Chapter

AI & Digital Platforms: The Market [Part 1]

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Abstract

This essay aims to describe the dynamics at play in the field of industrial AI, where the significant efficiency potential is driving demand. There are rapid technological development and increasing use of AI technology within the industry. Meanwhile, practical applications rather than technical development itself are creating value. The primary purpose of the article is to spread knowledge to industry. It is also intended to form the basis of the Swedish innovation program PiiAs ongoing work around open calls and targeted strategic innovation projects. The basic approach taken is to investigate both industry demand for AI and how the supply of technology is developing. AI takes in a broad and dynamic range of concepts, but it should also be considered in an even broader context of industrial digitalisation. The article has been divided into two sections: *The Market*, in which we assess the development and the 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 article concludes with four practical examples from the industry.

Keywords: AI, artificial, intelligence, PiiA, blue, institute, automation, algorithmisation, platform, data, process, industry, IndTech, digitalisation, digital, twin, ecosystem

1. Introduction

This article has two primary purposes: the first is to provide the industry with an evaluation of the importance of AI development as a force for change and the second to create an internal basis for the Swedish Innovation program 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.

Technological, industrial development is awash with grand ambitions that have turned into mere passing fads and 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 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.

2. 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 industry 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, the 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 will not 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' (see **Figure 1**). 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 1990s. Then in the 2000s, came the scalability, mobility and cost-effectiveness 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 the understanding of the value that the technology can potentially release grows. Various technological developments, which have been taken place over the past decade unbeknownst to the general public, are now coming to fruition and can directly be viewed within the context of analyses of potential economic effects and, increasingly, real-life business cases and investments.

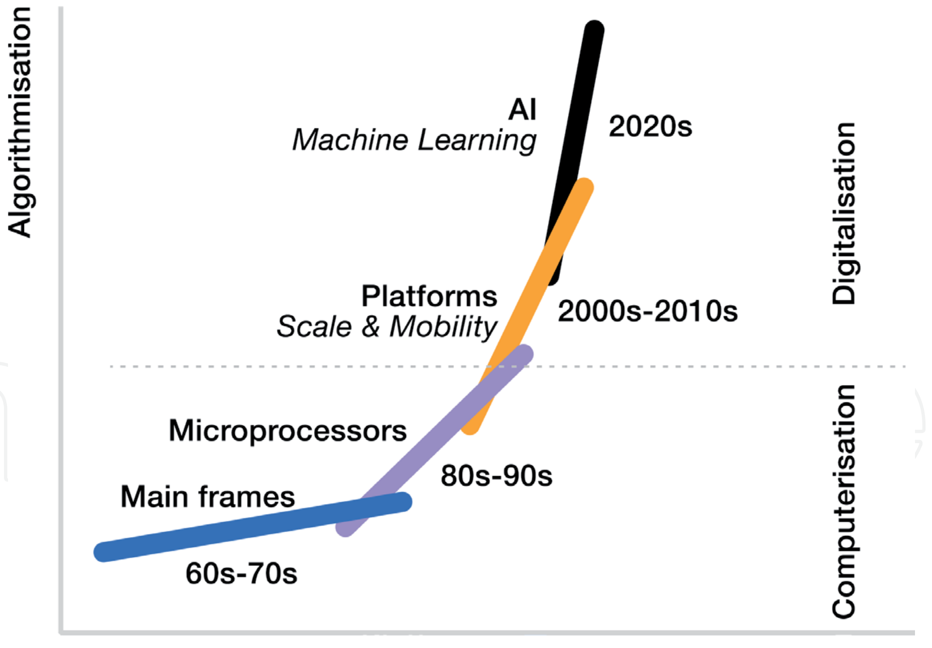

Figure 1.
AI and machine learning effectively add an extra 'gear' that will allow for increasingly advanced algorithms that increase efficiency and create new customer value within the industry. Source: Blue Institute (2019).

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

The million-dollar question is: Will we see an explosion of AI, and its disruptive establishment across the 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 real revolution for the production economy.

In this section, we will look at the forces underlying supply-and-demand development trends for AI within the industry. A functioning market dynamic is a crucial 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 the 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.

2.1 Demand

We start this section by looking at the demand side of things (see **Figure 2**), as well as discussing the stance companies might take. This includes examining

Figure 2.
The market for AI technical solutions and machine learning is expected to grow by 40% per year, while demand within the industry is expected to be driven by the significant potential value gains that can be created using the technology.

more significant 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.

2.1.1 Substantial value effects within production systems will drive demand for AI

Our fundamental hypothesis is that demand for AI within the industry will correlate with the value that can be extracted from production via more effective analytical tools. We assume that the expected growth effects within the sector 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 is evidence to suggest that the general growth potential within value creation might 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 are decoupled from physical systems and so allow for new organisational models that echo the transformation that 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 [1], McKinsey Global Institute [2] and PwC [3]. According to consulting company PwC, 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% higher than it would be without AI or the equivalent of China and India's combined GDPs.

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 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 timeframes.

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 impact 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 according to estimates in this study, or 3–6% per year of the global industrial sector's total assets.

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

'Added value of between SEK 22 and 45 billion per year could be unlocked for PiiAs industries'.

Placed in a Swedish context and related to PiiAs target industries, we estimate that added value of between SEK 22 and 45 billion could be unlocked per year. For PiiAs sectors this represents an average increase of between SEK 3 billion and SEK 7 billion per industry, 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 would certainly be significant. We conclude 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 a good reason to prepare in advance for the coming changes. Looking from a broader perspective, 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 placed. They 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. Still, they could use their particular strengths within specific 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.

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.

2.1.2 Systemic effects from digital platforms and business ecosystems

Among the most considerable value-creating effects 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 should not be read as a prediction of the demise of the production economy—preferably 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 the demand for AI and 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.

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 [4]. 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 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 [5].

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'. Adverse 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 critical prerequisite for effective networks is to use digital platforms and other features to increase in size, thus increasing the value generated via network effects.

2.1.3 Platform: a transformative concept

The concept of 'platform' is thus a transformative one with the potential to bring about significant 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 [6]. Platforms represent a transformation from linear structures to a matrix complex of relationships between connected producers and customers. They 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' [7] is vital. 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 vastly 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 [8].

2.1.4 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 (see **Figure 3**). 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 the 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 will not 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 will not 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.

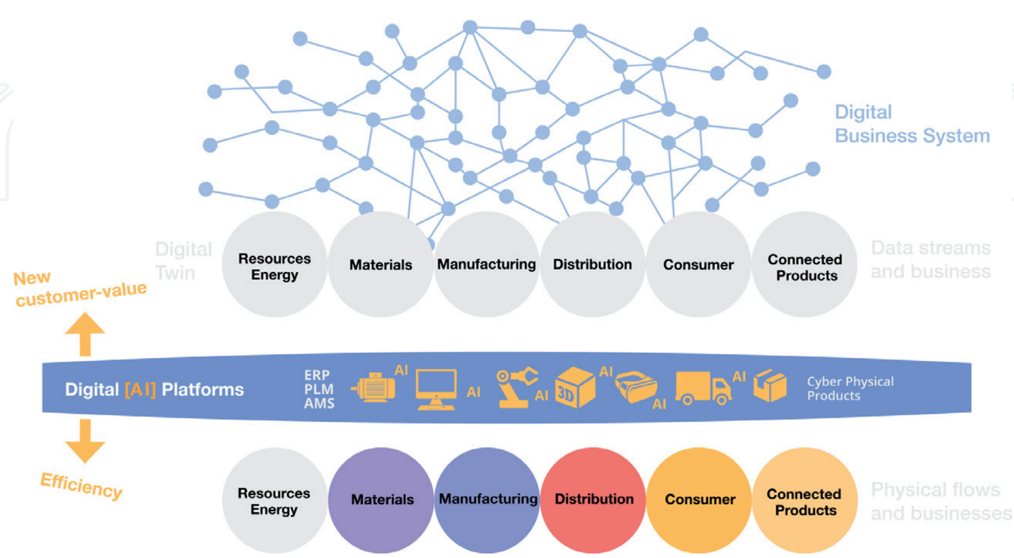

Figure 3.
Physical value chains and the flow of raw materials, materials and products are complemented by equally elementary data streams that enable digital twins at different levels, including entire processes and value systems. The technology and connectivity that makes physical production, as well 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.

Platforms also have the potential to change the 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% by 2025 and create 72 million full-time jobs [9]. It is not 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 the development between the machines.

We conclude that while the business economics doctrine will undoubtedly continue to exist once the resources, process and manufacturing industry becomes an information industry, how it is followed will be revolutionised.

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 most massive 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 several computer labs, and we see 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 define, describe and share data safely.

Ultimately, the transformation for classic industrial companies involves managing two different logics; the massive scale of the supply economy is not 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.

The use of the 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'. From the first mainframe computers, via the client-server model with its personal computers and networks, and into the era of digitisation, 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 objects, through the Internet of Things.

2.1.4.1 Industry case study: Mälarenergi Smart Flows: 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 the 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.

2.1.4.1.1 The challenge

Measuring, understanding and predicting flows of materials, gases and liquids are 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 considerable savings in energy and total costs, which in turn can create positive environmental effects.

Process flows are rarely in a constant state, and instead are continuously developing as demand changes, new infrastructure is expanded, or as customers come and go. As a result, there is a clear need to make the industrial systems adaptable and teachable. District heating systems are an example of a system in which changes take time.

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

From the time that production is increased at a plant, it can take several hours before consumers' scores of kilometres away can 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 manage historical and close-to-real-time data dynamically.

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 be individualised.

2.1.4.1.2 The experience

The system takes in more than 15,000 properties, ranging from private homes to commercial properties and industries. 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 have 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 concerning the heating needs of the building itself. Here, the weather is a substantial 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, there will be a massive potential impact on district heating. A variety of methods are being tested 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 is 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 is 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 feasible for the next time.

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

Source: PiiA, Mälarenergi, RISE.

2.1.5 In search of best practice

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 primary resources and materials, there is the potential to increase value for customers who can contribute to top-line growth.

Returning to the corporate and economic side of things, it is time to pose the question of whether the business case for AI is settled and whether now is the right time for significant 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 primary 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 the Blue Institute and PiiA are the S-curve (see **Figure 4**) [10]. 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 experiments and industry pilots, to move into the next stage with trailblazers leading the way in seeking a best practice that delivers results; we call this the 'best practice' phase.

Best practice, in turn, lays the foundation for an accelerated transformation of an industry. Experience from previous technological shifts has shown the power of good role models. For example, over 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.

Examining the development of applied industrial AI and using the empirical evidence we have through, among other things, PiiAs project base, we can identify three types of companies in different stages of the curve (see **Figure 5**):

- The majority of companies—an estimated 70%—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% 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% 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 involve creating appropriate change teams with the skills needed for the task ahead. Still, 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% of the global workforce will need to change their job duties as a consequence of AI [1].

Also crucial is data, both from an ownership perspective and a quality perspective. Information is the raw material of AI technology, which is then converted into money with the help of algorithms. The final fundamental prerequisite is security and risk management. These challenges also feature in Vinnova's 2018 study [11], and we will look more closely into these aspects in the second part of the report: The Technology.

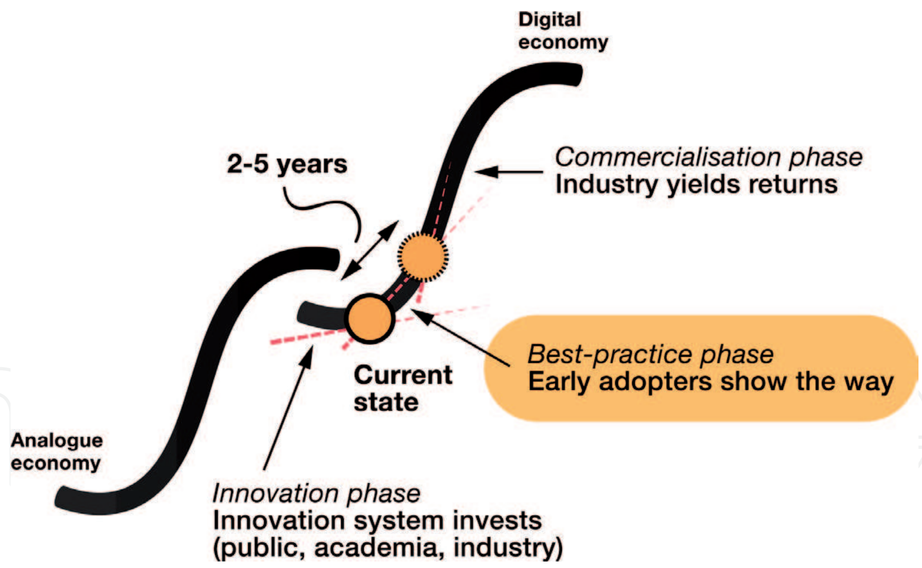

Figure 4.
Digital development with AI as an essential component leaves the pure innovation phase. After that comes the 'Best Practice' phase in which trailblazers dare to experiment and inspire others. Source: Blue Institute, 2019.

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, organisational data 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 is 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.

A study by McKinsey examined 400 AI applications in 19 different sectors. It found that in 69% of cases, AI was a means to improve existing, more straightforward, analytical methods. Entirely new applications accounted for only 16% of cases. In comparison, the remaining 15% 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.

2.1.6 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. A driven

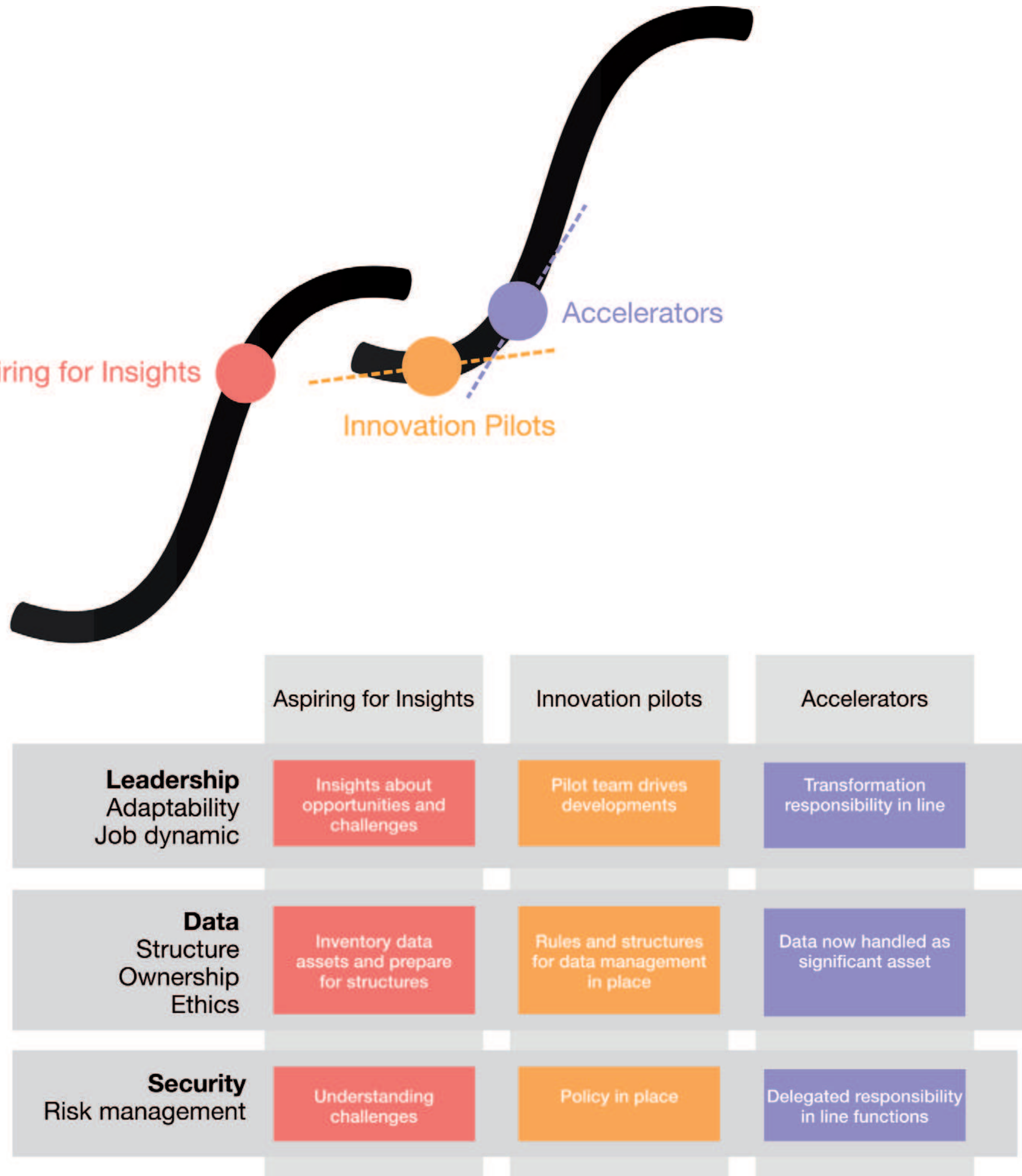

Figure 5.
Three typical development steps for implementing AI in an industrial context. From creating insight into opportunities and challenges, to the more full-scale transformation of a company's processes. Source: Blue Institute, 2019.

individual is 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 complicated 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 previously manual tasks were. AI systems, on the other hand, are designed to find patterns, to learn from experiences and to make consistent decisions. AI does not need specifically programmed paths to determine how it should behave in different situations (see **Figure 6**). 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.

2.1.7 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 AI that in a business context needs an 'inertia mass'—a combination of data, knowledge and energy that all interact with each other for a project to be successful.

From a business and company perspective, it is essential to create mighty 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

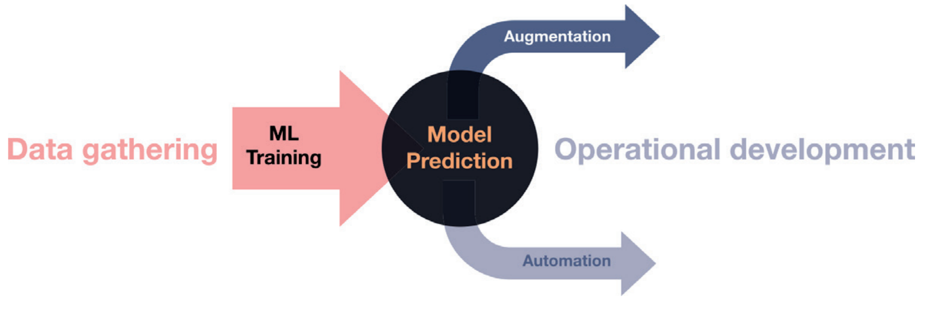

Figure 6.
The streamlining of the industry's supply chains is enabled using machine learning (ML) which makes predictions of process behaviour based on collated data. These predictions can then be used to enhance people's abilities or to automate processes fully. Source: Blue Institute, 2019.

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% in the first quarter of 2019 with an operating margin of 29%. 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 more prominent strategies possible.

The most common mistake when companies adopt AI is that they start 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 useful 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 can move relatively freely between production, process and operational development, as well as customer's needs and preferences.

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 is a potential to achieve flywheel effects at the company level.

Mining Magazine asked 115 mining companies where they saw the most significant 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.

2.2 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.

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 (see **Figure** 7):

- 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 unites 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. By and large, these private, public investments amount to 500 billion annually.

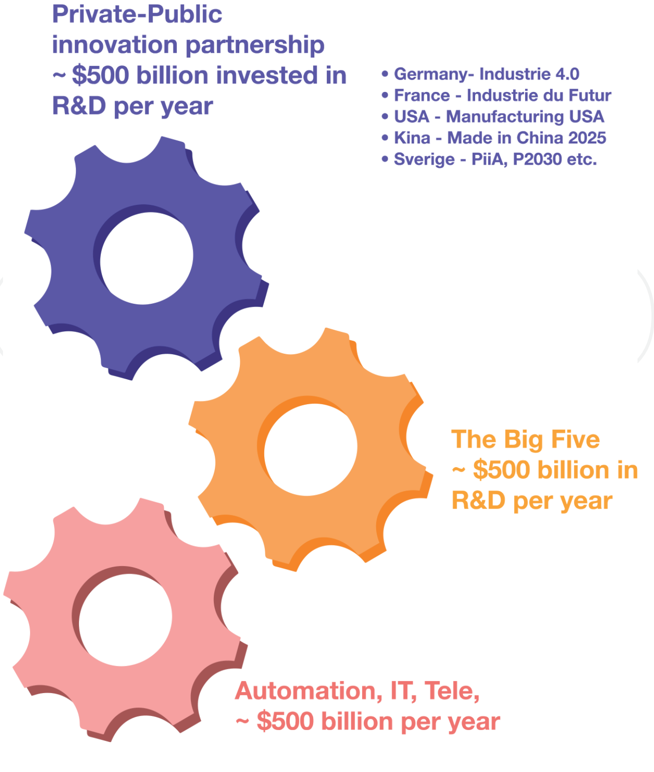

Figure 7.
The applied development of digital technology for the industry is being driven by historical investments in what can schematically be described as three fields of influence or developmental hubs. Each of these accounts for about one-third of an impressive 1.5 trillion invested in technology development each year. Source: Blue Institute.

- The second development hub consists of 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 in 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 robust 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 vast 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.

2.2.1 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 within where the value of the dispute is less than EUR 7000.

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 significant 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.

2.2.2 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 challenging to comprehend fully. 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.

A dominant theory for assessing the characteristics of AI systems is the so-called Turing-test [12]: a computer passes the test if a person, after having asked several written questions, cannot discern whether the answers have come from a human or a machine.

The set of abilities [13] which are considered essential to enable 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 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.

2.2.3 Narrow and broad AI

AI can be classified in many different ways, but a standard description is narrow versus broad or general AI. All the AI that exists today is narrow or rather; specialised. Our 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.

2.2.4 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 (see **Figure 8**).

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 continually being improved and adapted for various 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 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 more straightforward 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' 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 item 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.

Reinforcement learning is the latest 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 gained several commercial breakthroughs and is used, among other things, to streamline the operation of gas turbines, wind

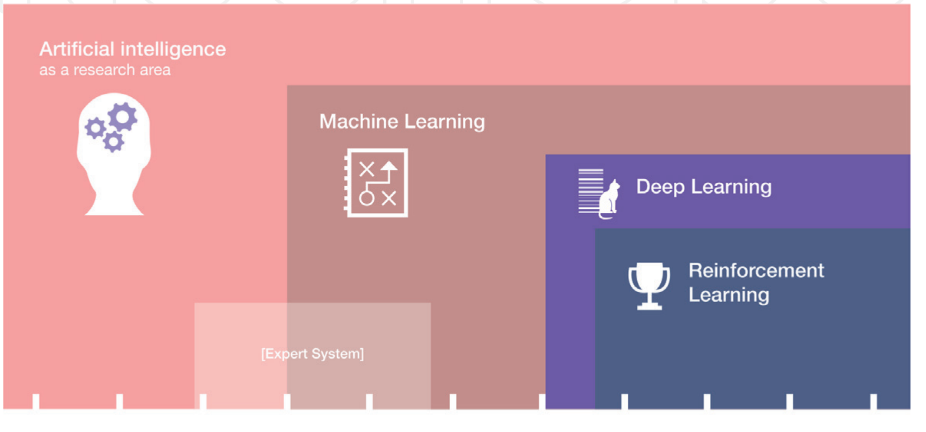

Figure 8.
AI and different learning methods put in a development perspective.

turbines and energy use in computer halls. The method has good potential for future industrial applications.

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

2.2.5 The availability of AI is dominated by significant 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 (see **Figure 9**). The development of automation suppliers means that industrial control systems will also get built-in machine learning capabilities. The telecommunication 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 contribute 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 [14], 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 a growth rate of almost 40%. 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 [15].

But it is 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. They account for 55% of the value of the Nasdaq 100 Index (see **Figure 10**).

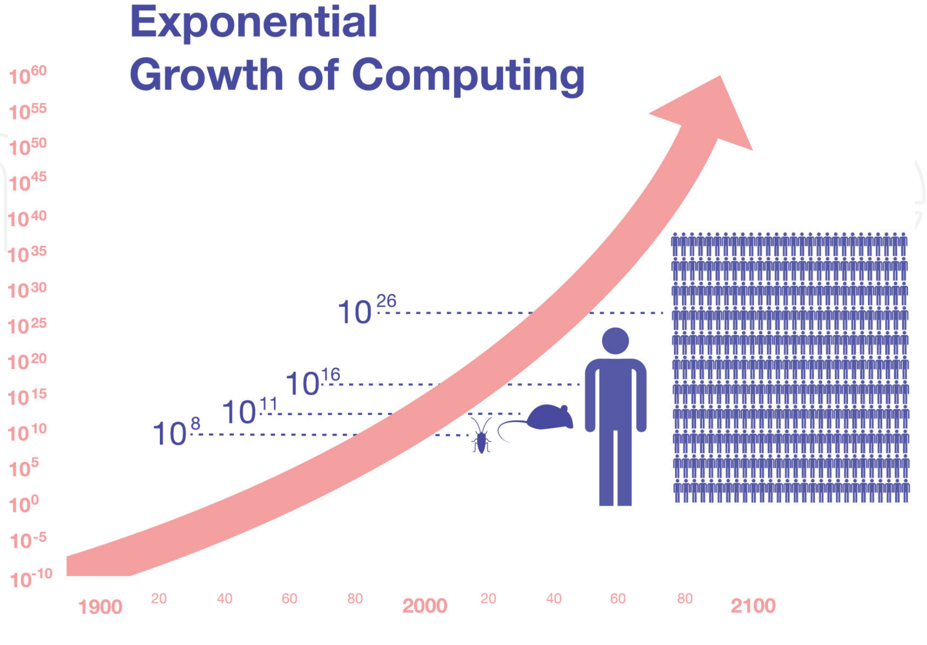

Figure 9.
Computing power is a prerequisite for the development of artificial intelligence. It took 90 years to reach the first million instructions per second (MIPS) per $1000—now 1.2 MIPS/$1000 are added every hour. Source: Ray Kurzweil and KurzwelAI.net.

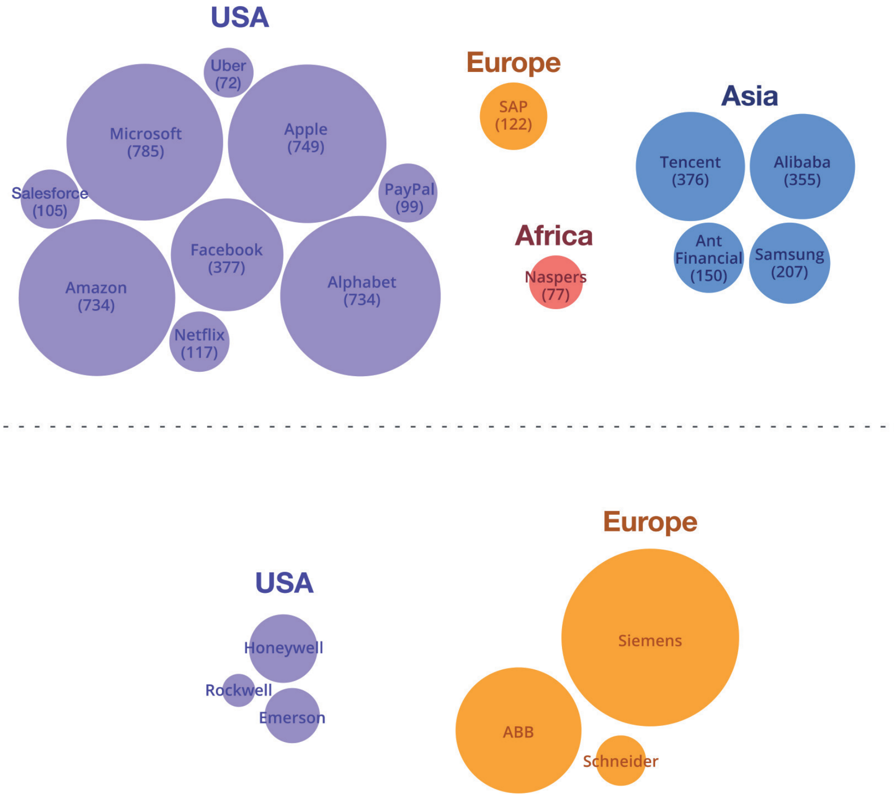

Figure 10.
Top: Platform companies in the US have a definite lead in the development of AI platforms. Market values December 2018. Below: Comparison between the three largest IndTech companies in Europe vs. the USA. Source: EC, EU industrial policy after Siemens-Alstom, Blue Institute.

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.

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. To ensure the availability of top academics from universities, employees are being offered high salaries, unlimited computer and computing resources and minimal bureaucracy [16].

The concentration of resources, expertise and access to data is therefore currently focused on a few global commercial players. This is a 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 can 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 (see **Figure 11**). Two groups of more independent initiatives flank these platform alliances and centres. One consists of companies that sell predictive analysis solutions and build individual platforms. According to a qualitative evaluation by analysis company Forrester [17], this segment is led by SAS, IBM and SAP, with a long tail of smaller players.

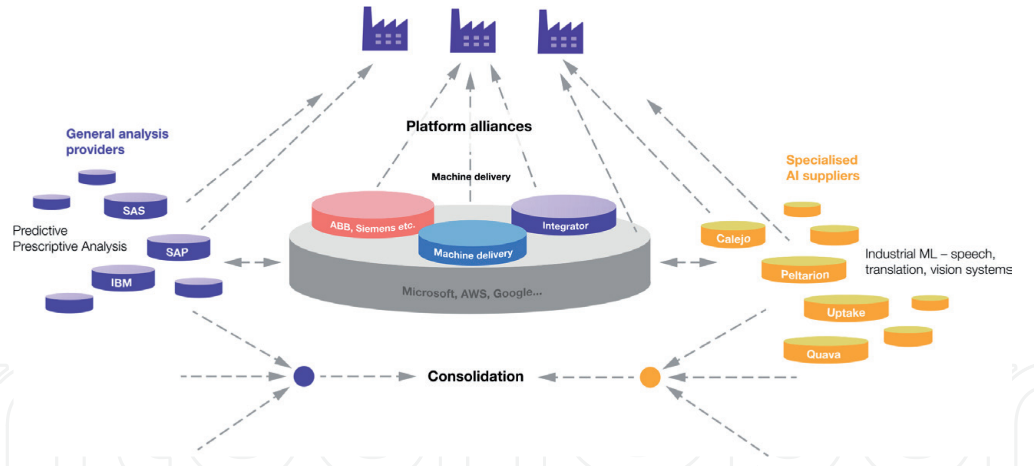

Figure 11.
For industrially applied AI, three groups of suppliers can be distinguished. In the middle are the large general platform providers, which are creating more and more alliances with companies that can serve as value-adding specialised channels of the platform suppliers' large-scale AI offering. 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.

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 is a similarly long tail of small and medium-sized players. The sector is immature, heavy with development and likely to undergo further consolidation.

2.2.6 Automation, industrial IT and digitalisation lead to IndTech

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 the 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% if the process industry and electricity industry increase the use of wireless communication [18]. 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.

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 more uncomplicated and more cost-effective and also to add new value. Intelligent apps in intelligent ecosystems are a development trend that has the potential for a significant 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 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 the 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. At the same time, the process flows will be held together using collaborative logistic systems.

2.2.7 Industrial case study: focus on mining companies: the ENSAF project: energy and safety diagnostics.

There is currently a significant interest in the early diagnosis of problems in underground mining facilities. There is a trend towards achieving fully automated mining, meaning that should hazard 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 continually 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 significant 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 mines and smelters, and it is working over the long-term to guarantee society's access to the base and precious metals; from the mining of ores (minerals) to the production and delivery of high-quality metals to the industry. Its production capacity is high due to experience, innovation and advanced technology, developed in collaboration with various Nordic technology and engineering companies. Approximately 5800 people work at Boliden, and its operations are conducted in Sweden, Finland, Norway and Ireland.

'In the event of a 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'.

2.2.7.1 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, wherein 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 a fire, the smoke, in particular, poses a severe threat to both people and appliances. It is, therefore, essential 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.

2.2.7.2 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, CO_2 and CO concentrations, relative humidity and flow) to each other via simulation models. The aim is to 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 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 conducted by Epiroc and Mobilaris, ABB and MDH, with Boliden acting as a sounding board 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 the 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, to detect not only the shape 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. hydra-like 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 3000. The sensors tested under ENSAF are now implanted in Certiq, which transmits 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% 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 to increase communication security locally and also with central systems that can give an overall picture of the situation.

Sources: ABB, PiiA, MDH.

This chapter continues in part 2.

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