AI

& Digital Platforms

A SYSTEMS ANALYSIS FROM
PIIA AND BLUE INSTITUTE

Swedish IndTech

How Artificial Intelligence & Digital Platforms are changing industry

About PiiA

PiiA (Process-Industry IT and Automation) is a strategic innovation program for the Swedish natural resources and process industry and Swedish technology suppliers. PiiA's goal is for industry, academia, and technology suppliers to work together to develop world-leading technologies, processes and businesses that create sustainable growth and allow for the attainment of an even greater share of the world market, both in terms of refined Swedish natural resources and industrial digitalisation. PiiA's work in this area is built around both outstanding knowledge of industrial digitalisation and solid networks within industry and academia. Project finance is provided by Vinnova.

PiiA is focused on IndTech for the following sectors: the forestry industry, the mining industry, steel and metals, the chemicals industry, food and pharmaceuticals, water and wastewater, as well as energy production and usage within the aforementioned areas.

About Blue Institute

Blue Institute helps individuals and organisations to better understand – and shape – their futures. We believe that learning and knowledge benefit from discussions in which participants are both aware of their own unique positions and open to taking on other perspectives. To achieve this, we create opportunities for individuals to meet, we drive processes, and we provide different types of analysis that help to produce better results.

Blue Institute was founded in 2007 with the aim of promoting research and the development of knowledge around marketing, enterprise, and organisation. We strive to achieve an increased understanding of the role leadership plays in change and for increased socio-economic growth.

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Contents

In 2018, a decision was made to develop and strengthen Vinnova's investment in initiatives related to artificial intelligence and secure data access. Over the next 10 years, SEK 200 million will be devoted annually to these areas, of which at least SEK 50 million will be directed to AI initiatives. The goal is to strengthen the development of collaborative environments focused on research, innovation and education, as well as to strengthen advanced infrastructures for data, testing and technology.

Vinnova's Strategic Innovation Programs (SIPs) are long-term investments in strategic innovation that Vinnova facilitates together with the Swedish Energy Agency and Formas. Some 17 programs are currently underway. None of the programs are in themselves geared towards artificial intelligence, but they have project activities that may be aimed at the development of artificial intelligence or related technologies and applications.

During 2019, the various programs will be developing strategies for integrating artificial intelligence into calls for proposals and projects, thereby helping to increase the potential for innovation in their respective fields. The programs will use external analyses (to understand the needs of their own working areas) and current situation analysis (of their own project portfolios) to identify gaps and needs. Focus is to be placed on both needs and possible applications, as well as on potential application areas.

This report is the result of the PiiA program's study of the field of AI and its conclusions for industry and the program's ongoing direction.

Foreword

This report has two primary purposes: to provide industry with an evaluation of the importance of AI development as a force for change, and to create an internal basis for PiiA's future development efforts, within which AI can be described as the next phase of industry's digitalisation. Both these objectives are naturally compatible with the overall ambition of the report: to reach our target group of industry leaders and to serve as a source of knowledge for ongoing activities within relevant companies.

There are countless cases within technological industrial development of ambitious plans promising much but eventually proving to be costly dead ends. With this in mind, throughout our work in assessing the development of AI we have endeavoured to take into account the magnitude and direction of different vectors of change.

On the one hand, we have attempted to understand the power of demand for AI by assessing the economic impacts at a macro level. We have focused on productivity and qualitative values at various stages of industry value systems. On the other hand, we have attempted to assess the range of available technologies by analysing initiatives taken on a global scale and through focused academic research. We have also put considerable effort into understanding the major commercial – or applied – forces that are crucial to development, both in the short and medium term.

We have also strived to place AI development in the context of current systemic developments, as characterised by the 'platformisation' of company IT resources. By this we mean the transfer of automation and IT support to the cloud – a trend that is creating new competitive dynamics.

Finally, we have attempted to translate this big picture into real impacts on the factory floor, and to revisit well-known concepts such as organisational development which – with the help of the raw power of AI technology – have the potential to make the previously impossible, possible.

The report has been divided into two main sections: ***The Market***, in which we assess the development and consequences on the factory floor; and ***The Technology***, which provides a more in-depth understanding of the structures of industrial IT and machine-learning technology. The report concludes with some practical examples from industry.

This project was a collaboration between PiiA and Blue Institute, with valuable input from Blue Institute's network of CEOs and industry leaders on all levels. A big thank you is extended to everyone who contributed to this study.

Västerås, September 2019

Peter Wallin
Head of Program, PiiA

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Executive Summary

This study aims to describes the dynamics currently at play in the field of AI: significant potential is driving demand; there is rapid technological development and increasing use of AI technology within industry; meanwhile, practical applications rather than technological development itself are creating value.

The primary purpose of this study to spread knowledge to industry. It is also intended to form the basis of PiiA's ongoing work around open calls and targeted strategic projects. The basic approach taken is to investigate both industry demand for AI and how the supply of technology is developing.

AI itself takes in a broad and dynamic range of concepts, but it should also be considered in the even broader context of industrial digitisation. It is not just a question of technology development, but equally about application and application knowledge. Realising the full potential of AI requires the ability for change within individual companies, but also the ability to handle exchanges and interactions in changing ecosystems.

Over the following pages, you will find a review of the main patterns we have distinguished in the market system, and the study's overall conclusions. We conclude the report with concrete recommendations for program operations within PiiA as well as for the wider innovation system, which in short involves a joining of forces through which the various strategic innovation programs' competences are pooled to benefit industry.

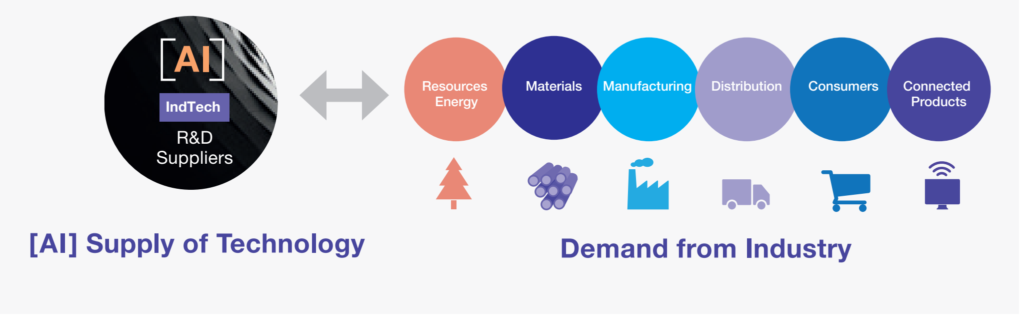

Figure 1: In this report, the development of AI is assessed partly from the perspective of demand from industry, which on an underlying basis is being driven by opportunities for value creation. It is also assessed from the perspective of the technological offering, along with research, development and restructuring of the supplier system.

> If this potential is realised, the effects of AI on productivity development will potentially outpace the technological shift from the steam engine to robotisation and IT, by at least a factor of two.

1 Strong driving forces for increased industrial value creation

Demand for industrial AI is increasing in pace with a growing understanding of the potential value that this technology stands to unlock. Technological developments that have been unfolding over the past decade, generally unobserved by lay people, are now coming to fruition and can be observed in tandem with analyses of potential economic impacts and increasingly practical applications and investments. Globally, this development could have major economic impacts, which are also important in the context of societal challenges linked to population growth, climate and the environment.

Several analyses of the effects of AI on global productivity and growth have pointed to an enormous potential. While the time horizons of each of these analyses and the industry orientations they focus on differ, the overall consensus is that the potential impacts are considerable. These potential impacts relate to labour productivity and flow-on effects at the buyer level, including tailored solutions, quality and time savings.

If this potential is realised, the effects of AI on productivity development will potentially outpace the technological shift from the steam engine to robotisation and IT, by at least a factor of two.

Using the same assumptions used in global analyses and adapting them to a Swedish context, we estimate that values of between SEK 22 and 45 billion per year could be unlocked in PiiA's target industries alone.

As such, the conclusion of this study is that the driving forces are so strong that AI is here to stay; that AI truly has the potential to change the world and the industry; and that AI will be looked back upon as a revolution in the production economy.

The question is whether the explosion of AI and its revolutionary implementation across industry will occur in the near future, or whether the technology will instead come into effect via smaller, scattered changes over the short term. This, in turn, depends on how far technological development has come and the extent to which industry adopts it.

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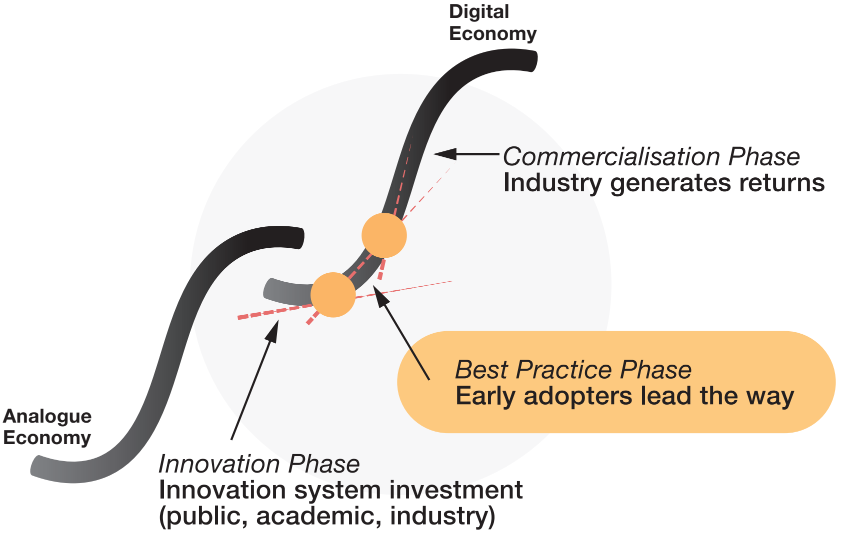


2 Harvest time for technological development

PiiA has for a number of years followed the development of industrial digitisation, and has, by assessing global R&D efforts, endeavoured to understand the strength of this development. Certain scope problems notwithstanding, our assessment shows that there have been initiatives amounting to SEK 1.5 trillion in recent years across three key stakeholder areas: *private-public national investments* (for example PiiA, P2030 and Industrie 4.0), *tech company investments* in the cloud and AI, and the *ICT + automation industry*.

These development projects are now leaving laboratories and are emerging into the market: first as innovation projects, then as best practice, before finally penetrating the market in a commercially meaningful way.

Our analysis shows that we are now largely in the *best-practice phase*. This assessment is partly based on the fact that R&D investments are starting to yield returns; partly on the fact that standardisation work is well on the way to showing results; and partly on the fact that the world's industrial leaders have woken up to the transformative effect of digitalisation on industry and are starting to act. Another force to be considered is the dynamics which arise as the three development foci start to propel each other, with developmental results reaching the market, which in turn leads to further increased momentum for the entire system.

Our conclusion is firstly that the timing is good for AI: a supply of technology is starting to reach the industry at the same time that demand is rising. Secondly, we can expect structural changes in the supplier system as entirely new concepts come to market and previous industry and supplier limits are transformed. There will be cause for both consolidation and repositioning in a variety of ways. The product ordering skills of the industries using the new technologies are yet to be tested.

> "In our estimation, Swedish industry can maintain a world-class position as digitalisation enters the AI phase.

3 Results through the application of AI

The above conclusions are based around macro-conditions being in place that allow for sustainable industrial growth. But the realisation of AI's true potential is also dependent on there being capacity in place to bring these concepts and value analyses down to the factory floor. The discourse in recent years has been mostly about Sweden's position in AI-related research, and less about the practical application of this. We believe that there is now a real need for an increased focus on applied AI capable of producing rapid effects in the industrial system.

During the creation of this study and the associated dialogue with industry and suppliers that took place, the importance of assembling teams with relevant competences was constantly highlighted. Solid domain knowledge about the actual process is required, as is deep process knowledge. In situations where the exact goals of an AI project cannot be clearly expressed, the chances of failure are very high. A solid understanding of mathematics and analysis methods is still needed, as is knowledge about the tools to be used. Last but not least, skilled change leaders are critical.

There is sometimes talk in Sweden about our modest abilities with regard to digitalisation and the AI domain. Yet, when one looks at various objective measures, it is difficult to understand the basis for such arguments. Sweden might not be able to compete with American universities or broad Chinese investments in AI, nor can it outperform companies such as Microsoft, IBM or Google. However, there are many areas in which we are at the forefront. These include, but are not limited to, *business-to-business*, applied technology for industrial IT and automation, and our capability in the resources, process and manufacturing industries. This also applies to our infrastructure and general knowledge capital.

PiiA understands that these capabilities exist within industry, consultants, system integrators and suppliers. Sweden is one of the world's leading nations in many of the major industrial sectors and IndTech is an area in which Swedish excels.

As with all other digital technologies, new commercial AI products can be expected to become available at the same time across the entire global market. Therefore, it is the will and ability of industry to use the technology rather than the technology itself that will determine who are the successful players. Motives and inducements are now needed to start a movement for change.

In essence, the application of AI is fundamentally a bottom-up movement, driven by the desire of companies to improve their position through organisational and process development. We believe that there is room for – and great initial value in – a focused effort dedicated to inspiring, motivating and supporting development at a company and factory level.

All in all, our conclusion is that Sweden has excellent potential to scale up what is already one of the world's most advanced industrial technology bases to a connected, intelligent structure that brings in value through integration, analysis and increased automation. It is our assessment that Swedish industry can maintain a world-class position as digitalisation enters the AI phase.

> "Our conclusion is firstly that the timing is right: a supply of technology is starting to reach the industry in tandem with rising demand. Secondly, we can expect structural changes in the supplier system as completely new concepts come to market and previous industry and supplier limits are transformed.

Recommendations: A shortcut to AI best practice

One conclusion of our study is that AI needs to be considered within the context of digitalisation and platformisation in general, and from a process and organisational development perspective in particular. The abilities and ambitions of companies are crucial to unlocking the potential present. Activities dedicated to accelerating and supporting the establishment of AI in Swedish industry are likely to be most effective when conducted in professionally established environments, where practical applications and real change can occur.

For this reason, established Strategic Innovation Programs (SIPs) would seem to be an effective tool through which key industries can access domain knowledge, relationships and trust in the system. The SIP system as a whole includes deep process expertise in sectors including forestry (Bioinnovation), mining (STRIM), steel and metals (Metallic Materials), and manufacturing (P2030). SIP PiiA's expertise is computer and systems science, control technology and automation with industrial specialisation in the resources and process industries.

A structure combining the knowledge of industry verticals (industry SIPs) and digitalisation/AI (PiiA) in a program to create a *shortcut to best practice* could prove successful and provide a powerful engine for change. It could also support other activities funded by the Swedish Agency for Economic and Regional Growth, such as Robotlyftet (the Robot Lift), DigiLean and DigiFuture, and so on.

PiiA therefore proposes that Vinnova finance the investigation of such a concept in collaboration with PiiA and any other interested SIPs.

PiiA also proposes exploring the possibilities of providing broad ongoing education for engineers in the industry, with machine learning and mathematics as the main focus. We believe that such a program could be successful through collaborations between industry organisations such as ITF Automation and the AI Competence for Sweden program. We propose further investigation of this suggestion.

The main conclusions for PiiA's program work are:

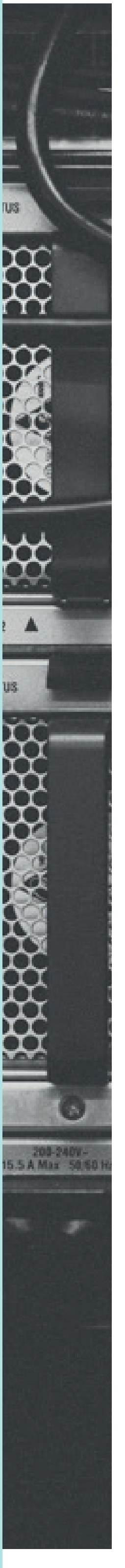
• **A basic view** is that AI cannot be regarded as a single phenomenon but rather something that has strong mutual dependencies with digitalisation in general and with the ‘platformisation’ of industry. PiiA thus approaches the whole area with a similar systemic approach.

• **The structural consequences of digitalisation** described in this report are a crucial strategic area that needs to be addressed. In this report, we describe one of these consequences as being *traditional industry excelling not only at production but also becoming an information industry* operating according to a new logic.

• **The concepts of collective and collaborative intelligence** are central. Models where people's intellectual capacity can be increased through smart collaboration methods (both person-to-person and man-to-machine) will be of great importance for industrial development. There is a need for more applied research and development in this area, as well as awareness-raising activities that engage industry. Therefore, PiiA will become involved in these issues.

• **We also see an opportunity to systematise the knowledge content** in PiiA's project base of almost 200 projects (many of which have content related to advanced analysis) to create an asset for further research.

• **Other activities** to support the industry in the upcoming transformation processes include the dissemination of knowledge in various ways, with the distribution of this report being a starting point.



Part 1: The Market

The computerisation of global industry began in earnest in the 1980s. The use of microprocessors made it possible to automate in new and efficient ways, and the process, automotive and electronics industries made significant productivity gains. Now, the world is entering a new technological and economic paradigm in the form of digitalisation, the first wave of which has already transformed the media and communications industries. In a second wave of change, the financial sector and trade will be transformed, and, under the third wave, wider industry will be transformed. At the same time, artificial intelligence is emerging as the next – and probably most significant – stage of digitalisation.

For the manufacturing industry, this will mean that many companies in subcontracting arrangements will have access to cost-effective technology that allows for further automation and productivity increases. The impacts of AI for the process industry won't be yet another emptying of factory floors, but rather an opening of the way to achieve levels of process development that were previously unobtainable. AI is also expected to bring new levels of integration to the entire value system, on the way to achieving the ultimate vision of self-organisation. It may also change the structure of the industrial landscape; concepts such as *ecosystems* and *platforms* are fast becoming commonplace descriptions, even in traditional industries.

Our current stage of development could be described as *increasing algorithmisation*. From a developmental context, it represents a megatrend that is both supporting human beings – and enabling us to be replaced by computers. The trend began with the mainframes of the 1960s and continued with the microprocessor revolution of the 1980s and '90s. Then in the 2000s, came the scalability, mobility and cost effectiveness

> "...concepts such as *ecosystems* and *platforms* are fast becoming commonplace descriptions, even in traditional industries.

of digital platforms. Now, with AI and machine learning emerging as the next phase, the pace of development is set to increase further.

Demand for industrial AI is growing as understanding of the value that the technology can potentially release grows. A range of technological advances that have taken place away from the public gaze over the past decade are now coming to fruition. These can be considered alongside potential economic impacts and, increasingly, real-life business cases and investments.

These changes have the potential to produce major economic impacts for global industry, and they may be particularly significant in the context of societal challenges related to population growth, climate and the environment.

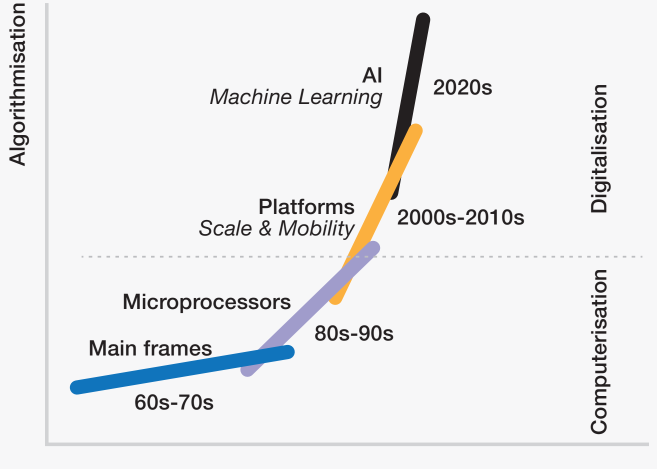


Figure 2: AI and machine learning effectively add an extra *gear* that will allow for increasingly advanced algorithms which increase efficiency and create new customer value within industry.
Source: Blue Institute 2019.

The million-dollar question is: Will we see an explosion of AI, and its disruptive establishment across global industry? Or, will this, still somewhat unwieldy technology lead to more sporadic changes in the short term? Either way, our considered assessment is that AI is here to stay, that AI truly has the potential to change the world and industry, and that AI will be looked back on as a true revolution for the production economy.

In this section, we will look at the forces underlying supply-and-demand development trends for AI within industry. A functioning market dynamic is a key prerequisite for ongoing industrial transformation pressure, something that we aim to highlight in this study by addressing three issues:

1. **What are the expected value-creating effects of AI?**
2. **Will AI development and the supplier system be able to meet the demand for AI technology that is arising from this potential value creation?**
3. **Is this development sustainable or are we seeing a 'hype' phase which will eventually fade, with the actual market breakthrough set to occur several years into the future?**

In addition to these issues, this report illustrates, from various perspectives, how the impacts of AI will benefit industry at the system/platform and operational development levels. The second part of the report will provide an in-depth study of the possibilities and challenges of AI technology.

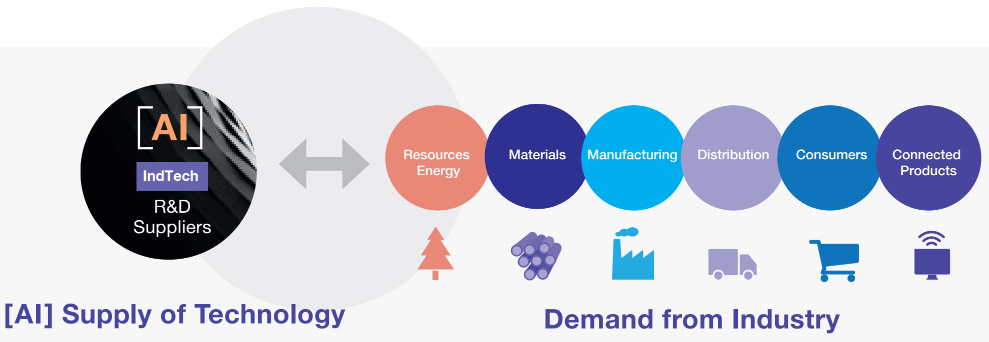


Figure 3: The market for AI technical solutions and for machine learning is expected to grow by 40% per year, while demand within industry is expected to be driven by the significant potential value gains that can be created using the technology.

Demand

We start this section by looking at the *demand side* of things, as well as discussing the stance companies might take. This includes examining bigger picture developments that will lead to a future digital economy based on business ecosystems and digital platforms. We also introduce the concept of *best practice* and provide an orientation model for individual companies wanting to assess their position and preparedness for change.

Demand for AI will be driven by substantial value effects within production systems

Our fundamental hypothesis is that demand for AI within industry will correlate with the value that can be extracted from production via more effective analysis tools. Our assumption is that the expected growth effects within industry will lead to activities at the company level, which in turn will drive demand for AI technology.

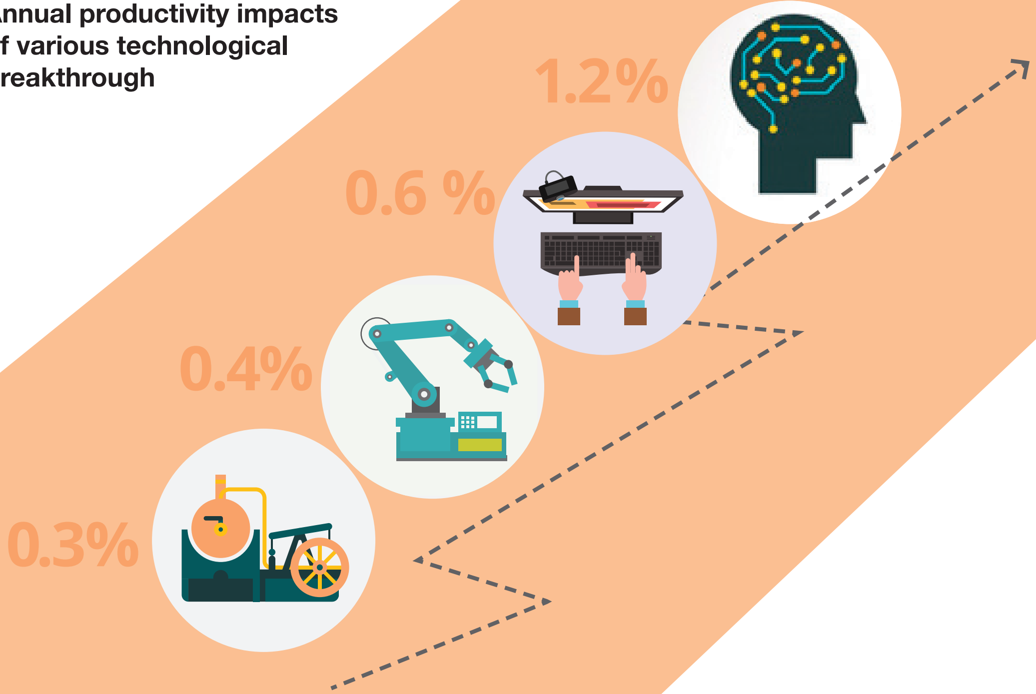
According to the Vinnova study *Artificial Intelligence in Swedish Business and Society*, there's evidence to suggest that the general growth potential within value creation could be realised twice as fast in an economy with extensive AI utilisation, compared to one with limited utilisation.

The many dynamic effects of AI development and the changing regulations around it, also come into play, and these are expected to produce growth effects for the world economy. AI will also contribute to systemic effects, as business ecosystems and digital platforms are developed that transform the manufacturing industry into an information industry. These virtual value systems will be decoupled from physical systems and so allow for new organisational models that echo the transformation that the media, finance and commerce sectors are already undergoing.

Several studies have attempted to estimate the economic effects of AI at the macro-level; in this work, we have incorporated insights from three reports by Accenture, McKinsey Global Institute and PwC. According to consulting company PwC[1)], AI's contribution to the global economy in 2030 will amount to an estimated USD 15.7 trillion. This means that in 2030, with the impact of AI, global GDP will be 14 percent higher than it would be without AI, or the equivalent of China and India's combined GDPs.

[1)] PWC, Sizing the Prize, 2017

Annual productivity impacts of various technological breakthrough



The productivity impact corresponds to USD 6.6 trillion, while USD 9.1 trillion is expected to be produced from impacts on the consumer side. PwC's analysis also includes areas such as trade, transport, finance and health care.

Consulting company Accenture[2)] believes AI's global economic impact will be equivalent to USD 4.8 trillion in increased profitability during the period up to 2022, which does not contradict McKinsey's or PwC's analyses that have other time frames.

In its report, *Notes from the AI frontier: Modelling the impact of AI on the world economy,* consulting firm McKinsey Global Institute (MGI) calculates that the effects of AI in all of the report's sectors will generate an effect of between USD 3.5–5.8 trillion or, when expanded to include all available advanced analysis methods, on top of machine learning, USD 9.5–15.4 trillion.

When limited to the resource, process and manufacturing industry's value system, it is in the range of USD 1.7–2.3 trillion[3)] according to estimates in this study, or 3–6 percent per year of the global industrial sector's total assets.

Industrial productivity improvements are estimated to amount to 1.2 percent per year until 2030, or in the order of USD 1 trillion. Comparisons can also be made with other major technological shifts. During the 19th century, the steam engine increased labour productivity by an estimated 0.3 percent per year (although the disruptive effect eventually became quite considerable). The robotisation of industry in the 1990s produced a 0.4-percent annual increase, and the effects of IT development during the 2000s are expected to deliver a 0.6-percent annual increase[4)]. AI has at least twice the inherent potential.

[2)]Accenture, Reworking the Revolution, 2018 [3)] Blue Institute estimate based on a sample of sectors from the study. McKinsey Global Institute, Notes from the AI frontier: Applications and value of deep learning, 2018. [4)] WSJ, The Impact of Artificial Intelligence on the World Economy, 2018.

> " Added value of between SEK 22 and 45 billion per year could be unlocked for PiiA's industries.

Placed in a Swedish context and related back to PiiA's target industries[5], we estimate that added value of between SEK 22 and 45 billion could be unlocked per year. For PiiA's sectors this represents an average increase of between SEK 3 billion and SEK 7 billion per sector, of which approximately half would be productivity related, with value also unlocked at the consumer level, through factors such as quality, time savings and better-targeted offerings.

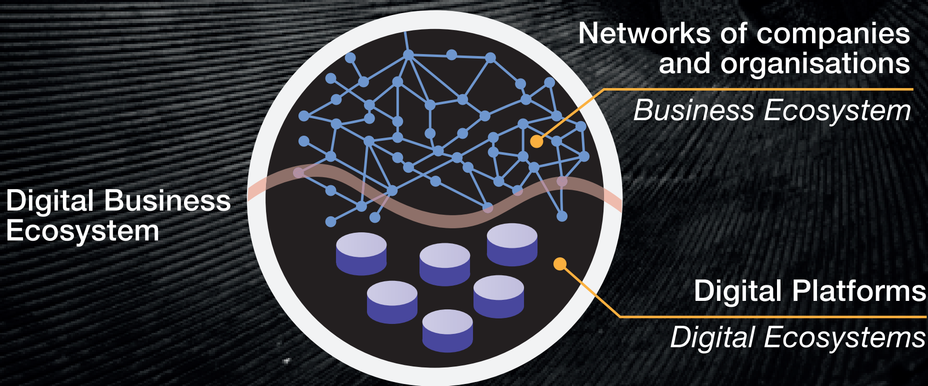
The purpose of the comparisons above is more to illustrate the order of magnitude involved than to present precise figures. Even if the cited studies were to be greatly exaggerated, the effects will certainly be great. Our conclusion is that the movement that has now been set in motion has few parallels in history in terms of change potential. For companies and businesses, it means there will be few, if any, players who can afford to pass up the competitive improvements that AI will eventually deliver.

And there is good reason to prepare in advance for the coming changes. Looking from a wider perspective, a lopsided distribution of AI development is likely, with an ever-increasing gap between the performance of various countries, companies and workers. In terms of countries, China and the United States are the two nations that currently account for the majority of all AI-related activities, and they are thus the best positioned. Developed industrial economies such as Germany, Japan and Canada and smaller commercial economies such as Sweden and Finland are well positioned and should also be motivated by low productivity-development gains in recent years.

Economies with more modest foundations, such as India, Italy and countries in Southeast Asia, generally have less favourable conditions, but they could use their particular strengths within certain categories to build specialised AI capabilities. However, developing economies with low investment capacity, weak skills and weak digital infrastructures run the risk of falling behind.

[5] The industries that PiiA aims to address are those within IndTech (automation, IT, digitisation), the forestry sector, the mining industry, steel and metal, the chemical industry, food and pharmaceuticals, water and wastewater, as well as energy production and usage within the areas mentioned.

In this section, we will work out how the concepts of AI, ecosystems, networks and platforms are interconnected. And how they contribute to value-creating market dynamics.



Systemic effects from digital platforms and business ecosystems

The largest value-creating impacts are expected to come from changes at the system level. As previously mentioned, we foresee development in a form that can best be described as *the transformation of the manufacturing industry towards becoming an information industry*. This shouldn't be read as a prediction of the demise of the production economy – rather one that business leaders will have to manage two logical frameworks.

This development has also been called the *platform economy*. In this section, we will work out the differences and connections between the concepts of AI, ecosystems, networks and platforms. We will also outline how they contribute to value creation and, as a result, to demand for AI and to market dynamics.

The connections between the concepts of *networks* and *platforms* lend themselves to being described with metaphors from biological ecosystems. These 'ecosystems' can be thought of as robust, scalable architectures that can automatically solve complex, dynamic problems, including self-organisation, self-governance, sustainability and scalability.

Figure 4: A model of the Business Ecosystem, consisting of two parts: (1) a business ecosystem in the form of a network of companies and organisations; (2) a digital ecosystem or, as it is more often called, a digital platform. *Source: Blue Institute 2019*

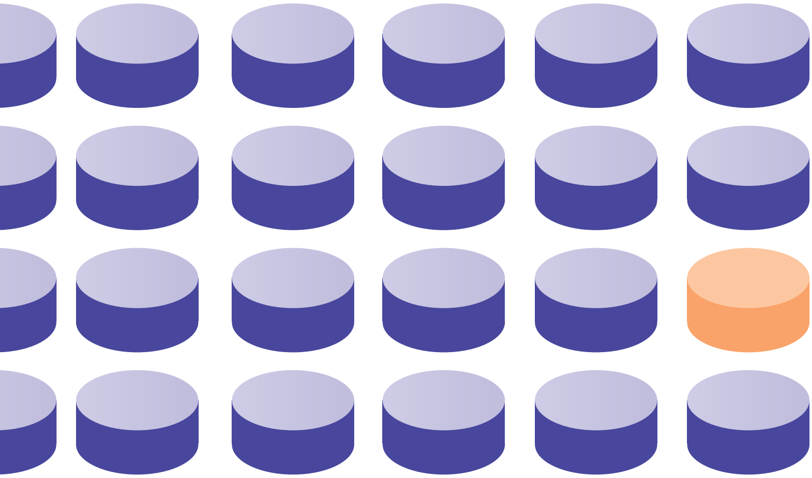
In the *business ecosystem,* there is a network logic between the companies involved which, in turn, is supported by a *digital ecosystem* characterised by a distributed peer-to-peer network model. The latter can also be described as a digital platform that makes relationships between companies and other organisations in the business network possible through transactions and technical support. A curated ecosystem reflects the balance between competition and collaboration in an open, dynamic and free market.

The term *business ecosystem* was first mentioned in a 1993 article in Harvard Business Review[6]. The article presents the idea that companies not only belong to industries but are parts of business ecosystems that extend across different industrial and knowledge sectors. The term *digital business ecosystem*[7] originated when the word *digital* was added to the business ecosystem concept as a reference to the socio-economic development made possible through information and communication technology.

The classic effects of network logic affect how the number of users in the network influences the value development for each user, i.e. the so-called *positive-network effect*. Negative network effects, on the other hand, occur in poorly managed networks that reduce value development for each user. The positive network effect is, of course, the foremost and most sought-after competitive advantage within network logic. Consequently, the key prerequisite for effective networks is to use digital platforms and other features to increase in size, thus increasing the value generated via network effects.

[6] Moore J.F. Predators and Prey: a new ecology of competition, HBR,1993

[7] Nachira, F. Towards a Network of Digital Business Ecosystems, 2002



Platform: a transformative concept

The concept of the *platform* is thus a transformative one with the potential to bring about major changes within business logic, economics, and society at large. Any company for whom *information* on factors such as supply-and-demand status, customer needs, trends, and willingness to pay is an essential asset is very likely to participate in the platform revolution.

The concept of *platformisation*, then, is used as a strategy for operating multi-faceted platforms and connecting buyers, sellers and other stakeholders, without necessarily owning the products or services being sold.

In textbooks, traditional linear value systems are likened to value chains or *pipes*[8]. Platforms represent a transformation from linear structures to a matrix complex of relationships between connected producers and customers who collaborate through the resources, properties and services provided by the platform's technology.

This development has, in its first wave, affected sectors where the product itself is information, such as the media, entertainment and financial sectors. The concept of *scale without mass* is key. Unlike physical products, which have high fixed costs plus substantial marginal costs that are reduced per unit should production be scaled up, digital products, for the most part, have near-zero fixed costs and marginal costs. With the internet as a distribution network, it is therefore possible for companies with small fixed assets and a low number of employees to quickly scale up to become international businesses.

The empirical evidence suggests that the platform model largely outperforms the linear value system when the right conditions are in place. Examples of such successes can be found among today's major tech companies, including Google, Amazon, Microsoft and Apple – all of which are also known as *mega-platforms*[10].

[8] Parker, G. et.al., Platform Revolution, 2016
[9] Brynjolfsson et al., Scale without Mass: Business Process Replication and Industry Dynamics, 2008
[10] Andersson Schwarz, Larsson, Plattformssamhället, 2018

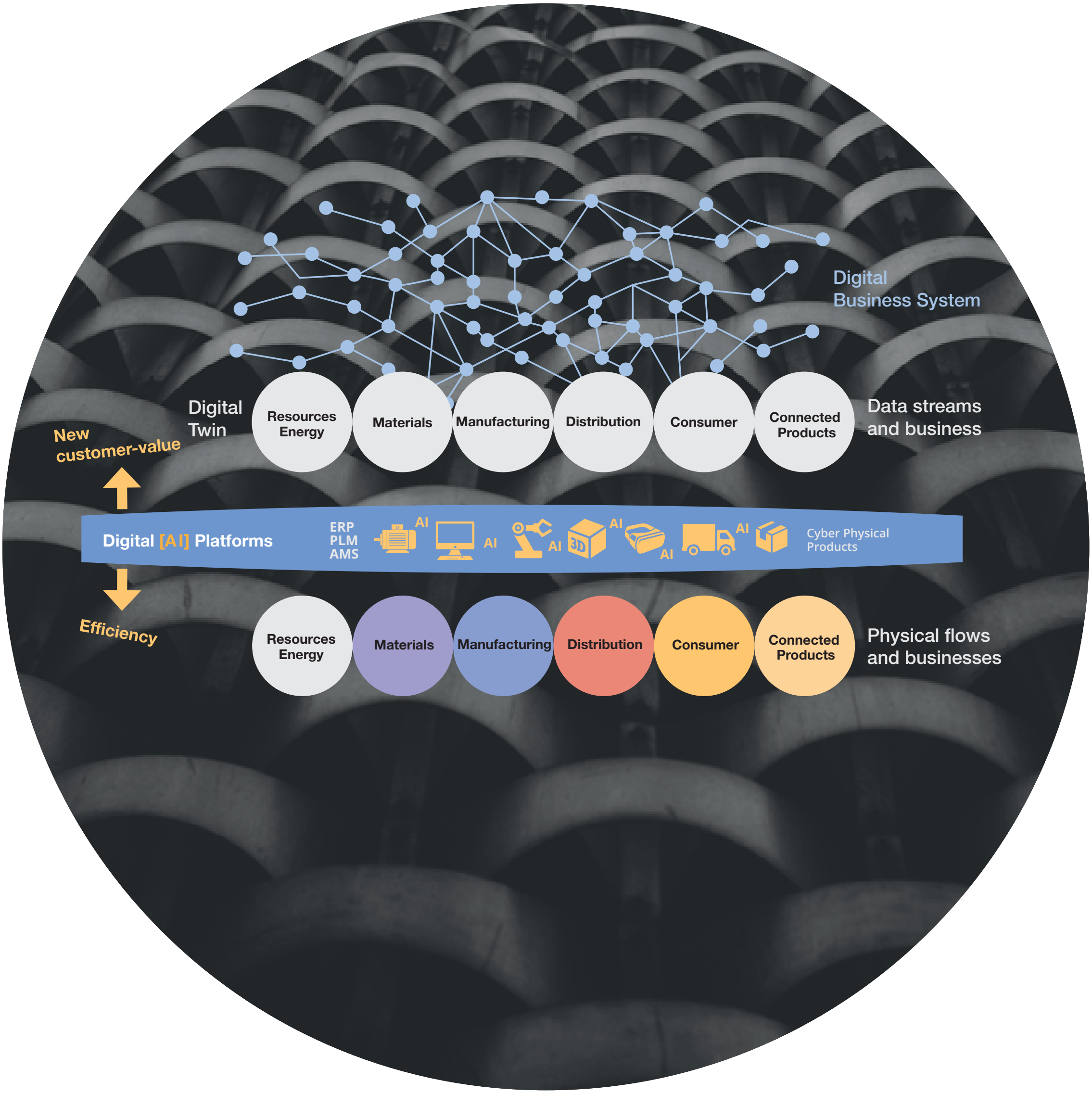


Figure 5: Physical value chains and the flow of natural resources, materials and products are complemented by equally important data streams that enable digital twins at different levels, including entire processes and value systems. The technology and connectivity that enables physical production as well as the digital twin describes the digital platform (or ecosystem). Data streams and twins make it possible to create Digital Business Ecosystems, i.e. meeting places where markets are created in new ways. *Source: Blue Institute 2019.*

How digital platforms are changing traditional industry

The uniting factor in both network and platform logics is the need to match and facilitate connections between producers and buyers, regardless of the type of goods being exchanged. Industry organisations will change as a consequence of the competitive advantages that platforms can provide within meeting places.

Platforms make it possible to bring new value for customers with low marginal costs to existing physical products – to achieve scale without mass – and we are already getting an early indication of how industry will separate physical production logic from virtual data-driven logic. The automotive industry is experiencing shrinking margins in vehicle manufacturing and is developing business models that address mobility while being based on AI platforms.

The industrial technology suppliers of tomorrow won't just sell hardware but will also develop into connected suppliers of efficiency and quality within production systems based on analysis, with machine learning delivered in collaboration between human and artificial intelligence. The process industry won't just sell materials, but also data on these materials based on AI analyses that increase the quality and efficiency of the manufacturing industry.

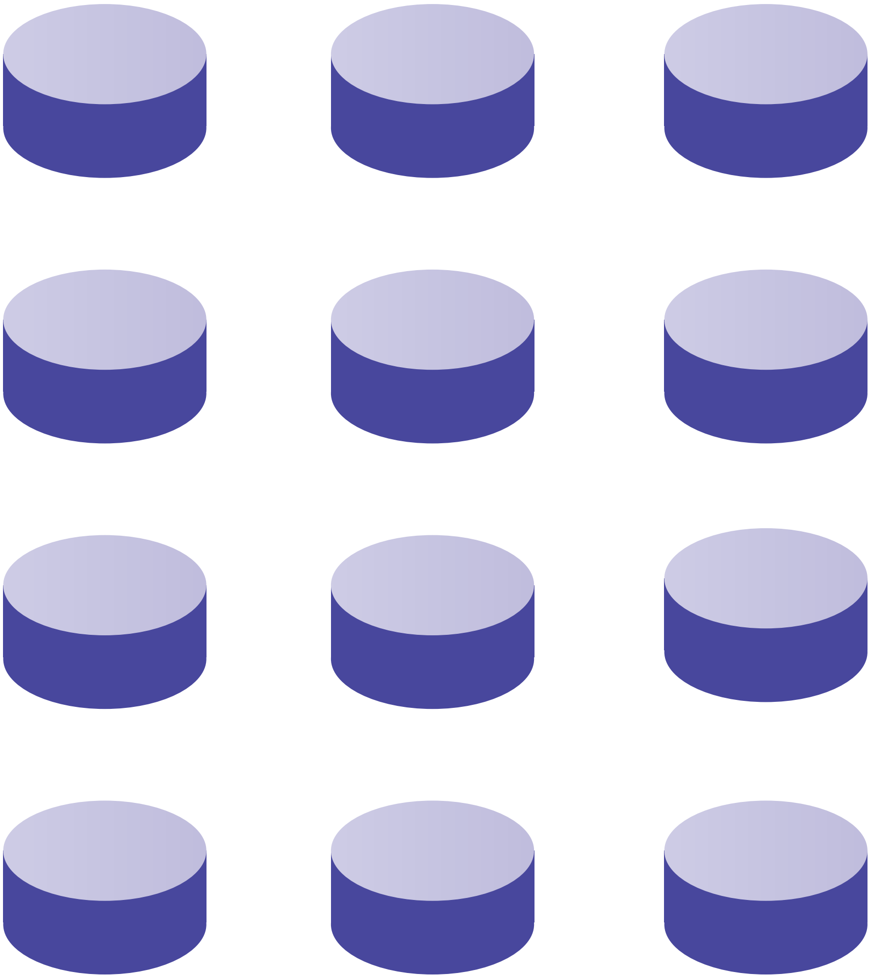
Uncoupling physical assets from the value they create also means that certain products can be marketed as services in the market for best possible use through greatest value creation, rather than being linked to a specific owner. The result is that both efficiency and value can increase – dramatically, in some cases.

> " We are in the process of leaving an industrial era in which scalability in supply-side economics has been the single biggest driver.

Platforms also have the potential to change cost structures and pricing in physical production. Once someone launches a digital AI platform that allows for trade and provides free marginal production capacity on a larger scale, purchasing prices for semi-manufactured products will theoretically fall at the same rate at which the available capacity is filled. Such a day is probably not too far away. There are also estimates that digital platforms that match labour to needs (once again with the help of AI) have the potential to increase global GDP by 2 percent by 2025 and create 72 million full-time jobs[11]. It's not totally surprising that a new word is being increasingly used: algorithm economics. In the same way that apps have changed people's communication with machines, AI algorithms will revolutionise development between machines.

Our conclusion is that while the business economics doctrine will certainly continue to exist once the resources, process and manufacturing industry becomes an information industry, the ways in which it is followed will be revolutionised.

[11] Microsoft, The Future Computed, 2019



The use of term *platform* as found in *digital platform* can be traced right back to the very early days of computerisation and the concept of *computing platforms.*

We are in the process of leaving an industrial era in which scalability in *supply-side economics* has been the single biggest driver; as more units are efficiently produced, the cost per unit diminishes. This has driven corporate mergers, globalised supply chains, oligopolies and monopolies. The largest companies have the largest volumes and cost advantages that are difficult for smaller competitors to achieve. In the transformation into a digital and AI-driven platform economy in which physical products are paired with digital scalable services, similar constellations will also be created through large-scale *demand economics.*

The demand economy is driven by aggregated and visible demand, social networks, app development and other phenomena that make networks bigger and more valuable to all users. The impacts will be just as difficult to absorb as within the large-scale production economy. Scale within the demand economy is the foundation for positive network effects and therefore a future driver of the global economy.

The advantages of platforms over linear value systems will lead to the disruption and dissolution of many industrial businesses. The continuous improvement of physical value chains will be complemented by developments through which data streams will become equally important for competitiveness. These data streams will pave the way for digital twins to be created of objects, machines, processes and, ultimately, the whole value system – all physical production and logistics. Advances are being made towards achieving the vision of self-organising value systems, one of the core concepts of Industry 4.0. The physical world and the computer world will become two sides of the same coin.

One problem that needs to be solved in this context is the ownership of data. Who owns the data that companies generate? Today, there is no real regulatory framework, and the various industries collecting data are uncertain about how much, and what kind of data they should share with other companies. In answer to this, initiatives are underway in a number of computer labs, and we are seeing examples of public, open laboratories in areas such as forestry and traffic data. This is one approach to systematising data collection. But better-defined structures and agreed-upon standards are needed to safely define, describe and share data.

Ultimately, the transformation for classic industrial companies involves managing two different logics; the large scale of the supply economy isn't going away, and at the same time the ability to create demand with economies of scale is becoming a significant differentiating competitive factor. The skill lies in being able to handle both.

From the early mainframe computers, via the client-server model with its personal computers and networks, and into the era of digitalisation, the word has been used to define hardware platforms and software platforms, or, to put it another way, general operating systems. The three development paradigms mentioned above are in turn called the first, second and third platforms. We are now in the era of the third platform, more complex and more intertwined than ever before, and characterised by the fact that computing power is found almost everywhere. Ready for use by people and for objects, through the Internet of Things.

Optimisation of the district heating network

Through its *Smarta Flöden* (Smart Flows) project, Swedish company Mälarenergi aims to use AI to optimise the production of district heating based on streaming data. Its goal is to avoid overproduction, while continuing to provide reliable district heating to customers. The project receives funding from PiiA and is a collaboration between Mälarenergi, RISE Västerås, Mälardalen University, ABB, Sigholm and Evothings Labs. The Smart Flows project combines learning systems with industrial IoT and cloud services to enable fully automatic optimisation of industrial process flows. The project is also part of larger-scale work to create a 'City Control Room'.

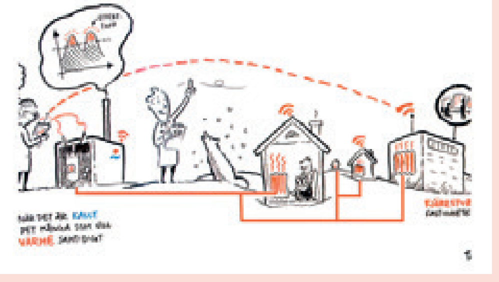
Mälarenergi AB is a commercial company that supplies electricity, district heating, water, district cooling and fast communication solutions, primarily within the Mälardals region. The company also sells electricity to private and corporate customers throughout Sweden. The Group is owned by the City of Västerås and has a turnover of approximately SEK 3 billion.

The challenge

Measuring, understanding and predicting flows of materials, gases and liquids is central to many process industries, and, as a result, these flows are often subject to continuous optimisation. Air flows in mine ventilation and distribution flows for wastewater are good examples of process flows. Optimising and automating these flows has the potential to produce large savings in energy and total costs, which in turn can produce positive environmental effects.

Process flows are rarely in a constant state, but rather in continuous flux as demand changes, infrastructure is expanded, and customers come and go. As a result, there is a clear need to make the industrial systems involved adaptable and

> "The hope is to eventually be able to create a hybrid solution between the learning system and the physical model.



teachable. District heating systems are an example of a system in which changes take time.

From the time that production is increased at a plant, it can take several hours before consumers several kilometres away are able to feel the benefits. But by using real-time data and a connected distribution network, plants will be able to anticipate needs and quickly make decisions about increased or decreased production. The Smart Flows project uses the Internet of Things and cloud services from Microsoft Azure to dynamically manage historical and close-to-real-time data.

The project also has an operational development dimension through which the goal is for customers to be able to buy services in the form of comfortable indoor temperatures which can be individualised.

The experience

The system takes in more than 15,000 properties, ranging from private homes to commercial properties and industrial plants. During the project's first year, significant time has been spent collecting data. Measurement data from all Mälarenergi's district heating plants over the past three years has been collected. The majority of values are hourly, but where possible, 15-minute values have also been sampled. Mälarenergi appointed an internal analysis group to analyse the more than one billion data points gathered.

Meanwhile, in parallel, a project team has conducted several user studies, creating profiles for different user categories to understand the operation's visualisation and analysis needs.

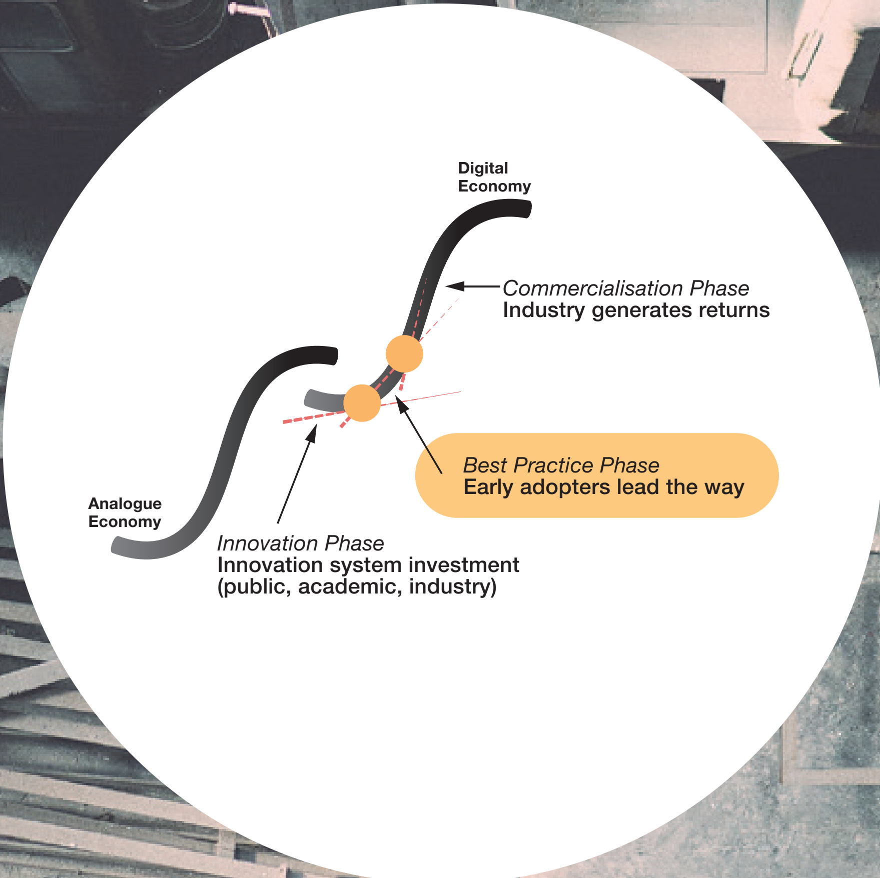
The first predictions made with the AI system were based on the factors of distribution time, weather, and social behaviour. The most successfully generated predictions have been made with regard to the heating needs of the building itself. Here, the weather is a strong contributing factor, and as long as there are good weather forecasts, predictions can be created that adequately reflect reality. The social behaviour of customers is the least reliable factor. If a single customer showers or runs a lot of hot water for a specific period of time, there will be a large potential impact on district heating. A variety of methods are being tested in order to improve the accuracy of social behaviour modelling.

The project has also tested physical models of the district heating network. The results show that the model can predict the dynamic/moving behaviour of the district heating system in terms of heat dissipation. The hope is to eventually be able to create a hybrid solution between the learning system and the physical model. A model with validation capability for the real-time learning system.

One example is where the learning system might want to send a certain amount of heat/water. The physical model can then say whether or not it's physically possible to do so and calculate whether this would result in the water reaching the customers on time. If it proves to be possible according to the laws of physics, then the sending of the heat can proceed. If it's not physically possible, then the exercise serves as a valuable input to the learning system. The algorithm will learn that this exact procedure is not possible for the next time.

During the period 2019-2021, the goal is to have a complete learning system in place covering all of Mälarenergi's district heating customers and that is compliant with industrial standards.

Source: PiiA, Mälarenergi, RISE



The old business wisdom to *follow the money* takes on new resonance for companies using AI as a transformation tool. In sectors where added value has traditionally been created through marketing and sales it may be prudent to focus AI effort in the same areas. If operational excellence is crucial – as is the case within the process and manufacturing industry – then there are good reasons to invest heavily in AI for the supply chain and production processes, but also to develop new products and to add new customer value. And in terms of basic resources and materials, there is the potential to increase value for customers who can contribute to top-line growth.

Figure 6: Digital development with AI as an essential component leaves the pure innovation phase. After that comes the 'Best Practice' phase in which Early adopters dare to experiment and inspire others.
Source: Blue Institute, 2019.

In search of best practice

Returning to the corporate and economic side of things, it's time to pose the question of whether the business case for AI is settled and whether now is the right time for major investment. There may be little question of the way things are heading when we look at the bigger picture, but as we all know, the devil is in the details. In general, machine learning is a powerful technology that so far requires specialised knowledge and incredibly careful preparations, tests and validations before it can deliver.

Against this background, the main purpose of this paper is to engage and contribute to Swedish industry's practical knowledge and preparedness for action, and to seek out best practice. While we are well aware of the current advantages and disadvantages of the technology, future developments may progress very quickly.

One model that is widely used within Blue Institute and PiiA is the S-curve. In the context of the digitally driven industrial shift that we currently find ourselves in, we are preparing to leave the S-curve's initial innovation phase with its lab studies and industry pilots, to move into the next stage with early adopters leading the way in seeking best practice that delivers results; we call this the *best practice* phase.

Best practice, in turn, lays the foundation for an accelerated transformation of industry. Experience from previous technological shifts has shown the power of good role models. For example, over the course of just a few years in the 1980s, the Swedish pulp and paper industry became the world leader in computerised automation. One explanation for this is that company leaders were inspired by their Swedish colleagues in the sector and shared their experiences. When industry leaders dare to take the lead, rewards await in the form of competitive advantages. If you can get others to follow, industrial benefits can be created on a large scale.

[12] Here, the S-curve is used to mean: Diffusion of innovation which is a theory that can explain how, why and at what rate new ideas are spread. The theory became popular in 1962 when Professor Everett Rogers wrote the book Diffusion of Innovations.

Examining the development of applied industrial AI and using the empirical evidence we have through, among other things, PiiA's project base, we are able to identify three types of companies in different stages of the curve:

- **The majority of companies – an estimated 70 percent – belong in the *aspiring for insights* category.** They realise that change is coming, but still lack readiness and ability, which must therefore be developed.
- **We are now seeing the rise of the innovation pilot category** to which an estimated 20 percent of businesses belong. They are engaged and have dared to take the first steps down the path to applied industrial AI or are receiving help in making preparations for applications on a larger scale.
- **The *accelerator* category includes a small group of pioneers,** estimated to be less than 10 percent of companies, who have found their own best practice solutions and are ready to scale up and transform their businesses using AI as a tool.

In this report, we return to three prerequisites for succeeding with applied AI in industry, examining them from different perspectives:

Leadership and adaptability involves creating appropriate change teams with the skills needed for the task ahead, but it also involves taking into account the job changes that AI will eventually lead to. This includes having the ability to collaborate between humans and machines – *collaborative intelligence* – and understanding the consequences this has on the organisation and working models. To put the question of jobs into perspective, an estimated 14 percent of the global workforce will need to change their job duties as a consequence of AI.

Also crucial is **data**, both from an ownership perspective and a quality perspective. Data is the raw material of AI technology, which is then converted into money with the help of algorithms. The final key prerequisite is **security** and risk management. These challenges also feature in Vinnova's 2018 study and we will look more closely into these aspects in the second part of the report: The Technology.

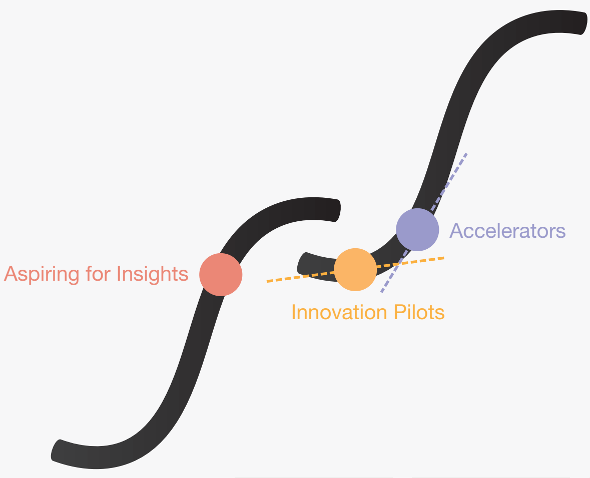
In the race to the top of the S-curve, it's crucial to address the challenges that crop up along the way. This starts with the 'aspiring for insights' category gaining the insights they need to understand the opportunities AI presents and to know the conditions within their own companies. Such companies may need to analyse their data management, data organisational strategy and the value of their data. It may also be a good idea to lay the groundwork for rules and relevant policies for data security management within the company. This might include minimising the risk of data breaches, as well as security measures for people and assets. It's increasingly common for policies for managing data in connection with AI applications to address ethics and the risks of skewed, biased data sets when learning specific analysis models.

Those in the 'innovation pilots' category, meanwhile, have gained insights and probably also received help with organising their data and testing machine learning on one or more suitable processes. Within PiiA's empirical data, we see companies at this stage that are trying out different methods and suppliers to gain knowledge and decision-making expertise for the next step, which we have referred to as 'accelerators' in this model.

Those in the 'accelerator' group now need to increase the pace of implementation and, therefore, transfer the responsibility for transformation to their line organisations, along with appropriate expert support. These development steps also come with increasing demands on the ability of companies to manage job transformation, as well as data as a strategic asset, as well as the security and ethical issues around data usage.

13) MGI, Notes from the AI frontier: Modeling the impact of AI on the world economy,

14) VINNOVA, Artificiell intelligens i svenskt näringsliv och samhälle, 2018



	Aspiring for Insights	Innovation pilots	Accelerators
Leadership Adaptability Job dynamic	Insights about opportunities and challenges	Pilot team drives developments	Transformation responsibility in line
Data Structure Ownership Ethics	Inventory data assets and prepare for structures	Rules and structures for data management in place	Data now handled as significant asset
Security Risk management	Understanding challenges	Policy in place	Delegated responsibility in line functions

Figure 7: Three typical development steps for implementing AI in an industrial context. From creating insight into opportunities and challenges, to more full-scale transformation of a company's processes. *Source: Blue Institute 2019.*

A study by McKinsey examined 400 AI applications in 19 different sectors. It found that in 69 percent of cases, AI was a means to improve existing, simpler, analytical methods. Completely new applications accounted for only 16 percent of cases, while the remaining 15 percent of cases were unable to benefit from deep learning technology for reasons including a lack of data.

McKinsey Global Institute, Notes from the AI frontier: Applications and value of deep learning, 2018

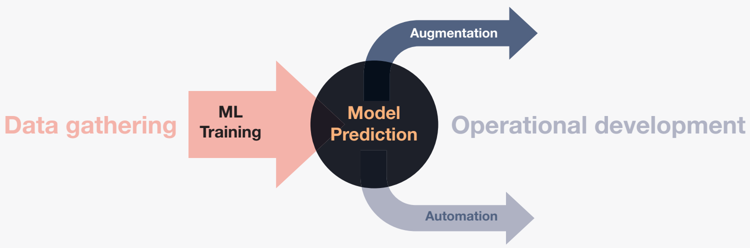


Figure 8: The streamlining of industry's supply chains is enabled by means of machine learning (ML) which makes predictions of process behaviour based on collated data. These predictions can then be used to enhance people's abilities, or to fully automate processes. *Source: Blue Institute 2019.*

> " Automated machines use data, AI understands data, so they complement each other.

Organisational development

Applying AI is essentially a matter of organisational development. It's a skill for which different corporate leaders will have different aptitude levels. Driven individuals are sure to see AI for the powerful tool that it stands to become and will also have the ability to create teams in which creativity, process knowledge, and a knowledge of tools, methods and good leadership all make a difference.

Most complex processes in the supply chain stand to benefit from artificial intelligence and machine learning.

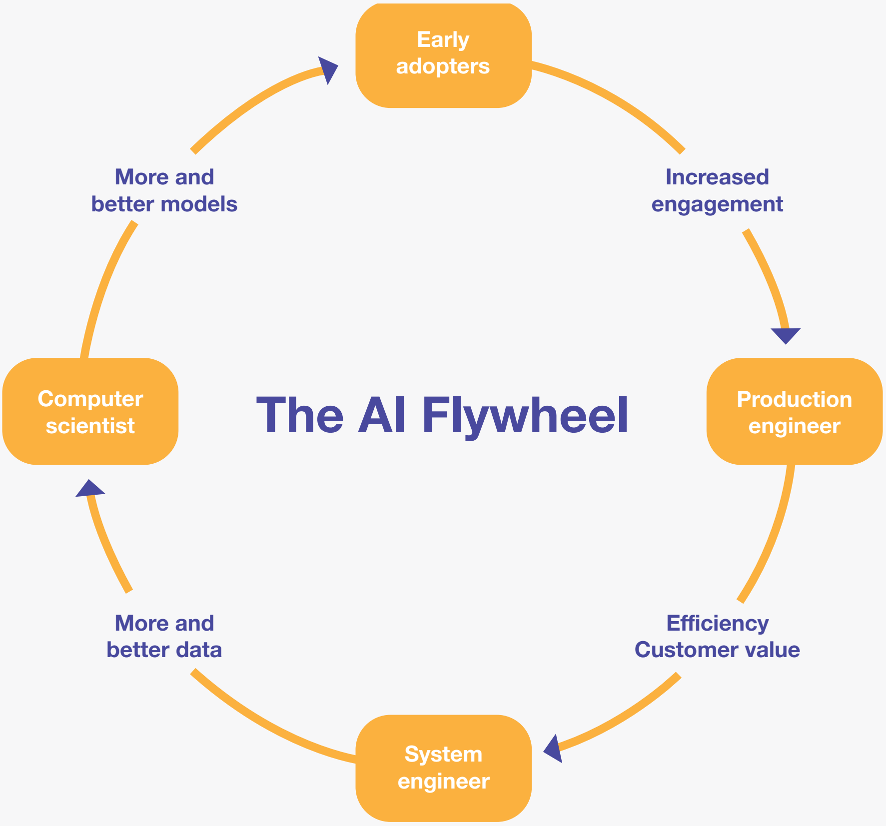
In simplified terms, the methodology can be divided into four parts:

1. **Data collection, preparation, and training of the model.**
2. **Using the trained model for analysis and prediction.**
3. **Using the analysis for augmentation, i.e. enhancing or increasing human abilities.**
4. **Using the analysis for automation, which can now be developed to new levels. It additionally becomes possible to introduce automation into areas where its implementation was previously seen as too complex and/ or expensive.**

AI and *automation* are often used as interchangeable concepts, but the underlying technology differs.

Automation describes systems that are programmed to perform specific repetitive tasks, such as an industrial robot which repeats the same step over and over again or a word-processing program which can repetitively perform what were previously manual tasks. AI systems, on the other hand, are designed to find patterns, to learn from experiences and to make consistent decisions. AI does not need specific programmed paths to determine how it should behave in different situations. Together, AI and automation may represent the next step in streamlining various processes within industry, whether these be in production or administration. Automated machines use data, AI understands data; so, they complement each other.

Augmented reality (AR), for example, has advantages in situations where people tend to perform poorly at consistently monitoring processes. AR can provide support when such monotonous tasks transition into critical business situations. AI-supported AR also helps warehouse workers and truck drivers to keep track of goods and products. AR can help process operators carry out routine checks on machines and processes, as well as providing support to service personnel, and speeding up emergency troubleshooting. The technology makes it possible to provide enhanced expert assistance remotely to production facilities far from the technology supplier's nearest expert centre.


Early adopters
Increased engagement
Production engineer
Efficiency Customer value
System engineer
More and better data
Computer scientist
More and better models
The AI Flywheel

The AI flywheel

We conclude this section with a metaphor for the successful application of AI – *the data or AI flywheel*. It is a concept that nods to the fact that AI in a business context needs an *inertia mass* – a combination of data, knowledge and energy that all interact with each other in order for a project to be successful.

From a business and company perspective, it's important to create powerful inertia masses, within which machine learning innovations (as a part of the company) fuel other operations, which in turn can become products or services, which in turn can provide leverage effects through additional AI, and so on. Those companies that are first to succeed in this area will be the few surprising 'platform' companies capable of growing with information – *scale without mass* (see also the section *How digital platforms are changing traditional industry*)

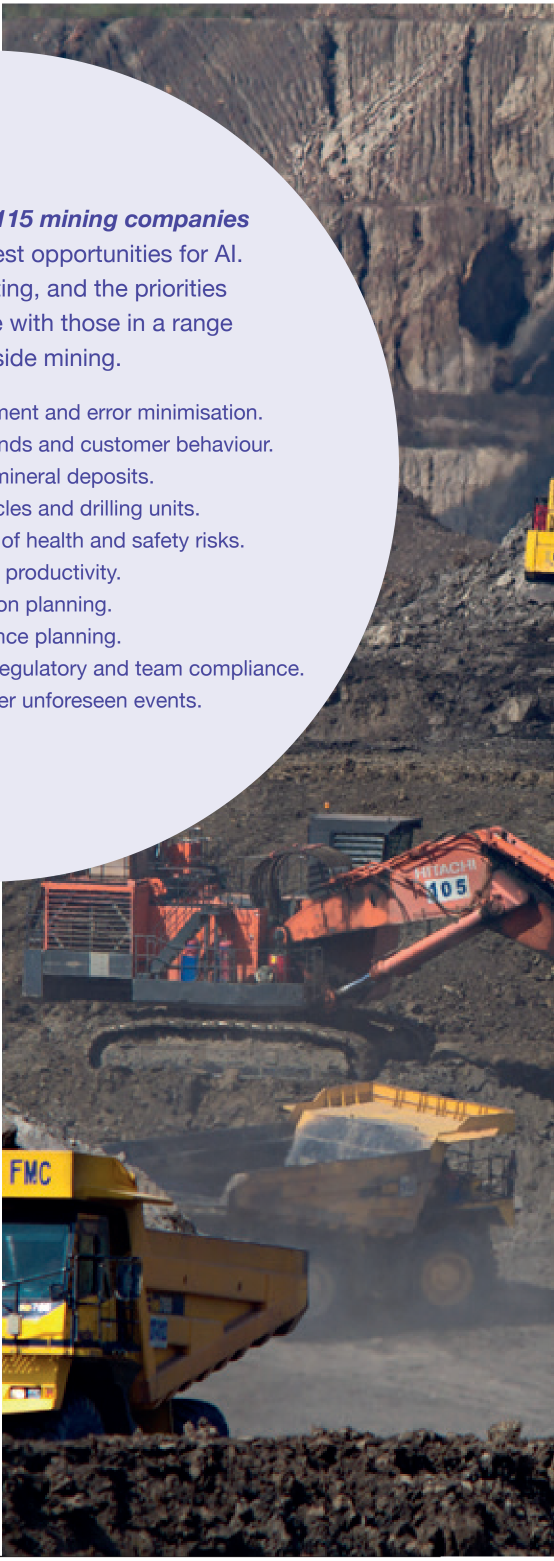
The AI Flywheel concept is often associated with Amazon Web Services (AWS). Amazon likes to use the word flywheel to describe how different parts of its business function as a perpetual motion machine, within which more data yields better products, more customers, and even more data and so on. The company's machine learning platforms create momentum throughout the organisation. Offering machine learning to outsiders as a paid service is in itself profitable. The fact that such projects also generate data provides even more leverage.

AWS grew by 40 percent in the first quarter of 2019 with an operating margin of 29 percent. Somehow, Amazon has cracked one of the business world's riddles; how to create small innovative teams within a much larger (bureaucratic) business. Agile teams that learn quickly, develop competence in many AI-related areas and then spread the knowledge to the rest of the organisation. In useful, coherent and collaborative ways that create value throughout the organisation. It is impressive. But how can traditional industry adopt the logic of the AI flywheel? In this context, we will content ourselves with exploring the concept of the basic organisation – the team – which makes bigger strategies possible.

> "Amazon likes to use the word flywheel to describe how different parts of its business function as an eternity machine, within which more data yields better products, more customers, and even more data and so on.

The most common mistake when companies adopt AI is that they start out focused on the technology and not the business needs. Hiring data scientists and giving them access to data to build *something interesting* is very likely to lead to a dead end.

As discussed, teams with different competencies are required, of which the four basic ones are: **product or production managers** (who can describe, in detail, which problem to solve), **systems engineers** (who know what data can be used), **computer scientists** (who know how to build good models), and **cross-discipline specialists**. This latter group can be called DevOps engineers or translators (*Development-Operations is a term borrowed from the IT industry and agile development, while translators is a term borrowed from McKinsey*). In this context, this invaluable category of people (usually made up of engineers) create commitment and knowledge, and are able to move relatively freely between production, process and operational development, as well as customers' needs and preferences.



Mining Magazine asked 115 mining companies
where they saw the greatest opportunities for AI.
The answers are interesting, and the priorities
identified would resonate with those in a range
of sectors outside mining.

1. Better decision management and error minimisation.
2. Understanding market trends and customer behaviour.
3. Discovering mineral deposits.
4. Autonomous vehicles and drilling units.
5. Automated monitoring of health and safety risks.
6. Increased productivity.
7. Production planning.
8. Maintenance planning.
9. Automation and support for regulatory and team compliance.
10. Rescheduling after unforeseen events.

The members of the team use different tools and work together to solve the group's challenges. But each is ideally a person with the ability to scale up their operations and fill the flywheel metaphor with power and torque.

Of course, more or less similar competence combinations have always been used to develop products and operations. What is new is machine learning technology and a requirement for expertise in this area, at least for the time being. For companies that are advancing in the AI world, it is necessary to take serious steps to create such pilot teams. For companies that are scaling up, the accelerators, such teams are still needed but should push up against the boundaries and away from regular business operations. In such circumstance there's potential to achieve flywheel effects at the company level.

Supply

We will now move on to analyse the supply side of things, by assessing technology development and the supplier system. We will do this firstly through an overview of the area of AI development with a brief conceptual summary, followed by describing the structure and strategic challenges of the supplier industry. The chapter ends with our conclusions about the effects on the market system.

The area of AI development

Behind the applied development of digital technology for the industry lie significant investments. In simple terms, they can be described as three development hubs, each of which, according to Blue Institute estimates, accounts for about one-third of an impressive SEK 1.5 trillion invested globally in R&D each year:

• **The driving forces for the first hub** – private-public innovation collaborations – consist of national ambitions along with industry insights on the values at stake in the fourth industrial revolution. These have generated significant investments through which private and public national capital unite in various programs around the world. *Industrie 4.0* in Germany is among the most renowned. In Sweden, the Strategic Innovation Programs have been established focusing on selected growth areas. These private-public investments amount to about 500 billion annually.

• **The second development hub** consists of the large tech companies' annual R&D investments in the construction of cloud services and investments in AI. *The Big Five* - Apple, Alphabet, Microsoft, Facebook, Amazon plus IBM – are estimated to invest nearly 500 billion a year.

• **The third hub** consists of the *traditional ICT industry plus automation providers.*

A significantly more fragmented industry, but a further estimated 500 billion is invested into research and development.

Development projects are now starting to leave the laboratories on all fronts and to arrive on the market, first as innovation projects, then as best practice, and then, eventually, as powerful commercial offerings.

The driving forces behind each hub are essential: a return is required on those large investments; standardisation work is about to yield results; and the world's industrial leaders are beginning to understand the huge sums and value at stake with the impending transformation of the industry. Last but not least, a dynamic is arising as the three developmental hubs start to propel each other, as development results are released onto the market. This means that the momentum for the whole system increases further.

Figure 9: The applied development of digital technology for industry is being driven by historical investments in what can be schematically described as three fields of influence or developmental hubs. Each of these accounts for about one-third of an impressive 1.5 trillion invested in technology development each year. *Source: Blue Institute.*

Significant breakthroughs in AI technology

Significant breakthroughs in AI are coming to the public's attention more and more frequently. This is occurring across all application areas. Initiatives within foundational research and product development are producing visible results and the development curve is growing steeper.

1 The most mundane and yet revolutionary example is personal assistants such as **Alexa, Siri, and Google Assistant,** which are continually learning more, and making themselves known via our phones and calendars.

2 **Estonia** wants to make its government and judiciary as efficient as possible and so is developing an AI model to act as a judge in minor legal cases where the value of the dispute is less than EUR 7,000.

Basic AI concepts

The concept of Artificial Intelligence (AI) lacks established, unambiguous definitions and demarcations. The nature of the field allows for broad philosophical, social and mathematical discussions. AI Research in itself is both specialised and dispersed across subfields that often lack contact with each other. This makes the area in its entirety difficult to fully comprehend. However, for this analysis, we have chosen to use the same definition that Vinnova used in its study of *artificial intelligence for the Confederation of Swedish Enterprise and Society, 2018*, namely:

"The ability of a machine to mimic intelligent human behaviour. Artificial intelligence is also the designation of the science and technology field that aims to study, understand and develop computers and software with intelligent behaviour."

AI can thus be defined as the ability of machines to perform cognitive functions that we associate with human minds, such as perception, reasoning, learning, interacting with the environment, problem solving and, ultimately, even creativity.

"In January 2019, a research group at Columbia University announced that they had made great progress by creating a robot that can imagine itself.

3 The **OpenAI** development institute recently unveiled a pre-developed language model (GPT-2) that can generate realistic texts in different kinds of style and prose. The text robot is so powerful that the Institute is refraining from releasing the fully trained model due to the risk that it may contribute to the spread of so-called *fake text*.

4 In March 2019, the Google company **DeepMind** presented a model capable of diagnosing complex eye diseases in real time. In thirty seconds, Google cloud algorithms can provide a detailed prognosis with the same precision as world-leading eye specialists.

5 In January 2019, a research group at **Columbia University** announced that they had made great progress by creating a robot that can imagine itself. After a day of intensive training, it was able to adapt to different situations, manage new tasks and detect and repair injuries in its own body.

A dominant theory for assessing the characteristics of AI systems is the so-called *Turing-test*[15)] :
A computer passes the test if a person, after having asked a number of written questions, cannot discern whether the answers have come from a human or a machine.

The set of abilities[16)] which are considered essential to enable an artificial intelligence to be experienced as humanly intelligent include:

- *Natural language management (NPL).*
- *The ability to store knowledge.*
- *An automated ability to reason.*
- *Machine learning to make discoveries tailored to given conditions.*
- *Vision technology in order to see.*
- *Robotics for moving or manipulating objects.*

Another central figure of thought in AI is the rational, intelligent agent. The agent is a piece of software, an algorithm, which is expected to operate autonomously and be able to sense its environment, endure for a long time and adapt to changing conditions, as well as setting up and reaching goals. All the properties of the Turing test are also valid for the rational agent to function.

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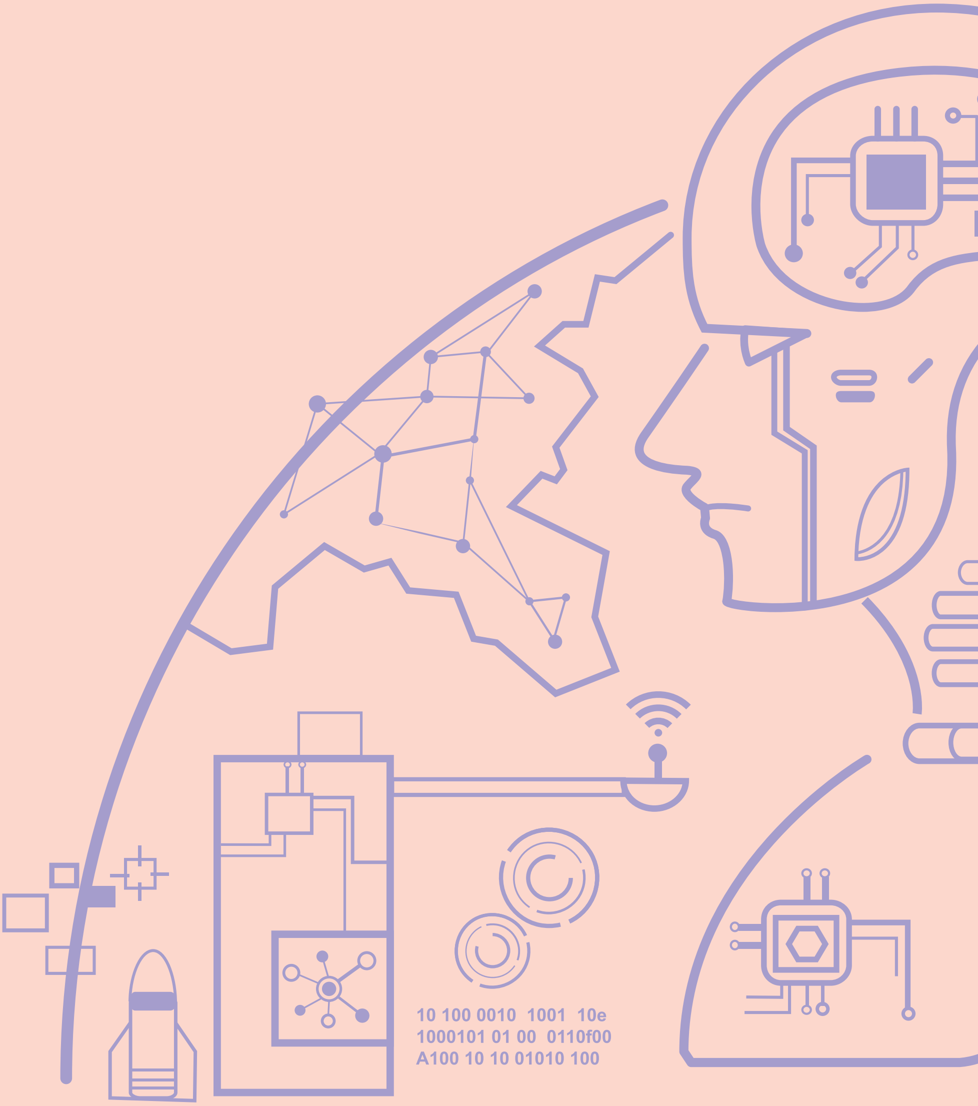
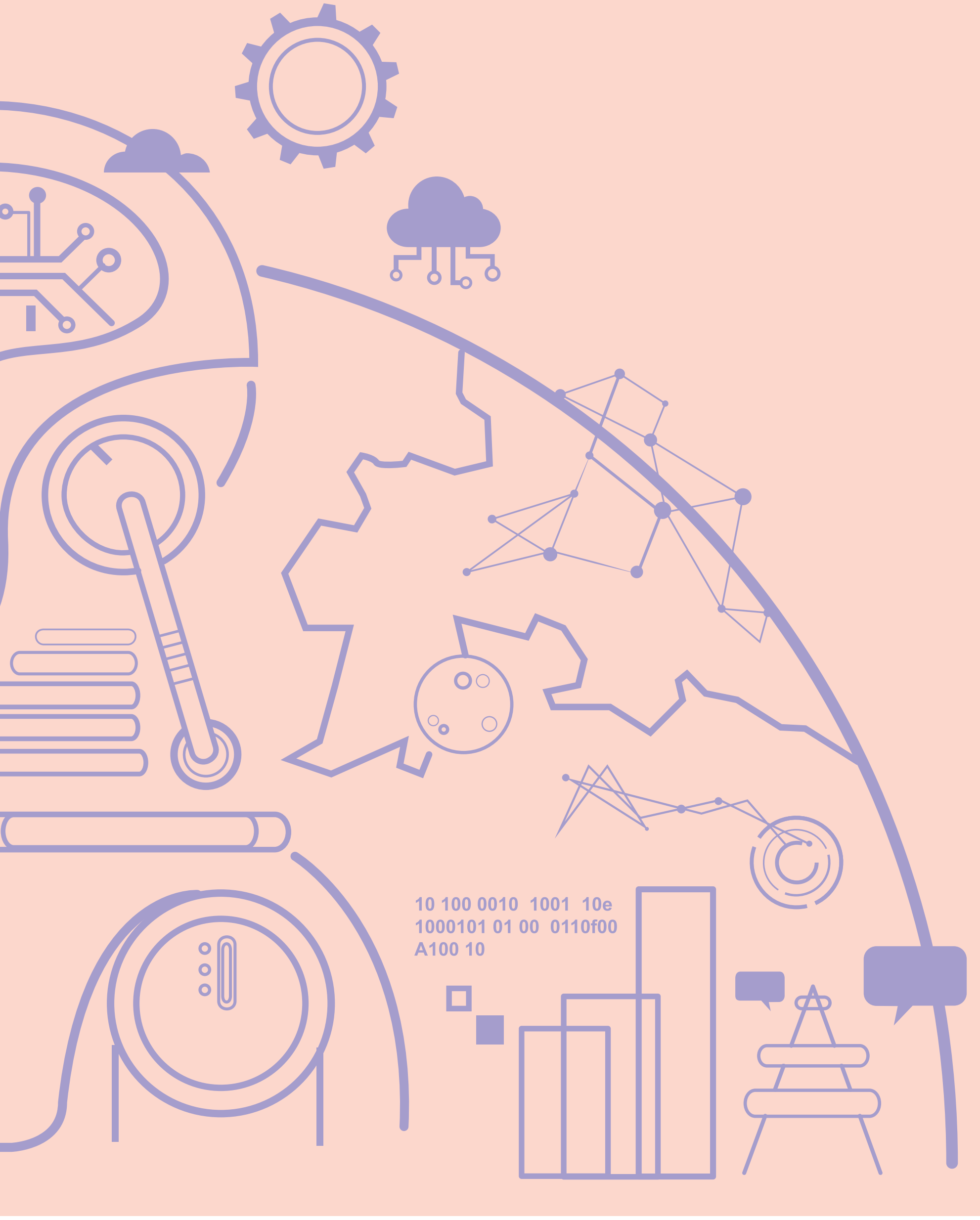
15) Turing Alan m, Computing Machinery and Intelligence,1950
16) Russel, Norvig, Artificial Intelligence, A modern approach, 2016

Narrow and broad AI

AI can be classified in many different ways, but a common description is narrow versus broad or general AI. In fact, all the AI that exists today is narrow or rather; specialised. Our own intelligence, however, is general. If, at some point in the future, AI becomes general, it will probably change society fundamentally. When, and if, this will occur is debated and time spans from ten to several hundred years from now – or never – have been suggested. A marginal part of AI and machine learning development today touches on general artificial intelligence. The majority of development resources are focused on making narrow/specialised AI more effective.



"According to various studies, AI development in the IT consultancy industry is seen as among the most pronounced technological breakthroughs of all time.



Machine learning

Machine learning is an area of computer science that explores methods of getting computers to learn from data without having been programmed for the task. The area is related to statistics and pattern recognition.

Machine learning has been the prevailing developmental track for practical applications of AI for a few decades. Progress has been made through the application of machine learning to increasingly larger sets of data. In a relatively short time, different machine learning subtypes have been developed, within which algorithms are constantly being improved and adapted for different applications.

Those in the sector talk of ***supervised learning***, which means that an AI algorithm uses sets of data to *train* while receiving feedback from people in order to learn when the relationship between given inputs and outputs meets the requirements. ***Unsupervised learning*** means that the network works without prior knowledge. The computer must teach itself the underlying structures only using the input provided and not through any pre-given response.

Deep learning is a type of machine learning that can process a wide range of data points, may involve simpler data processing, and can provide more accurate results than traditional machine learning approaches – although it requires a greater amount of data to do so.

Deep learning connects software based *neurons* together in a neural network. The network can receive large amounts of input and process it through multiple layers that learn more complex functions for each layer. Once the network has learned, for example, what an object looks like, it can recognise the same object in a new image.

Reinforcement learning means that the algorithm is rewarded when it is successful. For example, through the accumulation of points in a game using a step-by-step approach to reach the maximum score. The algorithm remembers the successful features and outcomes and corrects itself for ever better results. It learns by discovering. This method, which is inspired by the brain's dopamine system, is used when there is insufficient training data available, when the ideal, ultimate goal cannot be defined explicitly or when the only way to learn about the environment is to get started and interact with it.

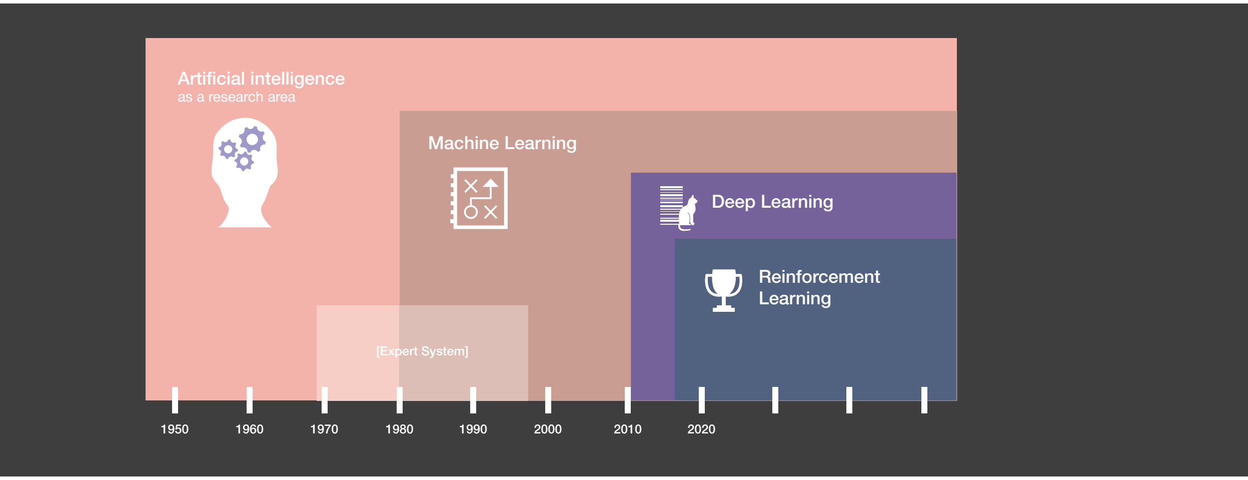


Figure 10: AI and different learning methods put in a developmental perspective.

Reinforcement learning is the latest major breakthrough in machine learning and received widespread publicity when the AlphaGo computer program from Google-owned DeepMind in 2015 defeated one of the Chinese champions in the board game Go. Since then, the technology has attained several commercial breakthroughs and is used, among other things, to streamline the operation of gas turbines, wind turbines and energy use in cin data centres. The method has good potential for future industrial applications.

For an in-depth look at machine learning, refer to Part 2 of the report. In this section, we will continue with an analysis of the supplier system.

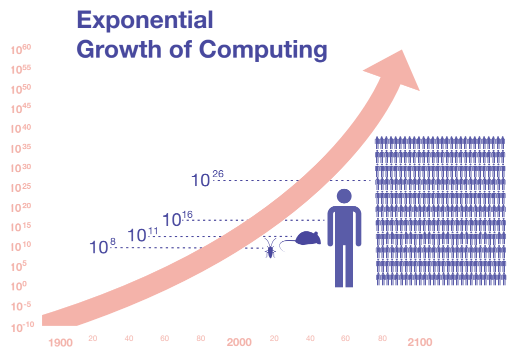


Figure 11: Computing power is a prerequisite for the development of artificial intelligence. It took 90 years to reach the first Million Instructions Per Second (MIPS) per $1,000 - now 1.2 MIPS/$1,000 is added every hour. *Source: Ray Kurzwel and KurzwelAI.net.*

The availability of AI is dominated by the major platform suppliers

The range of applied AI technology is increasing at a rapid pace: we are seeing infrastructures, tools, algorithms, data and pre-trained AI models for various purposes, all offered as standard products by all major platform providers. The development of automation suppliers means that industrial control systems will also get built-in machine learning capacity. The telecommunications industry is beginning to offer distributed and cloud-integrated *edge technology* that shares IoT concepts. There is also an increase in specialised AI providers for different applications.

Technology providers of all categories are contributing to the quick commercial distribution of machine learning technology and several market studies show strong anticipated growth in the coming years. According to the analysis company Markets & Markets[17] , the market for machine learning, language management and vision systems will grow from about USD 22 billion in 2018 to more than USD 190 billion in 2025.

This corresponds to an annual growth rate of almost 40 percent. IT consultants and system integrators are also seeing business opportunities and are gaining knowledge around the new tools. According to various studies, AI development within the IT consultancy industry is seen as among the most pronounced technological breakthroughs of all time[18].

But it's the big tech companies that are driving the lion's share of commercial AI development. The platform companies Apple, Alphabet, Microsoft, Facebook, Amazon and IBM together have an estimated value of over USD 4 trillion and account for 55 percent of the value of the Nasdaq 100 Index.

It is these companies that are behind the commercialisation of AI in the West. In Asia, Tencent, Alibaba and Samsung are dominating, while Europe lacks corresponding strengths. In comparison, however, Europe has advantages in industrial technology companies (IndTech). The European companies ABB and Siemens are significantly larger than their US counterparts.

[17] Markets & Markets, Artificial Intelligence Market, 2017
[18] Konsultkompaniet, Så blir it-branschen 2019, 2019

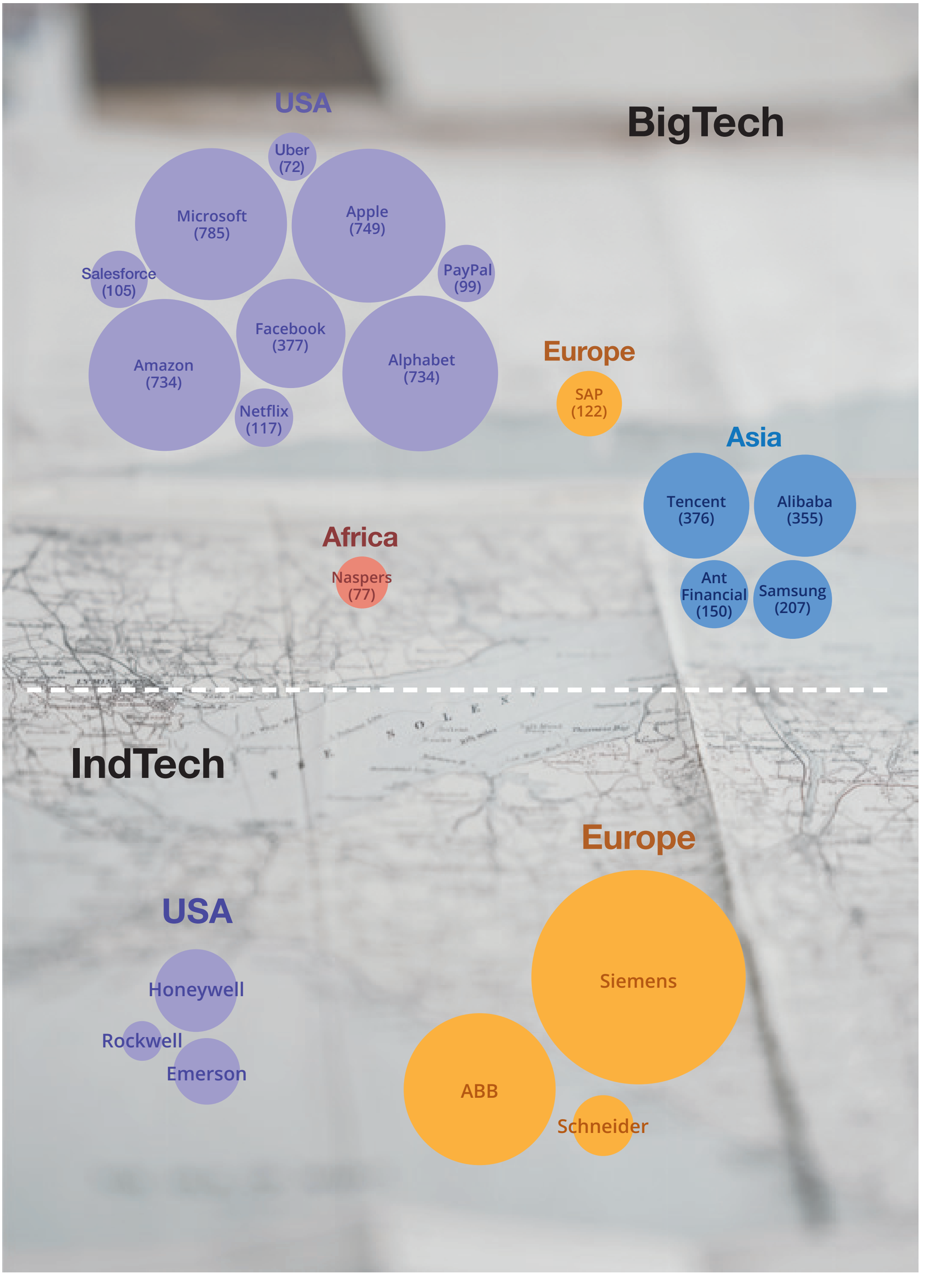


Figure 12: Top: Platform companies in the US have a definite lead in the development of AI platforms. Market values December 2018. Below: Comparison between the three largest IndTech companies in Europe vs USA.
Source: EC, EU Industrial Policy after Siemens-Alstom, Blue Institute.

The long-term AI strategies of the platform companies include a large R&D component reinforced by acquisitions. For example, Google's purchase of DeepMind for USD 400 million, Twitter's acquisition of Magic Pony for USD 150 million and Microsoft's purchase of Github for USD 7.5 billion. In order to ensure the availability of top academics from universities, employees are being offered high salaries, unlimited data and computing resources and minimal bureaucracy.

The concentration of resources, expertise and access to data is therefore currently focused on a few global commercial players. This is part of the *platform war*, the battle for market domination over cloud services within which the mightiest battle is between Microsoft, Amazon Web Services and IBM.

Underlying this growing market landscape is the quiet market dominance of the platform companies. Generic cloud products reach end-users directly or via domain providers. Within the industrial context, automation, process and machine suppliers are able to add industry-specific value.

Automation suppliers operate in this way, serving as targeted market channels that increase the value of the platform companies' large-scale production of computing power and machine learning. These platform alliances and centres are flanked by two groups of more independent initiatives. One consists of companies that sell predictive analysis solutions and build individual platforms. According to a qualitative evaluation by analysis company Forrester, this segment is led by SAS, IBM and SAP, with a long tail of smaller players.

The second flank is made up of specialised companies that supply systems for speech, language, vision and generally applicable machine learning platforms for industry and others. There's a similarly long tail of small and medium-sized players. The sector is immature, heavy with development and likely to undergo further consolidation.

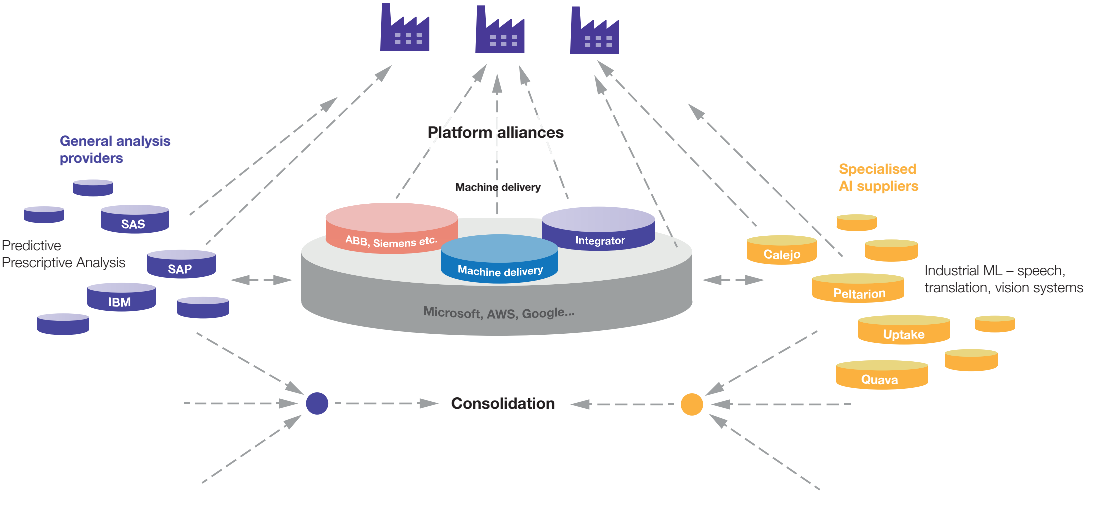


Figure 13: For industrially applied AI, three groups of suppliers can be distinguished. In the middle are the large general platform providers, which are creating more and more alliances with companies that can serve as value-adding specialised channels of the platform suppliers' large-scale AI offering. These are flanked by general analysis players, within which there are several large companies, as well as specialised industrial suppliers of various sizes. The dynamics of the industry are expected to give rise to significant consolidation. *Source: Blue Institute 2019.*

[23] Financial Times AI academics under pressure to do commercial research, 2019
[24] The Forrester Wave™: Predictive Analytics and Machine Learning Solutions, Q1 2017

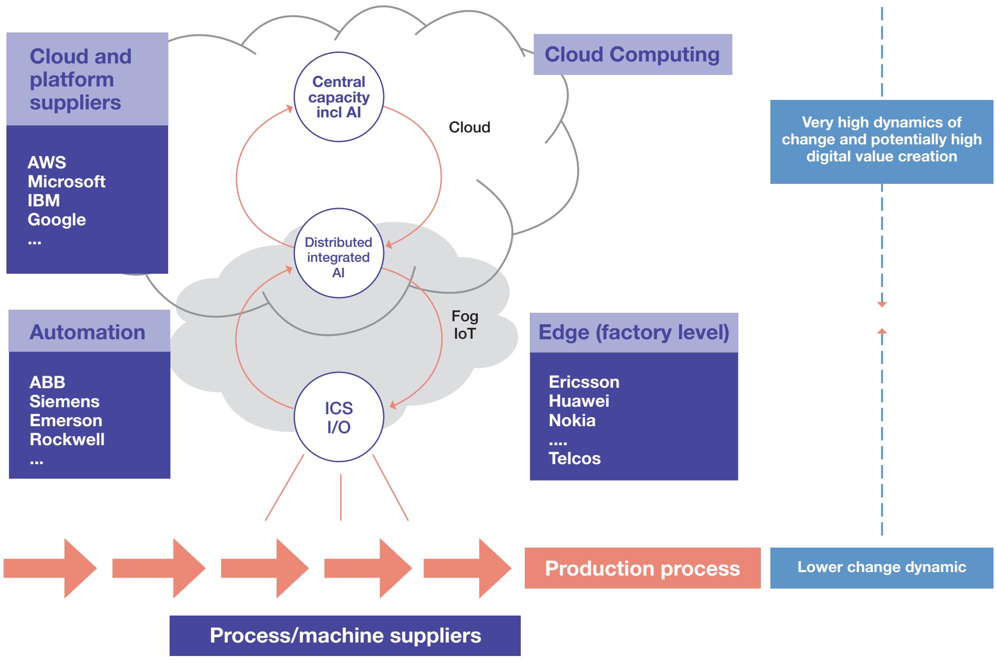


Figure 14: The changing IT/automation landscape. Traditional automation players face new conditions as cloud services sweep across industry. The effect is reinforced when the telecommunications industry seeks return on 5G investments, and process and machine suppliers within technology development have a greater opportunity to solve more problems themselves. *Source: Blue Institute 2018.*

Automation, industrial IT and digitalisation lead to IndTech [21)]

As demand for digital platforms increases and the boundaries between industrial IT, automation and other domains become blurred, more and more players are becoming interested in industrial technology. Cloud service providers Microsoft, IBM and Amazon are building alliances and challenging traditional automation providers such as ABB, Siemens, Emerson and Rockwell.

A second challenge for automation suppliers comes in the form of ICT companies. Ericsson, Cisco, Huawei, Nokia, Samsung and other industry operators are looking for applications for 5G technology and they consider industry's Internet of Things an opportunity. The goal of 5G is to make wireless technology available for applications that have significantly higher bandwidth, speed and reliability requirements than personal use applications. According to Ericsson, operators stand to increase revenues by 34 percent if the process industry and electricity industry increase their use of wireless communication[22)]. Ericsson is supporting this development through its IoT *Accelerator Platform* Initiative. This is a *one-stop-shop* that will make it easy and safe to connect IoT modules and that will also assist in translating the technology into a business setting.

Suppliers of industrial IT and automation now need strategies to deal with platform companies as well as IoT infrastructure.

[21)] The term IndTech refers to digital technology and automation for the industrial sector.
[22)] ISvD, Ericsson ikapp och förbi Huawei I 5G-racet, 8 sep 2017

The dominance of the platform suppliers makes it impossible for automation companies to avoid dependency on their resources, and the challenge for them will be to create relationships that develop the industry's strengths (industrial, process and customer relationships) and increase customer value without becoming marginalised in the platform war. The platform and ICT companies can, by extension, be expected to contribute to making automation solutions simpler and more cost effective and also to adding new value. Intelligent apps in intelligent ecosystems are a development trend that has the potential for a major impact, thanks to the fact that platform companies are opening up their APIs.

Platforms provide process and machine suppliers with additional automation and the potential for advanced in-house analysis. Machine suppliers and the automation industry share an ambition to build connected competence centres for optimisation and for fault remediation in customer facilities. By extension, this strategy is also about competition for the valuable data that can be mined from industrial manufacturing.

A new image for industry's suppliers is emerging, where the ability to create real customer value will distinguish winners from losers. If IndTech suppliers succeed in this, they will have a much more developed role in future industrial value systems as highly specialised vertical suppliers of efficiency and quality, while the process flows will be held together using collaborative logistic systems.

Industry case study: focus on mining companies

The ENSAF project: Energy and Safety Diagnostics

There is currently significant interest in the early diagnosis of problems in underground mining facilities. There is a trend towards achieving fully automated mining, meaning that should hazards arise underground, increasingly there are few or no personnel around to address them. This makes it crucial to have a capacity for early detection of risks from fires caused by factors such as the overheating of vehicles, equipment, cables, and so on.

It is possible to detect the risks of overheating early by placing sensors in facilities and on mining vehicles, which then continuously transmit information to a central diagnostic system. With this approach comes the need to continuously train staff in different fire scenarios and in managing different situations.

Project ENSAF (a PiiA funded project) is a collaboration between ABB, RISE, Mälardalen University and Epiroc, which owns one third of Mobilaris. With the assistance of the Swedish mining companies, who are involved in helping set project requirements and who act as sounding boards for the work, the project is aiming to find a solution to the major challenges that fires pose in mines. The proof of concept, which involves the fitting of suitable sensors to one of Epiroc's vehicles in one of Boliden's mines, is planned to start at the end of 2019. Data collection will continue into 2020.

Boliden is a high-tech metals company with its own mines and smelters, and it is working over the long-term to guarantee society's access to base and precious metals; from the mining of ores (minerals) to the production and delivery of high-quality metals to industry. Its production capacity is high due to experience, innovation and advanced technology, developed in collaboration with various Nordic technology and engineering companies. Approximately 5,800 people work at Boliden and its operations are conducted in Sweden, Finland, Norway and Ireland.

> "In the event of fire, the smoke in particular poses a serious threat to both people and appliances. It is therefore important to be able to detect if a fire is about to start.

Industry case study: focus on mining companies

The challenge

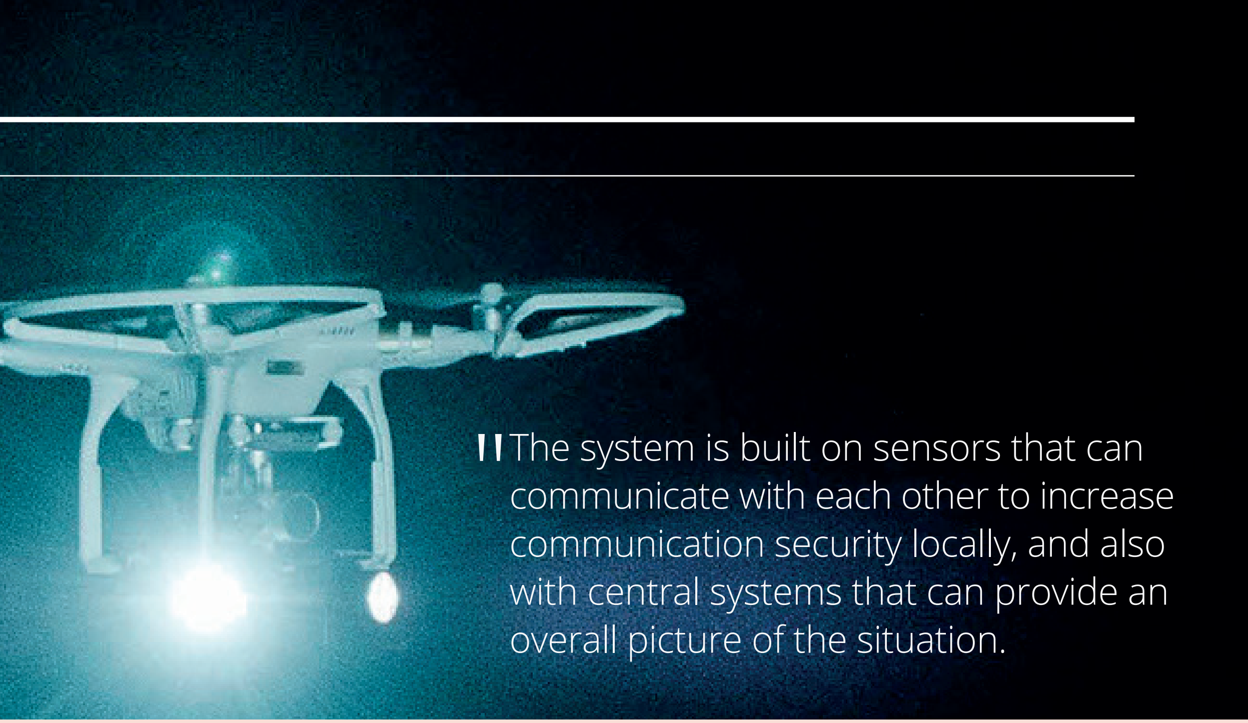
The destructive impacts of mining fires can be significant, both in terms of human suffering and in terms of costs and lost revenues. On an annual basis, about one fire per week occurs in a Swedish mine, with the majority started by vehicles moving about the mine. Sweden has been spared from major mining fires in modern times, but in the global sector it happens all too often. Take the well-documented case of the Pike River coal mine in New Zealand, where in 2010 some 29 people died following several gas explosions. In addition to all the human suffering, the accident put the plant out of service for 45 days due to fire extinguishing and remediation work. The production loss corresponded to half a billion Swedish Crowns, in addition to all the restoration costs and elevated insurance premiums. Additionally, large penalties can be imposed if the root cause of a mining accident can be attributed to safety deficiencies.

In the event of fire, the smoke, in particular, poses a serious threat to both people and appliances. It is therefore important to be able to detect if a fire is about to start. Other types of risks that can arise include leaks on hydraulic lines, which may cause oil under high pressure to produce intense sprays or fog formations.

The experience

The ENSAF project is creating a system that leverages all existing fixed measuring sensors in mines and on vehicles, and links various measurements (such as temperature, hydrocarbons, CO2 and CO concentrations, relative humidity and flow) to each other via simulation models. The aim is to both identify problems at an early stage and nail down as precise a location for the problem as possible. The information collected is used as input to a decision-tree model to assess the risk of fire and also to determine the content of any toxic gases that may be hazardous to humans or to machinery through corrosion. It will be possible to follow real time developments in the mine and compare the measurement data collected with the simulations.

Development of the system is primarily being conducted by Epiroc and Mobilaris, ABB and MDH, with Boliden acting as a sounding board



"The system is built on sensors that can communicate with each other to increase communication security locally, and also with central systems that can provide an overall picture of the situation.

and contributing with experience on mining conditions. RISE contributes, among other things, with knowledge around fire and protection, as well as conducting fire tests in its premises in Borås. ABB sees the potential, through conceptualisation of development, for a complete solution that could be offered commercially, incorporating its automation system. Epiroc provides the measurements from the mining vehicles, with the data collected in its Certiq system. It then communicates the safety information to Mobilaris.

In terms of sensors, the project has been able to detect, among other things, gas formations caused by cables loaded with currents higher than they are rated for. Smoke detectors are used, not only to detect the formation of smoke, but also oil mist that can occur through leakage. Thermal cameras can be used at longer distances to detect temperature increases on, for instance, cables.

Today, Certiq collects object data (e.g. hydraulic oil level, engine power, etc.) 24/7 from several thousand mining vehicles across the world. Since the establishment of ENSAF, the system has gone from communicating and gathering data from a few hundred vehicles to some 3,000. The sensors tested under ENSAF are now implanted in Certiq, which communicates sensor data to Mobilaris. Here, gas values from the vehicles in the mine shaft, for example, can be monitored and may trigger alarms. In a fire situation caused by a mining vehicle, it is possible to correlate all available data and perform root cause analyses, and, with the help of deep learning, provide answers to the cause of the fire. In the future, artificial applications could anticipate possible fire situations and suggest appropriate maintenance activities to avoid fires.

Using measurements and analyses, ventilation can be adapted to suit real needs. This can save energy without risking functionality and provide a good working environment for both people and machines. Close to 50 percent of the energy consumed in an underground mine goes to ventilation. In the case of a fire hazard, the system is set to minimise the risk to underground personnel. The system is based on sensors that can communicate with each other in order to increase communication security locally, and also with central systems that can give an overall picture of the situation.

Sources: ABB, PiiA, MDH

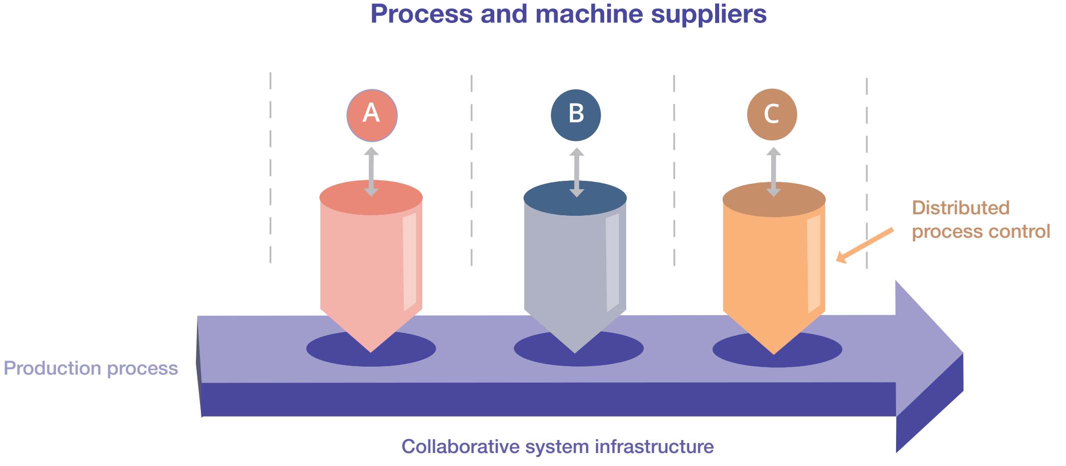


Figure 15: In tomorrow's industrial value systems, IndTech suppliers can take on a far more developed role as highly specialised vertical suppliers of efficiency and quality. Meanwhile, process flows are kept in check with the help of collaborative logistics systems. *Source: Blue Institute 2019.*

One Platform to rule them all ...

One Ring to rule them all was the theme of Tolkien's Lord of the Rings. The parallel with the power of algorithms – and thus the importance of platforms – isn't so far removed from that idea. In the platform war, there is currently a battle for dominance of the market, with resource concentration an ongoing feature.

At the same time, most companies have unique needs for which the general services that the big tech companies offer in their public clouds are not enough. Most companies, therefore, now have some form of a privately-owned platform (private cloud). One trend in the market is for *hybridisation* between one or more public clouds and a company's own private environment.

The issue of cloud complexity is becoming increasingly topical as more and more specialized domain-specific clouds/platforms are launched to the market. The concept of *vertical clouds* has taken hold and complements the original 'general' clouds which are now also called *horizontal clouds*. Vertical clouds represent industrial verticals and subprocesses within each vertical. They typically take the form of

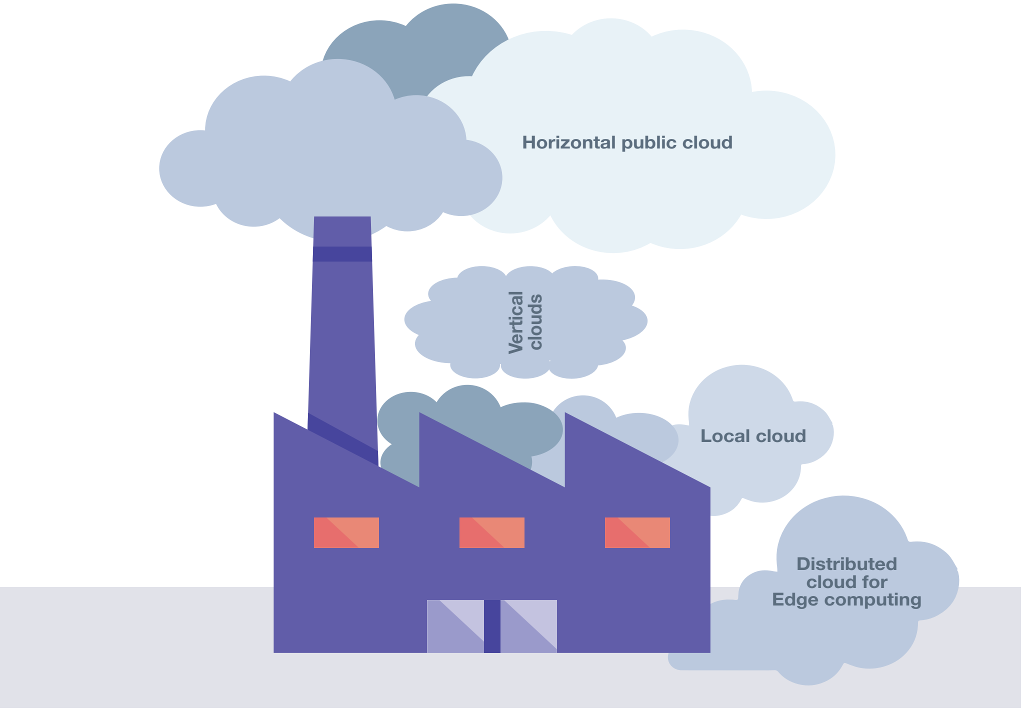


Figure 16: Cloud structures are becoming increasingly complex. Public, vertical, local and distributed clouds are four varieties of cloud with related services and infrastructures. These platforms are suitable for coordinating through hybridisation and, in the longer term, common standards. *Source: Blue Institute 2019.*

a PLM cloud, an MES cloud, an automation cloud, and so on. Here we can see, as described above, how automation vendors are now adding vertical domain-specific clouds or platforms to their offerings.

Another contemporary trend is locally distributed clouds known as *edge computing* or sometimes *fog*, which we touched upon earlier in the report. Edge computing is expected to have increasing significance as AI technology increasingly requires local capacity to complement the core resources of server rooms.

One practical, short-term solution to get all these clouds working together is through hybridisation solutions. The big hope for a long-term solution for industry in operational applications lies in standardisation which would make it possible for different environments to be combined in the same physical facilities. Standardisation work is going on within ISO, among other areas. The idea that we, like Windows, would become a de-facto standard is not likely, even though Microsoft is the provider that is currently the most successful in production-related applications.

Automation suppliers

There is currently a developmental trend that has the highly consolidated automation industry and leading companies such as ABB, Siemens, Emerson and Rockwell all moving in the same direction.

Their common goal is to achieve market platforms that are specifically tailored for the industry. While these structures can be likened to operating systems for IoT, they meet the criteria for platforms as they match different types of users against each other. (See also the section on vertical clouds on the previous page.)

AI is being used as a management and administration tool within these platforms and can also be used to produce products in the form of smart apps. These can be tailored to different applications and are available for purchase with one click via corporate app stores.

Specialist centres are also being created for various product and industry applications, and being linked to production facilities to allow for online optimisation and troubleshooting by experts.

Schneider Electrics' IoT platform is called EcoStruxure Platform and uses Microsoft Azure.

In 2018, **Emerson** acquired GE's famous Predix Platform, which uses services from Microsoft Azure and Oracle, among others.

Rockwell has Connected Enterprise and Factory Talk, which also use Microsoft Azure.

Siemens' investment in this area is called MindSphere and rests on resources from Microsoft Azure, IBM Watson, SAP and even Amazon Web Services.

Microsoft has taken a firm grip on the close-to-production IoT market through its partners. Microsoft Azure is its platform and includes services, tools, and infrastructures that can, among other things, simplify AI development.

Service offerings include Microsoft Cognitive Services, a set of pre-built AI features including vision, speech, language, and search functions. Everything is in the cloud and can be integrated into applications. Some features are customisable and can be optimised to transform and enhance organisational or industry-specific processes.

ABB's venture is called Ability and is built on solutions from Microsoft Azure and IBM Watson.

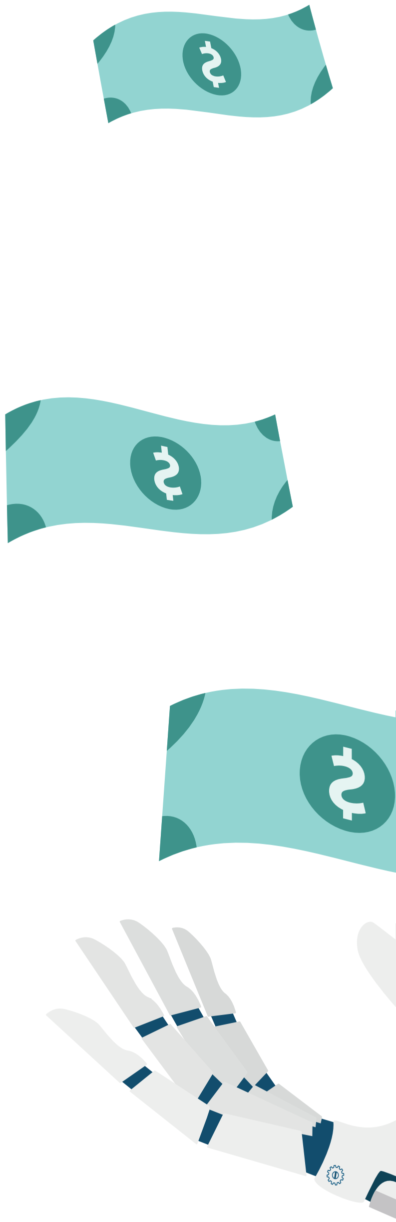
> "The world market for IndTech is worth USD 340 billion

The world market for IndTech – products and systems for industrial digitalisation and automation – is worth USD 340 billion and has a growth rate of 6-7 percent. The area can be divided into IT and OT (operational technology). The IT share is USD 100-110 billion, while operational technology for production and logistics accounts for USD 230-240 billion. Within OT, the distribution is 45 percent for automation for the manufacturing industry and 55 percent for process automation.

OT includes different types of industrial control systems and field equipment such as instrumentation, drive systems and robots. A special growth area is industry's Internet of Things which complements traditional system environments. Several platform suppliers are now also launching dedicated and distributed systems for machine learning at a local level. Edge capacity on the factory floor can thus effectively be integrated into the cloud. For example, in 2018 Google released the third generation of the Tensor Processing Unit (TPU) chip.

This parallel development has led to several automation companies developing stand-alone AI modules with neural networks that can be plugged into control systems. With this comes pre-customised type solutions for different processes or process objects.

Is AI expensive?



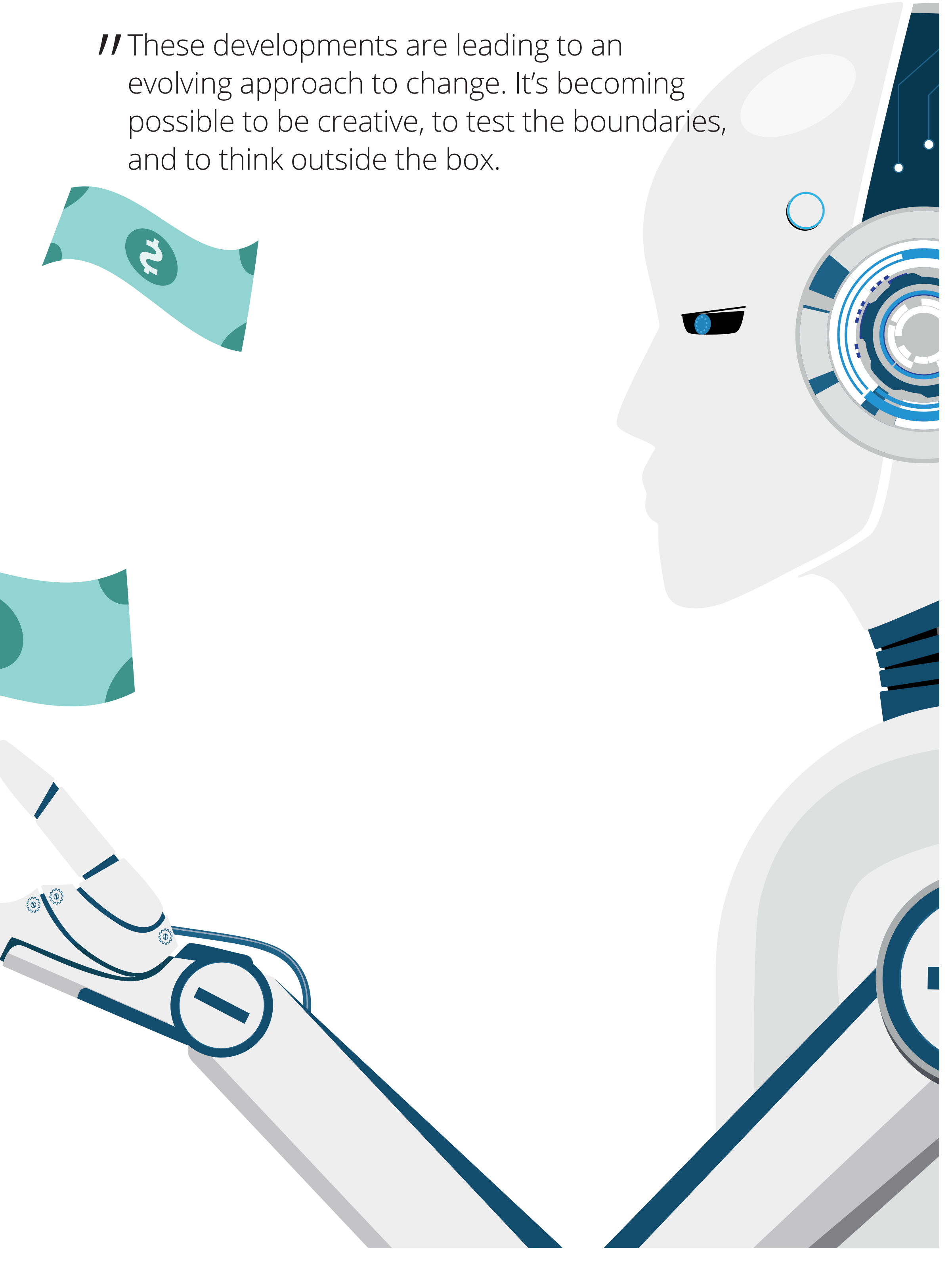
The computerisation of industry in the 1980s and 90s cost a large amount of money. Machines were replaced and investment focused largely on large process control systems and specialised computers, while thousands of kilometres of cable were laid. Air-conditioned data centres were built, along with control rooms and cross-connection spaces. In short: it was expensive, but a good investment, nonetheless, as productivity and key quality figures skyrocketed. This type of basic investment will always be needed when rebuilding or when new investment is required, but the nature of digitalisation alters the equation. Consider the so-called *logic of small streams*, where a large number of spread-out, smaller initiatives can come together to produce great results.

Today, you don't need to build air-conditioned data centres and to buy servers to bring good ideas to fruition. It's easy to order as much computing power and functionality as you require – including AI tools – from the cloud at comparatively low prices. The majority of the data monitoring and collection infrastructures one might require are already in place. If sensors and hardware are needed, there are – or will soon be – cost-effective IoT modules that will meet even the strictest precision and environmental requirements. Communication solutions are also expected to be wireless, reliable and inexpensive in the future.

These developments are leading to an evolving approach to change. It's becoming possible to be creative, to test the boundaries, and to think outside the box. Huge investments will not be required to unlock parts of the hidden value within plant and production processes and to outperform both competitors and customers' expectations.

The challenge with succeeding with AI is less about expensive investments in computer technology and more about obtaining the right skills in the right constellations. Experience shows that good AI projects are characterised by successful teams where domain and process knowledge, knowledge of analysis, and the right tools, all play a key role.

"These developments are leading to an evolving approach to change. It's becoming possible to be creative, to test the boundaries, and to think outside the box.



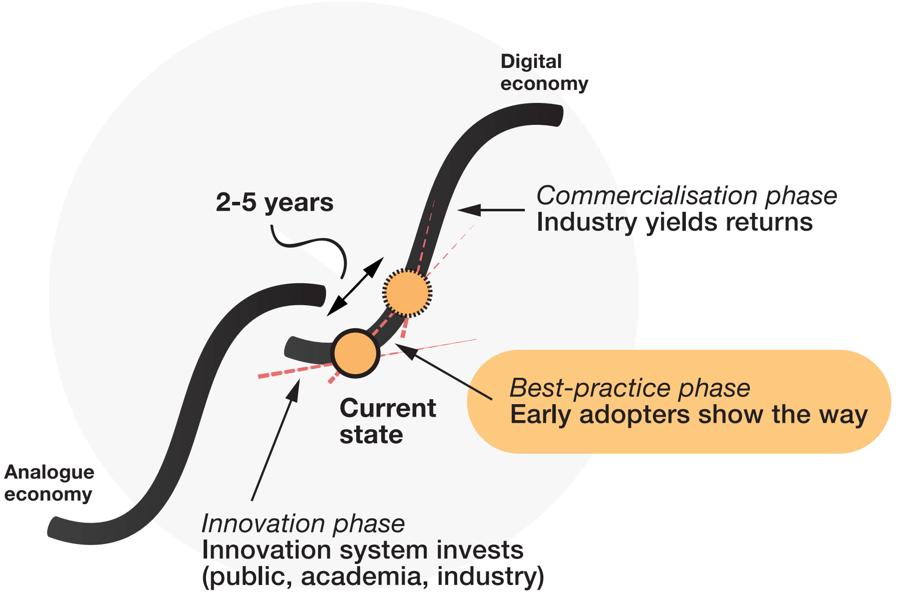
Conclusions

Our first aim was to examine the expected value-creating effects of AI and, based on the evidence we have studied, we have found that AI's effect on productivity development is expected to outpace by a factor of two previous, generic technology shifts, such as the introduction of steam, robotisation and IT. According to PwC, global GDP in 2030 could be as much as 14 percent higher due to the AI effect. Global impacts on industrial sectors leading up to 2030 could amount to as much as USD 2.3 trillion.

Our second ambition was to examine whether the development of AI and the associated supplier system could meet the demand for the technology that is being generated by the potential value creation it brings. Our view is that the focus of development is now leaving the initial innovation phase and moving into the *best-practice phase*. This assessment is based partly on the fact that the large R&D investments being made need to yield profits, and partly on the fact that standardisation work is well on the way to showing results. In addition, industry leaders around the world have come to realise the huge sums at stake in the coming transformation of industry. Furthermore, there is also a dynamic that will arise when the three developmental hubs begin to work together, once development results reach the market. This is likely to produce an increase in torque for the entire system.

Thirdly, we wanted to understand whether this development was sustainable or whether we are currently seeing a hype effect that will wear off, with the actual market breakthrough coming much further down the track. Looking at Gartner's (often challenged) model *Gartner's Hype Cycle for Emerging Technologies*, there are different technical aspects of AI spread out across the different phases of the model. For example, deep learning using neural networks – which can be viewed as representative of the industrial use of AI – is currently at the 'peak of inflated expectations' stage (Aug 2018) but could move to the *'plateau of productivity'* within two to five years.

Our assessment and our S-curve model suggest that digitalisation in a broad sense has now reached the beginning of the 'plateau of productivity': best practice. It is difficult to make timing predictions around the introduction of AI to industry. On the one hand, there is a spread over different verticals with different conditions, and there are also different activities underway, ranging from management and administration to forecasting and foresight, to operational functions in production and logistics. In some areas, AI is already an established technology, while in others it is still in the developmental phase.



But we also found via our empirical evidence that machine learning is being quietly tested in many more places than you might imagine. Safety reasons dictate that the incubation period for new technology within heavier industries is much longer than in other commercial areas and longer still than the consumer area. With this in mind, two to five years seems not a long time, but rather a reasonable action period for translating ideas into operational benefits. A two-to five-year timeframe for the more permanent establishment of AI technology is also in line with our own analyses, with the focus point shifting from a 'best practice' situation to a commercial production breakthrough on the S-curve.

Our conclusion is that the massive underlying forces driving both the demand for and supply of technology guarantee a solid development outlook for AI for industrial applications.

Within the period mentioned above, the timing seems good for a match between technology reaching the industry and the spreading of insight into the possibilities of this technology. This has the potential to create a significant industrial movement and thus deliver increased commercial demand at the company level and the achievement of previously unachievable results in production systems.

We also expect structural changes in the supplier system as completely new concepts reach the market and previous industry and supplier limitations cease to be valid. There will be incentives for both extensive consolidation and repositioning in many areas.

Preventive Predictive Maintenance

Two hundred and sixteen centuries is a long time to wait for a lift. That figure is an estimate of the cumulative annual stopping time of the twelve million lifts in the world, moving about one billion people every day. To improve the maintenance of lifts, escalators and conveyor belts, the two suppliers Kone and ThyssenKrupp have begun to use machine learning. According to the companies, it is just a taste of what is to come.

The idea is to anticipate errors before they happen, and the experience gained from these large-scale, global applications is expected to provide a valuable knowledge base for the broader development of AI in preventive maintenance – something that is expected to be required in most industries.

The challenge

Predictive maintenance is not a new concept. Industries that require high availability such as pulp and paper, chemistry, oil, gas and steel production, to name a few, have long used statistical analysis tools to forecast interruptions and improve maintenance work. But machine learning provides a new level of accuracy and efficiency and makes predictable maintenance possible on a large scale on a large installed base.

It is possible to identify common error patterns over hundreds of thousands of lifts, and at the same time, using algorithms, detect anomalies and specific behaviours for each individual lift plant. While two lift plants might be of the exact same model, their practical use will differ from day to day, as will the infrastructure around them.

It is simply not possible to apply simple sets of rules across such large and heterogeneous environments – which is why machine learning represents a real breakthrough in this context. Until now, predictive maintenance has involved identifying fault thresholds using a range of sensor data, which in turn can statistically indicate faults in lift plants. Machine learning involves using historical data in which fault events have been identified to allow the system to learn to find new faults – all without operators having to tell the AI what a fault pattern looks like.

The experience

In 2015, ThyssenKrupp launched a service called ‘Max’ based on data from IoT sensors, control system data and data from the company's ERP environment and CRM systems from SAP and Oracle. In collaboration with Microsoft, a cloud-based data storage facility was created based on the Azure Cloud Platform. ThyssenKrupp currently provides the service to approximately 120,000 lifts and other systems, or to 10 percent of the installed base.

Open source code is used to build classification and regression models. A combination of models across different data streams and types of objects is compiled to achieve highly relevant and reliable results. The various predictive models are also gradually becoming outdated, due to lifts and escalators wearing out, being rebuilt and maintained, and so continuous re-learning is carried out.

The goal is to send field technicians to a facility before it fails. Although the maintenance system currently is not reaching that goal, the technician is often on the road when the call from the customer arrives. Once in place, the system has already done much of the troubleshooting work that would otherwise be started only once service staff are in place.

The introduction of AI technology at ThyssenKrupp has led to a review of some organisational boundaries between its service departments, IT and other functions. According to ThyssenKrupp's own data, the system (used by 20,000 service technicians worldwide) has so far reduced the stoppage times of over 40,000 customers. It's not just the development of machine learning that has made this possible. Lower mobile data costs and the development of cloud technologies have also been enabling factors.

From an organisational development perspective, the project is not primarily technology driven. From the outset, a broad group of different professions has been involved. Field technicians have been at the centre of the action and they have been complemented with an IT team with skills in cloud and machine learning, as well as the skills to bring together and prepare the data. HR, legal, construction, production and other divisions have also become involved.

Kone – one of ThyssenKrupp's competitors – has developed its own service offering along with IBM and Watson IoT systems. The partnership was launched in February 2017, and Kone has since equipped the facilities that use the service with IoT sensors to measure around 200 different parameters, such as movement, temperature, air pressure and forces within the machine.

"Kone and ThyssenKrupp show that technical industries with large dispersed installation bases can use AI and machine learning technologies in the cloud to build predictive models that plan and make maintenance more efficient.

Data is transferred to the IoT cloud platform as well as data and error status from the control systems. IBM Watson's natural language learning and machine learning processes have also been able to analyse information in maintenance logs and manuals accumulated over several decades. Watson can also be applied to images, sounds, and vibration patterns. Some generic components such as rotary machines have been modelled with general data from the installed base, and models have since been refined with more data specific to each machine.

The result is that customers see significantly fewer stops and errors, and they experience a higher level of service. Future plans include adding more data and expanded infrastructures that will further develop the customer offering. There is a plan to let people interact with the lifts so that the lifts, for example, sense when someone leaves a hotel room and then ensure that a lift is available on the right floor. Kone sees great quantifiable benefits from applications like these, which will drive AI to integrate into other applications as the technology improves.

Kone and ThyssenKrupp show that technical industries with large dispersed installation bases can use AI and machine learning technologies in the cloud to build predictive models that plan and make maintenance more efficient. But just as we have noted before, there are challenges when it comes to developing and applying the computer models, especially concerning data management. This means that these techniques are likely to be mainly applied where the return is greatest.

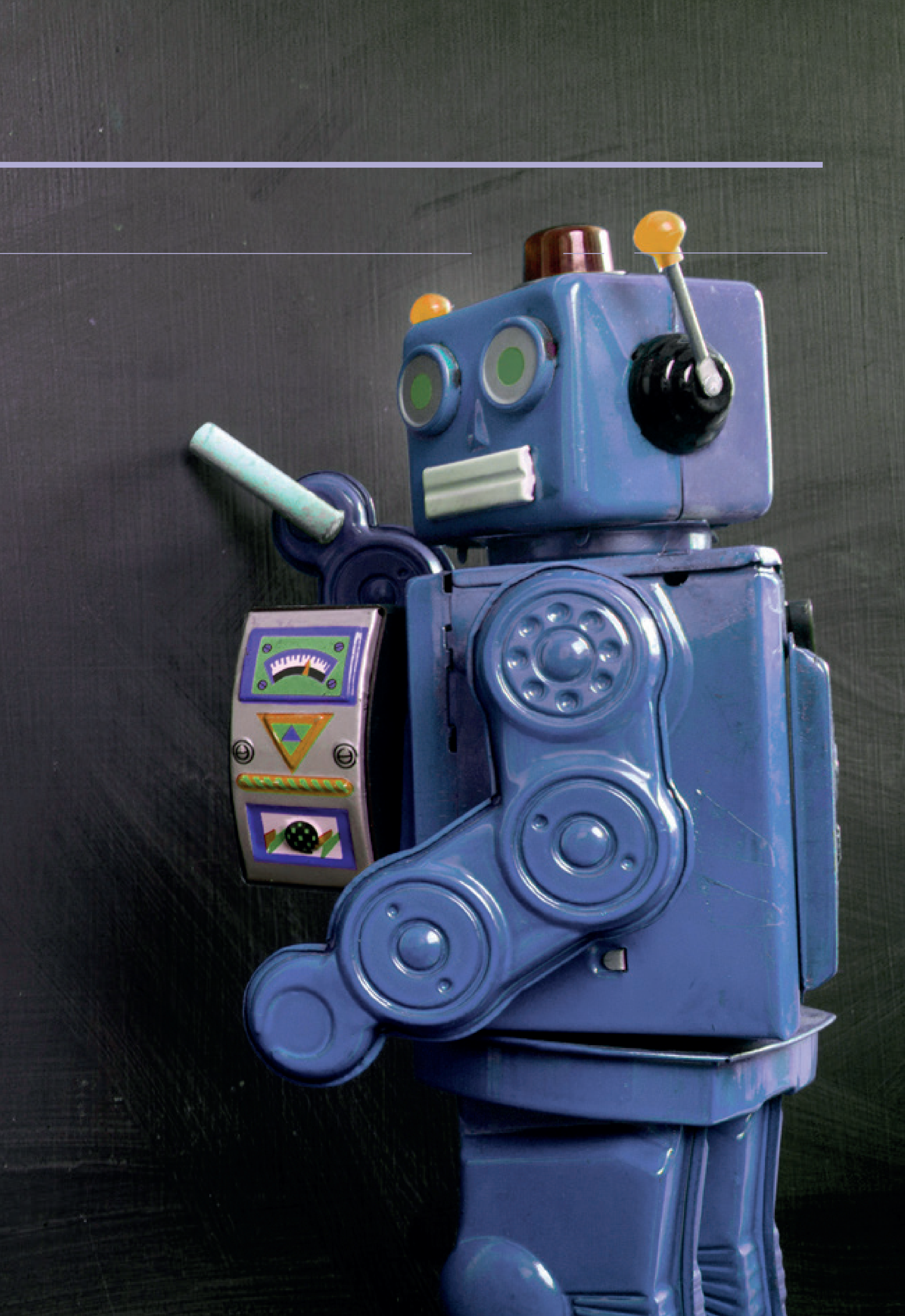
Sources: ThyssenKrupp, Kone, Computer Weekly

Part 2. Technology

In the summer of 1956, a select group of researchers met at a seminar at Dartmouth College in the United States. The topic was artificial Intelligence and the optimistic goal of the summer meeting was to "*achieve significant advances in the AI field*".

Convening the Dartmouth Summer Research Project on Artificial Intelligence was a young assistant mathematics professor who would later become legendary. His name was John McCarthy and, in his invitation, he wrote:

> " We propose that a two-month, ten-man study of artificial intelligence be carried out during the summer of 1956 at Dartmouth College in Hanover, New Hampshire. The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. .... We think that a significant advance can be made in one or more of these problems if a carefully selected group of scientists work on it together for a summer.



The seminar marked the beginning of a favourable period for American AI research. Support, in the form of considerable funding from the defence authorities during the Cold War, led to great academic freedom and a creative research climate. But the 1970s brought troubles. AI researchers had underestimated the challenges, and a series of setbacks followed. Both American and British-oriented AI-foundational research was deprived of its funding. The research was criticised for a lack of realism and a lack of results.

The 1970s came to be called the first AI winter. Several setbacks would come later, as hype around the field repeatedly rose and fell. The so-called LISP machines and expert systems of the 1980s were market failures that once again reduced development grants and led to new freeze periods.

However, in the late 1990s and early 21st century, AI development quietly began to make progress. Expert systems using the technology could be used commercially for logistics and medical diagnosis. These successes came from better methods and more, and cheaper, computational power. The 21st century, and especially the period after 2010, has shown that AI is now an established commercial field that is growing rapidly.

Consumer applications from Amazon, Google, Microsoft and Apple are being rolled out on a broad scale, while AI support is now built into finance, media, trade and industrial applications. AI for language management is expected to grab the largest share of the market in the coming years, while healthcare applications are forecast to have the highest growth rate. Meanwhile, industrial applications are also expected to grow rapidly, a trend that is supported by our analysis in the first part of this report.

The current commercial breakthrough of AI technology is the result of the simultaneous coming to maturity of several underlying fields. The rapid expansion of the Internet from the 1990s onwards means that large amounts of data are

> " AI in the form of machine learning is an established commercial technological field making significant achievements within all verticals in all markets.

readily available today. Data is the raw material of AI technology and is transformed into money and growth using algorithms.

In parallel, other developments mean that the cost of computer capacity is now rarely a limiting factor. Algorithm technology has gone through a similar process. All this comes on top of unprecedented growth within tech companies and their large appetites for investing trillions of dollars in AI development, as well as general conditions that have allowed for the spread of AI. The overall picture is clear: AI in the form of machine learning is an established field of commercial technology that is achieving significant breakthroughs within all verticals in all markets.

The purpose of this concluding section of the report is to provide a somewhat deeper technical perspective to complement the report's market focus in the first part.

We will start with an overall picture of *IndTech* and the scope of industrial IT, automation and digitalisation in general. This will be followed with a description of machine learning technology, and finally a discussion of the data challenge, the concept of collaborative intelligence and the future of AI.

IndTech – an overview of industry as an application area

The concept of IndTech brings together IT with both operational technology on the factory floor and digital development. It has a special significance in that it is where technologies from a range of different fields and periods of time come together. In addition to helping to transform industry, the IndTech movement is creating a world market for industrial technology worth SEK 3.5 trillion per year[23]. IndTech is a hidden and yet giant industry and a field of excellence for Sweden, with numerous renowned companies operating in the field across the world.

The installed base of automation and industrial IT in the world is estimated to be SEK 50 trillion. This is where technology with roots in the 1980s meets with digital innovations generally not even developed for industry; something that's hardly surprising given that a range of other sectors encountered digitalisation far earlier.

The picture of the field that is emerging is thus one of great opportunities but also significant challenges.

The traditional view of system support for industry has been a pyramid-shaped hierarchy, with operational technology closest to production, and IT for administrative processes located above it. The idea that this hierarchy, the Automation Pyramid, might be dissolved in favour of more flexible structures has long been the subject of discussion. How this might actually happen has been less clear.

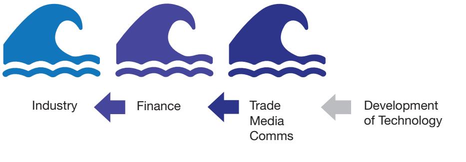
Incremental change scenarios seem the most likely given industry's installed base of 1990s technology, much of which has a significant remaining life span, and the need for extensive standardisation work. In the short term, the focus may be on removing silos through better, more practical integration between computers and organisations, both within companies and in supply chains. In the longer term, the focus is likely to be on interoperability in the shape of the full interchangeability of information, without manual intervention, based on accepted industry standards.

In order to understand the general impact of digitalisation on industry, it's important to consider which existing structures could simply be replaced by new technologies (a less common scenario), and which are likely to go through incremental changes over a long period of time (the more common scenario). The challenge going forward will be to use digital platforms and information transparency to address market fluctuations with new organisational approaches and ways of doing business.

Industry's experience with previous technology shifts has demonstrated the importance of creating an overall conceptual picture, as well as having clear objectives from the outset and working towards them one step at a time. These objectives should include at a bare minimum: having digital infrastructure delivered through one, or several, specialised cloud services from different providers; using AI analysis for automation, augmentation and a collaborative approach between people and machines; using the Internet of Things as a general application platform to lower prices and simplify hardware and software.

Together, these three verticals form a digital platform with the potential to resolve information hierarchies over time. One of these verticals pertains to advanced analytics, an area in which machine learning, if applied correctly, can be a very powerful tool. We will now examine this field in more detail.

The three waves of Digitalisation



[23] Blue Institute, PiiA Insight, Swedish IndTech, 2018

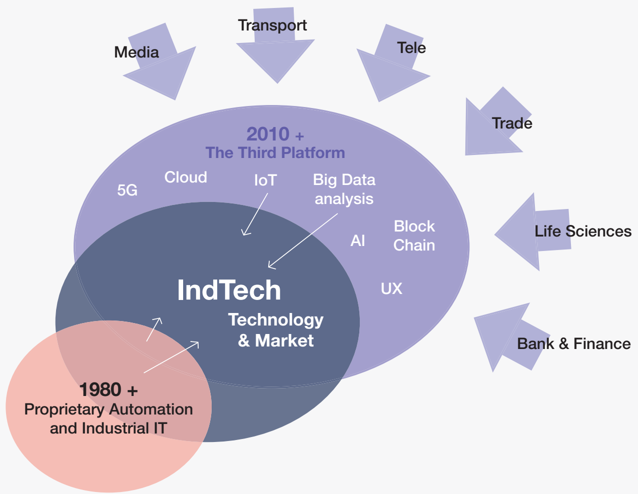


Figure 17: The model for IndTech: traditional and new technologies come together and make ‘smart industry’ possible. Classic automation and industrial IT meet digitalisation and create new digital platforms and business ecosystems. *Source: Blue Institute 2019.*

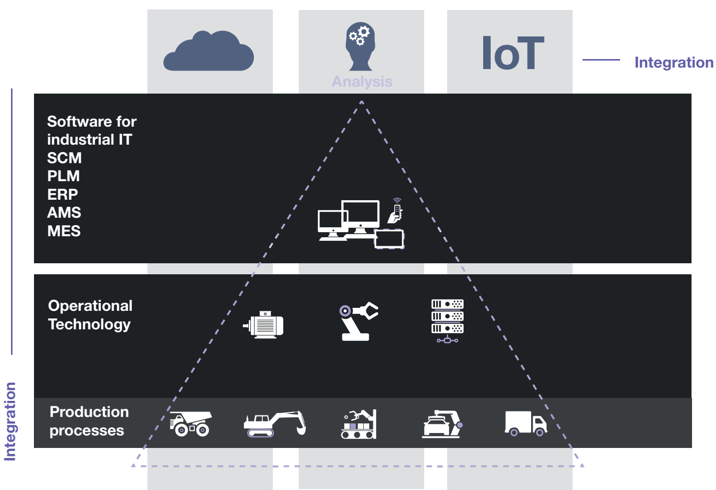
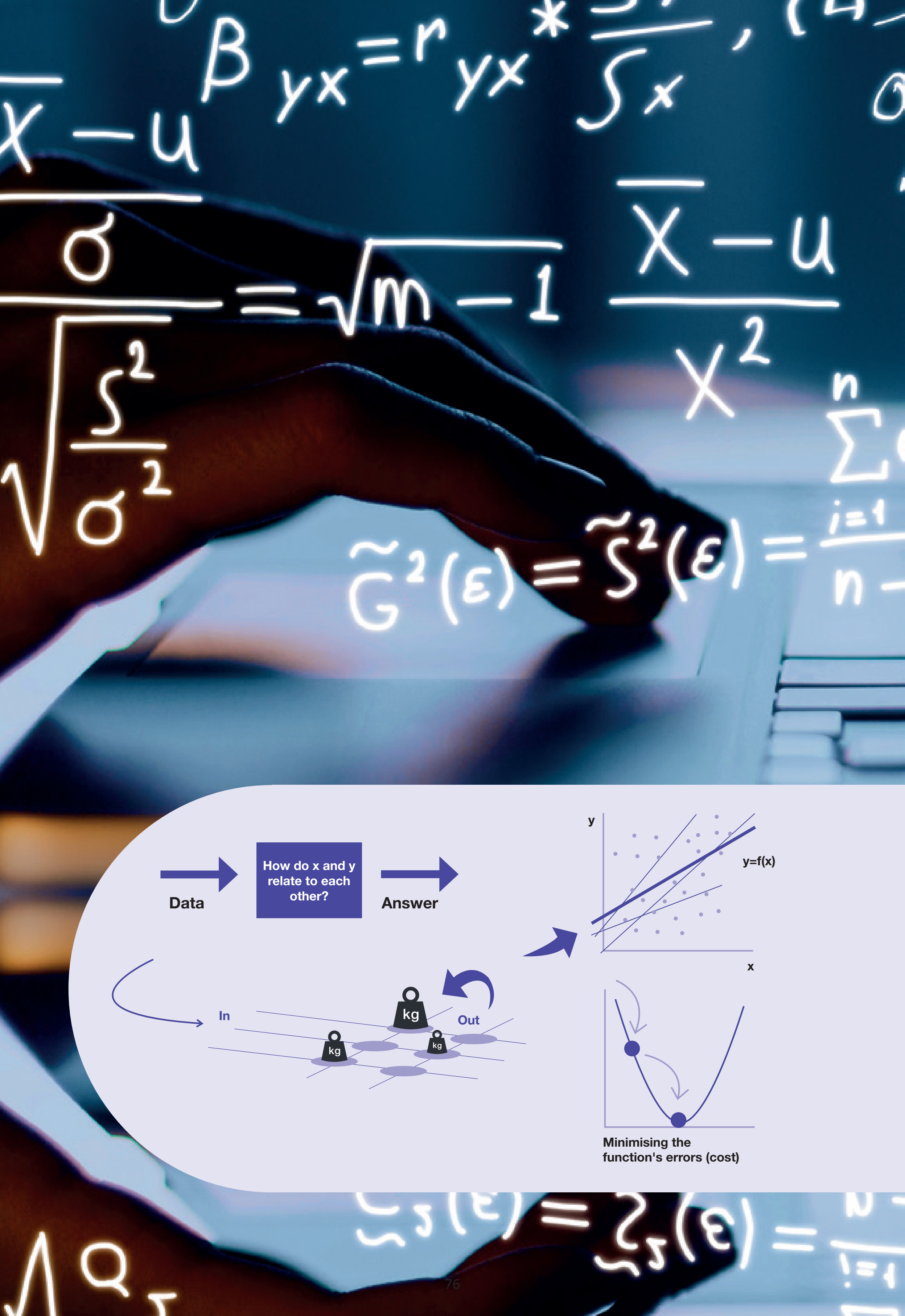


Figure 18: Development can be summarised as integration in vertical and horizontal directions, and through new technology fields that both complement, improve and challenge the traditional environments and hierarchies. *Source: Blue Institute 2019.*


Data
How do x and y relate to each other?
Answer
y
y=f(x)
x
In
Out
kg
kg
kg
Minimising the function's errors (cost)

AI analytics with machine learning

Artificial intelligence is often seen as something almost supernatural, and the media is often prone to highlighting its more sensational aspects. But as we will see, machine learning might just as well be called data analysis or applied mathematical statistics. The principles are very logical even if the calculation processes are wide ranging and complex.

Advances in AI development are typically based around machine learning being applied to larger and larger sets of data and the development and efficiency of learning algorithms. Machine learning is therefore the technology behind most types of AI we see today.

While traditional computer programs adhere to predetermined explicit program instructions, machine learning algorithms scan data to detect patterns and then learn to make predictions. The algorithms adapt gradually, and the experience they gain is utilised and improves efficiency over time.

The mechanism behind machine learning centres on the way in which tasks are presented as an input to a matrix-like structure; a neural computer network inspired by the functioning of the brain.

A machine learning algorithm expresses a function between the data it is fed and the data produced by the model: $y = f(x)$. This function is always unknown, as it cannot be precisely determined mathematically, and this is where the finesse lies in machine learning: estimating the target function as accurately as possible. Correspondingly, if it is possible to determine the function in some other way, machine learning is not needed.

The output of the network, the prediction, depends on how the junction points in the network where the data meets during the process are given different values, called weights. These weights are the secret to the system's learning. (The junction points can be likened to the neurons of the brain.)

The problem lies in how to calculate the weights. The most common way is to start by giving them random values and seeing how big the errors emerging from the model are. Each error is measured and then used to gradually change the weights and eventually approach a solution where the error is as little as possible. In other words, minimising the function's cost. A central part of the learning process is a mechanism called 'back propagation' that tells the network which mistakes it makes.

A great amount of data is required to train and validate a model. Some models can automatically separate data into different clusters and see the context and patterns themselves, but many forms of neural networks require data with guidance. This includes examples of what should be entered and what the expected results should be. For this purpose, collections of open training and test data are created of various kinds, such as those for traffic images, with a *label* that classifies them as representing a traffic light, a pedestrian, etc.

As we have often returned to in this study, the amount, structure and quality of data are the most challenging parts of machine learning, requiring significant man hours and investment.

The results of machine learning, what emerges from the model, can be summarised into four common types of output: *classification, regression, clustering and association* (please see the elaboration in the text box on the right).

For industry, the technology is useful in: optimising the sourcing and the supply of materials; optimising internal and external logistics; planning production and forecasting demand and capacity utilisation; for process management and energy optimisation; for creating maintenance plans and working with preventive maintenance; for understanding customer behaviours; and for simulating cash flows. In summary, for operational development.

The key to success using analysis as a method for operational development lies in good domain knowledge, that is knowledge of the company's operations and processes, and in the ability to create an analysis culture with solid knowledge of both mathematics and statistics. The tools needed are rapidly being commercialised and are becoming both cheaper and easier to use.

"The results of machine learning, what emerges from the model, can be summarised into four common types of output: ***classification, regression, clustering and association***.

One of the simplest methods of classifying items through supervised machine learning, and also one of the most accurate, is called **the 'nearest neighbour' method**. The method is to measure the difference between two objects, or the distance between the objects. A large number of objects are collected with each object labelled with a class affiliation. This is called the reference quantity. When a new unknown object is found, it is compared to the reference quantity until the object that differs the least from the new one is found. The unknown object is then considered to be of the same class as its nearest neighbour from the reference quantity.

Regression analysis, or regression, is a branch of statistics where the goal is to create a function that best fits the observed data. Linear regression is a method commonly used in machine learning contexts that has its limitations, but compensates for these with simplicity, interpretability and efficiency. Simple linear regression assumes that a straight line can be adapted to the data and the regression equation can be described as $y = a + b\ x$. The intercept with the y-axis A and the slope B is calculated so that the error compared to the observed data is minimal. The error can be calculated using, for example, the least square method or maximum likelihood.

Logistic regression is an appropriate method of analysis when the dependent variable is binary. Like all regression analyses, logistic regression is a predictive analysis. Logistic regression is used to explain the relationship between a dependent binary variable and one or more independent variables.

With clustering, the aim is to divide the inputs into several groups. A difference between clustering and classification is that with clustering it is not clear what the groups are in advance. This is typical of unsupervised learning.

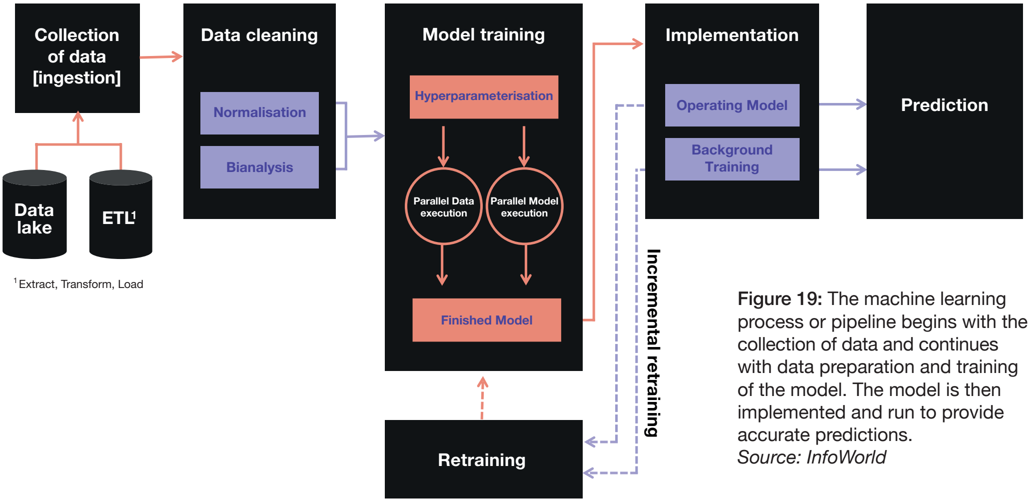


Figure 19: The machine learning process or pipeline begins with the collection of data and continues with data preparation and training of the model. The model is then implemented and run to provide accurate predictions.
Source: InfoWorld

How data becomes money – the machine learning process

A fundamental difference between neural networks and conventional computer programs is that the former develop in two stages. In the first stage, which can partly consist of regular programming, the width and depth of the network is determined, along with how it is to be provided with data and how it will be connected with the rest of the application and the process to be automated or optimised. The next stage is that the network begins to be trained.

The machine learning process – *the pipeline* – begins with data collection in a procedure called ingesting and includes the cleaning and normalisation of the data so that, for example, numerical scales of values are aligned with each other. This is a time-consuming part of the process and can take as much as eighty percent of the project time.

The data sets need to be representative, and it is important to analyse how bias can affect the model. The key issue is how data is selected and how it is normalised. Distortions and prejudices built in by algorithms are one of the greatest risks of machine learning because these actually undermine the entire purpose of the technology. The old truth about "you put garbage in, you get garbage out" applies in the highest, amplified, degree to machine learning.

In many cases, the process involves working with streaming data. In that way, it is possible to choose to first save the data in a database or to collect the data continuously to fine tune existing models. The alternative is to occasionally build new models and train them with new data. The decision affects the choice of algorithms, as some algorithms are suitable for fine tuning and others are not.

The next phase is comprised of training the model, or to put it another way: determining the weights in the function relationship so that the model delivers the best possible results. The procedure for setting the weights is called *hyperparameterisation*. A hyperparameter is a setting that controls how a model is to be created based on an algorithm.

In reality, the process of teaching a model by seeking the 'correct' weights can include millions, perhaps billions of iterations. To increase performance during modelling, there needs to be multiple, parallel work processes running. That is, copies of a program that run simultaneously at different locations. The parallelisation calculations utilise special hardware. CPUs originally used for graphic drivers (GPUs) have proven to be excellent in these cases.

In the summer of 2019, there was an emerging discussion over the impact of machine learning technology on the environment and the climate, given the energy-intensive GPUs that run the learning processes. A recent article from the University of Massachusetts[24)] has found it is the marginal fine tuning of models, in particular, that consume energy, thus leaving an imprint on the climate if the computers are driven by, for instance, coal power. This is also one of the reasons why Sweden is a country of interest for the localisation of data centres.

The final phase of the process is to use the pre-trained model. The model is now run with new, live data to make predictions that can then be translated into intermediate values such as quality, time and efficiency, which in turn can be assigned a price. Data has thus been transformed into money.

Typical problem types and methods of analysis

1 **Classification,** which means that based on a set of training data, new input data is categorised into one of several different categories. An example of classification is identifying whether an image contains a specific type of object or if a product from a manufacturing line is of acceptable quality.

2 **Continuous estimates** calculate the next numeric value in a sequence based on a set of training data. These types of problems are sometimes described as 'predictions', especially when applied to time-series data. An example of continuous estimates might be to forecast the sales demand for a product based on inputs such as previous sales, consumer preferences and the weather situation.

3 **Cluster comparisons i**nvolve creating sets of categories where the data instances have common or similar characteristics. An example of cluster formation is different consumer segments based on data from individual consumers, including demographics, general preferences and consumer behaviour.

4 **Anomaly detection,** which, with a set of training data, determines whether specific input data falls outside of a norm. For example, a system that has been trained with historical vibration data from a machine can determine whether a new data batch suggests there is a fault in the machine. Anomaly detection can be considered a subcategory of the classification approach.

5 **Ranking** involves algorithms being used for information retrieval problems where the results of a request need to be set against a criterion. Recommendation systems that, for example, suggest prioritised purchases of products use these types of algorithms to sort the suggestions by relevance before they are presented.

6 **Recommendations** are systems that provide recommendations based on a set of training data. A common example is a system that suggests a "next purchase" for a specific customer based on the buying patterns of similar people and the observed behaviour of the particular person.

7 **Data generation** requires a system that can generate appropriate new data based on the training data. For example, a music composition system can be used to create music pieces in a certain style after being trained on pieces of music in that style.

24) Strubell, Emma et.al, University of Massachusetts, Energy and Policy Considerations for Deep Learning in NLP, 2019

Natural language generation (NLG)

Production of narrative text from data. Used in customer services, report generation, and automatic data summaries.

Examples of suppliers
Attivio • Automated Insights • Cambridge Semantics Digital Reasoning • Lucidworks Narrative Science • SAS • Yseop

Text analysis and NLP

Utilises and supports text analysis by facilitating the understanding of sentence structures and sentences, emotions and intent through statistical and machine learning methods. The technology is used to detect fraud, for data security and for applications that search through unstructured data.

Examples of suppliers
Coveo • Expert System • Indico • Knime Lexalytics • Lingamatics • Mindbreeze Sinequa • Stratifyd • Synapsify

AI-Optimised hardware

Graphics processing systems (GPUS) and machines specifically designed to efficiently perform AI-oriented computational work.

Examples of suppliers
Alluviate • Cray • Google • IBM Intel • Nvidia

Virtual agents

From simple chat bots to advanced systems that can be used in networks with people. Currently used for customer service, support and smart-home applications (such as Alexa, Siri, etc.).

Examples of suppliers
Amazon • Apple • Artificial Solutions Assist AI • Creative Virtual Google • IBM • IPsoft • Microsoft • Satisfi

Robotics

Technology, scripting and other methods to automate tasks and to support efficient business processes. Used where it is too expensive or inefficient for people to perform a task or a process.

Examples of suppliers
ABB • KUKA • UiPath • WorkFusion

Decision Management

Rules/logical engines for AI systems used for installation, training, maintenance, etc. A mature technology used in various applications for automated decision making.

Examples of suppliers
Advanced Systems Concepts
Informatica • Maana • Pegasystems
• UiPath

Deep Learning Platforms

A special type of machine learning consisting of artificial neural networks with multiple layers. The technology is used for pattern recognition and classification that is supported by very large data sets.

Examples of suppliers
Deep Instinct • Ersatz Labs
Fluid AI • MathWorks • Peltarion
Saffron Technology
Sentient Technologies

Speech recognition (ASR)

Conversion of human speech into formats that are useful for computer processing. Speech recognition is used in dialogue systems and mobile applications.

Examples of suppliers
NICEN • Nuance Communications
OpenText • Verint Systems

Biometrics

For natural interactions between humans and machines, including image and touch recognition, speech and body language.

Examples of suppliers
3VR • Affectiva • Agnitio
FaceFirst • Sensory
Synqera • Tahzoo

Deep Learning Platforms

Machine learning platforms, commonly in the cloud. Used to provide algorithms, API's, development and training tools, data and computing power to design, practice and deploy models to applications, processes and machines. Used for applications that include predictions or classification.

Examples of suppliers
Amazon • Fractal Analytics • Google • H2O.ai
IBM • Microsoft • SAS • Skytree
Sentient Technologies

• **Bad** - means that the quality of available data is substandard, even though it has a clear physical significance. This makes it difficult to compensate for flaws in quality by adding more data of more or less the same type. The latter is a method that can work for applications using deep learning, such as image recognition.

• **Broken** - means that data that has been collected to train a machine learning model lacks the essential qualities of validity/relevance and contains error conditions. This then leads to false positives or negatives in the online implementation of the model. This is a serious problem because even a few or occasional erroneous statements can endanger the reliability of the system, and industrial AI applications typically have major potential to impact on assets and personal safety.

• **Background** – means the data patterns in industrial contexts can be transient. The processes involved are volatile, fluctuating and fast. Interpreting such data often requires deep domain knowledge, and it's not enough to simply dig for more numerical data. In addition to precision around predictions and quality of performance, an ability to find the roots of possible anomalies is also required.

The data challenge

One of the biggest challenges with AI concerns the quality of the data needed to make predictions, create forecasts, and recognise patterns. It is a widespread issue, and a great deal of monotonous, routine work takes place behind the sometimes simplified depictions of AI that we see.

In autumn of 2018[25], BBC News brought attention to a new concept: *labelling farms*. This is a rapidly growing global sector involving data centres that have been located in low-cost countries for economic reasons. Labelling farms today employ thousands of people whose only task is to help AI algorithms interpret data.

Pixel by pixel, the content of millions of images is classified; a car is identified as a car, a dog as a dog, a road sign as a road sign, and so on, so that self-driving cars have the capacity to recognise real world objects.

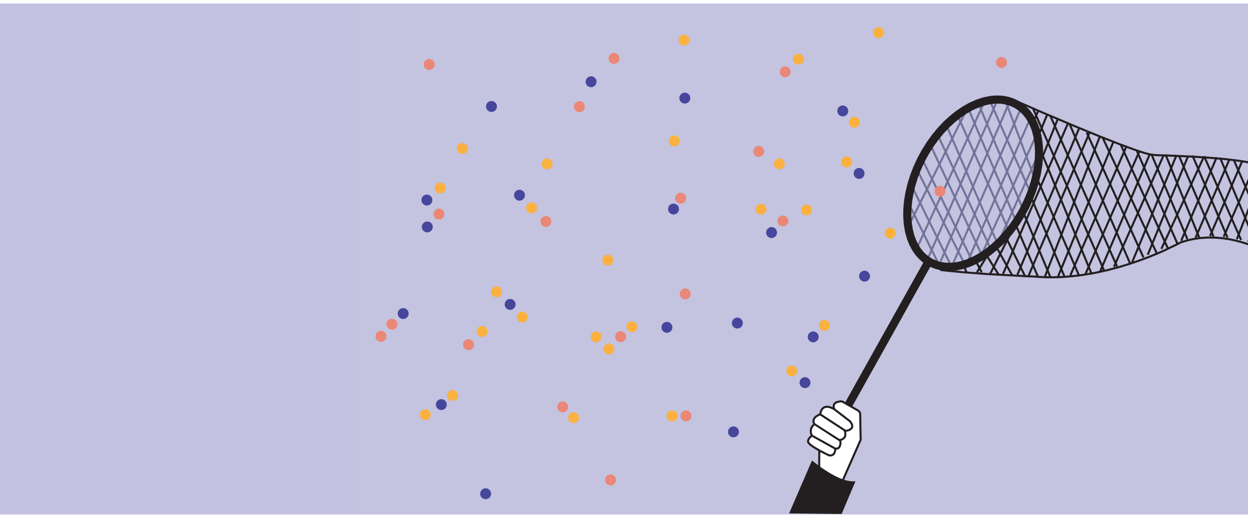
Similar data challenges are being encountered everywhere that AI is to be applied. The high cost of data preparation means that there are financial incentives to solve the data problem, and a number of projects are being carried out with the help of even more AI in a bid to find new solutions and better methods.

> "Industrial AI is about transforming raw data into "intelligent" predictions in order to make decisions.

Industrial AI involves transforming raw data into "intelligent" predictions in order to make decisions. In industrial processes – in a steel mill or a paper mill – quick decisions are made in real time at the millisecond level in models representing physical reality. Several challenges arise in such processes. Real-time requirements mean that the cost-effective and almost endless resources of the cloud need to be supplemented with locally distributed computational and storage capacity, also known as 'edge'. But the most fundamental challenges also concern the availability and the quality of the data.

Since the 1980s, industrial control systems have been producing enormous amounts of information. *Industrial Big Data* is available in every factory, and yet while industrial data is generally well structured, it often lacks quality. You sometimes hear talk of the *three B's* of Industrial Big Data: *Bad, Broken & Background.*

[25]) BBC, Why Big Tech pays poor Kenyans to teach self-driving cars, 2018



Teams of people who possess both process knowledge and computer science are required for the development of good adaptive models. There is also a need for method development, with experience teaching us that data preparation demands a disproportionate amount of work. This is a serious issue that needs to be continuously addressed and prioritised, lest it become an obstacle in releasing industrial value.

Solutions to data deficiency and the manual intervention

Much of the success of modern AI applications is based upon *bottom-up strategies* within which models are trained using large, well-structured data sets typically collected via the Internet. For example, the GPT-2 text bot mentioned in the text box on page 45 was trained using a data set of eight million web pages. Intelligent assistants like Apple's Siri or Amazon's Alexa use thousands of terabytes of data in order to perform their tasks, and self-driving cars consume about forty terabytes per eight hours of driving, according to INTEL[26].

For operational industrial applications, large amounts of information are being collected. However, critical processes, in particular, lack the volumes needed to train good models. There is a lack of data in marginal or edge cases, and it is not always easy to deliberately address such deficiencies (by inducing errors in physical processes). The errors they represent correspond to significant costs due to major production disruptions. This is a problem that also applies to other, normally data-rich applications. One of the big challenges in the development of autonomous vehicles is managing the most unusual of operating cases. Another characteristic of today's AI technology is that it tends to easily become *confused* if circumstances deviate significantly from what is expected.

Methods are in development to overcome these weaknesses. Similar to human intelligence, they involve working in a more flexible, top-down manner, which allows for reduced data requirements and enhanced speed. There are a number of trends related to the development of more natural systems worth keeping an eye out for in the near future.

[26]) IDG, Just one autonomous car will use 4,000 GB of data/day, 2016

8 trends

1 The first trend involves giving robots conceptual properties (both physical and artificial) that in turn give them a greater ability to perceive themselves – and their environment. See the text box on page 45, describing how researchers at the University of Columbia have succeeded in giving a robot such properties.

2 Another developmental avenue involves something of a renaissance of the concept of 'expert systems' within which computers become better at doing what human process operators do by making adjustments in real time to optimise processes. Siemens has developed data-efficient methods such as these based on *'reinforcement learning'* to control the company's gas turbines, an area where traditional neural networks would take up to a hundred years[27] to learn the complex combustion processes. The method has subsequently been developed to increase the efficiency of the company's wind turbines. Google is also using the technology to successfully reduce the energy consumption of its data centres.

3 A third way to address the weaknesses of today's AI algorithms is to give computers more *common sense*[28]. According to an article in Harvard Business Review[29], the Allen Institute for Artificial Intelligence is working on developing test data that can be used to verify what common sense means to a machine. Meanwhile, DARPA is investing USD 2 billion in AI research through, among other things, creating models that mimic human cognition. And Microsoft and McGill University have jointly developed a system for distinguishing ambiguities in natural language, a challenge needs to be solved if, among other things, computers are to be able to communicate with human beings in a human way.

4 A fourth track is the possibility of letting computers make similar balances of probability assumptions to those that humans intuitively make. This is being made possible through stochastic *Gaussian processes* that are able to function and recognise patterns within limited data sets and learn from experiences. Another feature of this method is that processes are traceable if something goes wrong, unlike with the black boxes of neural networks.

5 Yet another method of advancement is *Probabilistic Programming* for the applications described above. This method brings together the best methods for mimicking human intelligence such as probability theory for modelling, statistical methods for drawing conclusions, and neural pattern recognition networks, along with symbolic program languages that hold the system together.

[27] Siemens.com/presse/inno2017
[28] Common sense philosophy is a branch of philosophy developed by Thomas Reid in the 18th Century. The concept is based on Aristotle's beliefs that our senses allow for the creation of uniform and universal human perceptions of objects.
[29] H. James Wilson et.al., The Future of AI Will Be About Less Data, Not More, 2019

6 ***Explainable AI* is an adjacent developmental track.** The black box phenomenon of machine learning can be problematic. Therefore, it's important that systems are able to justify how they have arrived at their conclusions. It's also important to ensure that human beings can have trust in the way that such systems arrive at their results and decisions when, for example, traffic situations, legal support or medical diagnosis become automated.

7 ***Federated machine* learning is another method showing promise.** The idea was launched in 2017 by Google as a concept within which the ability to train a model is decoupled from the up-until-now necessary central storage of data in the cloud. The method can train a single machine learning algorithm over several decentralised servers that store data, without actually exchanging data with other servers. It allows multiple actors to build a common, robust machine learning model without sharing data, thereby addressing critical issues such as data privacy, data security, data access rights, and access to heterogeneous data. It also enables capacity in distributed applications.

This way of working is based on the idea that a distributed device, such as a phone, downloads an existing shared model, improves it by learning the data that is locally available on the phone/device and then summarises the changes as a small concentrated update. Only the update is sent to the cloud, via encrypted communications, where it is immediately computed and integrated with other user updates to improve the shared model. All training data remains on the local unit, and no individual updates are stored in the cloud.

The technology can contribute to breakthroughs for industrial operational applications based on conventional automation or IoT, where distributed capacity is both a prerequisite and a natural part of the current concept of control and monitoring.

8 **Finally, *AutoML* or Automatic Machine Learning looks like the holy grail for solving the many and long routine steps** found in today's *state of the art* technology. Automated machine learning involves automating the process from *end-to-end*. As we have noted, typical machine learning projects involve extensive pre-processing before the dataset can be made available for actual machine learning.

Pre-processing is followed by selection of the algorithm, hyperparameterisation and fine-tuning to maximise predictive performance in the final model. In addition, many of these steps require both experience and specialist knowledge. What could be more logical, then, than to suggest AutoML as an artificial intelligence-based solution to these growing challenges? Automating the process would be an effective productivity-enhancing method, which in addition would be likely to provide solutions and models that exceed manually designed ones.

AutoML solutions with drag-and-drop-based user interfaces, and that do not require any coding in the regular sense, are now on the market and are offered by all major platform providers such as Google, MS Azure and IBM, along with many specialised smaller companies. The technology is evolving rapidly and will further lower the threshold for users.

Industry case study: BillerudKorsnäs in Gävle, Sweden

Deep Process Learning

DEEP is a project that will show how deep process learning (deep learning) can be used for the next step in process automation. The project takes advantage of data that already exists in process control systems and uses it to suggest the measures required to improve selected key performance figures. The project, which is a collaboration with PiiA, consists of a consortium between BillerudKorsnäs, Peltarion, PulpEye and FindIT.

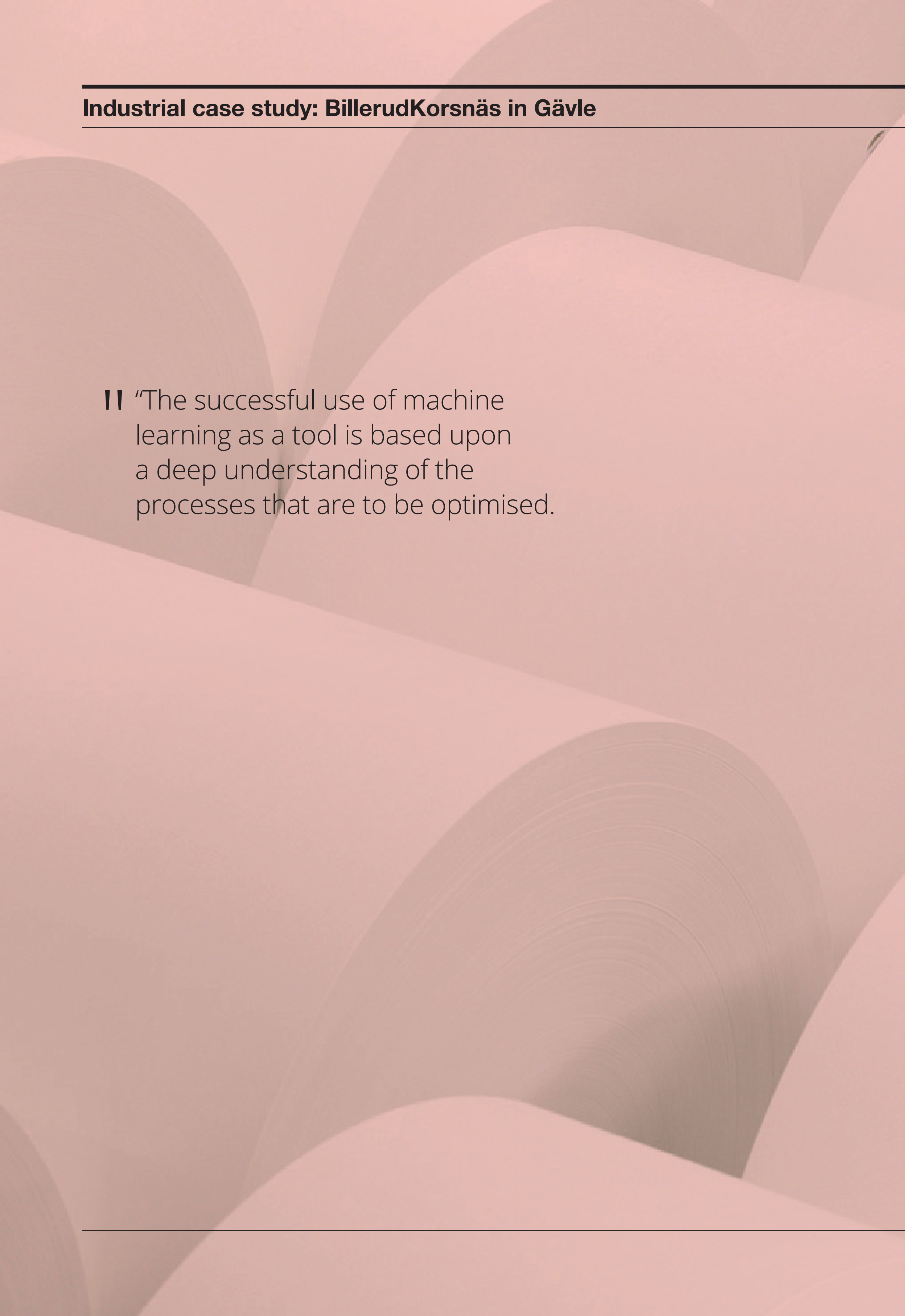
The process industry accounts for almost half of all industrial production in Sweden. So, the achievement of efficiency and productivity improvements within it is certain to have a major impact on the Swedish economy. The forestry sector has an advanced supply chain with multiple levels of complexity and difficult, resource-intensive processes: from felling to barking and chipping the wood, to boiling, washing and bleaching the pulp before it reaches the paper machine to be refined to produce paper and cardboard of various grades.

"The forestry sector has an advanced supply chain with multiple levels of complexity and difficult, resource-intensive processes...

Process industries produce huge amounts of data and have a high degree of automation, but they also face a variety of challenges. These challenges can't always be addressed through traditional analysis methods. As such, the data produced can be a valuable asset, capable of being refined through AI to generate insights, predictions and automation algorithms – thus creating the next stage of productivity, quality and automation.

BillerudKorsnäs is a forestry company that supplies packaging materials and packaging solutions. The company has three divisions: Division Board, which manufactures and sells liquid and non-liquid packaging board, as well as fluting and liner; Division Paper, which manufactures and sells high-quality kraft and sack paper; and the Solutions Division, which meets the needs of brand owners for efficient packaging solutions and systems.

During a feasibility study for DEEP, BillerudKorsnäs and Peltarion jointly led a machine learning project to predict the kappa number of pulp after boiling. The kappa number is a measure of residual lignin in the pulp, and determines the boiling process required for different pulp qualities. The project was successful and resulted in a useful technique for predicting the kappa number. This success encouraged further development of the approach in other process steps.



> "The successful use of machine learning as a tool is based upon a deep understanding of the processes that are to be optimised.

The challenge

Paper machine 4 in Gävle is a cardboard machine that manufactures liquid packaging board for juice and milk packaging, among other things. The purpose of the DEEP project has been to realise the efficiency potential identified in the manufacturing process by proposing optimal machine operational parameters. An essential feature of the finished liquid packaging board is the carton's bending stiffness. This property is determined by complex relationships between the different stages of the manufacturing process, not least by the pulp's fibre properties. The goal is to produce strong packaging using less raw material.

In order to meet the quality objectives at optimum production speed, process settings must be constantly evaluated and adjusted. In the DEEP project, data is being collected to support the online optimisation of such decisions. The data used in the project consists of high-resolution microscopy images from PulpEye's analyser which provides information about the pulp's fibre properties and camera images from the drying cylinder which provides information about the de-watering of the pulp, in combination with measurement values from different sensors in the system. In the next step, data will be used to develop a suitable model to predict quality properties.

During the DEEP project, many different attempts were made using different methods, including deep learning with Peltarion's self-developed platform.

The experience

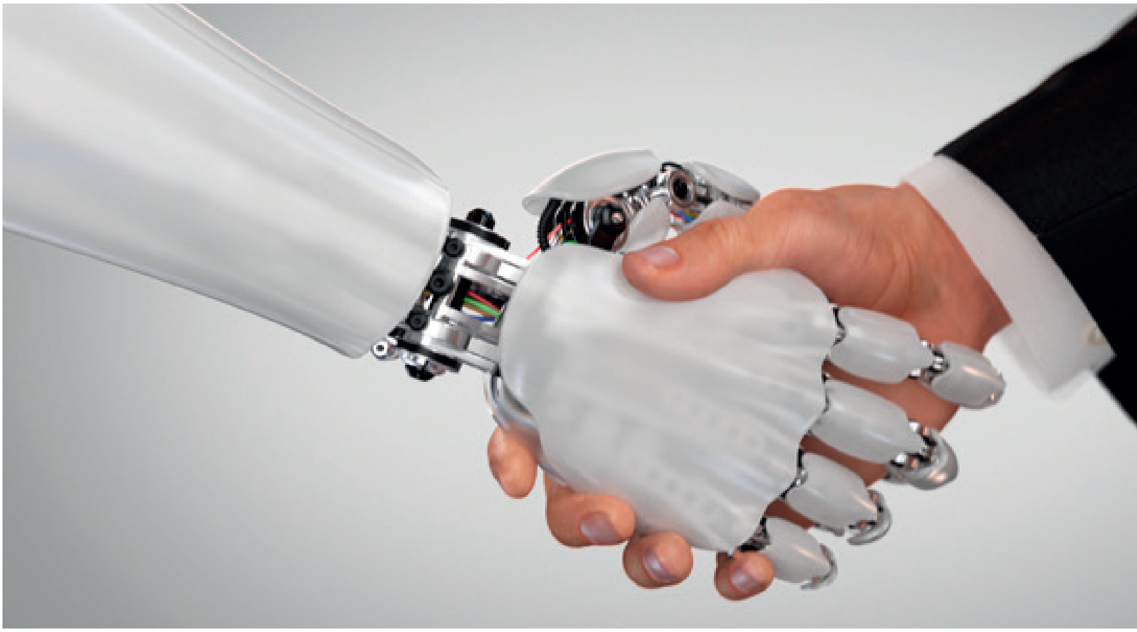
BillerudKorsnäs has formed a digitalisation team with different competences from different parts of the organisation and that initiates and runs transformation projects. The company's various AI initiatives are part of that transformation process.

BillerudKorsnäs' experience shows that deep learning technology is ripe for use in various types of classification problems and for further increasing the degree of process automation. The process industry is characterised by a combination of large amounts of data and a high degree of automation, which partly produces conditions that differ from other fields that apply deep learning and machine learning. Over time, the technology will find its place in process analysis and control, and will solve many more problems that affect efficiency, quality and logistics.

One of the most important takeaways from BillerudKorsnäs' AI projects is the need for domain knowledge and the ability to formulate the right problems. The successful use of machine learning as a tool is based on a deep understanding of the processes that are to be optimised.

BillerudKorsnäs is continuing its work on developing processes with the help of AI, and another project will be launched in collaboration with PiiA in the spring of 2019. This time, it will be led together with Finnish Quva OY as data analytics provider.

Sources: PiiA, BillerudKorsnäs, Peltarion



Man and machine: collaborative intelligence

It was once said that we should, "Let the machine take care of the details and let man think and dream". And, as Anders Ynnerman, a professor at Linköping University states, "*for every AI system that we have where we add on the human aspect, we get a much better system*." [30)]

At the same time, there is a fear that AI will eventually push people out the labour market. The latter is hardly inevitable or even the most plausible outcome. Never before have digital tools been better suited for collaboration with people. And while AI will surely change the way work tasks are performed, and who performs them, the role of machines in future will be to reinforce and supplement human abilities rather than to replace them.

The concepts of collective and collaborative intelligence are also worth bearing in mind. Models where people's intellectual capacity can be increased through smart collaborative methods, either working with other people or with machines, will have a major impact on industrial development. Man's abilities in leadership, teamwork, creativity and social interactions will complement AI's speed, scalability and quantitative ability to keep track of large complex data sets. Industrial activities require both.

But the above line of reasoning also demonstrates the need for changed processes and in many cases radical transformations of both business activities and the way people and machines interact on a practical level. An article in Harvard Business Review[31)] notes that the business effects of artificial intelligence clearly depend on the ability to "rethink" activities so that they both incorporate AI and cultivate related abilities in human employees, in addition to allowing creative experimentation and having clear AI strategies. Last, but not least, it is important to manage data in both a relevant and responsible manner.

[30)] Linköpings Universitet, Sätt människan i centrum för AI-forskningen, 2018
[31)] Harvard Business Review, Collaborative Intelligence: Humans and AI Are Joining Forces, 2018

" For every AI system that we have where we add on the human aspect, we get a much better system.

Anders Ynnerman,
Professor at Linköping University

AI will lead to more automation and to more advanced automation. One of the major advantages of automation is avoiding errors caused by people not being able to repeat tasks efficiently. A robot that is asked to do the exact same motion a thousand times makes the same motion a thousand times – as long as the sensors and the mechanics work. A person might be able to perform it three times but is at the same time a master at interpreting their senses and dealing with new unexpected situations.

The process of how this might happen is not yet clear and making machines that act in a human-like manner is a complex matter. The recent accidents involving a highly advanced Boeing aircraft model have, in a frightening way, also shown that for every human mistake that a machine eliminates, there is a risk that a new one will be introduced. There are endless possibilities for misunderstandings to occur between human intelligence and machines. In the industrial context, the challenge boils down to establishing collaborative intelligence, and how well the interface between human and machine works. This developmental field is known as UX – *user experience* – or in the AI context it's perhaps more appropriately called MMC, *man machine communication*.

Issues with misunderstandings and mistakes have the potential to intensify as the degree of automation increases further. Humans will no longer have full control over machines. Overall, this will lead to a decrease in those parts of industry domain knowledge that include artisanal process knowledge. At an operational level, the challenge for the machine operator will be to monitor a process over a significant amount of time and to be prepared to take over the moment something goes wrong. Problems in this area have the potential to be costly in a process industry and utterly catastrophic within aviation.

One conclusion that can be drawn is that machines that don't allow people to keep up with the processes they are managing aren't optimal in events where people are forced to take over. Another conclusion is that the best kind of automation isn't necessarily where the computer automatically does most of the work, but rather where there is an optimal distribution, and a realisation that people and machines will probably never understand each other perfectly. We have two pilots in the cockpit and two operators in the control room, and unfortunately, both can sometimes be expected to do unexpected things.

Looking ahead

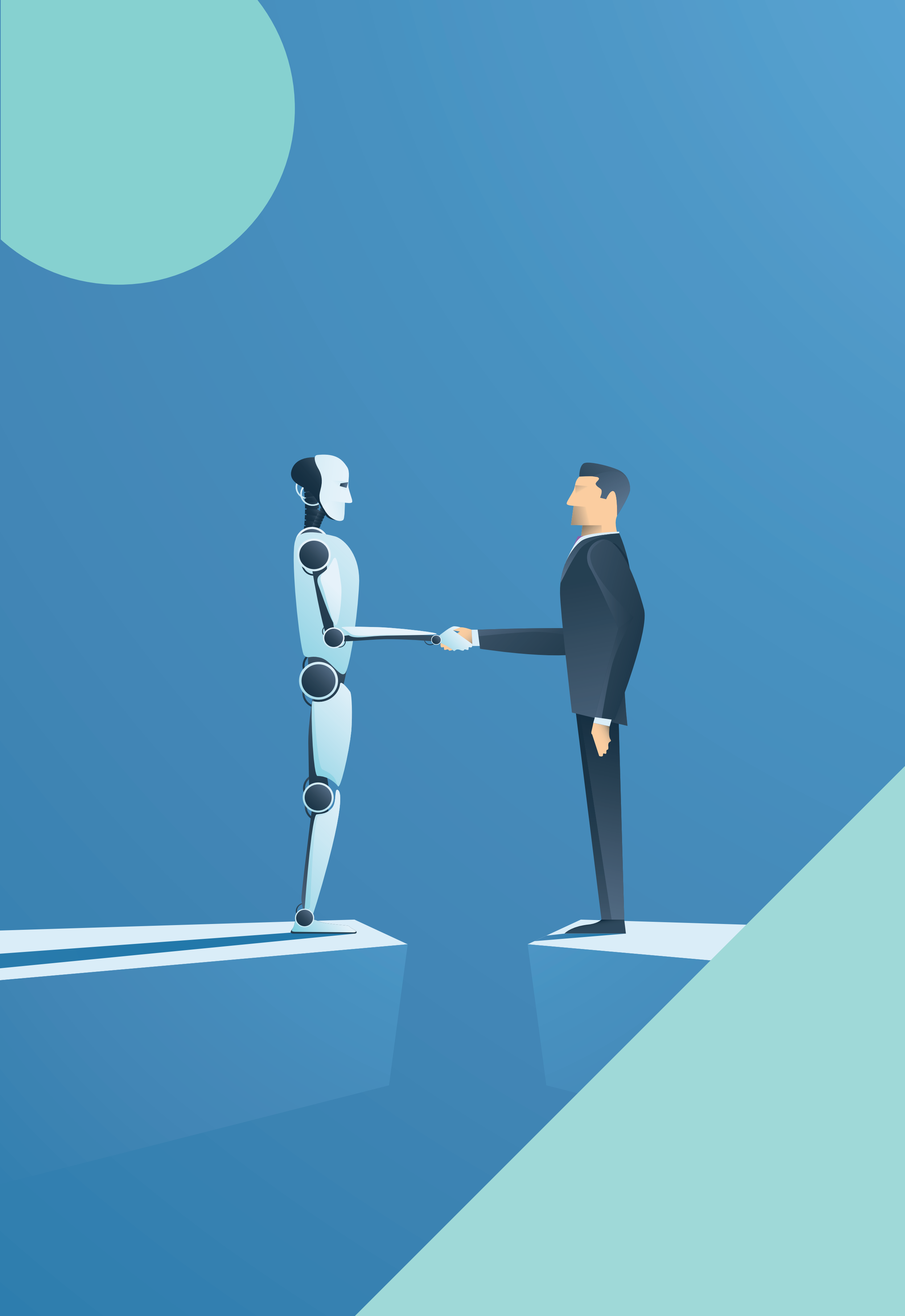
In this section, we have skimmed over some of the concepts and constructs that may come in handy from an applied industrial perspective. Of course, there are countless other aspects of AI that could potentially be taken into account when assessing a technology which proponents claim to be 'intelligent'. Many of these issues relate to morals and ethics. As society and industry move ahead, we will likely encounter machines with questionable intentions and distorted development, whose intent is to benefit individual stakeholders. AI will influence people's attitudes; false correlations and self-reinforcing feedback will eventuate – and algorithms may influence reality to gain even more influence, even though their base assumptions are false. The origin and quality of data will continue to be an issue and, last but not least, we will face uncertainty around what is real and true: will we, in future, be able to trust what we see and hear? Will we be able to trust pictures, movies and sounds?

> "Will we in the future be able to trust what we see and hear? Will we be able to trust pictures, movies and sounds?

From an industry development point of view, our hopes for AI and machine learning might be for them to provide greater flexibility than that currently found in our simple neural networks which are only capable of performing one task at a time and are expensive and arduous to retrain. We might also hope to see significant productivity gains in system development, while there is also room for improvement in the deployment of models.

But we can rest assured that these are areas that are currently being addressed by research. Likewise, the huge data requirements, the need for manual intervention, and the problems with *edge data* all need to be addressed. The actual learning process with its hyperparameterisation needs to be further automated. Another potentially growing problem is the lack of transparency in neural networks, which for the most part resemble black boxes.

It's impossible to know how and when these issues will be addressed. It could take years or there may be sudden breakthroughs, such as when the AlphaGo defeated one of the world's best Go players with the help of *reinforcement learning*. But it does not change the fact that AI and machine learning are already powerful enough tools to change industry, and that those who acquire knowledge, experience and an upper hand when it comes to applying the technology have everything to gain.



Swedish development initiatives within in the field of AI (July 2019)

As we have described in this report, AI development is now entering a more commercial stage, with major underlying economic interests involved. This does not eliminate the need for long-term fundamental research in disciplines such as mathematics and computer and systems science, nor for industrial activities of a more applied nature including activities aimed at disseminating knowledge and contributing to a high qualitive level of operational activities. Below is a compilation of current programs and projects. The source is, in most cases, Vinnova's compilation: AI-Environments in Sweden, 2019.

Vinnova (AI Innovation of Sweden)

From 2011 to June 2019, Vinnova granted approximately SEK 900 million to some 580 projects. In 2018, the decision was made to develop and strengthen investments in initiatives related to artificial intelligence and secure data access. Over the next ten years, SEK 200 million will be invested annually, of which at least SEK 50 million will consist of targeted AI investments. The goal is to strengthen the development of collaborative environments that work with research, innovation and education, as well as to strengthen advanced data, testing and technology infrastructures.

In order to mobilise, and to increase visibility and activity in applied artificial intelligence, Vinnova supports the development and establishment of a number of nodes – *AI Innovation Sweden*. These will ensure coordination and synergies. It is therefore important that the nodes are open and accessible to all parties wishing to connect.

AI Innovation of Sweden is a national and neutral venture aiming to act as an engine in the Swedish AI ecosystem. The focus is on accelerating the application of AI through the sharing of knowledge and data, co-location and collaborative projects, all with a strong focus on ethics, transparency and security. AI Innovation of Sweden establishes shared resources, such as the 'Data Factory', which will make data available in a new and unique way, and 'Co-Location sites'. Over 40 organisations and companies – from business, academia and the public sector – have joined, and more are expected to join in the future.

Elements of AI is a free online course that describes artificial intelligence basics. Theory is combined with practical exercises and examples. It does not require any programming or maths skills. The goal is for artificial intelligence to become comprehensible to all.

The course is offered by AI Innovation of Sweden, AI Competence for Sweden, Linköping University and Vinnova together with the University of Helsinki and Reaktor. The goal is for 100,000 Swedes to take the course.

Vinnova also mapped AI environments in Sweden in a study. The overview contains 39 AI environments that are working towards the development of artificial intelligence. Most are based in universities, colleges or institutes, while others are international.

The Swedish Research Council

The Swedish Research Council has financed around 30 projects in 2013–2017, giving up to about SEK 95 million. KTH and Uppsala University were the largest recipients of funding. The most common theme was computer vision and robotics (autonomous systems), followed by computer science (computer science), then signal processing and control technology.

[36] VINNOVA, AI-Miljöer i Sverige, 2019

SFF

The Swedish Foundation for Strategic Research (SSF) has invested approximately SEK 1 billion in AI projects in 2012–2017. They have implemented thematic investments in Information Intensive Systems and Smart Systems. Within these, several AI projects have been launched.

The KK Foundation

The KK Foundation has estimated that AI-related research and competence development has financed around SEK 1 billion over the past 10 years. The projects include semantic robots and big data research.

Knut and Alice Wallenberg Foundation (KAW) (WASP)

WASP Knut and Alice Wallenberg Foundation's AI initiative is taking place within the Wallenberg AI, Autonomous Systems and Software Program, WASP, which was launched in 2015 and will continue to run until 2025. It is the largest Swedish venture, as a result of its SEK 3.5 billion investment in research and education in the AI sector. The AI initiative has an emphasis on data-driven AI and the new mathematics that are necessary in the field, but also covers other areas such as robotics, computer vision or visual recognition that are already being researched within WASP. The focus of both quantum and AI efforts is on long-term competence building by creating large research schools and recruiting young researchers from the rest of the world to Sweden. Together, these efforts contribute to the training of about 200 new doctors and the recruitment of up to 40 new research groups.

AI Competence for Sweden

The need for in-depth knowledge of artificial intelligence (AI) is great in the labour market and in society. The government is now investing another 20 million in higher education in AI. The initiative will also promote lifelong learning. Seven universities are participating in the initiative: Chalmers University of Technology, Gothenburg University, Royal Institute of Technology, Linköping University, Lund University, Umeå University and Örebro University. More educational institutions may join the initiative in the future.

The Swedish Agency for Economic and Regional Growth

The Government has commissioned the Swedish Agency for Economic and Regional Growth to map and promote the ability of small and medium-sized companies to use data as a strategic resource.

Many small and medium enterprises (SMEs) need to become better at strategically using data. The Swedish Agency for Economic and Regional Growth is now tasked with helping them to exploit the potential of data-driven innovation and data as a resource. Initially, the Swedish Agency for Growth will identify sectors and industries where there is the greatest potential for data-driven innovation and strategic use of data.

The Swedish Agency for Economic and Regional Growth will also implement knowledge-enhancing efforts such as seminars and pilot projects in the lab environment. National security, protection of personal integrity and issues regarding sharing, exchange, access, ownership, data collection and storage will be taken into consideration in this work.

The Swedish Agency for Economic and Regional Growth shall be reported to the Government Offices no later than February 1, 2021.

Statistics Sweden (SCB)

The Government has commissioned Statistics Sweden to survey the use of artificial intelligence in companies and public administration, including the university and higher education sectors.

Through a broad statistical foundation, SCB will highlight variation in the use of AI and analysis of large amounts of data within and between sectors and industries, as well as factors that influence its use.

SCB will use AI, in the form of text analysis and machine learning, in order to estimate the extent of the use of AI among Swedish companies. In this work that is due to be reported to the Government Offices no later than 30 November 2020, SCB will be in close dialogue with Vinnova, DIGG, Growth Analysis and SKL.

Glossary

The report contains a number of terms that may need clarification. Key terms include:

Artificial Intelligence (AI)

The term *'Artificial Intelligence'* (AI) does not actually have any clear definitions or delineations. AI research itself is both specialised and spread across many subfields. For this analysis, we have chosen the definition also used by Vinnova in the study Artificial intelligence in Swedish business and society, 2018".

This is: "The ability of a machine to mimic intelligent human behaviour. Artificial intelligence is also the designation of the science and technology field that aims to study, understand and develop computers and software with intelligent behaviour."

When we talk about AI in an industrial context, we are primarily referring to machine learning technology with neural networks.

Algorithmisation

Algorithmisation is a mega-trend within which more and more value-adding activities are managed and controlled by algorithms instead of human beings

IndTech

IndTech is used to describe the development, companies and markets that arise when traditional automation and industrial IT meets digitisation. IndTech companies include:

- Suppliers of industrial automation, such as ABB or Siemens.
- Suppliers of industrial IT software, such as SAP or IBM.
- Providers of digital platforms, such as Microsoft or Amazon Web Services.
- IoT providers, such as Ericsson or Nokia, and operators, such as Telia or Telenor.
- System integrators and machine suppliers who base their process or mechanical engineering offerings on digital technology. These include companies such as Sandvik, Epiroc, Valmet and many more.

Platformisation

Platformisation can be used to describe the general movement of various companies' automation and IT support to the cloud, and also to describe the movement of platforms created by open standards to platforms owned and controlled by a particular actor. Because the value of a platform tends to increase for all involved as more people use it, there is a tendency for already-large platforms to grow even bigger.

Operational Development - OD

We have chosen to use the term *operational development* to encompass the operational changes in processes or in organisations that lead to increased efficiency or increased customer values. Within this area, AI can be a very powerful tool.

Bibliography

Accenture, ***Reworking the Revolution,*** 2018

Alan M Turing, ***Computing Machinery and Intelligence,*** 1950

Andersson Schwarz, Larsson, ***Plattformssamhället,*** 2018

BBC, ***Why Big Tech pays poor Kenyans to teach selfdriving cars,*** 2018

Blue Institute, PiiA Insight, Swedish IndTech, 2018

Brynjolfsson et al., ***Scale without Mass: Business Process Replication and Industry Dynamics,*** 2008

EU, Digital Single Market, The Digital Economy and Society Index

Financial Times AI academics under pressure to do commercial research, 2019

H. James Wilson et.al., ***The Future of AI Will Be About Less Data,*** Not More, 2019

Harvard Business Review, ***Collaborative Intelligence: Humans and AI Are Joining Forces,*** 2018

IDG, ***Just one autonomous car will use 4,000 GB of data/day,*** 2016

Konsultkompaniet, ***Så blir it-branschen 2019,*** 2019

Linköpings Universitet, ***Sätt människan i centrum för AI-forskningen,*** 2018

Markets & Markets, ***Artificial Intelligence Market,*** 2017

McKinsey Global Institute, ***Tackling Europe's Gap In Digital And Ai***, 2019

MGI, ***Notes from the AI frontier: Modeling the impact of AI on the world economy,*** 2018 samt

Microsoft, A***rtificial Intelligence in Europe,*** 2019

Microsoft, ***The Future Computed,*** 2019

Moore J.F. ***Predators and Prey: a new ecology of competition, HBR***, 1993

Nachira, F. ***Towards a Network of Digital Business Ecosystems,*** 2002

Parker, G. et.al., ***Platform Revolution***, 2016

PWC, ***Sizing the Prize,*** 2017

Russel, Norvig, ***Artificial Intelligence, A modern approach,*** 2016

Siemens.com/presse/inno2017

SvD, ***Ericsson ikapp och förbi Huawei I 5G-racet,*** 8 sep 2017

The Forrester Wave™: ***Predictive Analytics and Machine Learning Solutions, Q1*** 2017

VINNOVA, ***Artificiell intelligens i svenskt näringsliv och samhälle,*** 2018

WSJ, ***The Impact of Artificial Intelligence on the World Economy,*** 2018

This report is about artificial intelligence.

Artificial Intelligence has very quickly risen to become a highly topical subject of debate. Discussions revolve around integrity, security, ethics, the issue of jobs, autonomous vehicles, military systems and science-fiction--like scenarios. The reason for this is that technological development, which up until now has been taking place with gusto behind the scenes, is now becoming increasingly visible. Almost every day, new AI applications are launched, and these are having noticeable effects on our everyday lives.

The goals of this study are specific to industry. With industry leaders and other decision makers as a target group, it aims to offer an overview and assessment of the sector's driving forces and dynamics from an industrial market perspective.

An essential insight from the study is that industrial AI is not something that will arrive at some point in the distant future; it is a current reality and one which every industry leader needs to take into account. Our view is that AI is a powerful addition to the methodology toolkit for analysis, and that it can be used for optimisation and automation within industry. But AI needs to be considered in the right context. The major effects only arise in the boundary between domain and analytics knowledge, the capability for creative operational development, and integration into digital platforms. AI needs to be considered in a transformative context. Under these conditions, our assessment is that, on an international level, Swedish companies are well placed for adopting this new technology and translating it into efficiency gains and business success.

AI development is now progressing at high speed. Competence and resources are being built up at a rapid pace by suppliers, consultants and system integrators. We believe it is a good idea to combine this knowledge with industry's process know-how and to start testing and transforming; to establish best practice. We also believe that a good way to activate AI in Swedish industry is to be open and to share experiences. It is not the first time that curiosity, inspiration and competitiveness has led Swedish industry to the top.

PiiA Process Industrial IT and Automation

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