Fig. 10).

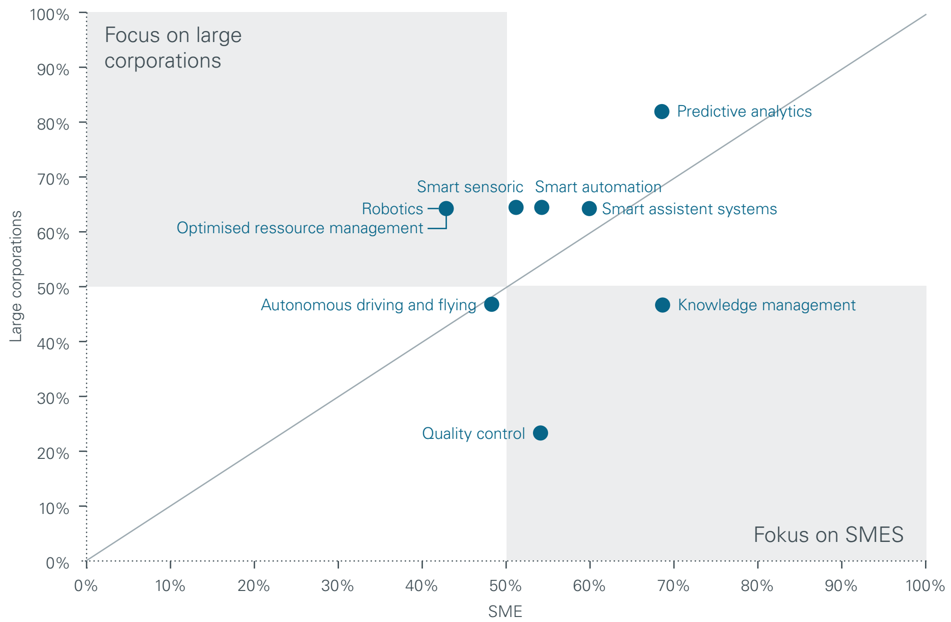


Fig. 10: Share of users surveyed in large corporations and small and medium-sized enterprises attributing high to very high disruptive potential to the respective AI applications (source: iit)

4.1.2 Assignment of AI technologies and AI applications

This section focuses on the question regarding the AI technologies on which the respective AI applications are based. The results are based on the assessments of both providers of AI technologies and researchers.

Fig. 11 shows the distribution of the answers as a heat map. The darker the colour, the greater the share of researchers and AI technology providers who assign the respective technology to the corresponding application. On the one hand, this shows which technologies are used in which applications. On the other hand, it is also possible to identify important cross-cutting technologies which are important for many different applications.

Fig. 11 shows that some applications are based on a few individual technologies and others on a wide range of underlying technologies. These differences can also be found between the above-mentioned AI applications that offer the highest potential. Predictive analytics, for instance, is almost exclusively based on machine learning, whilst all AI technologies, with the exception of neuromorphic computing, are relevant for smart assistance systems. Computer vision, machine learning as well as action planning and optimisation as well as cognitive modelling are important for robotics. Smart automation primarily uses machine learning as well as action planning and optimisation and, to a lesser extent, computer vision. Smart sensor technology, on the other hand, is primarily based on machine learning and computer vision.

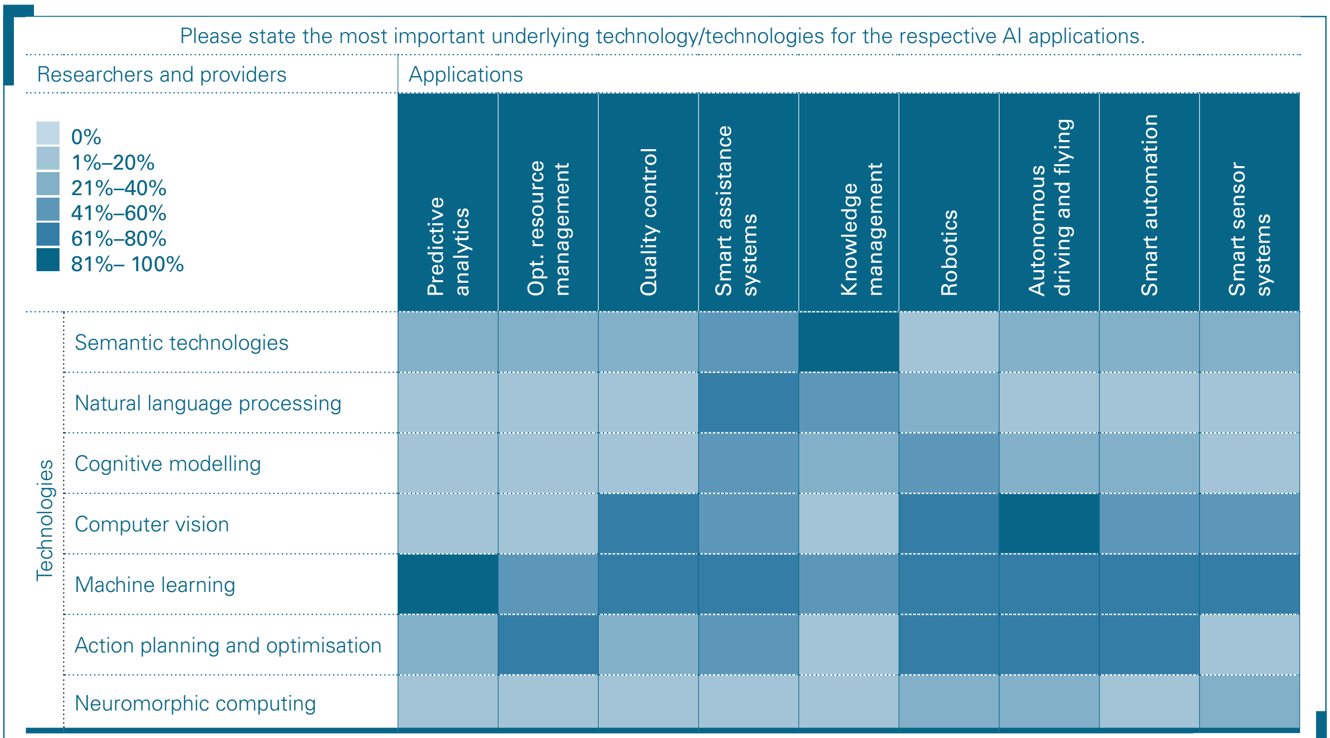


Fig. 11: Share of providers and researchers who assigned the respective AI technologies to the corresponding AI applications (source: iit)

Fig. 11 also clearly shows that the AI technologies that can be attributed to the rational approach (computer vision, machine learning, action planning and optimisation, see section

2.2.3) are used equally in many different AI applications and therefore constitute important cross-cutting technologies of strategic importance. Machine learning, in particular, plays an important role in all AI applications without exception. Behaviour-orientated technologies, on the other hand, are used specifically where the focus is on direct interaction with humans. This is primarily the case in smart assistance systems and knowledge management. Only semantic technologies can also be considered to have a certain cross-cutting character, albeit at a significantly lower level. Biologically inspired neuromorphic computing, on the other hand, is relatively insignificant for all AI applications. This hardware technology is still under development in many respects and, unlike most other AI technologies, has not experienced major growth momentum in recent years driven by the availability of large amounts of data and increased computing power.

4.2 Current use of AI in the manufacturing sector

This section shows the extent to which AI is already being used in manufacturing today. Further key points of the analysis are co-operation between users and external providers as well as relevant system requirements.

4.2.1 Current use of AI along the value chain

In order to outline the current status of the use of AI technologies in Germany's manufacturing sector, users were asked about the current use of AI in the various stages of the value chain. Taking the total of nine stages of the value chain, an average of 25% of large corporations and 15% of SMEs stated that they are using AI technologies at least to a small extent.

Large corporations identified research and development, logistics, service/after-sales service, marketing/sales and planning as the main areas of AI use so far. Similar to large corporations, up to now SMEs have mainly worked with AI technologies in research and development, service/after-sales service, marketing/sales and planning. The largest differences are found in logistics and production, where only 6% and 8% of SMEs, respectively, use AI technologies (see Fig. 12).[11]

11 Two factors must be considered when it comes to assessing the sometimes very high share of companies who state that they already use AI technologies at the respective stages of the value chain. On the one hand, it can be assumed that involvement of the participants of the BMWi-funded technology programmes means that early adopters of new technologies are more strongly represented within the group of respondents than in the total population of manufacturing companies. On the other hand, Fig. 12 also includes companies that use AI technologies to a very limited extent only or which merely experiment with them.

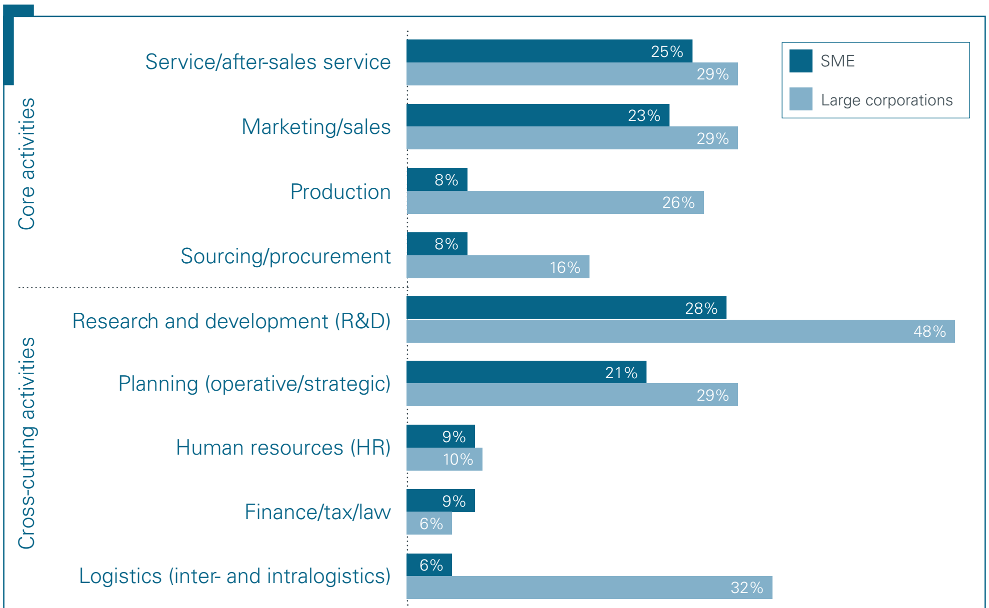


Fig. 12: Share of large corporations and SMEs already using AI technologies at least to a small extent in the respective stages of the value chain (source: iit)

Based on the results, the users were asked which share of activities in their company was already performed by AI systems at the time of the survey. The focus was expressly on the degree to which decisions are automated. A degree of automation of 0% means that process optimisation decisions are exclusively made by humans, whilst 100% corresponds to the case of fully autonomous machine decisions for the control of processes using artificial intelligence.

Fig. 13 summarises the user responses in the form of a heat map. It becomes clear that the vast majority of SMEs do not yet have any activities at the respective stages of the value chain carried out by autonomously acting machines.[12] Only a minority of SMEs indicate that 10% and more of process control decisions are made by autonomous AI systems.

In the case of large corporations, the share of companies where 10% or more of process optimisation decisions are automated is slightly higher in many stages of the value chain than at SMEs. However, the majority of large corporations also say that they do let AI systems make any process optimisation decisions autonomously.

12 This does, of course, not mean that these companies do not use automation at all. However, all decisions In automated environments are still made by humans and not by AI-based systems.

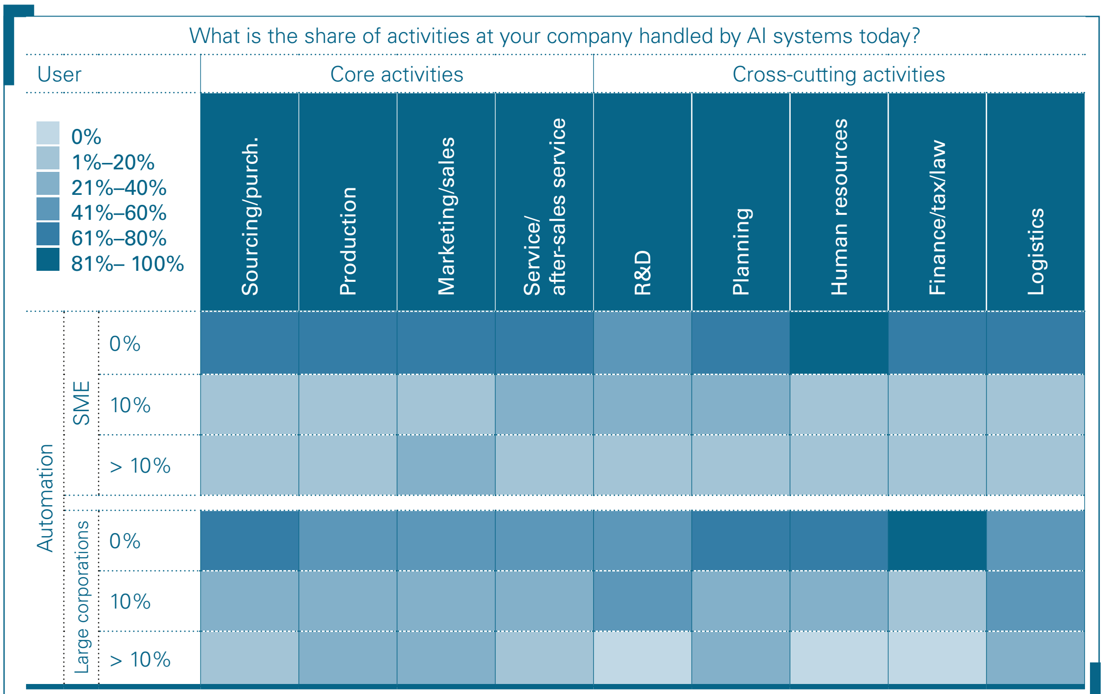


Fig. 13: Degree of automation of decisions at SMEs and large corporations (Source: iit)

In order to determine which AI applications are used at the individual stages of the value chain, the providers were asked about their relevant areas of application. Fig. 14 shows this distribution in the form of a heat map. This leads to a differentiated picture, depending on the stage of the value chain and the AI application.

Although Fig. 12 shows that production as an area of AI application comes only sixth for large corporations and seventh for SMEs, this stage of the value chain can offer most application potential for AI applications. Furthermore, broad application possibilities exist for AI applications in service/after-sales service and logistics. The same applies to research and development, albeit at a much lower level. In contrast, the main applications in marketing are knowledge management, smart assistance systems and predictive analytics. Optimised resource management, predictive analytics and knowledge management are used primarily in planning. Sourcing/procurement, personnel management and finance/tax/law are up to now areas with the smallest potential for applications. This result is also reflected, among other things, in Fig. 12 in the small shares of companies that use AI technologies at these stages of the value chain.

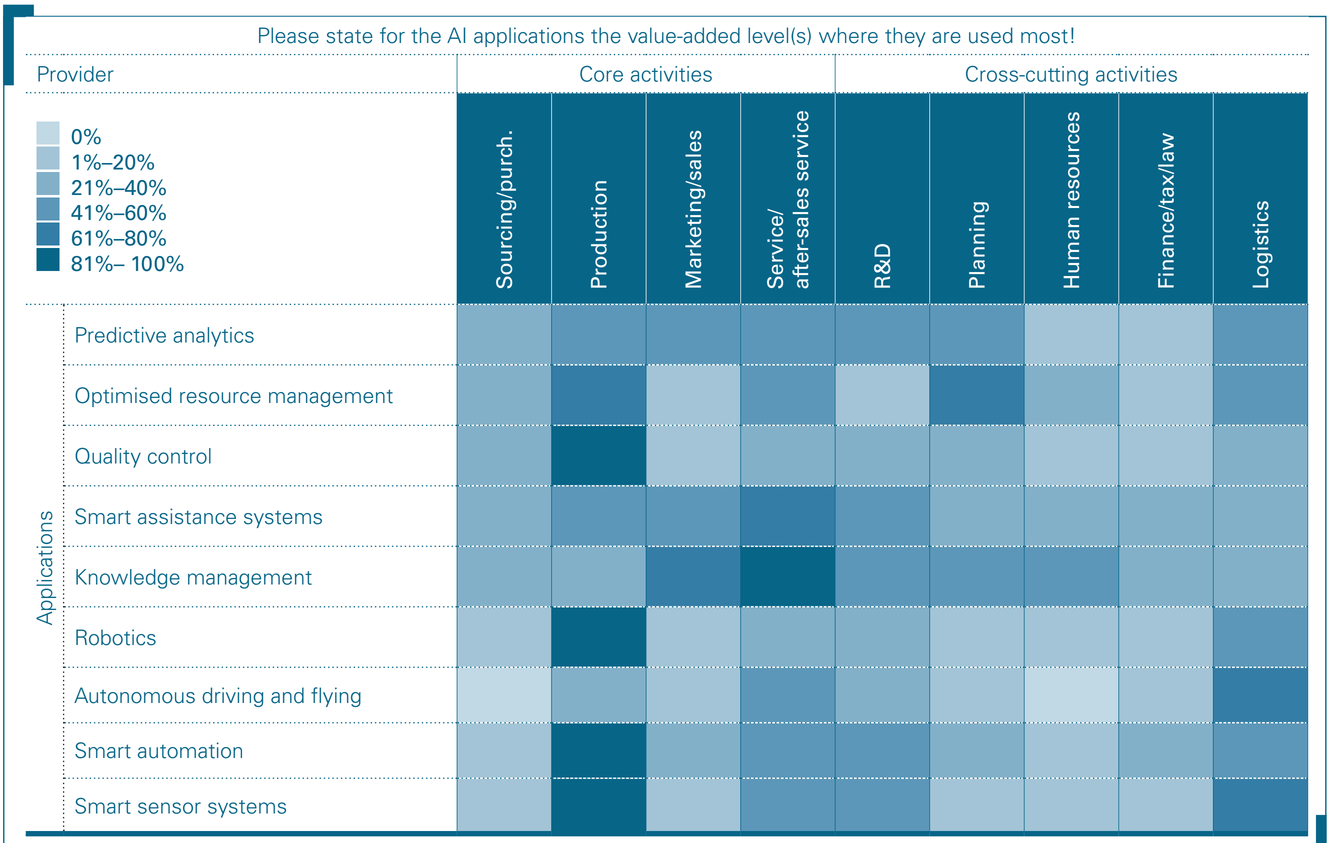


Fig. 14: Use of AI applications in the individual stages of the value chain (source: iit)

4.2.2 Co-operation with external service providers

In order to draw a comprehensive picture of the use of AI technologies in the manufacturing industry to date, the analysis also focuses on the distinction between in-house developments and co-operation with external service providers. For this purpose, the users who stated that they use AI technologies at the respective stages of the value chain were asked about the stages in which they co-operate with external AI providers (see Fig. 15).

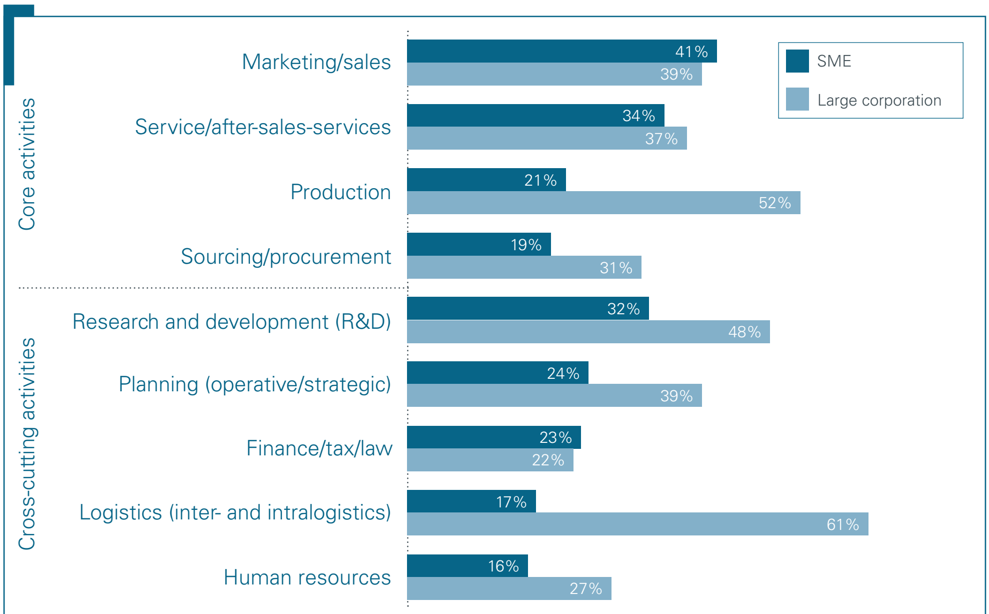


Fig. 15: Share of SMEs and large corporations surveyed already working with external AI providers in the respective stages of the value chain, in as far as they use AI technologies (source: iit)

A comparison between SMEs and large corporations shows a number of key differentiating features. Whilst only 21% and 17%, respectively, of SMEs that use AI technologies in production and logistics also co-operate with external AI service providers, the figures for large corporations are significantly higher at 52% and 61%, respectively. In research and development and planning too, more large corporations than SMEs work with external service providers. This result is remarkable in that it can be generally assumed that large corporations have greater potential for in-house development. Overall, large corporations seem to trust external service providers more than SMEs do.

4.2.3 Relevant system requirements

Another aim of the present study was to identify and evaluate relevant system requirements for the use of AI technologies. To this end, respondents were asked to assess the relevance of the requirements stated in the expert interviews. Table 4 describes the system requirements that were identified.

System requirements	Explanation
Cloud computing	Provision of the powerful IT infrastructure for complex calculations, data storage and execution of Internet-related software applications
Sensor systems	Technologies for the recognition, measurement and control of changes in the environment or in a technical system
Edge computing	IT infrastructures for decentralised data storage and processing
Data sovereignty, access	Legal provisions governing the use, access and exploitation of data
Data quality	Completeness of data, uniform formatting or degree of detail, interruption-free data recording
Robustness of algorithms (response to unexpected situations)	Reliability of data analysis results, response to outliers and unexpected situations
Training duration and effort for algorithms	Time and manpower spent for the reliable identification of objects or actions resulting from collecting and annotating training data
Computing effort/energy efficiency	Complex calculations of motion sequences during action planning, process or parameter optimisation taking several optimization criteria into account
IT security	Protection of sensitive company data against cyber attacks
Functional safety	Reliable and safe operation of industrial systems, minimisation of the risk of personal injury
Interoperability of AI procedures and data	Transferability of AI procedures to other data sources, consistency of data models and formats for reuse of data and algorithms

Table 4: System requirements for the efficient use of AI (source: iit)

Fig. 15 shows the assessments of the system requirements by both providers and users. This is compared with the share of users and providers who rated the corresponding system requirements to be significant to very significant. The assessments by providers and users are generally very homogeneous and underline the relevance of the previously identified system requirements. The majority of respondents consider most of the requirements to be significant or very significant. Both sides say that robust algorithms, data quality, sensor systems as well as data sovereignty and access to data are the most important requirements. Compared with providers, users also place greater emphasis on IT security and functional security as well as interoperability of AI procedures and data. The comparison of the assessments by SMEs and large corporations as users, on the other hand, did not show any significant differences.

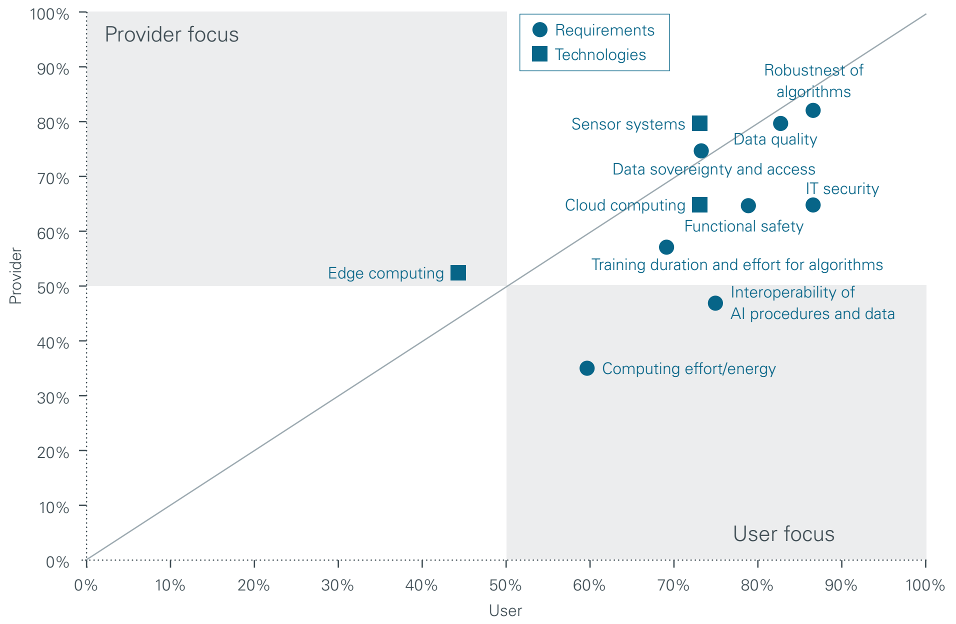
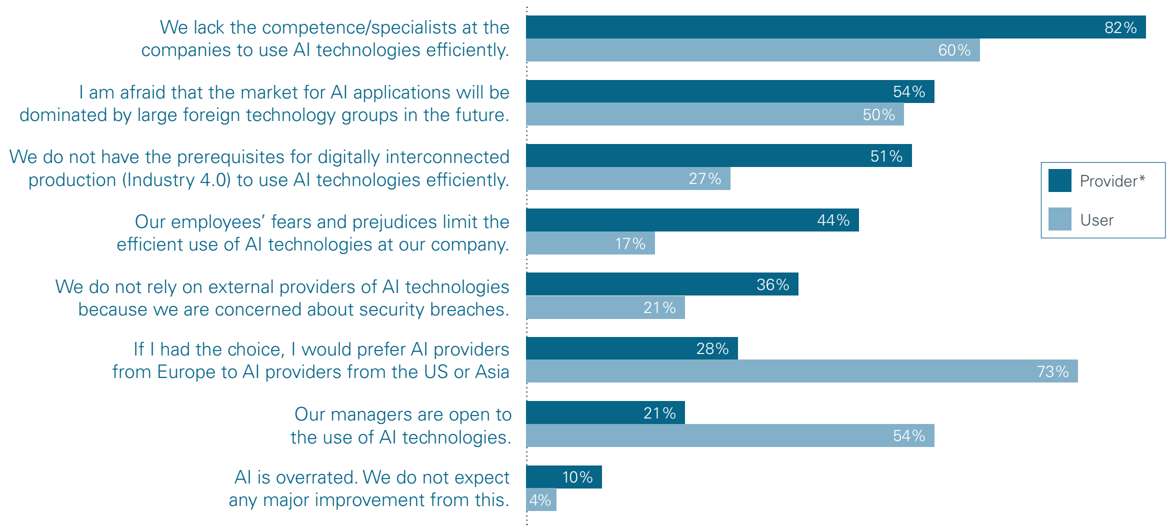


Fig. 16: Share of providers and users surveyed who consider the respective system requirements for the use of AI to be significant to very significant (source: iit)

The expert interviews also revealed further possible success factors for and obstacles to the efficient use of AI as well as attitudes and prejudices at the user end which were also to be evaluated.



* Slightly changed question: Providers were asked the question in relation to all the companies in the manufacturing sector.

Fig. 17: Share of providers and users surveyed who agree or fully agree with the respective statements (source: iit)

Fig. 17 shows that the lack of internal competence and skilled staff in the manufacturing sector is one of the greatest obstacles to the use of AI technologies. Users and providers also agree that there is a risk that the market for AI applications could be dominated in future by large foreign corporations, with around half of the companies surveyed endorsing this statement.

Interesting insights, however, arise especially from the differences between the views expressed by users and providers. A good half of providers, for instance, complain that the manufacturing industry lacks the necessary prerequisites for digitally interconnected production. In contrast, only 27% of the users surveyed share this view. This indicates that some companies in the manufacturing sector underestimate the necessary requirements for the use of AI, so that there is a certain need for information.[13]

Moreover, 44% of the providers surveyed stated that concerns and prejudices among employees of manufacturing companies restrict the efficient use of AI at these companies. However, only 17% of users estimate that this applies to them. A similar picture can be seen with regard to the open-mindedness of managers. 54% of users believe that their managers are open to the use of AI. In contrast, only 21% of providers consider this open-mindedness in the manufacturing sector to be a given fact. Even if a possible early adopter bias among users may make the differences appear larger than they actually are, the assessments by AI providers in Germany should be taken seriously in this respect.

Another relevant finding is that the providers of AI technologies surveyed are hardly aware of their competitive advantage as German companies. Only 28% of the suppliers surveyed believe that manufacturing companies would prefer European suppliers to those from the US or Asia, but 73% of the users surveyed express precisely this preference, thus voting strongly in favour of technological sovereignty. It is evident that providers are not always aware ofthe competitive advantage they have as European companies.

13 For the sake of completeness, the early adopter bias within the user sample should be once again mentioned at this point. It is therefore not possible to fully rule out that the share of users surveyed who have in fact created the necessary preconditions is greater than in the total population of manufacturing companies.

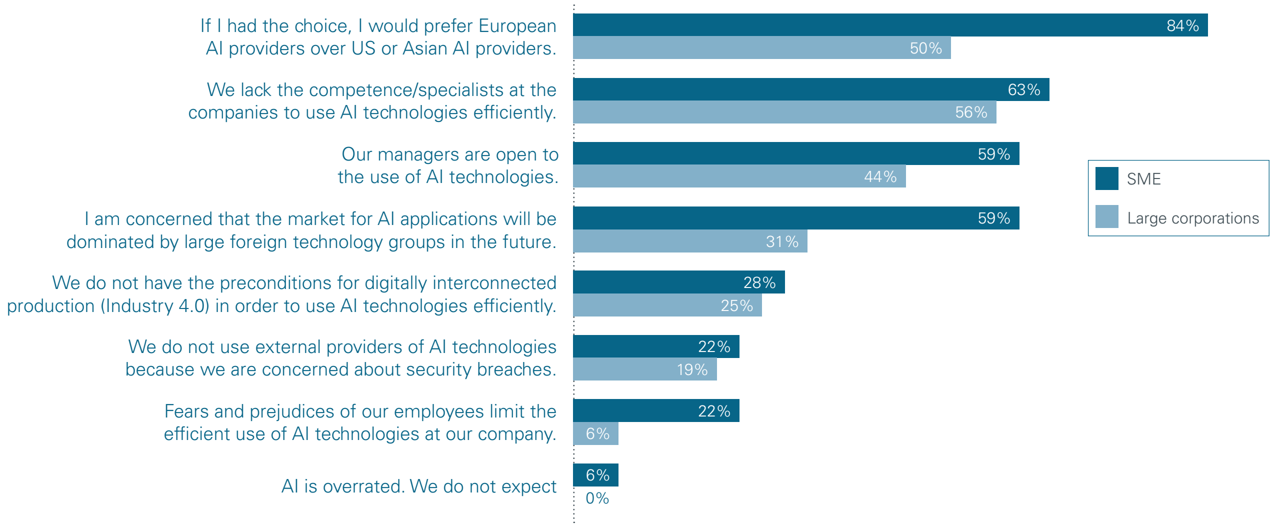


Fig. 18: Share of providers and users (large corporations and SMEs) surveyed who agree or fully agree with the respective statements (source: iit)

The statements made by SMEs were also compared with those of large corporations regarding success factors and obstacles (see Fig. 18). It becomes clear that preference for European AI providers is stronger among SMEs than among large corporations. In the latter case, this only applies to half of the respondents. Furthermore, SMEs tend to be concerned about the dominance of large international corporations on the market for AI applications. This underlines the assumption that SMEs are generally more sceptical about the security of AI applications and are therefore reluctant to enter into co-operation relationships.

4.3 Effects of the use of AI

The following analysis addresses expectations regarding the future use of AI in more detail. The analysis additionally looks at future co-operation with external service providers as well as the assessment of the stakeholders' current and future competitiveness.

4.3.1 Expectations regarding the future use of AI along the value chain

This section presents the results of the expected changes in industrial value chains resulting from AI. Fig. 19 compares the shares of companies that stated that they already use AI technologies today and that they will probably use AI five years from now at the individual stages of the value chain. The result clearly shows that companies in the manufacturing sector are planning to use AI technologies more in the future without exception at all stages of the value chain. More than half of the companies expect to use AI technologies in 5 years for all of their core activities. Most companies expect this in service/after-sales service and marketing/sales. For cross-cutting activities, at least 40% of companies expect to use AI technologies in five years. The majority of companies expect this in research and development as well as in planning.

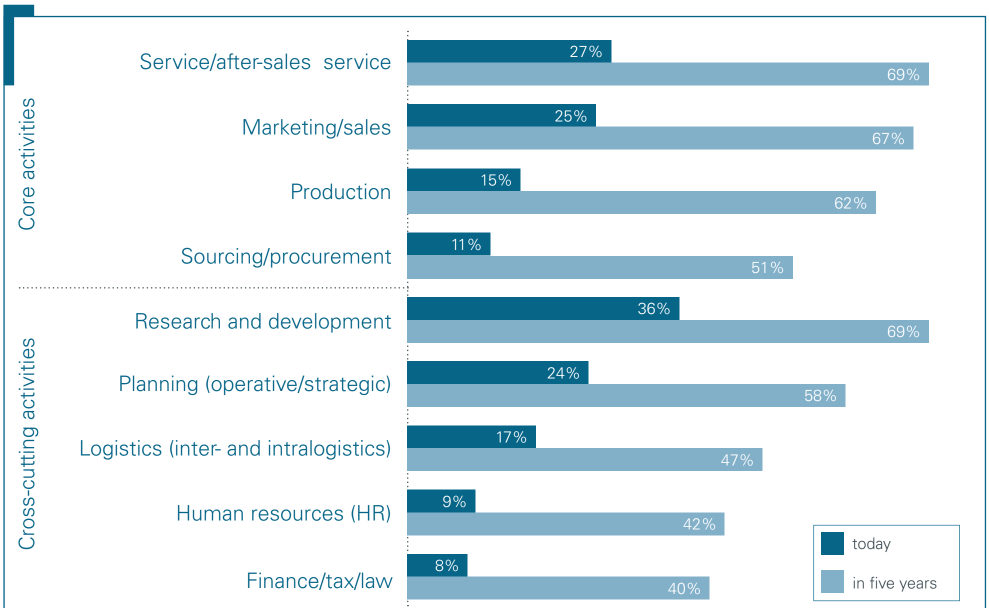


Fig. 19: Share of users surveyed who use AI technologies in the respective stages of the value chain today and probably in five years at least to a certain extent (source: iit)

In a more differentiated picture, Fig. 20 compares the expectations of large corporations and SMEs, showing the shares of large companies and SMEs that expect to use AI technologies in five years' time for each stage of the value chain. Overall, the expectations prove to be very homogeneous for the majority of the stages of the value chain. More than half of the SMEs and large corporations expect to use AI technologies in five years in research and development, marketing/sales, production, service/after-sales service and planning. Moreover, large corporations have a stronger focus on logistics and sourcing/procurement. In both areas, significantly more than half of large corporations, but less than half of SMEs, expect to use AI technologies.

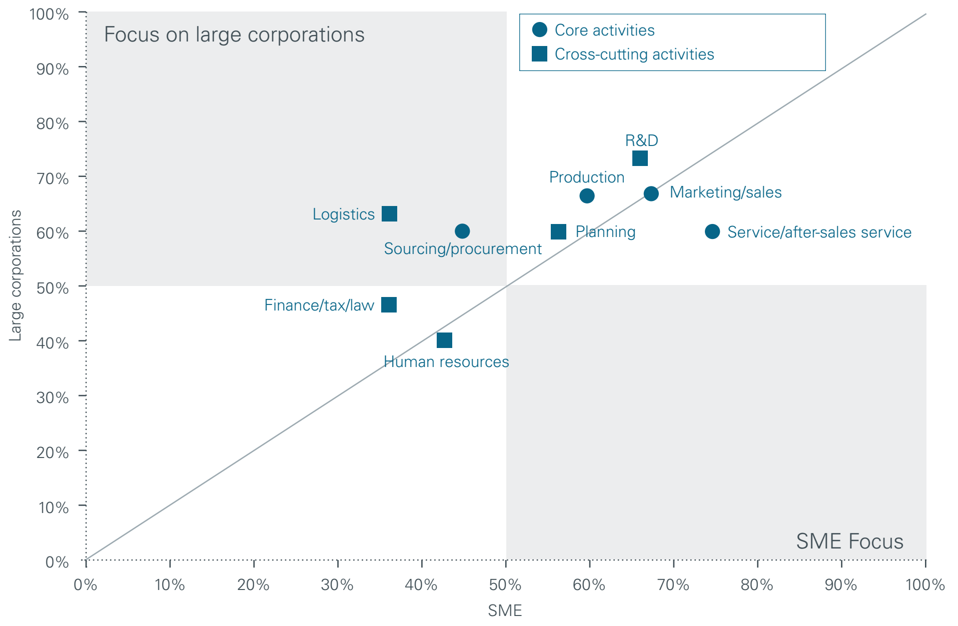


Fig. 20: Share of users surveyed (large corporations and SMEs) who will probably use AI technologies at least to a small extent in the respective stages of the value chain in five years (source: iit)

To illustrate the planned scope of the use of AI technologies, Fig. 21 shows the median values of the expected future use of AI along the users' value chain.[14] Fig. 21 clearly shows that half of the companies surveyed plan to use AI at least to a medium extent across all stages of the value chain. The highest values are reported for production, marketing/sales, service/after-sakes service as well as research and development.

14 The median divides all respondents into two equal halves, i.e. one half states a lower and the other one a higher value.

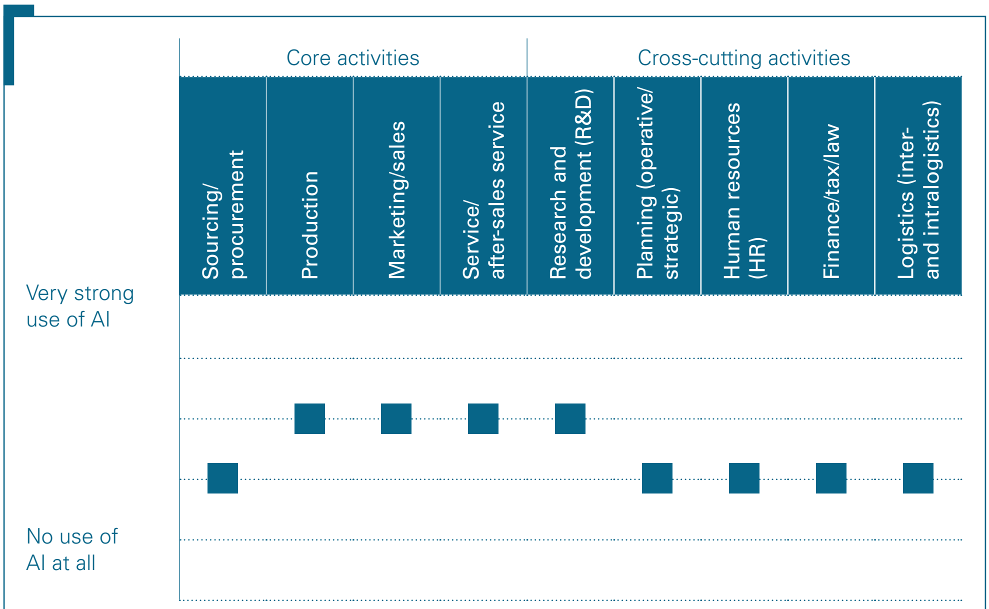


Fig. 21: Average value (median) of the users surveyed who are expected to use AI technologies in the respective stages of the value chain in five years (source: iit)

The expectations of companies shows a similar picture with regard to the share of activities at the stages of the value chain which will be taken over in the future by autonomous systems. As already shown, this share is currently still 0% for the majority of companies, but most companies expect that in five years' time this share will have increased to more than 10% at almost all stages of the value chain (Fig. 22).

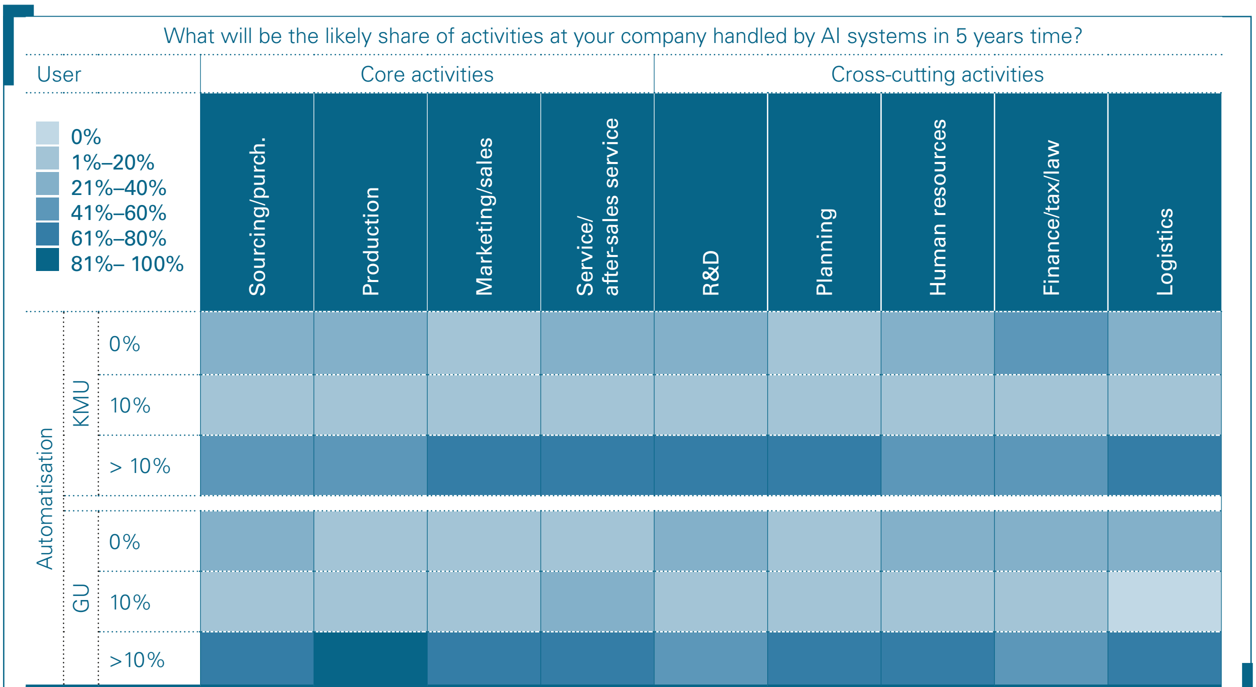


Fig. 22: Future expected level of automation of decisions (in five years) (source: iit)

4.3.2 Expectations for co-operation with external service providers

After the previous chapter identified missing internal competence and skilled staff as a significant obstacle to the use of AI technologies, the question now arises as to how the expectations described above can be implemented. One option is co-operation with external AI service providers. As shown above, 20% of companies consider security concerns to be an obstacle. SMEs, for their part, have more concerns in this respect than large corporations. Fig. 23 therefore compares the current willingness to co-operate with external AI providers with the expected future inclination to co-operate and shows a clear increase. While 19% to a maximum of 40% – depending on the respective stage of the value chain – of companies which already use AI rely on the services of external providers, far more than half of all companies expect to co-operate with external service providers at all stages of the value chain in five years' time. One can hence conclude that the majority of companies are pursuing an outsourcing strategy for the future implementation of AI technologies.

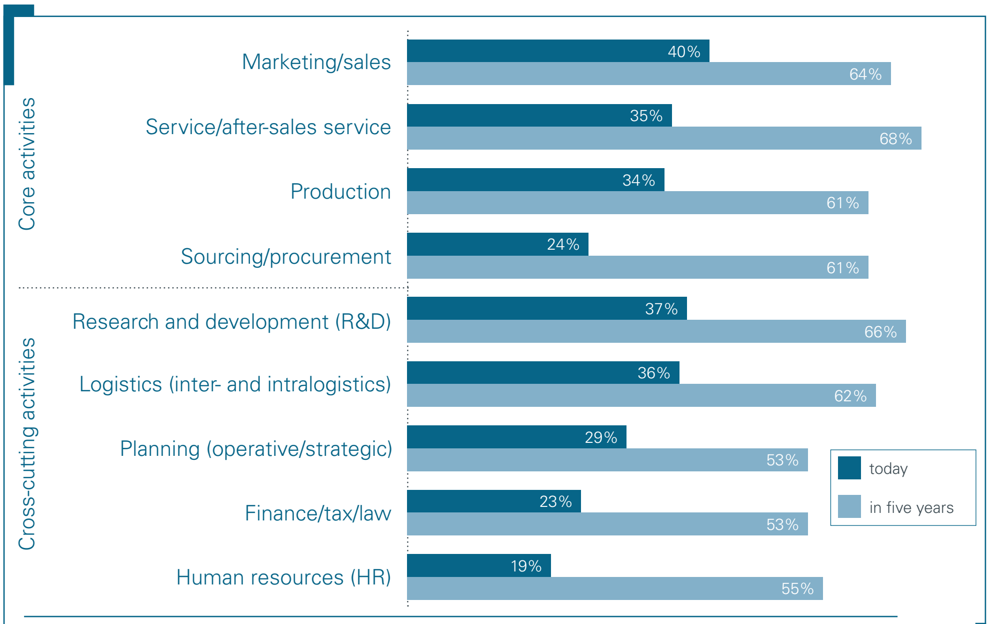


Fig. 23: Share of users surveyed who use external AI providers in the respective stages of the value chain today and probably in five years (source: iit)

The comparison between users and providers of AI technologies in Fig. 24 again shows that the majority of users and providers expect increased use of AI technologies in five years from now in the areas of research and development, service/after-sales service, production, marketing/sales and planning. Providers naturally take a somewhat more optimistic view, so that all data points are above the 45° diagonal.

A demand pull effect, where user expectations are not reflected by similar expectations among providers (lower right quadrant), is therefore not visible. However, a certain degree of technology-push-induced innovation potential can be seen in the areas of logistics, human resources and finance/tax/law (left upper quadrant). Less than half of the users expect that AI will be used in future for these stages of the value chain. At the same time, however, a clear majority of providers expect AI technologies to be used in these areas in the future. It can therefore be expected that the providers will develop corresponding products and place them on the market.

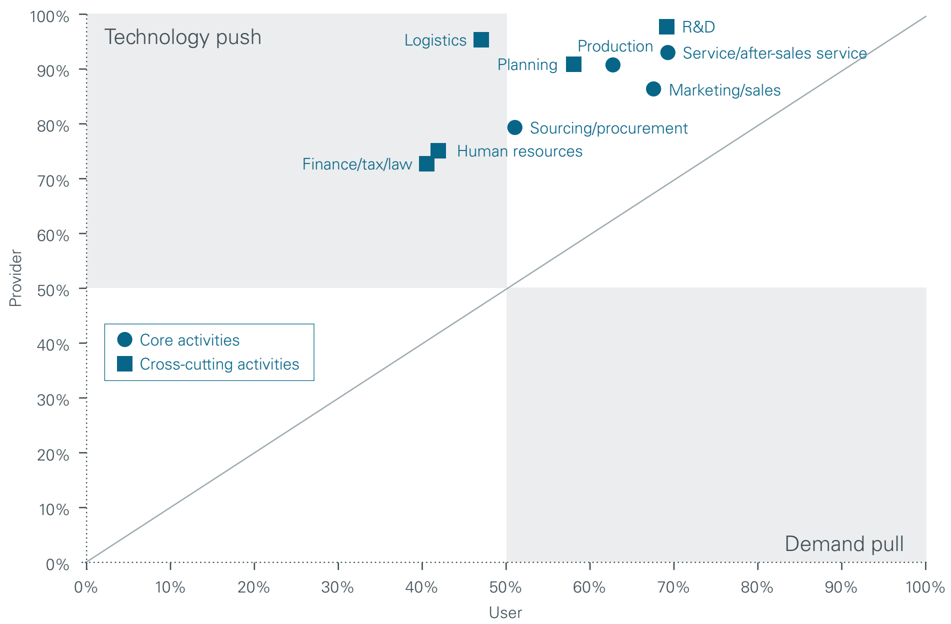


Fig. 24: Share of providers and users who expect to use AI technologies in the next five years in each stage of the value chain (source: iit)

4.3.3 Assessment of competitiveness by the stakeholders

The assessments by AI providers and AI researchers are compared in order to map the current level of competitiveness with a view to AI. The comparison provides a first idea of the degree of success to which research results are transferred from basic research to application. It becomes clear here that the matching between research results and their transfer to application in individual research areas is fraught with difficulties.

This is demonstrated by the fact that, even though researchers consider Germany to be an international leader in the field of natural language processing and cognitive modelling, these technologies are not among the areas where providers consider Germany to have a leading role. Assuming that the assessments given by the two groups for themselves are in each case correct, it is reasonable to conclude that German research results from these two areas are not sufficiently passed on to German technology providers. Looking to the US, it is noticeable that providers are considered to be very competitive, which corresponds very well with excellence in research. The high degree of agreement indicates that the US economy appears to be very well able to absorb the results of basic research (Fig. 25).

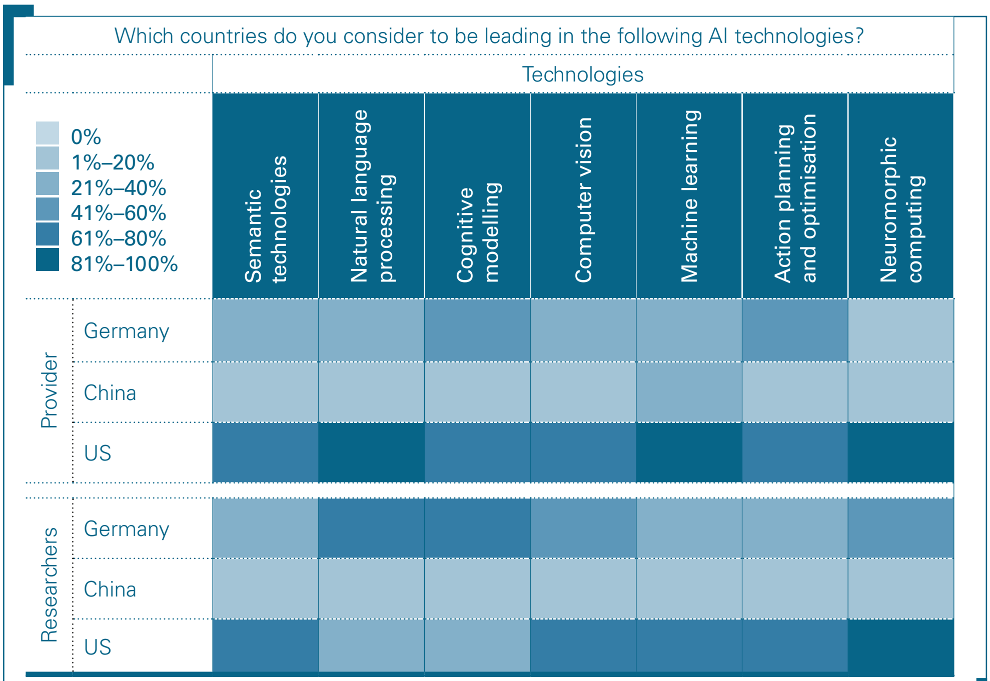


Fig. 25: Leading countries in terms of different AI technologies (assessment by providers and researchers) (source: iit)

A look at AI applications shows that the transfer of research results to concrete applications in Germany is not a general problem. Here, both researchers and providers surveyed see clear advantages for Germany in the areas of quality control, smart automation and smart

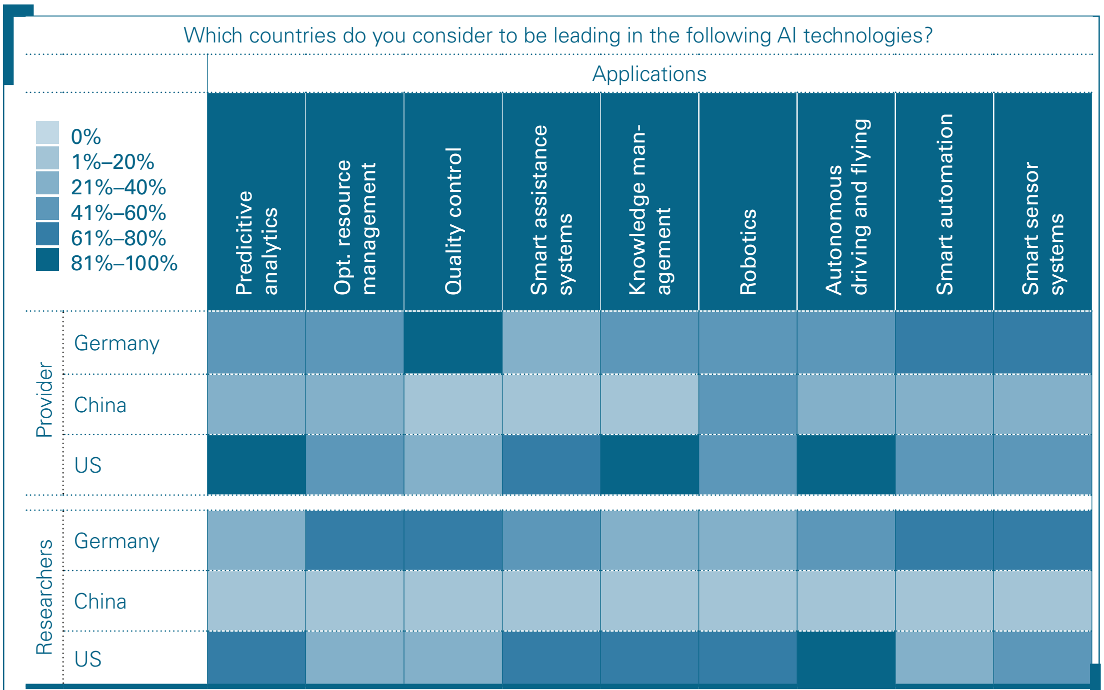


Fig. 26: Leading countries in terms of different AI applications (assessment by providers and researchers) (source: iit)

sensor technology (Fig. 26). In these areas, Germany seems to be good at combining AI technologies and generating applications on this basis. This ability to translate technical innovation into marketable applications and products is known to be one of the central strengths of the German innovation system.[15]

The technology providers surveyed currently perceive US companies to be their biggest competitors. With a view to China, competition is expected to increase in the future, but Chinese companies are currently hardly seen as competitors. That being said, it is expected that providers from China will also enter the German market in the future (see Fig. 27). However, the assessment of China's current importance in the field of AI by the researchers and providers surveyed is to a certain extent contrasted by China's publication strength as shown in Chapter 5 and the exceptionally high number of Chinese AI start-ups. It is obvious that, despite China's high level of commitment, the respondents do not yet consider China to be a leading location for AI technologies and applications in the manufacturing industry.

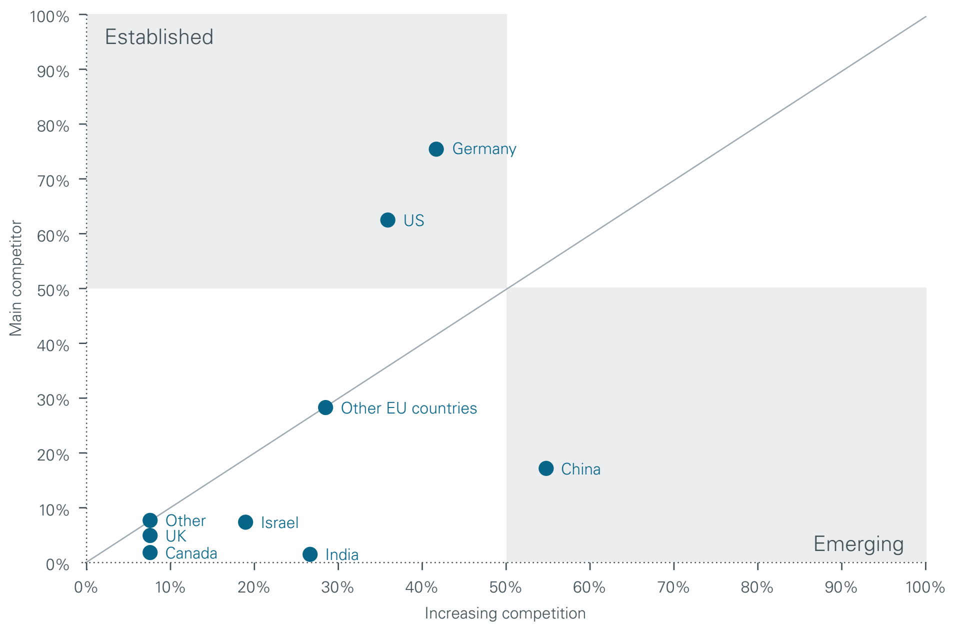


Fig. 27: Share of suppliers stating that their main competitors are based in the respective countries and expecting increasing competition from these countries (source: iit)

15 This is also reflected, for instance, by the iit indicator which systematically analyses the innovative capacity of economies where Germany currently ranks fourth (see iit 2018).

5 Technology transfer for AI in Germany

A comprehensive description of the innovation system is provided by the EFI Commission of Experts (2018) whose current report concludes that Germany is well positioned in basic research, but shows weaknesses when it comes to transferring research results to industry. This aspect will therefore be examined in greater depth by looking at the output of the German science system, the start-up ecosystem and the regional structure of technology transfer players in the field of AI.

5.1.1 Scientific output

With a view to academia, Germany has the advantage that it is well positioned in AI basic research. After the emergence of AI research in the 1970s and 1980s, there was for a long time a lack of relevant application possibilities due to insufficient computing capacity and data. Whilst many countries consequently reduced research into AI significantly, Germany maintained these efforts all the while, for instance, at the German Research Center for Artificial Intelligence (DFKI), which has existed since 1988 and conducts research at three locations.

This is also reflected by the scientific publications and patents on AI where Germany, together with other nations, plays a leading role: 4.8% of AI publications in the last ten years came from Germany.[16] More publications in this area only originated from China (23.7%), the US (14.5%), India (7.4%) and the UK (5.1%). The efficiency of the science system is also reflected by the fact that 9.5% of the most frequently cited and thus most influential contributions at renowned AI conferences over the past ten years came from researchers in Germany. Together with the US, China, the UK, France and Canada, Germany is thus a leader in the field of AI research (EFI Commission of Experts 2018).

At present, however, Germany is slightly lagging behind in the international comparison. Whilst five years ago German researchers were able to present the largest number of conference papers after the US, they are currently only fifth. It seems that in the course of the current AI boom other countries are overtaking Germany in stepping up their R&D efforts on the topic of AI.

According to the EFI Commission of Experts 2018, Germany is well positioned in terms of patent applications for autonomous systems for autonomous driving and hostile environments, and in the mid-range for smart homes and industrial production. However, the present study shows that a generalised view of entire fields of application or industries does not do justice to the complexity of these applications and industries. Instead, differentiation is mandatory with regard to the different AI applications. As shown in Chapter 4.3.3, the researchers surveyed regard Germany as a leader in the AI applications of smart automation, smart sensor systems, quality control as well as optimised resource management which are important for the manufacturing industry. In contrast, they see the US in the top position in predictive analytics and robotics.

With a view to AI research, Germany generally has a solid basis for accelerating innovation efforts. At the same time, one can see that other countries are investing more in AI than in the past. In order to remain internationally competitive, research activities in Germany must also be stepped up further.

16 Data basis: Web of Science (Clarivate Analytics 2018). Publications in the 'Computer Science, Artificial Intelligence' web-of-science category since 1 January 2008 were considered here.

5.1.2 Start-ups

A key factor for Germany's future competitiveness is the dynamic nature of the start-up community with a focus on AI innovation. In order to gain an insight in this respect, the study evaluated data on the AI start-up environment (based on the Crunchbase 2018 database). In addition to the number of AI start-ups, the database also provides information on company acquisitions as an important indicator of the importance and quality of the AI companies founded.

One result is that the US produces a very large number of AI start-ups in an international comparison. The US records around one and a half times as many AI start-ups as the entire European Union and almost fifteen times as many as Germany (Fig. 28).

The US is thus extremely successful in transferring results from basic research to industry via the start-up channel. The fact that Germany has a deficit here becomes clear when comparing it with the UK since both countries are comparable in terms of size and research performance. The database identifies around two and a half times as many AI start-ups in the UK as in Germany. Drawing on further sources, the study by Lemaire et al. (2018) on the process of founding a AI companies shows comparable relations, but also the large number of Chinese and Israeli start-ups which occupy second and third place, respectively, behind the US. At an international level, only a relatively small number of AI start-ups can be directly assigned to the manufacturing sector. In Germany, for example, these are only eight out of a total of 175 start-ups.

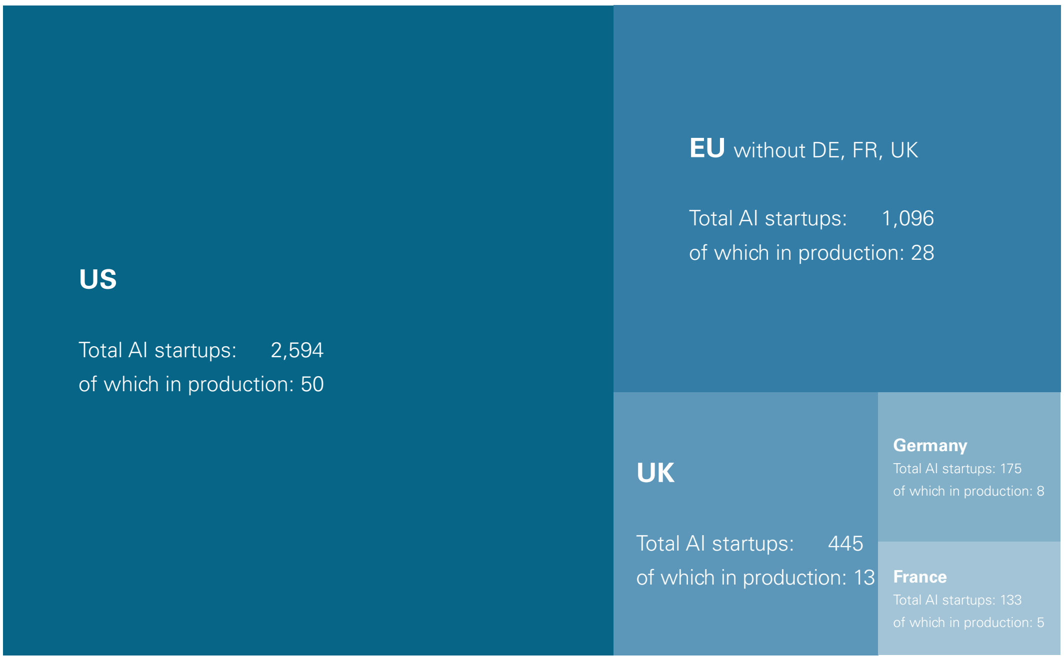


Fig. 28: AI start-ups in the US, Europe, UK, Germany, France and the EU (source: iit, data basis: Crunchbase 2018)

An important channel for technology transfer is the acquisition of start-ups by established companies. Especially for these companies, it can be a successful strategy to acquire start-ups in order to integrate their AI know-how into the buyer company. The Crunchbase database also provides information on such company takeovers. Data on start-ups was evaluated specifically with a view to the frequency of acquisitions. In this case too, it can be seen that US companies are much more agile. They account for a good 72% of global AI start-up acquisitions (Fig. 29). Besides leading Internet groups, other players (such as Salesforce, Teradata) are also making targeted investments in AI start-ups. Considering the dominance of US-based groups in the IT industry, it is not surprising that German companies account for just about 3% of AI start-ups recorded in the database. After all, the two large German Internet groups, i.e. SAP (three acquisitions) and Software AG (two acquisitions) are strategically positioned here (see Fig. 29).

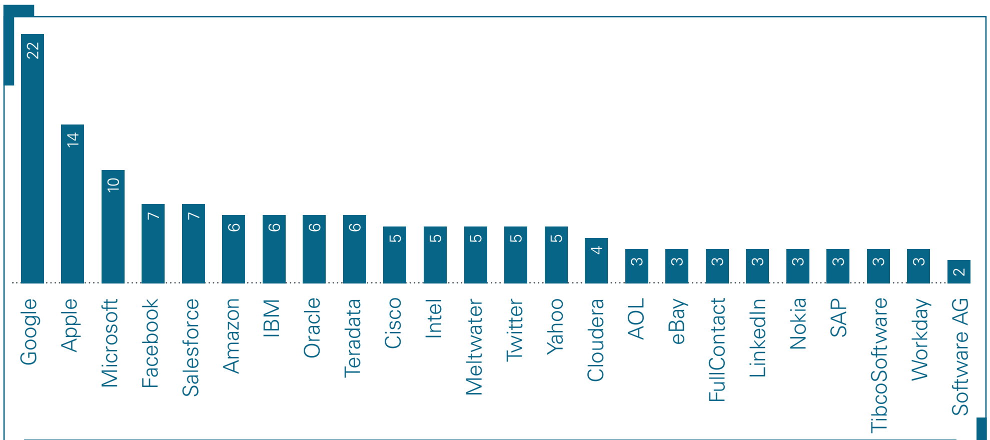


Fig. 29: Companies that have acquired most AI start-ups worldwide (source: iit, data basis: Crunchbase 2018)

The number of start-ups acquired also shows to a certain extent the innovative content and/or economic attractiveness that investors attribute to the start-ups. This also reflects the high potential of the US start-up landscape. Significantly more than half of AI acquisitions were US start-ups, with the UK, Germany, France and Canada are lagging far behind.[17]

The transfer of technology to AI start-ups and from AI start-ups to established ICT companies thus shows too little competitiveness by international standards. The backlog is by no means limited to Germany alone, but also affects other European countries (EFI Commission of Experts 2018).

17 However, the search for external know-how can lead to regional bias (see Broekel and Binder 2007) with the consequence that US groups, for example, first become aware of US rather than European start-ups.

5.1.3 Geographical distribution of basic research and technology transfer players

Despite mobility and digitalisation, technology transfer still depends on the geographical proximity of transfer partners. It is therefore worthwhile taking a look at the regional distribution of basic research institutions and the places where scientific transfer takes place.[18]

Basic research: Research in the GEPRIS database of the German Research Society (DFG, Deutsche Forschungsgemeinschaft) (DFG 2018) serves as the starting point for identifying the main players in basic research as the central funding source for basic research for AI in Germany. The state-funded Max Planck Institutes with their focus on computer science and smart systems are also included in the analysis. The institutes of Fraunhofer Gesellschaft, which specialise in AI, are seen as important stakeholders in application-orientated AI research. However, the main research activities in application-orientated AI areas are carried out at the German Research Center for Artificial Intelligence as the lead organisation, which is another focus of the analysis.

Fig. 30 shows the local concentration of AI research in Germany, which also includes other research institutions, such as universities. The blue circles represent research strength, measured by the number of AI publications in the Web of Science (Clarivate Analytics 2018), and show that German AI research competencies are widely spread and cover a number of locations.

The different locations are heterogeneous in terms of the characteristics of the AI technologies and fields of application where research takes place. The different fields of specialisation of universities and research institutions are also reflected in AI funding measures. For example, DFG supports AI research into action planning and optimisation (for production) in Aachen (EXC 128), into natural language processing in Saarbrücken (EXC 284), into cognitive modelling and natural language processing for human-machine interaction in Bielefeld (EXC 277) and into action planning and optimisation for logistics in Dortmund (SFB 876).

The Max Planck Society and the federal state of Baden-Württemberg support the specialisation of the Tübingen and Stuttgart locations in machine learning, computer vision and robotics with a special focus on autonomous driving applications (Cyber Valley Initiative), while the Fraunhofer Society concentrates its efforts in the field of semantic technologies in the Bonn-Sankt Augustin area (Fraunhofer Institute for Intelligent Analysis and Information Systems).[19] As expected, the publications are closely linked to the science locations.

18 The analysis is based on different data sources. A clear distinction between the different groups of players (AI researchers, providers, users) was not always possible because of the combination of the data from these different sources. Applied research institutes, for example, are often both AI researchers and AI providers; many companies (especially large corporations) are active in research and therefore cannot be seen purely on the demand side (users). The results therefore present a qualitative picture of research activities in Germany.

19 A systematic analysis of the local specialisation of the German AI research locations would require further in-depth investigations. What becomes apparent, however, is that AI technology expertise in Germany is roughly spread over a lower two-digit number of locations that are characterised by local specialisation in specific AI technologies and/or applications.

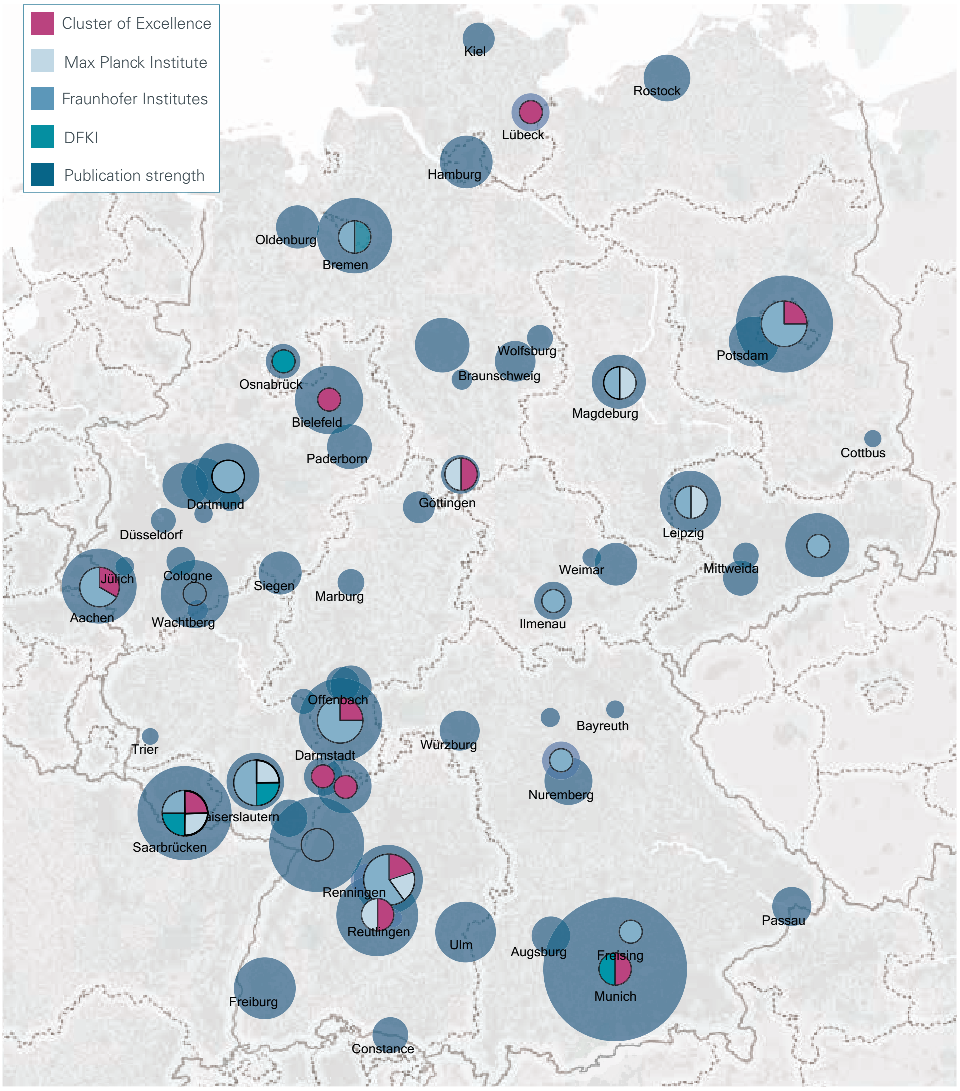


Fig. 30: Regional publication strength in AI over the last 10 years (source: iit, data basis: Web of Science: Clarivate Analytics 2018, GEPRIS: DFG 2018)

Technology transfer: Two main sources of technology transfer can be typically identified, i.e. collaborative projects by science and industry as well as start-ups. Fig. 31 shows the geographical distribution of AI start-ups combined with the allocation of funding. It includes the current projects by BMWi (218 in total), BMBF (215 in total) and the EU (87 in total).[20]

20 Only the current BMBF projects with reference to smart learning systems and BMWi projects with reference to smart systems as well as projects funded within the framework of the Smart Service World I & II and PAiCE technology programmes are considered, without limiting the search to the manufacturing industry. The BMBF projects were included in the evaluation because the majority of them are also application-orientated and their division into basic and applied projects would be rather arbitrary. The selection of the EU projects includes the 'smart' or 'intelligent' search criteria in the aims as well as a restriction to the FoF 2015 17, ICT 2015 17 programmes with the 'Innovation Action' and 'Research Innovation Action' funding schemes. AI projects funded by other parties, such as BMEL, BMVI or BMJV, the federal states and the EU, were not included due to their small number in order to avoid excessive complexity.

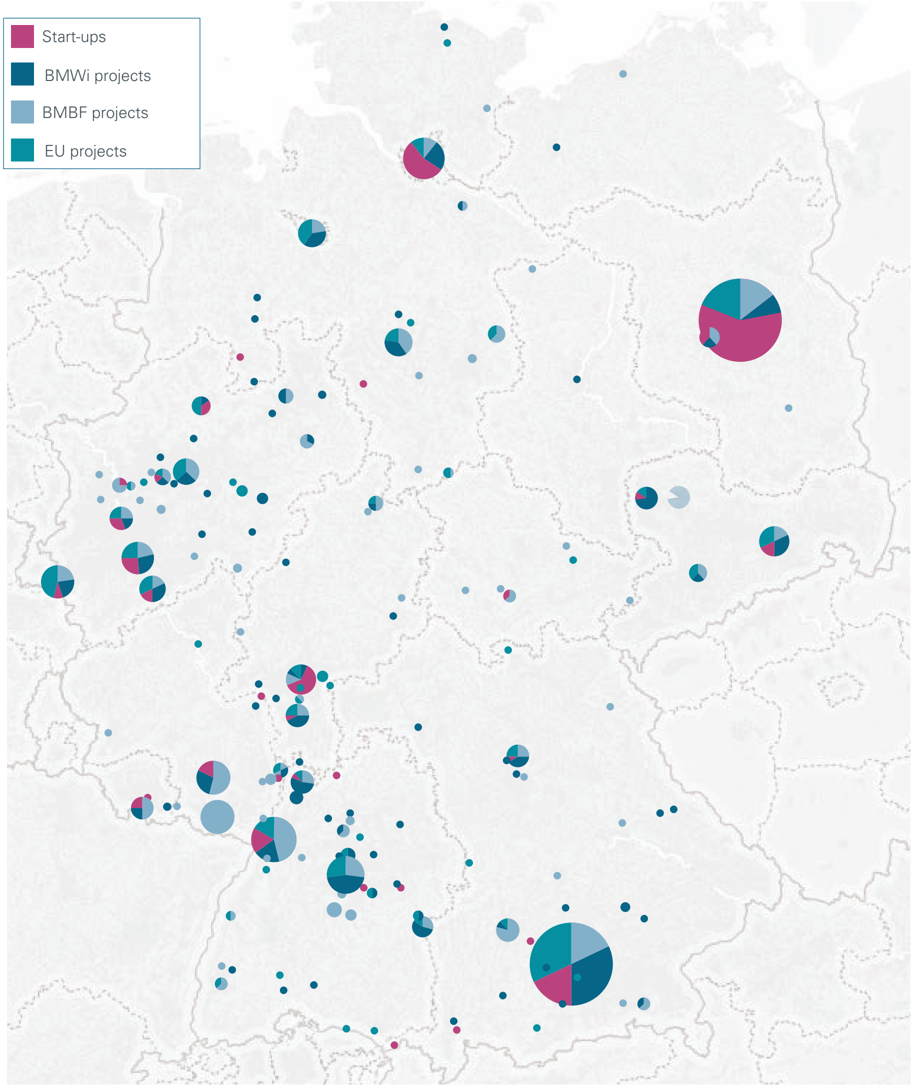


Fig. 31: AI development projects in Germany combined with the number of AI start-ups (source: iit, data basis: Funding Catalogue of the federal government: BMBF 2018, Crunchbase 2018, EU funding database CORDIS: European Commission 2018).

The 169 AI start-ups of the Crunchbase database are additionally covered by the illustration. One striking observation regarding AI start-ups is that they are located almost exclusively in large cities (Berlin, Munich, Hamburg) and, to a lesser extent, at locations (see also Fig. 30) of large AI research institutions, such as the Karlsruhe Institute of Technology. However, there is no strong correlation between the start-ups and the projects funded or research institutions.

The analysis thus supports the impression that the transfer of results from basic research to industry in the form of spin-offs from academia and applied research projects has not yet reached its full potential. There is an overall need for action in this field.

6 Focus on China

The analysis of the current development of AI in China shows that recent political programmes of this country focus hugely on R&D for AI. The Chinese central government considers AI to be a key technology to accelerate the country's economic development. What's more, the individual regions in China have extensive decision-making powers and support companies in their economic activities.

But IT companies from China are also becoming increasingly powerful at the supplier end. Although China's economy continues to be driven to a relatively large extent by the government's politically controlled top-down process, Chinese (IT) companies have recently achieved considerable market success. Today, IT groups, such as Alibaba, Tencent and Baidu, are perceived as global players. At the same time, it is evident that companies are often still strongly influenced by politics.

The areas of application considered in this study as well as in the main research areas (see NSFC guidelines) were found to overlap with the topics and questions addressed in Germany and internationally. The topics include, for instance, language technologies, robotics, autonomous driving and cloud computing.

In its future R&D programmes, China will place a clear emphasis on AI research. For example, a new development plan for AI ('Development Plan for a New Generation of Artificial Intelligence') was adopted in 2017. This was the framework for announcing the establishment of a joint 'Development Planning Office for a New Generation of Artificial Intelligence' (DPO NGAI) that involves the relevant ministries and research institutions of the country.

Development Planning Office for a New Generation of Artificial Intelligence	
Responsible ministries	• Ministry of Science and Technology (MOST) • Ministry of Industry and Information Technologies (MIIT) • National Development and Reform Commission (NDRC) • Ministry of Education MOE (universities, university research/university spin-offs, etc.)
Ministries with a departmental reference	• Ministry of Transport (MOT) • Ministry of Agriculture (MOA) • Health and Family Planning Commission
Research organisations	• Chinese Academy of Sciences CAS (including research institutes and spin-offs, etc.) • Chinese Academy of Engineering (CAE) • National Natural Science Foundation of China (NSFC) • China Association of Science and Technology (CAST)
Military institutions	• Office of Central Military and Civilian Integrated Development Commission • Equipment Development Department of the Central Military Commission • Military Science and Technology Commission

Table 5: Members of the Chinese DPO-NGAI (source: iit)

The institutions listed in Table 5 are to be understood as the central stakeholders of China, each of which has its own competencies with regard to AI. By involving the Ministry of Education (MOE), the state universities and the Chinese Academy of Sciences (CAS) as well as other application-orientated research institutes are also involved in the process (Manyika et al. 2017).

In view of the new initiatives to strengthen AI in China, it is advantageous that the country's Internet companies are highly competitive. Internationally renowned IT groups include Alibaba, Tencent, Baidu, iFlytek, Sogou, Didi Chuxing and Xinmeida (Global Times 2017), as well as Telecommunications supplier Huawei.

It could turn out to be an obstacle to innovation that politics continues to have a strong regulatory influence on the leading Internet companies. Unlike most OECD countries, and despite emphasis on market economy policy, politics continues to exert considerable influence over Chinese IT companies which often have no alternative and are called upon to implement politically controversial political interests. This is repeatedly illustrated by individual cases, such as Alibaba's role in the development and implementation of the social credit system (Gruber 2017) which subjects Chinese citizens to digital surveillance.

Western IT companies active in China are equally restricted in their market activities by the regulations of the central government. At the same time, however, Western IT companies find it much more difficult to pursue their own interests compared to their Chinese counterparts. In this sense, Western IT companies tend to be more cautious than Chinese IT companies in their interaction with political decision-makers.

With regard to recent developments in the field of AI, it is not yet possible to finally assess whether China with its comprehensive ITA measures can even succeed in becoming the world's leading AI country. Recent developments, however, suggest that China may be able to close the still existing gap to leading industrialised nations.

The catch-up process is supported by innovation co-operation with US and German partners in the field of Industry 4.0. However, international research co-operation can also be seen as an opportunity for Germany and the US because it enables the transfer of geographical advantages and country-specific priorities to companies which could benefit both sides.

The economic framework conditions are ultimately China's greatest challenge with regard to AI. Strong Internet regulation means that even companies that are formally privately owned are not free in their activities. The innovation potential for AI is exposed to new threats resulting from increasing political controls on science and business under President Xi Jinping.

This means that the innovation policy framework remains unfavourable despite extensive research funding, together with a situation that is likely to lead, for instance, to inefficiencies in the government's R&D investments. Stringent top-down planning and the identification of innovation topics deserve special mention in this context. Education, science and labour market policies also continue to hamper innovation due to strong regulatory requirements. It is therefore reasonable to assume that the innovation potential associated with AI will develop at a slower pace in China than in less strongly regulated OECD countries.

At the same time, China has great ambitions. This opens up opportunities for players from Germany to co-operate in R&D and benefit from programmes and the dynamic developments in China. Possibilities exist here: For example, ongoing co-operation on the 'German-Chinese Industry 4.0 Project' is opening up opportunities to transfer co-operation projects that already exist in certain areas of application or technology to AI-relevant topics.

6.1 Important planning and programme documents

The following planning and programme documents are particularly relevant for the promotion of AI in China at a strategic planning level:

Strategic plans of the Chinese government	Year of publication
Medium-to-long-term plan for the development of science and technology (2006-2020)	2006
Made in China 2025	2015
Action Plan to Promote the Development of Big Data, State Council	2015
Internet + AI three-year action and implementation plan	2015
National Development Plan for Robotics (2016-2020)	2015
Development plan for a new generation of artificial intelligence	2017

Table 6: Strategic plans of the Chinese government (source: iit)

Medium-term 2006 to 2020 planning does not yet expressly mention artificial intelligence, but the topic is indirectly addressed by the focus on AI robotics. AI robotics became a central component of China's 'leapfrogging strategy' as well as the strategy on 'indigenous innovation' which pursued the goal of implementing independent, globally leading innovation under Chinese intellectual property and copyright law. The National Development Plan for Robotics (2016 to 2020) stipulates that China should continue to build up expertise in the field of industrial robotics and make the relevant investments in order to manufacture industrial robots in the country. These are expected to reach international technical and quality standards. By 2020, the market share of Chinese companies in high-end robotics is expected to reach 45% (Molnar 2017).

The 'Development Plan for a New Generation of AI' from 2017 is extremely important for R&D policy. Key goals in this area are:

AI is to support Chinese economic growth, and to this end investments in AI are to be increased to over CNY 1 trillion (around EUR 128 billion) by 2020. An expansion of the investment volume to over CNY 10 trillion (around EUR 1.28 trillion) is planned by 2030.

Several intermediate objectives have been defined for this purpose:

- China is expected to catch up with the world market leaders in AI technologies and applications by 2020. The targets specifically address the market capitalisation of companies. The value of Chinese AI companies is expected to exceed CNY 150 billion (around EUR 19 billion) in 2020, and by 2025 the volume is even expected to rise to CNY 400 billion (around EUR 51 billion). The growth targets thus amount to an average of 50 percent per year. The increase defined for 2020 already means a tenfold increase in investment volume compared to 2017 (Jia and Zhanqi 2017).
- AI research is to be strengthened parallel to this. China's declared goal is to achieve further breakthroughs in AI research by 2025. Building on this, the country aims to become a globally recognised centre of AI innovation, technologies and applications by 2030.

The overarching strategies specify the areas of application which are to be promoted for this purpose. According to the 'Internet+ and AI Three-Year Action and Implementation Plan' issued by the Ministry of Industry and Information Technology (MIIT) in 2015, the following AI issues are of particular importance:

- Accelerated development of text, voice, video, map and other files in public repositories for large group training and public full-service platforms for basic resources, as well as building/support of a new type of computing clusters for large-scale deep learning
- Creation and establishment of public service platforms for industry
- Research of full life cycle services for network security
- Integration of cloud services and network technologies
- Integrated security services
- Development and application of smart image and speech recognition in industry
- Biometric identification methods
- Natural language processing
- Smart decision-making and control
- Technologies for human-machine interaction.

Representatives of leading IT companies have a far-reaching say when setting the agenda for the R&D funding priorities. R&D policy is thus used as a targeted instrument to support the competitiveness of companies. These topics are translated into policy programmes by the relevant ministries and organisations (such as MOST, MIIT, CAS, NSFC, etc.). All of the AI applications and technologies identified for this study are important for China's R&D funding (see Table 7). Key areas (as of 2017) are predictive analytics, quality control, robotics, autonomous driving, smart automation and smart sensor technology.

Various programmes are available to support these topics. Quality control, robotics and smart sensor systems have been relevant target areas so far, especially at the higher 'Made in China 2025' programme level. Predictive analytics (with a special focus on autonomous driving and smart automation) is already integrated into existing programmes. The topic of AI was, for instance, included in the funding guidelines of the National Natural Science Foundation of China (NSFC) in 2017 (which can be considered to be the Chinese counterpart to the US National Science Foundation or the German Research Foundation (DFG)). More concrete areas of technology, where targeted efforts are made to promote their development, can also be found in the above-mentioned development plan for a new generation of artificial intelligence.

National Natural Science Foundation of China: artificial intelligence research project guide

Forefront of AI :	Intelligent autonomous mobile robots:	Theories and key technologies intelligent decision-making in complex manufacturing processes:
• Cross-domain collaborative multi-modal efficient perception and augmented intelligence • Machine understanding of perception and behaviour under uncertainty in an open environment • Complex tasks planning and reasoning of new methods • New mechanisms of machine learning theory and methods • (e.g., deep reinforcement learning, adversal learning, brain-like learning) • Brain-inspired new computing architectures and methods • New methods of man-machine cooperation mixed intelligence • Chinese semantic computing and deep understanding (such as machine reading comprehension and creation, man-machine-dialog) • New artificial intelligent-oriented computing devices and chips • Intelligent computing methods and platforms for heterogeneous public core parallel • Machine intelligence for test models and evaluation methods	• Cognitive modelling and learning of intelligent autonomous mobile agents in open environment • Cross-media integrated reasoning for environment / scene adaptation • Interaction models and methods of intelligent autonomous mobile agents • Cognitive computing for "people in the loop" (hybrid enhanced intelligence) multiple autonomous intelligent motion agents • Intelligent evaluation systems and methods for intelligent autonomous mobile agents	• Intelligent modelling of complex dynamic processes with combined data and mechanism analysis • Intelligent prediction and self-healing control for abnormal conditions • Endpoint prediction and visualization analysis with artificial intelligence-driven performance indicators • Decision knowledge feature extraction and knowledge discovery based on multi-source heterogeneous data • Intelligent decision making architecture and methods with predictive and self-optimizing functions • Man-machine cooperation for optimized decision making and mutual learning in uncertain, open environments • New approaches for artificial intelligence-driven automation

Table 7: NSFC guidelines (source: Global Times 2017)

A short Global Times (2017) study analyses the competitiveness of Chinese companies in the field of AI. Key areas of this short study are machine translation, speech recognition, image recognition, cloud computing, autonomous driving and big data. The study concludes that Baidu's development activities have the broadest and generally strongest position in all of these areas. But other Chinese IT companies also have strengths, such as Alibaba in cloud computing and big data. iFlytek is the Chinese leader in translation and speech recognition. Sense Time ranks second after Baidu in the field of image recognition technologies (Global Times 2017).

The analysis shows China's potential in the field of AI. On the one hand, this topic receives comprehensive support from the government and, on the other hand, individual IT companies in the country are extremely efficient. However, the limited independence of the companies could have a negative impact. Their innovative strength continues to suffer from strong regulatory intervention. Therefore the economic impulses which the Chinese government's investments in AI will ultimately generate remain to be seen.

7 Summary and recommendations for action

The study focuses on three key questions: Which are the concrete technologies and applications behind AI systems? Where are they being used up to now? In which stages of the value chain do they unfold their greatest potential? Answers to these key questions of the study are given in the previous chapters. This concluding section summarises the key findings in the form of a SWOT analysis (strengths, weaknesses, opportunities and threats) and translates the findings into recommendations for action for policymakers.

7.1 Strengths/weaknesses analysis

Strengths: With regard to AI, one of the key strengths of the manufacturing sector in Germany is that companies are testing AI applications, albeit at a very low level. German suppliers have strengths in the important AI applications of smart automation and smart sensor systems. Overall, the breadth of research on AI can also be interpreted as a strength. In an international comparison, research from Germany shows remarkable publication performance. In the opinion of the researchers surveyed, the institutes are international leaders in the AI technologies of natural language processing and cognitive modelling.

Weaknesses: However, weaknesses can also be identified besides the strengths mentioned here. For example, SMEs face greater obstacles to the implementation of AI applications at the company. Germany is seen behind the US in important cross-cutting technologies, such as computer vision, action planning and optimisation and, above all, in machine learning. The vast majority of companies also complain about the availability of skilled staff. At the same time, there is considerable potential for AI providers from Germany and/or Europe, but only very few AI providers are aware of the fact that this location advantage exists. The transfer of research results to the economy (in the form of business start-ups, joint projects, etc.) can be seen as another weakness. In many regions, the volume of research results transferred to industry is insufficient.

Opportunities: The market for AI in Germany offers considerable opportunities and substantial potential for added value. Studies assume that AI will account for around one third of average economic growth in the future. Opportunities exist across the entire value chain. Industrial production is the core for AI applications, but supporting areas, such as marketing and sales, human resources or after-sales service also benefit from AI. Companies have recognised this potential and are relying on the increased use of AI at companies. The market for AI technologies and applications can be generally expected to grow. Providers from Germany and the EU enjoy a high level of trust in AI. This opportunity must be seized.

Threats: The market-related threats also result from strong competition for future market shares. In technological terms, US-based providers are generally superior or are perceived to be superior. Emerging countries, such as China, are increasingly becoming serious competitors. The fact that German providers have some catching up to do from a technological point of view is illustrated by the fact that the US is a leader in central AI applications, such as predictive analytics and smart assistance systems, as well as in relevant cross-cutting technologies, such as computer vision, action planning and optimisation as well as machine learning. One possible threat here is that German companies (especially providers) may not invest sufficiently in AI and thus run the risk of missing up on the opportunity from an international perspective.

Recommendations for action can be derived from the key findings of the study. The results are orientated along the following dimensions: technological potential, value creation potential, innovation system, system requirements and international competition.

7.2 Recommendations to policymakers

AI has a key role to play in the future growth of Germany's manufacturing sector. This is recognised both by AI providers and potential users. The challenge for companies is to survive in strong international competition. The present study highlights some of Germany's structural weaknesses in this respect.

- The pace of technology transfer from science to start-ups and AI technology providers and ultimately to manufacturing companies is too slow.
- Shortage of skilled staff is a key obstacle to the use of AI technologies at companies.
- AI providers complain that their customers' managers in the manufacturing sector in Germany are not very open-minded and employees have fears and prejudices.
- Although companies in the manufacturing sector clearly express their desire to co-operate with European AI providers and thus opt for technological sovereignty, AI providers in Germany are hardly aware of this competitive advantage.

This generally leads to slower adaptation of AI technologies by the manufacturing industry in Germany. These structural weaknesses must be overcome with government support.

7.2.1 Technological potential

AI applications differ in terms of the added value which they generate in the different areas of application. At the same time, AI applications exist that are based on multiple AI technologies (for example, predictive analytics is essentially based on machine learning, whilst smart assistance systems and robotics use many different AI technologies). The study also showed that one of the strengths of German companies is their ability to combine technologies to form applications. This strength must be exploited.

It is advisable to focus specifically on competences in the field of autonomous (assistance) systems in production. To this end, it is possible to draw on a well-established community of researchers and technology providers who are driving innovation processes in industry-led collaborative projects.

Computer vision, machine learning as well as action planning and optimisation are AI technologies of a particular cross-cutting character. Semantic technologies are also of a cross-cutting nature, but are primarily used in knowledge management and smart assistance systems. Semantic technologies too offer considerable potential for the economy because they are becoming increasingly important for the interoperability of AI systems.

Targeted support should be provided for AI technologies with a cross-cutting character, such as computer vision, machine learning, action planning and optimisation. This allows a large number of different applications to be addressed. From an economic point of view, these cross-cutting technologies generate the highest return on R&D investments. Swift and far-reaching dissemination must be ensured.

7.2.2 Value creation potential

The share of companies currently using AI technologies is still too low. The use of AI technologies leads to major changes at all stages of the value chain and in company structures. The experts interviewed complained that these change processes are taking place too slowly, both at SMEs and at large corporations. At the same time, the analysis of value added shows that around one third of average economic growth is connected to AI. Industry recognises this potential to a large extent, with stakeholders indicating a high degree of willingness to invest in AI applications and technologies. This 'momentum' in the economy in general and in the manufacturing sector in particular must be taken up and leveraged with the help of government support.

Providers and users see differences in the importance of individual AI technologies and applications. Very high potential is, for instance, seen in AI applications such as predictive analytics, smart assistance systems, smart automation and robotics as well as smart sensor technology.

An AI strategy should be developed here that is capable of addressing the potential and challenges in the individual sectors of the economy in a targeted way. This requires dialogue between politics, industry and research to be quickly organised in order to prioritise and coordinate the implementation of the measures planned.

When it comes to prioritising individual AI technologies, differences can be seen between large corporations on the one hand and small and medium-sized enterprises on the other. Whilst large corporations currently focus stronger on the AI applications of robotics and optimised resource management, SMEs put greater emphasis on knowledge management and quality control.

Due to their outstanding importance for the German economy, SMEs are the focus of German funding policy. This means that future AI support and funding measures should also address the concerns of SMEs in a targeted manner.

Nevertheless, the experts pointed out in the interviews and workshops that the focus should also be on projects with a lighthouse character that promise particularly high value creation and transfer potential across companies and industries. SMEs must be actively involved in order to consider their specific needs.

7.2.3 Technology transfer

Funding of AI basic research, at times also by DFG, has resulted in numerous clusters of excellence, collaborative research centres and postgraduate projects which demonstrate outstanding competence both in terms of publication strength and the quality of their scientific work. Non-university research institutions, such as the Max Planck Institutes, are also very well positioned in research into AI technologies. In addition, there are the German Research Center for Artificial Intelligence (DFKI) and the Fraunhofer Institutes specialising in AI which can support transfer to industry, especially in the area of application-orientated research. This can be achieved through research co-operation on the one hand and through spin-offs from institutes on the other. The start-ups themselves are then active as providers of AI technologies and applications, thus strengthening Germany as a production location. In particular, a comparison with other countries has shown that Germany still has some catching up to do when it comes to transferring research findings into applications. Measured in terms of the economic importance of AI and the performance of the research system, the number of AI start-ups is definitely too small.

Start-ups in the AI context should be specifically addressed by support programmes for the start-up process.

Companies in the manufacturing sector, as potential users of AI technologies, expect to see a considerable increase in co-operation projects with external AI providers. From a user perspective, this could be hampered by lack of information regarding the supplier market.

It is therefore recommended that the information situation be improved in a targeted manner and that AI users be given with the necessary information on AI providers. Key information regarding providers, service companies as well as R&D co-operation partners can be made available, for example, in the form of a publication/information brochure and an AI map. Editing and provision of use cases and best practices can help users to recognise the potential of AI. SMEs would especially benefit from such a product.

7.2.4 System requirements

The most important requirements for the use of AI are robust algorithms, data quality, data sovereignty and access, security as well as sensor systems and cloud computing. Users attach greater importance to aspects of security and interoperability, for example. Transparent procedures for the validation and verification of AI-supported systems and, in particular, the traceability of machine learning procedures are essential if they are to be used across all stages of the value chain and, in particular, in autonomous decision-making systems. Data quality and access to data is an important precondition for AI-based optimisation. IT security of the interconnected systems is the basis not only for the use of AI, but also for interconnecting IT systems. Special importance must be attached to interoperability, for instance, so that AI models based on training data can be used across the board. Interoperability of AI models enables the use of pre-calibrated models at different companies, and this also saves training time, adaptation effort and ultimately also costs. One major obstacle to the use of AI is currently the lack of in-house skills and skilled staff. Both AI providers and AI users rely on highly qualified staff with AI competence.

The expert interviews and validation workshop provided detailed proposals for action on all these points:

When planning political programmes and initiatives, these key system requirements should be kept in mind, and issues, such as data access, data quality, IT security and interoperability, should be specifically addressed. From a user perspective, suitable guidelines would be helpful in this respect.

With a view to strengthening data access and data quality, it is recommended that existing open data initiatives be extended to include specific AI requirements. Further work will be needed in order to enable free access to public data and research data as training data.

In order to strengthen interoperability, the issue should be addressed even more extensively than before at EU level. Existing initiatives should be used as a basis in this case too. The Industry 4.0 platform, for instance, can be used for this purpose and extended by adding AI aspects and requirements.

Furthermore, swift development and expansion of vocational and academic education as well as further professional qualification and training courses on AI topics are recommended.

7.2.5 International competitiveness

Users have general concerns regarding the dominance of international IT groups. At the same time, the market for AI technologies is only just beginning to develop, so that companies from Germany or Europe also have the opportunity to assert themselves against international competition. The existing presence of international AI providers should not be seen as a threat, but as a challenge.

German AI providers should be increasingly involved in funded collaborative and lighthouse projects in order to guarantee technological sovereignty in the field of AI.

A Appendix – Detailed description of AI technologies

AI technologies can be roughly described by two dimensions as characterised by Russell and Norvig (1995) in their book 'AI a Modern Approach'. On the one hand, there are AI systems whose thinking or acting imitates humans (here: 'human-like AI'). On the other hand, there are systems that think or act rationally (here: 'rational systems'). Here we focus on this distinction between human and rational AI systems.

In the history of AI, there is a long tradition of taking beings with natural intelligence as role models for the development of artificial intelligent systems: on the one hand, as a scientific instrument in order to understand man and, on the other hand, as an inspiration to build intelligent systems that are as flexible as humans in dealing with ambiguous, changing and unpredictable circumstances. Accordingly, the 'human-like AI' approach deals with systems that reproduce human thought processes, knowledge representations and related actions in decision-making and/or problem-solving. Mental limitations and systematic errors of the human brain are also investigated and copied in artificial cognitive, computational models. Limitations and errors, such as those that occur due to the limitations of the human body in the form of perceptual illusions (Geisler and Kersten 2002), are often the expression of optimal strategies and show mechanisms for how a system can take a smart approach in order to handle erroneous or unreliable data. Cognitive modelling also focuses on the special characteristics of mental knowledge representations and problem-solving strategies.

However, artificial systems do not always have the same limits or challenges as humans. The rational approach aims to apply mathematical and predominantly statistical methods in such a way that, regardless of the human model, they act as optimally and appropriately as possible, or, in other words, always do the 'right thing'. When implementing these systems, AI researchers who follow the rational approach access all available methods and tools from the fields of engineering, mathematics and computer science in order to implement both the hardware and software components of the smart agents in such a way that a task is optimally performed according to predefined criteria. In 1997, for example, the IBM chess computer Deep Blue defeated world champion Gary Kasparov by evaluating 12 million possible chess moves per minute, which is simply impossible for a human being (Krauthammer 1997). Such AI systems are not human but intelligent because they think or act rationally.

Beyond the classification system of Russell and Norvig (1995), we have added here biologically inspired hardware systems as a third category. These systems imitate the mechanisms of biological intelligence in order to exploit the advantages of biological systems which in some respects are superior to existing hardware systems, mostly in the form of von-Neumann architectures. However, this biological 'intelligence' cannot be measured by behavioural success (rational or human) since it is initially only about a hardware architecture that neither executes code nor performs an intelligent function until it is integrated into an application. These systems can therefore neither be classified as human-like thinking and acting nor as rationally thinking and acting systems.

A.1 Behaviour-orientated AI technologies

Semantic technologies

Digital information processing is based on the execution of syntactic rules. Normally, a computer does not understand what it is processing. Sometimes, however, it is necessary for computers to also draw content-based conclusions, for instance, in the case of search engines (identifying similar topics), for targeted advertising (identifying relevant customers) or for answering content questions through assistance systems. In order to consider the meaning – the semantics – of information, AI systems have a knowledge base that links the semantic connections between facts, events, concepts, things and classes of things with the help of relations and functions or derives them from large amounts of data with the help of statistical methods. The structured representation of information is called ontology in computer science. The crucial advantage of ontologies is that, by means of so-called inference rules, new knowledge can be derived from existing knowledge about the connections, be they functions or relations, between the individual things and classes of things.

The principle of semantic knowledge representation is used in various fields, such as medicine, chemistry and, for some years now, also in Industry 4.0. The 'eCl@ss' product data standard (eCl@ss 2018), for instance, describes the relationships between the individual components of a production system, such as sensors with mechatronic components, i.e. such as cylinders or stoppers, for example. This ontology for Industry 4.0 describes the components that match and can be assembled using functions such as 'connection'.

Some ten years ago, semantic knowledge representations and especially the terms 'Semantic Web' and semantic search were on everyone's lips. This topic was also extensively researched in Germany as part of the Theseus technology programme (BMWi 2018). The search results in the Semantic Web go beyond conventional, more verbatim hit lists. The semantic links extend the term searched for by its meaning, so that the context of the search, such as components for a specific assembly step and synonyms of the term searched for, also appear in the hit list.

Several years ago, the US company Google extended the original concept of semantic ontology-based knowledge representations to include additional multimedia content, such as images, video and audio files and linked this concept to the geographical dimension. The merger of semantic fact knowledge with visual representation and geoinformation is called knowledge graph. Thanks to semantic linking, not only websites, but also pictures related to the search term can now be found on the Internet. Address information, for instance, is linked to the unambiguous position on a geographical map. The concepts and the implementation of knowledge graphs were provided by Google as open source to the worldwide developer community. Knowledge graphs are used in modern knowledge-based systems worldwide.

Natural language processing

Understanding and interpreting natural language is a very well established field of research in artificial intelligence. Humans exchange information primarily through (spoken or written) language and this natural language differs in many ways from the formal, command and performance-based languages that computers use to exchange information. Humans, for instance, use irony, metaphors and comparisons for communication which are based on semantic understanding of language – i.e. meaning – which computers do not have. The peculiarity of natural language is the ambiguity of some words or concepts. The English sentence 'Time flies like an arrow but fruit flies like a banana' is translated into German as follows: „Die Zeit fliegt wie ein Pfeil, aber Fruchtfliegen mögen eine Banane". The words 'flies' and 'like' have completely different meanings in the two sentences ('flies': from the verb 'to fly' and the insect 'fly'; 'like': 'as a comparative particle and 'like' from the verb 'to like'). Algorithms find it very difficult to handle ambiguities like these in natural language. Natural language processing (NLP) techniques aim to replicate all aspects of human language processing, such as text recognition from language and language generation from text, machine translation, contextual meaning recognition (semantics, pragmatics), grammar comprehension and correction, etc. Translation systems are now so advanced that simple dialogues can be carried out in different languages. However, translation systems are still reaching their limits: Microsoft's Bing search engine, for example, translated 'Mes chers compatriotes' (Dear fellow citizens) as 'Dear fellow Americans' in the speech of French President Macron to his citizens, because, statistically speaking, the term 'fellow citizens' in the mostly American training data almost always means 'American fellow citizens' (Bryson 2017). The success of NLP systems has been the subject of the famous Turing test for more than 60 years: A human test subject in a closed room communicates simultaneously with an NLP system and with a human being via a screen. The test subject does not receive any information about who/what the conversation partner is behind the screen. At the end of the test, the test subject is asked to decide which of the two dialogue partners is a human and which an NLP system. So far, no NLP system has successfully passed the Turing test.

Cognitive modeling

Cognitive models go deeper into the understanding of human intelligence and aim to map the functioning of human cognitive processes, such as working and long-term memory, logical thinking and reasoning. Cognitive modelling has contributed significantly to the understanding of human perception and information processing processes. Interestingly, cognitive scientists validate cognitive models on the basis of errors that humans systematically make in solving certain tasks, since systematic errors allow conclusions to be drawn about the rules implemented in human information processing. To illustrate this with an example: Look at the following question: "How many animals of every kind did Moses take on his ark?" Although it is common knowledge that Noah, not Moses, built the ark and saved the animals, many people answer the question with "two". This phenomenon, known as 'The Moses Illusion' in cognitive science literature (Park and Reder 2004), is an example of how people often confuse terms that are semantically similar to each other, making it obvious that people always take semantic information and especially semantic distance into account when processing information. A regular (or rational) software system would try to correct this objective error, a cognitive model would try to replicate such errors by simulating the underlying process (noisy conclusion in the semantic space).

Such computational cognitive models, which simulate cognitive phenomena in the form of both software and hardware, are used to simulate human behaviour or, in part, to solve problems in fields of application which are dynamic and characterised by open-ended requirements where human heuristic problem-solving strategies, such as path-finding and orientation, are still superior to modern computers.

A.2 Rationally thinking and acting systems

Computer vision

Machine vision (computer vision) is about the recognition of objects in images and videos, which traditionally involves many processing steps that seem intuitively simple to humans, such as feature recognition (corners, edges), followed by segmentation (dividing the image into continuous regions despite masking, shadowing, variable lighting conditions, ignoring texture), subdivision into foreground and background, inference of depth information (3D reconstruction), colour recognition despite variable lighting conditions, object recognition (which regions belong together and what do they represent?). A particularly demanding task is the detection of actions in camera recordings, i.e. motion detection in realtime.

In the field of computer vision, deep neural networks, i.e. multi-layered neural networks, have in recent years managed to solve many computer vision problems (in particular, object recognition) that were previously regarded as insufficiently solvable.

Machine learning

Machine learning (ML) refers to processes and computer algorithms that train or learn optimal or successful behaviour from data without having to explicitly program each and every individual case. The following procedures are currently becoming more relevant and important.

So-called supervised learning is used for the classification of data or also for predictions based on previously recorded examples.

Monitored learning procedures require training data that is labelled with the meaning of the data. The labels usually have to be assigned by humans to data sets that are used to train the algorithms, for instance, for emotion recognition on facial images, or they can be measured in the environment, for instance, for stock price performance.

In contrast to supervised learning, unsupervised learning does not require annotated training sets, but automatically recognises statistical structures in data. These methods are typically used to recognise patterns by clustering the available data (such as cohort recognition in marketing: Before training, the algorithm neither knows how many nor which user groups exist which are characterised by different behaviour).

So-called reinforcement learning makes it possible to independently learn a strategy for solving a problem or a task from a feedback function. The feedback function is linked to a reward system that determines the successful behaviour of the intelligent system. The feedback function can map both negative and positive experiences of the intelligent agent. In an industrial context, reinforcement learning is increasingly used in combination with deep learning methods in realistic scenarios, such as 'peg-in-hole' operations in assembly tasks that require particularly high precision (Inoue et al. 2017).

Different classes of machine learning exist which are characterised by different architectures, strengths, weaknesses and basic assumptions. Neural networks are thus made up of computing units that are modelled according to the human brain cells ('neurons') which are responsible for signal transmission in the human body and exchange impulses with each other in a network structure. AI refers to artificial neural networks that simulate the biological function of neurons. Artificial neural networks are used both in the context of supervised learning for classification tasks – text, writing or object recognition – and for unsupervised learning – for pattern recognition.

Deep neural networks are neural networks with very large numbers of neuron layers, which makes it difficult to train them (high CPU load, large training sets), but which enable them to learn very abstract correlations between input data and the desired output (such as object recognition in computer vision or meaning recognition in natural language processing).

However, a variety of machine learning techniques also exists besides neural networks, such as tree models where decision trees are learned, statistical techniques, such as Bayesian classifiers or support vector machines, evolutionary algorithms that mimic natural selection, as well as ensemble methods that execute different machine learning techniques parallel and then intelligently combine their decisions.

Action planning and optimisation

The motion sequences of an industrial robot without AI require complex programming during the construction phase of a production system in the form of command sequences for actions, such as gripping, moving and shifting. AI-based approaches, on the other hand, can calculate movements, such as gripping an object on a shelf or loading the object into a box, independently or learn from training data. In order to calculate the correct motion sequences, classical computer vision methods for the recognition of objects are used and combined with methods for learning motor control (such as control engineering methods or special motor learning algorithms for robots).

Robotic process automation (RPA) is a technology for the automation and optimisation of IT-supported processes at companies. RPA was inspired by industrial automation. The individual interactions of workers with the IT-based tools and communication systems of the company are captured and digitised using an RPA system. The interactions and processes stored are linked in the RPA system in such a way that certain routine processes (such as sending e mails or activating a reminder function, finding appointments among several colleagues or project partners) can be automatically triggered and completed. This is made possible by a smart knowledge base that is used as a basis for process optimisation and automation.

A.3 Biologically inspired hardware systems

Neuromorphic computing differs from other AI technologies in that it is not primarily about achieving intelligent (human or rational) functions. Neuromorphic computing imitates the structures of the vertebrate brain purely mechanically in the form of hardware. Such neuromorphic systems are 'artificially intelligent' because, like the vertebrate brain, they process information parallel and analogously and can thus achieve much higher computing performance for certain tasks than traditional computers based on von-Neumann architecture. Neuromorphic computing is still in its development phase in many respects and has not benefited to the same extent as other AI technologies from 'big data' and advances in the computing power of traditional computers. In this respect, neuromorphic computing is to be regarded more as a technology of the future, which is why it is not yet applied to any specific application in technology application assignments.

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