5 Artificial intelligence: Changing landscape for SMEs

Artificial Intelligence (AI) could trigger a new production revolution, radically transforming business practices and conditions. This chapter aims to provide an understanding of what AI is, its potential impact on SME activities, and barriers to adoption. The first section examines the rise of data-driven AI systems. The second section looks at the implications of these technological changes on SME practices and business environment. It looks at how AI can drive greater efficiency in the SME sector, across different industries and along SMEs' internal value chain, as well as how AI can improve SME business conditions. The third section discusses how AI diffuses differently within the SME sector, and elaborates on the barriers and challenges smaller businesses face when they consider AI adoption. Overall, this work intends to stress some areas where policy intervention could be considered.

In Brief

Highlights

- **Recent progress in the field of Artificial Intelligence (AI) is largely due to the wide adoption of data-driven statistical methods and breakthroughs in machine learning**, supported by greater data availability, increased computing power and growing algorithmic efficiency.
- **AI systems are built on sensors** (to capture data), **an operational logic** (to analyse data and infer decisions), **and actuators** (to intervene in the physical or virtual world). They are trained with data, and machine learning algorithms can adjust constantly while processing information, with little human supervision.
- **The self-improving nature of AI poses challenges**, with a risk that AI systems could be prejudicial to the real world (i.e. an over reliance on biased or poisoned data, and a lack of explainability of algorithms). In addition, the scope for replicating and scaling up AI solutions remains limited because their features are little transferable from one environment to another.
- **The main business applications of AI relate to automation, image/face recognition, natural language processing, data analytics and predictive capacity**.
- **New AI systems make possible to automate non-routine tasks**. Automation could help SMEs increase productivity, e.g. by refocusing activities on higher value-added functions, or by reducing costs. Such systems could also help small businesses overcome administrative bottlenecks and increase responsiveness.
- **AI allows a significant drop in prediction price and facilitates decision making**. SMEs can execute predictive analytics to lower their exposure to risks, automate business forecasts with real-time data, or increase efficiency in asset management. Enhanced prediction capability also allows for greater market segmentation and opens new opportunities for SMEs to innovate.
- **AI can be applied to most sectors**, including services and low-tech sectors, as well as to all business functions, from pre-production to post-production. Marketing and sales, supply chain management and production are functions where AI could have great impact. Retail trade, transport and logistics services, or automotive and assembly manufacturing are sectors where AI could contribute to creating significant value.
- **AI can substantially affect SME business environment**, by enhancing the efficiency of public administration, courts and tax authorities, reducing red tape, securing digital infrastructure, improving SMEs' access to finance, easing skills management and job matching, or reducing the costs of experimentation and innovation. At the same time, algorithms increase the risk of tacit collusion on product and labour markets, and of (likely large) firms sustaining profits and prices above a fair competitive level, at the detriment of smaller businesses.
- **Evidence suggests different degrees of AI diffusion across countries, sectors and firm sizes**. This is not without consequence on the capacity of governments to reduce inequalities and achieve greater inclusiveness. There are concerns that most of the AI benefits could be reaped by first adopters, while laggards have low or no benefits at all.
- **Businesses in most countries show low level of data analytics adoption with leading countries tend to head the ranking in all sectors**, while lagging countries tend to lag in all of them. New AI practices are diffusing across all sectors, with services adapting faster than

manufacturing or construction. In information and communication services, there is already an early majority of enterprises that are performing data analytics.

- **There is also evidence of an SME gap in using data analytics and/or implementing AI solutions**. SMEs face several barriers to adoption: a lack of data culture; a lack of awareness about what AI could bring; a need for retraining managers and workers; high sunk costs for internalising AI, plus a need for engaging complementary investments; few evidence and little visibility on the returns on investment; and reputational and legal risks.
- **SMEs can source external AI expertise and solutions from knowledge markets** that typically compensate for a lack of internal capacity. Cloud computing-based Software as a Services (SaaS) and Machine learning as a Service (MLaaS) offer advantages such as the scalability of AI solutions and costs, no prerequisite of technical knowledge (for Saas), digital security features directly embedded in the software.
- **However, SaaS and MLaaS raise additional challenges related to data ownership and portability, and lock-ins effects**. Moreover, since both are cloud-based, SMEs need an access to a minimum speed and quality internet connection. Although digital network infrastructure has gained in reach, speed and sophistication, smaller firms remain less connected.
- **Data is the key**. Governments have a role to play in supporting SMEs in building a culture of data and improving digital risk management practices.
- **The human factor is critical**. Raising awareness among SME managers and workers on AI benefits, and building the conditions of a trustworthy transition are required. National and local governments should also co-ordinate actions for reskilling SME managers and workers, and ensure a participatory approach in redesigning work processes and training AI models.
- **The issue of financing should be addressed**, first by building more evidence on the return on investment of AI business applications, in order to inform not only SME managers and business owners, but also investors and financial institutions, and by identifying mechanisms for bridging the financing gap until AI can deliver its full promises.
- **Regulators and policy makers should ensure the well-functioning of knowledge markets** that provide cloud solutions embedding AI technologies, as well as the transfer of knowledge that could enable SMEs to scale up their capacity before being eventually able to develop their own AI solutions.
- **Adopting a differentiated industrial approach on AI transition(s)**, through sectoral studies and business use cases, **could help inform relevant stakeholders** and account for the low transferability of AI knowledge across environments.
- **Supporting mutual learning**, through platforms such as the OECD Digital for SMEs Initiative and the OECD.AI Policy Observatory could help better understand the role large firms, business associations, chambers of commerce, academia, national and local governments, international organisations, and SMEs as well, could play to advance on these different agendas.

Artificial Intelligence in a nutshell

Artificial intelligence (AI) has regained attention in the last decade, after “winters” of general pessimism regarding the promise of the technology. The capacity of computing systems has expanded with greater data availability, increased computing power and storage capacity, and substantial improvements in algorithmic efficiency. Continued improvements in hardware and software and the convergence of complementary technologies, e.g. sensors, robotics, Internet of Things (IoT), have paved the way for a new generation of more autonomous AI systems that require less human intervention (if at all), for adjusting and upgrading.

AI is becoming increasingly prevalent across diverse spheres of the business and social life, given its ability to enhance the automation and prediction capacity of firms and organisations, or to bring natural language processing and image recognition to a new level. Applications are pervasive, embedded in software, devices or platforms, foreshadowing far-reaching consequences on the functioning and performance of firms, industries and places.

All firms are not placed on an equal footing in embracing the AI revolution (OECD, 2017[1]), and in orchestrating the changes in mindsets, practices or processes that are yet required. Small and medium-sized enterprises (SMEs) face greater disadvantages in the transformation, and the OECD recognises the need to give them special attention when designing AI policies in order to ensure a fair transition (OECD, 2019[2]; Daor et al., 2020[3]).

This chapter aims to better understand what AI is, its business applications and their potential impact on SME activities, and barriers to adoption. The first part examines the recent conceptual and technological developments around AI and the shift in AI paradigm. The second part looks at the implications of these technological shifts on SME practices and business environment. It looks at how AI can drive greater efficiency in the SME sector, how AI applications can benefit SMEs across different industries and along their internal value chain, as well as how AI can improve SME business conditions and help level the playing field. The third part of this chapter discusses how AI diffuses differently within the SME sector, and elaborates on the barriers and challenges smaller businesses face when they turn to AI adoption.

Main characteristics of AI

The idea of objects being capable of conducting formal reasoning has existed for long. The concept became more concrete during the mid-20th century with the introduction of the term “Artificial Intelligence”. Box 5.1 presents some insights on the early development of AI.

Box 5.1. A brief history of Artificial Intelligence over the 20th century

The confluence of disciplines, including computer science and neurology, in the early 20th century supported concerted efforts to create machines with human-like cognitive capability. Such concepts and systems were named in different ways, such as “electronic brain” (Walter, 1950[4]) and “learning machine” (Turing, 1950[5]).

“The Dartmouth Summer Research Project on Artificial Intelligence” held in 1956 is widely considered as the cornerstone of AI (Moor, 2006[6]; Negnevitsky, 2005[7]). A small group of researchers, gathered to exchange their vision on self-improving intelligent machines, which paved the way for a new academic discipline on AI. A computer programme named Logic Theorist was developed during the conference, which later came to be known as the first AI programme.

Thereafter came a series of research and development (R&D) programmes of sophisticated computers that aimed to further mimic human intelligence, from solving algebra word problems to having basic conversation with humans. Early successes in the field of AI, followed by ambitious predictions of what the future of the technology could be, garnered much attention from both the private and public sectors. However, the enthusiasm of techno-optimists soon faded away, as progress in the field did not meet the early expectations. The community expressed growing concerns about what results could be effectively achieved. This time was referred to as "AI winter," depicting general pessimism regarding the promise of the technology, which lead to cut back in R&D funding and a downscale of the field (Hendler, 2008[8]; Agrawal, Gans and Goldfarb, 2018[9]).

The AI winter began melting as from the mid-1990s. However, researchers on computer-engineering methods, avoided labelling their work as such, in order to circumvent the negative perception of the technology. Instead, they associated themselves with subfields of AI, e.g. computer vision or expert system, without mentioning AI. The private sector was also reluctant in using the term AI to describe their solutions. For example, when promoting Deep Blue, a chess-playing computer that won against human chess champion in 1997, IBM explicitly stated that the computer did not use Artificial Intelligence, although it integrated computing techniques that are considered today as AI along the current standard (Korf, 1997[10]).

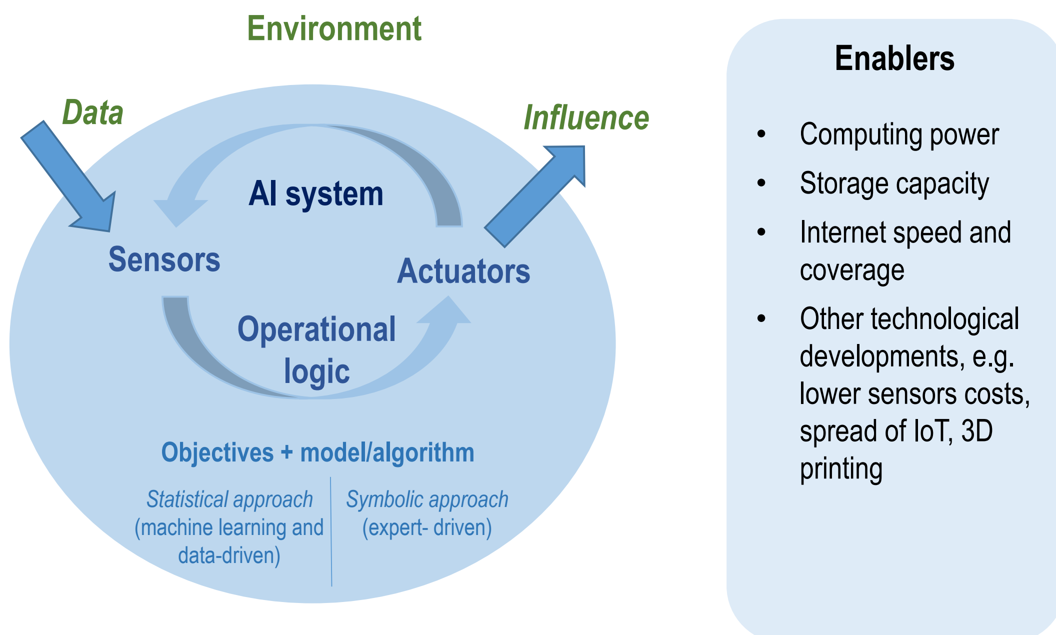
Since its early developments over the 20th century, the boundaries of AI research and applications have been expanding, along with the development of new methodologies and the deployment of complementary technologies. Although AI is often referred to as a single technological concept, it consists of a variety of technology subfields that are often inter-related. Examples include natural language processing, speech recognition, image processing and robotics. From the 1990s onwards, noticeable advancements in AI have enabled systems to learn and adapt to changing environments and perform increasingly sophisticated tasks.

Despite a broad use of the term, until recently, there was no internationally accepted definition of AI. In 2018, the AI Group of Experts at the OECD (AIGO) came up with a description of AI that aimed to be understandable, technology-neutral and encompass AI definitions commonly used by the scientific, business and policy communities. The AIGO definition also aimed to inform the development of the OECD Recommendation of the Council on Artificial Intelligence (OECD, 2019[2]). Therefore, the OECD defines an AI system as "*a machine-based systems that are able to infer models and formulate predictions, recommendations, or draw decisions, that can in turn influence environment, whether real or virtual, according to objectives defined by human*" (OECD, 2019[2]).

An AI system is comprised of three key elements: sensors, operational logic and actuators (Figure 5.1). Raw data from the environment is collected by sensors. Data is then processed according to a given set of objectives that are encoded into an operational logic. An AI model constitutes an important part of the operational logic as it reflects the environment and describes its structure and/or its internal dynamics.

An AI model can be built based on knowledge and data generated by humans, automated tools, or a combination of both. Model inference shapes the model outcomes in the form of prediction, recommendations or decisions.

Figure 5.1. Conceptual view of an AI system



Note: Based on OECD (2019[11]), *Artificial Intelligence in Society*, OECD Publishing, Paris, https://doi.org/10.1787/eedfee77-en.

A shift in AI paradigm

Research on AI can be largely categorised into symbolic approach and statistical approach (OECD, 2019[11]). While the former processes data with pre-defined rules, the latter utilises statistical methods to find patterns in the data.

From classical expert-driven to modern data-driven AI

Symbolic AI is commonly referred to as classical or traditional AI, as it reflects an early paradigm of AI research. Symbolic AI utilises explicitly stated logics and rules in order to generate outputs. The making of symbolic algorithm requires a detailed coding of decision structures and knowledge that represent the state of the real-world environment.

Expert system is an exemplar of symbolic AI system, as the rules of the system were programmed in the form of "If-Then" statements, by using human-understandable symbolic logic. The approach was, however, not suitable for integrating unexplainable knowledge or tacit decision-making logic. As it was difficult to codify complex systems with too many rules, the problems needed to be narrow and well defined in advance. Expert systems were costly, time consuming to develop, and required manual update of new knowledge (Harmon, 2019[12]). In addition, the systems were often difficult for people other than the system creator to maintain (Clancey, 1983[13]), further limiting business applications and the scalability of AI solutions.

Statistical AI processes large amounts of data to induce rules from patterns observed in data. Box 5.2 explains the changes in complementary technologies that enabled the development of statistical AI. A notable subset of the statistical AI methodology is machine learning, which is a branch of computational statistics where a system learns and modifies algorithms from input data without the need for explicit instruction from a human (OECD, 2019[11]). This implies the self-improving nature of AI systems by use of data. Deep learning is a subfield of machine learning, where large sets of "neural network" techniques are used to replicate how a human brain processes information.

Significant progress in machine learning have been made, even outside the core AI research areas and computer science, with some of the most interesting AI developments taking actually place in fields such as health, medicine, biology and finance (OECD, 2019[11]).

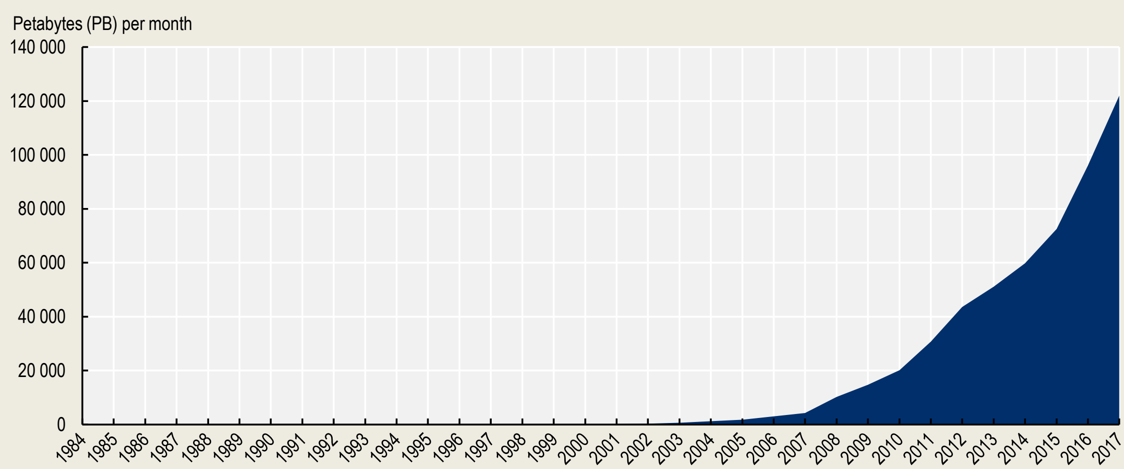
Box 5.2. Stepping stones towards statistical AI

A substantial increase in computing power is seen as one of the main factors that led the transition from a knowledge-driven approach to a data-driven approach in AI. Insufficient computational power posed challenges in developing statistical approaches in the previous era (Smolensky, 1987[14]). The performance of microprocessors enhanced on a biennial basis, driving down the cost of computing power.

The growing algorithmic efficiency of AI systems also played a role in the expansion of AI capabilities. Findings from OpenAI (2020[15]), an AI research organisation, suggest that between 2012 and 2019, the performance efficiency of the state-of-the-art AI systems increased by 44 times, with current cutting-edge AI solutions consuming much less energy in conducting the same tasks than their seven-year-old predecessor. The study further suggests that the algorithmic efficiency of investment-intensive AI systems has surpassed that of hardware efficiency.

In addition, recent technological developments made it easier to produce and access large volumes of data, often referred to as “big data”,[1] which are used to train statistical AI models. Broader internet coverage, along with faster internet connection, contributed to a significant increase in data creation and exchange. Over a 33-year period, between 1984 that marks the beginning of the Internet, and 2017 when latest data are available, internet traffic has increased by 8.13 billion times (Figure 5.2). Most of the data generated through online activities is multimedia data, where internet video consumption generates around half of the global internet traffic (Cisco, 2018[16]).

Figure 5.2. Global Internet Protocol Traffic, 1984-2017



Note: Internet Protocol traffic includes both landline broadband and mobile traffic. 1 Petabyte = 1 024 Terabytes (TB) = 1 048 576 Gigabytes (GB) = 1 073 741 824 Megabytes (MB). As a comparison, a chat on Skype would consume 30 MB per minute. Most smartphones store 64 GB or 128 GB of data (apps, music downloads, etc.) per device. 7 GB is consumed per hour of Netflix streaming in 4K Ultra HD. The Hubble Space Telescope generates about 10 TB of new data every year.
Source: Based on Cisco’s White Paper series “Cisco Visual Networking Index: Forecast and Methodology.”

StatLink https://doi.org/10.1787/888934227830

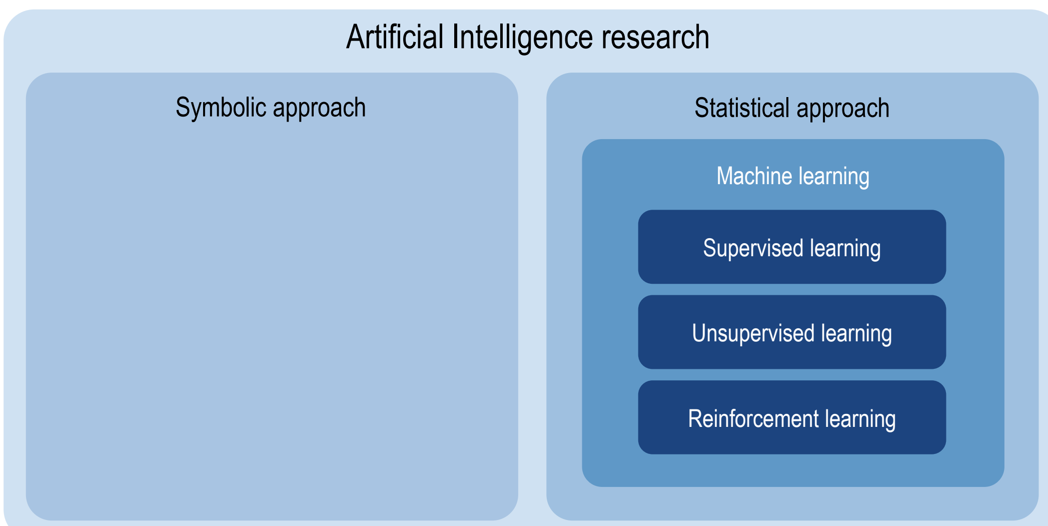
The growing adoption of IoT and the deployment of cheaper and faster sensors further contribute to increase the volume, variety and velocity of data exchanged. Between 2004 and 2018, the average cost of sensors decreased by 70%, falling below USD 0.5 per unit (Microsoft, 2018[17]), driving the costs of producing real-time data down.

Source: (Smolensky, 1987[14]; OpenAI, 2020[15]; Cisco, 2018[16]; Microsoft, 2018[17]).

Methods of machine learning

Machine learning could largely be categorised into three subsets of learning methods: supervised learning, unsupervised learning and reinforcement learning (Figure 5.3). In addition, semi-supervised learning combines supervised and unsupervised learning methods. Various types of data can be used to induce machine learning, ranging from texts for natural language processing, to videos for object recognition.

Figure 5.3. Methods of machine learning



Note: Modification based on the diagram titled "The relationship between AI and ML", presented in *Artificial Intelligence in Society.* Size of diagrams does not represent neither volume of research conducted nor significance of the research field.
Source: OECD (2019[11]), *Artificial Intelligence in Society*, OECD Publishing, Paris, https://doi.org/10.1787/eedfee77-en.

- In *supervised learning*, raw data is annotated, manually and/or automatically, to train the system. Labelled data provide a reference for the AI model to identify characteristics in the dataset. A hypothetical example of AI in terms of image recognition is featured in Figure 5.4 (a). Objects are delineated and labelled, such as buildings (green) or humans (yellow). Data is processed through an algorithm to identify similarities among labelled objects, which in turn are used to analyse new input data. The accuracy of such model is determined by the granularity and the volume of data used to train the AI model. The method is commonly used for classification, with use cases including face recognition and spam email filters.
- *Unsupervised learning* systems identify patterns in large data sets without labelled data. AI models developed through unsupervised learning find structure in data based on data attributes, i.e. their properties within the dataset.[2] Typical usages of the unsupervised learning techniques include cluster analysis, anomaly detection and association discovery. Figure 5.4 (b) depicts density-based

clustering, where boundaries are drawn for the two clusters based on similarity of data attributes. Large sets of data are required to ensure precision of the results, but assessing the accuracy of an unsupervised learning-based algorithm could be challenging (Salian, 2018[18]).

- *Reinforcement learning* stems from the idea of learning from feedbacks. This AI model is fed with information reflecting the state of the external environment and the objective of the system. With this learning method, the algorithm evolves as it interacts with the environment. AlphaGo, which defeated the world's best Go game player, is a well-known example of an AI system combining supervised and reinforcement learning. Developed by Alphabet's DeepMind, AlphaGo's AI model was trained by playing (Silver et al., 2016[19]). The case of AlphaGo also shows that machine learning methods are complementary.

Figure 5.4. Examples of supervised learning and unsupervised learning

Examples of supervised learning with annotated data (a) and unsupervised learning with clustering method (b)

Note: Example of clustering presented above depicts "density-based clustering," which is a subset of clustering methods.
Source: (European Commission, 2018[20]; Google Developers, 2019[21]).

New methodology, new challenges

Similar to previous AI systems, current AI systems are trained to carry out precise tasks and the knowledge acquired is little transferable to other environments. Although AI systems are being created to mimic humans' cognitive process, it is largely agreed that current developments are insufficient to create an Artificial General Intelligence (AGI), an AI capable of applying learned skills and knowledge in varying contexts (Agrawal, Gans and Goldfarb, 2018[22]; Brynjolfsson and Mcafee, 2017[23]). Current AI systems are trained to carry out precise tasks, which are defined as Artificial Narrow Intelligence (ANI). Knowledge processed by current AI systems do not generalise, meaning that knowledge obtained by AI in a specific area is not transferrable to other domains. To put it into perspective, AlphaGo Zero's AI system, the successor of AlphaGo equipped with faster learning capability, is not capable of conducting autonomous driving (Sample, 2017[24]).

However, while traditional AI methodologies required manual intervention for modifying algorithms, machine learning algorithms constantly adjust themselves while processing input data. Recent advancement in AI demonstrates the capability of AI systems of making predictions and decisions based on real-time data, as seen from applications such as playing real-time strategy games against humans (The AlphaStar team, 2019[25]) and providing autonomous ride-hailing services on public roads (Chu, 2019[26]). However, despite AI systems' ability to sift through vast amounts of data faster than human beings, in various areas, from medicine (Wakefield, 2020[27]) to law (Thomas Suh, 2018[28]), the self-improving nature of the current wave of AI poses challenges.

Examining the robustness of statistical AI systems poses challenge. Unlike symbolic AI systems that are built with syntax that humans can understand and amend, statistical AI systems require uncommon ability in comprehending the conclusion process of mathematical models. In contrast to conventional software that are programmed manually, machine learning algorithms improve as they process more input data, making it sometimes difficult for humans to understand the statistical logic behind the results (Garcez et al., 2019[29]). AI algorithms are often dubbed as a black box (Castelvecchi, 2016[30]; H. James Wilson, 2018[31]) and their lack of explainability limits the scope for human intervention to correct unintended results. In addition, an algorithm could yield different results after multiple runs, albeit being trained with identical data sets (Rogel-Salazar, 2018[32]). The rules designed at the initial phase of the machine learning process, and input data, may not be sufficient in explaining the output of the AI systems.

Data play a critical role in training statistical AI, and their characteristics influence the predictions and decisions of AI systems. In other words, having adequate data is crucial in building viable AI algorithms. AI systems that follow a statistical approach are based on a certain level of confidence that the data used to train the model actually reflect the real-life environment, while this may not be the case (Brynjolfsson and Mcafee, 2017[23]). When data fed into AI systems are biased or poisoned, AI systems' outputs reflect these same biases and preferences. Therefore, the output could be skewed due to an over- or under-representation of some sub-populations in the training data, or because of pre-existing reliability issues in data, implying that AI systems could be partial and prejudicial to the real world. In addition, the challenges of interpreting biased results are exacerbated because diagnosing and correcting errors in algorithms is difficult. For example, AI-based hiring tools have been recognised to be based on unproven metrics (Harwell, 2018[33]), discriminate female candidates (Dastin, 2018[34]) and are "far from perfect" (Wright, 2019[35]). Therefore, the applications of AI should be guided in order to limit negative externalities.

Acknowledging the risk of unintended effects from AI systems, efforts have been made both at the national and international levels to provide guidelines for ethical and trustworthy AI. For example, the High-Level Expert Group on AI (AI HLEG) set up by the European Commission published "Ethics Guidelines for Trustworthy AI" in 2019, which calls for lawful, ethical and robust AI (AI HLEG, 2019[36]). International organisations, including the OECD (Box 5.3), as well as UNESCO, have published reports and guidelines on AI ethics.

Box 5.3. The OECD Principles on AI call on governments to pay special attention to SMEs in their national policies

The OECD recognises AI as a general purpose technology that can have a profound impact on societies and economies. They set standards for governments and other actors to promote use of AI that is innovative and that respects human rights and democratic values. As an OECD legal instrument, the Principles represent a common aspiration for its adhering countries to shape a human-centric approach to trustworthy AI.

The Principles were adopted by the OECD Council at Ministerial level on 22 May 2019. In June 2019 the G20 adopted the same AI Principles, providing the beginning of a global policy and ethical benchmark. As of March 2020, 44 countries, both member and non-member states, are adherents to the Recommendation (OECD, 2019[2]).

The Recommendation is the first AI standard at the intergovernmental level. It provides five principles for the responsible stewardship of trustworthy AI.

- First, *inclusive growth sustainable development and well-being*. Stakeholders should engage in creating trustworthy AI that can contribute to inducing outcomes that are beneficial for people, as well as for the planet.
- Second, *human-centred values and fairness*. The values of human rights, democracy, and rule of law should be incorporated throughout the AI system's lifecycle, while providing appropriate mechanisms and safeguards such as human intervention.
- Third, *transparency and explainability*. AI actors that develop or operate AI systems should provide information to foster an overall understanding of the systems among stakeholders, in which people affected by AI systems could comprehend the outcome and challenge the decision when needed.
- Fourth, *robustness, security and safety*. AI systems need to function appropriately while ensuring traceability, while AI actors need to apply systematic risk management approach to mitigate safety risks.
- Fifth, *accountability*. AI actors should respect the principles and should be accountable for proper operation of AI systems.

The Principle further calls for special attention to Small and Medium-sized Enterprises (SMEs) and recommends the adherents to implement national policies and international co-operation while having in mind SMEs.

The OECD (2019[2]) also provides five recommendations for national policies and international co-operation in creating trustworthy AI. The recommendations include 1) investing in AI research and development; 2) fostering a digital ecosystem for AI; 3) shaping an enabling policy environment for AI; 4) building human capacity and preparing for labour market transformation; and 5) international co-operation for trustworthy AI.

To help implement the OECD AI Principles in policies and practices, the OECD launched the OECD AI Policy Observatory in early 2020 and formed a multi-stakeholder and multi-disciplinary OECD Network of Experts on Artificial Intelligence (ONE AI). ONE AI is developing practical guidance to assist countries in developing and monitoring trustworthy AI systems through three working groups focusing on: i) classifying AI systems; ii) implementing trustworthy AI; and iii) identifying good practices for national AI policies as well as iv) a task force on AI compute.

Source: OECD (2019[2]), *Recommendation of the Council on Artificial Intelligence*, OECD Legal Instrument, OECD, Paris, https://legalinstruments.oecd.org/en/instruments/OECD-LEGAL-0449 and OECD (2020[37]), *OECD Policy Observatory: A platform to share and shape AI policies*, www.oecd.org/going-digital/ai/about-the-oecd-ai-policy-observatory.pdf (accessed on 27 February 2020).

Implications of AI on SME business environment and practices

AI can affect and benefit SMEs in two ways: by altering their business environment and easing the conditions under which they do business, or by enabling them to change their business models and practices, which could ultimately allow them to increase productivity and outreach, and scale-up. Obviously, these two dynamics are closely interrelated, as SMEs adapt to changing business conditions by transforming their processes and products, or alter market conditions by innovating.

How can AI drive a revolution in the SME sector?

With recent improvements in machine learning, AI creates the conditions for a fundamental change in businesses from the prior wave of computerisation (Brynjolfsson, Rock and Syverson, 2017[38]). Before the introduction of machine learning, the transfer of knowledge-intensive tasks and functions in the business process to computer systems was limited to explicit knowledge. In addition, building classical AI systems required extensive efforts of codification. Enhanced capability of sensors and advances in data processing, such as computer vision, enable machines to learn tacit knowledge that would otherwise be challenging for workers to fully explain. Based on the patterns identified in data sets, AI systems can learn embodied expertise on their own, which is then utilised to provide recommendations or predictions.

AI presents the characteristics of a general purpose technology (GPT) in the sense that the technology is generic, has a pervasive effect across industries and can spur the development of other technologies or innovation, with high positive externalities. Box 5.4 provides further explanation of GPT.

Box 5.4. General purpose technology: The case of electric motor

A general purpose technology (GPT) is the kind of technology that could have long-term pervasive effects on the economy by raising its productivity potential. Examples of GPTs include steam engine, electric motor and semiconductor (Bresnahan and Trajtenberg, 1995[39]). GPT typically offers substantial room for economic improvements compared to existing technologies. Due to its generic and pervasive nature, it has the potential to be used across industries and be improved over time. It also spurs complementary technologies or innovations that could further foster advancements in the GPT. GPT can transform production systems, as well as organisations, industries and business models (OECD, 2010[40]).

However, a wide adoption of GPT requires time and effort. The case of integrating electricity in production process illustrates the slow transition process. The electrification process in the US started in the early 1880s. However, the diffusion of the technology has been slow, with more than half of the manufacturing businesses not connected to the electricity grid 30 years after (David and Wright, 2006[41]). Atkeson and Kehoe (2007[42]) point to a manufacturers' reluctance in adapting to new knowledge as the main reason.

Companies that adopted electric motors in lieu of steam engine were replacing large steam engines with equivalently large electric generators as a single power source. They often reverted to the old production system, as businesses were not able to see noticeable increase in profit. This was because the manufacturers failed to overcome their inertia, with insufficient understanding of the potential benefits of electrification, and were unable to absorb innovation induced by the new technology (Henderson, 2006[43]). The benefits of adoption came much later, when production systems were reconceived. Rather than having a large electric motor to convey kinetic energy, a small electric motor powered individual machine, which facilitated maintenance and increased the efficiency of the production. The new system enhanced labour productivity and streamlined manufacturing process (Brynjolfsson, Rock and Syverson, 2017[38]; Harford, 2017[44]).

The main business applications of AI relate to automation, image/face recognition, natural language processing, data analytics and decision making, with the latter including enhanced information management and predictive capacity. The following section discusses benefits for businesses in using AI-based applications. The biggest benefits for enterprises could come from the ability of AI to broaden the boundary of task automation and enhance prediction, which are closely interrelated.

Automation of a broader range of tasks

By identifying patterns in datasets and learning from tacit non-structured knowledge, new AI systems make possible to automate non-routine tasks that previously required human intervention. Process automation is not limited to manufacturing and could also be used in providing services (Huang and Rust, 2018[45]). With ability to learn from the environment, automated machines could perform more tasks that are hard or dangerous humans, such as loading/unloading charges (e.g. from trucks) or precision tasks that require an acute perception of the environment (e.g. precision welding) (Duobao, 2019[46]).

AI-enabled automation could free workers from repetitive low value-added tasks, provided their jobs could be re-organised and their skillset upgraded (Box 5.5). For example, AI-integrated chatbots and voicebots can perform pre-programmed contact centre tasks. While the former provide text-based responses, the latter simulate conversation with customers. The AI call centre solutions can provide standard responses to inquiries such as product stock availability, opening hours, and reservation cancellation (Google, 2020[47]). Multiple requests could be addressed simultaneously, answering customers' inquiries without waiting time. In case of complex requests, the AI tools can analyse conversations and reroute the calls to relevant human interlocutors while providing them with necessary information from the previous conversation.

These new waves of automation, enabled by AI systems, could help SMEs increase productivity, e.g. by refocusing business activities on higher value-added functions, by reducing human and economic costs associated with accidents or injuries, or improving work environment and conditions (e.g. dirty tasks). The implementation of such systems could also help small businesses overcome administrative bottlenecks and increase their responsiveness at lower costs, for instance by responding to customers' simple inquiries and enabling customer interaction 24/7.

Box 5.5. To which extent will AI replace jobs?

Empirical studies suggest that AI diffusion may not translate into a complete job replacement. Actual work replacement by automated machines could be lower than past projections suggested (McKinsey Global Institute, 2017[48]). Frey and Osborne (2017[49]) estimated that about 47% of US employment was at high risk of automation. Nedelkoska and Quintini (2018[50]), with more granular occupational data, found that 14% of all jobs across the OECD were at a high risk of automation, while another 32% were likely to be significantly affected. Arntz et al. (2016[51]) even found, for a sample of 21 OECD countries, a risk rate of 9%.

Current ANIs are capable of substituting specific tasks that consist in jobs and some occupations actually face high risk of automation (e.g. food preparation assistants, drivers and mobile plant operators, labourers in mining, construction, manufacturing and transport, stationary plant and machine operators and refuse workers, etc.) (Nedelkoska and Quintini, 2018[50]). As the geographic distribution of these jobs varies across OECD countries and regions, the risk of automation is also highly variable from one place to another (OECD, 2018[52]). Regions with smaller risk of automation are characterised by a larger proportion of workers with tertiary education and jobs in services, and are highly urbanised.

Some jobs are, however, considered safer from automation. These are those that imply performing: i) tasks linked to perception and manipulation (e.g. dexterity), ii) tasks that require creativity, such as artistic activities or coming up with original ideas, problem-solving or teaching abilities; iii) tasks that rely on social intelligence, such as being persuasive, negotiating aspects of a project or caring for others (Frey and Osborne, 2017[49]; Nedelkoska and Quintini, 2018[50]).

Early use cases show that AI also induces substitution and complementary effects, which modify workers' task composition and reinforce their skillset, rather than replacing them entirely (OECD, 2019[53]). Furthermore, whether an occupation might be replaced by automation would also depend on technological factors such as the direction of the technological change, as well as firm-level factors, such as the sector of activity (Ekkhehard, Merola and Samaan, 2018[54]).

Lastly, the application of AI is likely to induce a demand for new skills as observed during previous waves of automation (Acemoglu and Restrepo, 2018[55]). It could also be expected an increase in demand for the tasks that cannot be automated.

Increased efficiency in predictive analytics for decision making

AI systems are capable of making statistical predictions, which means inferring diagnosis and analysis based on the information previously obtained, while sifting through big data and adjusting their algorithms. The use of advanced statistical techniques for deriving prediction is commonly referred to as predictive analytics, which is a subset area of data analytics.

The main difference from conventional predictive modelling is that AI allows a significant drop in prediction price and facilitates data-driven decision making in the business context (Agrawal, Gans and Goldfarb, 2018[22]), since lower prediction cost could ease access to a wider range of prediction methods. SMEs can execute predictive analytics to map uncertainties and lower their exposure to risks, while identifying possible opportunities. AI-based prediction tools could automate business projections such as sales and budget forecasts and inventory management, making it easier for companies to forecast their businesses with real-time data.

For instance, AI can increase efficiency in asset maintenance and management. Predictive maintenance enables identification of when and where an asset is likely to malfunction, and repairing of its parts before they break down. Information on the condition of assets is collected in real-time through IoT sensors, which are combined with historical life cycle data to diagnose the status of assets and detect anomalies. Compared to reactive maintenance, predictive maintenance presents substantial benefits by reducing downtime (or risks of), and subsequently reducing cost of production or business interruption in case of incident, while avoiding unnecessary routine maintenance.

Enhanced prediction capability allows for a greater market segmentation and price differentiation and gives SMEs a possibility to innovate and adapt business processes, as they can better predict individual customer behaviour and price sensitivity, and can anticipate shifts in demand (OECD, 2019[56]). Based on German firm-level data, Niebel et al. (2018[57]) found that the use of data analytics increases the likelihood of a firm becoming a product innovator and achieving market success through its innovation.

How can AI applications benefit SMEs?

AI can be applied to most industrial activities, from optimising multi-machine systems to enhancing industrial research (OECD, 2019[11]). McKinsey Global Institute (2018[58]) identified retail, transport and logistics, travel, automotive and assembly and consumer packaged goods as sectors that AI could contribute substantially in creating value. Evidence from recent surveys suggest that transportation, logistics, automotive and technology sectors already lead in terms of the share of early AI-adopting firms, while process industries (such as chemicals) lag behind (Boston Consulting Group, 2018[59]). The 2019 OECD report on Artificial Intelligence also presents several sectors where AI technologies are seeing rapid uptake: transport, finance, marketing and advertising, as well as science, healthcare, security or the public sector. In these sectors, the report highlights that AI systems can detect patterns in enormous volumes of data and model complex, interdependent systems to improve decision making and cost efficiency (OECD, 2019[11]).

Table 5.1 presents some examples of recent business applications of AI in sectors that are traditionally dominated by SMEs (OECD, 2019[56]).

Table 5.1. Examples of business applications of AI in SME-dominated sectors

Sectors	Business applications of AI	Changing business practices in SMEs	Potential benefits for SMEs in the sector
Agriculture	Agri robots and drones, equipped with sensors, cameras and combining satellite data, computer vision, image recognition and predictive analytics.	New methods for harvesting, and improved monitoring of crops, soils and weather conditions for precision farming.	Increased productivity and speed in harvesting as well as reduced losses from climate hazards.
Construction	3D Building Information Modelling (BIM), simulator-type of digital twins of the buildings, drones and sensors on construction sites, and data analytics based on the real-time data collected on-site.	New practices for optimising building modelling (e.g. the routing of plumbing and electrical wiring), enhanced information sharing, co-ordination among construction professionals, and sites monitoring (e.g. security, work progresses, flows of people and materials).	Efficiency gains due to reduced costs of materials, improved construction design, better co-ordination and preventive maintenance.
Retail trade (B2C)	Machine learning for matching buyers and sellers (e.g. online platforms), big data analytics (e.g. browsing and consumption patterns, behavioural insights) based on consumer data (see also marketing).	Mass customisation, greater diversification ("Segment of One"), big-data-optimised offerings, mix of offline-online models.	Increased sales (i.e. higher production and/or price) and economies of scope, due to product differentiation. Broader market outreach, including abroad.
Wholesale trade (B2B)	Machine learning on supply operations data, combined with use of sensors and radio-frequency identification (RFID).	Enhanced integration of operational systems, from manufacturing to end-to-end value chain. Greater use of customer data in product conception and early development.	Cost and time efficiency, due to improved supply operations, stock management, and greater capacity for just-in-time production/delivery.
Accommodation and food	From AI-powered chatbots (e.g. booking, ordering), to face recognition (check-in), to smart devices (heating), and automation (bartending, cooking, room service), machine learning based on customer, occupancy and guest feedback data.	24/7 automated service, greater personalisation of offers and services, occupancy and pricing optimisation (to reduce uncertainty regarding seasonality), streamlined maintenance process.	Cost efficiency (e.g. predictive maintenance, stocks management) and increased revenues, due to increased client loyalty and enhanced personal recommendations.
Transport and logistics	Use of autonomous vehicles and ride sharing by using greater prediction of traffic and trajectories via networks of sensors.	Changing business models for taxis, trucks and delivery services, with also implications for the automotive industry and the chains of part suppliers.	Fewer crashes, less congestions with potential savings on maintenance, insurance, fuel consumption and driver wages. Improved real-time fleet management.
Marketing and advertising services	Personalised advertising and pricing, and click prediction systems, through machine learning (e.g. natural language processing) using big data (social media posts, user reviews, emails, web navigation, etc.). Improved online shopping experience through augmented reality.	Changing products and services on e-commerce with more tailored marketing campaigns, enhanced targeting capacity, new online shopping markets. Implications for retail trade and "brick-and-mortar" shops that have to adapt to new demand and forms of competition.	Increased sales and revenues, improved return on investment of marketing campaigns and activities.
Professional, scientific, and technical services	Machine learning on big data, incl. economic, financial, business, market, legal or regulatory data (see also construction or marketing), to detect patterns. Use of automatic text generation.	Digitalisation of expertise, greater personalisation of professional services, new generations of "medtech", "lawtech", algorithmic trading in stock markets.	Increased cost and time efficiency in searching and processing data; increased analytical capacity (e.g. for risk assessment and management).
Healthcare services	Self-monitoring tools and trackers, real-time feedback, combined with data analytics using electronic health records. Use of high-resolution medical imaging, smart applications, and IoT devices for more personalised healthcare service and prescription of precision medicine.	Changing market conditions with more personalised offers and optimised clinical decision making. Changing health systems, since AI also affects drug discovery, clinical research, information dissemination, or healthcare systems management.	Reduced cost of care, delays in diagnosis or reaction, and risks of errors. Improved quality of services. Improved epistemology capacity at potentially lower costs.

Sources: Authors' elaboration based on (OECD, 2019[56]), (OECD, 2019[11]), (OECD, 2020[60]).

Another way to look at how AI can benefit SMEs is through the changes it can make along the internal value chain of firms. AI can affect multiple business functions, altering the cost structure, as well as the process of value creation within the firm. Marketing and sales, supply chain management and production are seen as the business functions where AI could potentially have the greatest impact (McKinsey, 2018[58]). A study of the top 75 companies by revenue in various manufacturing industries shows that predictive maintenance and quality control accounts for 29% and 27% of use cases implemented (Capgemini, 2020[61]). Some examples are provided in Table 5.2.

Table 5.2. Examples of AI applications in SME functions

SME functions	Business applications of AI
Direction, strategy, planning and management	Support in decision making, increased predictive capacity, business projections and scenarios, with greater ability to integrate and co-ordinate operations and functions.
General administration (including HR, accounting, finance and internal communication)	HR analytics to better attract workers and differentiating in terms of working conditions, wages, fringe benefits or responsibilities. Automation of administrative and routine tasks (e.g. accounting, reporting, payroll etc.), enhanced capacity to comply with tax obligations.
IT systems and networks	Increased capability of detecting data breaches and cyber-attacks, and repairing and analysing vulnerabilities. Increased digital security risk management capacity.
Pre-production functions (including R&D, design, exploration)	Data analytics on corporate, production and customer/user data to identify areas of productivity and quality improvement. Automation of scientific processes and identification of cheaper experiments, e.g. for the development of new products, devices or processes. Greater capacity for factoring costs, identifying the best design and prototyping, especially if combined with 3D printing.
Sourcing, procurement and supply chain	Data analytics on contract management and strategic sourcing. Optimisation of resource allocation through better anticipation of shortages and better management of purchases. Enhanced capacity of risk management, e.g. vis-à-vis supplier reliability, especially if combined with blockchain. Enhanced capacity in identifying invoicing errors, monitoring commodity and intermediary pricing, and anticipating market fluctuations. Greater ability for asset tracking and strategic routing in real-time, especially when combined with IoT.
Production and operations, including stock management and maintenance	Better planning capability through optimisation of operations, production/process/quality control and product availability. Lean management, increased capacity for just-in-time production, greater responsiveness to end-use market variations. Use of predictive maintenance to reduce risks of incidents and costs associated with production disruption. Enhanced overall safety and increased cost efficiency, e.g. regarding intermediary or energy consumption.
Logistics and content delivery	Automation of warehouses and vehicles. Seamless connection between factories, distribution platforms and end markets, especially when combined with IoT. Increased reliability and integrity of the supply chains. Smart roads reducing congestion and time (and cost) for transportation, and improving safety conditions (less casualties, damages and insurance cost). Automation of back office and administrative tasks for increased cost efficiency.
Marketing, sales, advertising, branding, customer services and external communication	Greater market segmentation, sales forecasting, price differentiation and targeted advertising. Automation of basic and repetitive customer services (eg. chatbots, videobots) and content curation and generation, e.g. for websites or reporting.

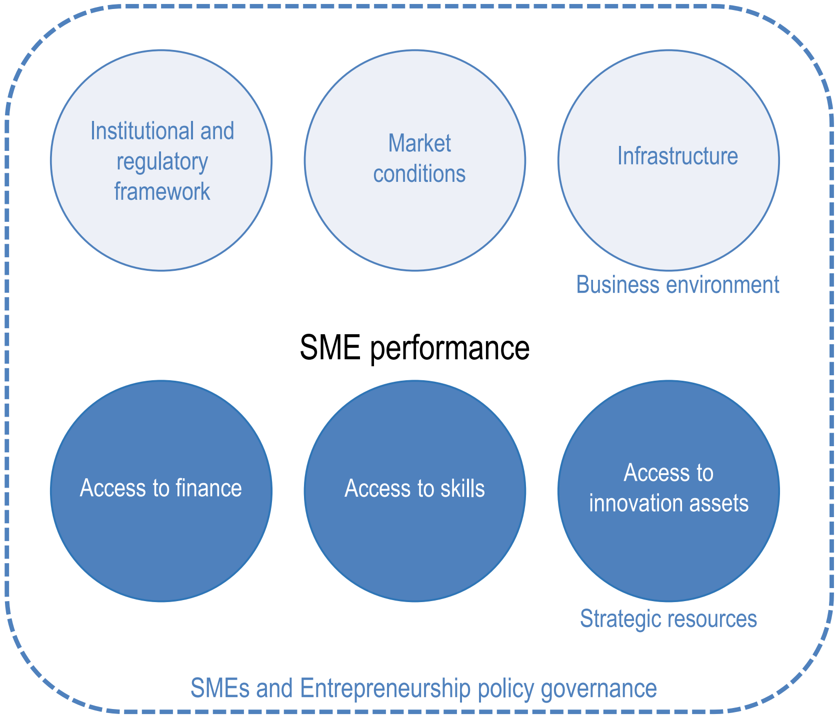
Source: Authors' elaboration.

How can AI affect SME business environment?

SMEs are typically more dependent on their business ecosystem than larger firms. SME business environment is made of institutions, infrastructure, firms, people and interrelated markets and market relationships. Smaller firms usually divert a larger proportion of their internal resources to administrative functions than large firms. They also trade smaller volumes to compensate for the fixed costs they incur.

SMEs are therefore more vulnerable to deficient framework conditions, administrative burden, market failures and economic shocks. Inefficient infrastructure hampers their access to markets and the strategic resources they need to operate. Although financial, human and knowledge-based capital are key production factors and determinants for their competitiveness, smaller firms are also typically at disadvantage in accessing funding, appropriate skills and innovation assets, either in their tangible or intangible forms. SMEs' performance also depends on good public policy practices and governance.

Figure 5.5. The 6+1 pillars of SME performance



Source: OECD (2019[56]), *OECD SME and Entrepreneurship Outlook 2019*, OECD Publishing, https://dx.doi.org/10.1787/34907e9c-en.

AI as a GPT can substantially affect SME business environment along multiple dimensions. To give a few examples:

- *AI and public administration*: The potential of AI for public administrations is manifold (OECD, 2019[11]). The average civil servant spends up to 30% of their time on documenting information and other basic administrative tasks (Viechnicki and Eggers, 2017 cited in (Berryhill et al., 2019[62]). Machine learning and automation can enhance the efficiency and quality of public administration and procedures, save time for civil servants in dealing with administrative tasks, and improve understanding of user needs (OECD, 2020[63]). Policy makers could also apply machine learning techniques to gather and analyse policy evidence at a granular level for better informed SME policies (OECD, 2020[64]).
- *AI and tax compliance*: The OECD (2014[65]) highlighted the importance of finding better ways of securing good tax compliance by SMEs. AI adoption can help tax authorities better prevent tax default, or increase transparency in tax process but also implement a “tax compliance by design” approach for SMEs, either through centralised data management (e.g. data analytics) or through reliance on a secured flow of relevant information from the taxpayer’s own systems (e.g. accounting software) (Berryhill et al., 2019[62]).
- *AI and courts*: Increased court efficiency could help SMEs reduce the internal resources they divert for solving commercial disputes. Use of language processing and AI-enhanced ability to mine documents to make connections and detect patterns could make case examination, law enforcement and dispute resolution more efficient, faster and cheaper. Effective civil justice system and contract enforcement are key to business confidence in the integrity of markets, the predictability of business relationships and investment returns, and business entry and growth (OECD, 2019[56]).

- *AI and market competition*: Market structure and conditions are critical for SMEs to do business and compete. Entry costs, factor endowment and sunk costs are important determinants of firm size and its capacity to scale up (OECD, 2019[56]). Algorithms are fundamentally affecting market conditions for competition (OECD, 2017[66]). By providing firms with powerful automated mechanisms to monitor prices, implement common policies, send market signals or optimise joint profits with deep learning techniques, algorithms could enable firms to achieve tacit collusion, create cartels and sustain profits above a fair competitive level, without necessarily any agreement.
- *AI and infrastructure*: AI systems are increasingly relevant for the digital security of information and communication technology (ICT) infrastructure, and transport and energy infrastructure. Machine learning can help address the rising number of cyber-attacks, the skills shortage in the digital security industry and the growing sophistication of threats (see Chapter 3 on cybersecurity). Conversely, AI can also make cyber-attacks even more damageable and difficult to defeat, placing physical and virtual infrastructure at risk.
- *AI and access to finance*: The bank and finance industry has long used statistical approaches for credit scoring. Neural network techniques enable the analysis of vast amount of credit report data, also lowering default risk and the cost of lending, and making it more profitable for credit institutions to serve some segments of the SME population that were left aside (e.g. small informal businesses or those operating in remote areas). In addition, AI can further facilitate SMEs' access to credit, especially to SMEs with no records and credit history, as alternative data sources (e.g. social media activities, online shopping information, shipping data, insurance claims, etc.) allow Fintech actors to better assess SMEs' creditworthiness (OECD, 2020[67]).
- *AI and labour markets*: AI is expected to change the world of work (OECD, 2019[53]). While discussions often touch upon the issue of job replacement by automation, the use of AI and "people analytics" in the workplace has far-reaching implications for occupational health and safety, privacy, evaluation of work performance and hiring and firing decisions (OECD, 2019[68]). Collusion on labour markets cannot be excluded either. However, AI creates enhanced possibilities in matching skills needs and supply, or in creating new solutions for training workers on the job through interactive augmented and virtual reality.
- *AI and access to knowledge and innovation assets*: As scientists may have reached a "peak reading", the automation of science can accelerate scientific discovery, reduce the costs of experimentation, ease (robot) training and improve data sharing and reproducibility (OECD, 2018[69]; OECD, 2019[11]), bringing frontier knowledge within the reach of a greater number.

Considering the wide range of issues at stake, the following part of this report focuses more specifically on the potential of AI in steering SME transformation and on the barriers to AI adoption.

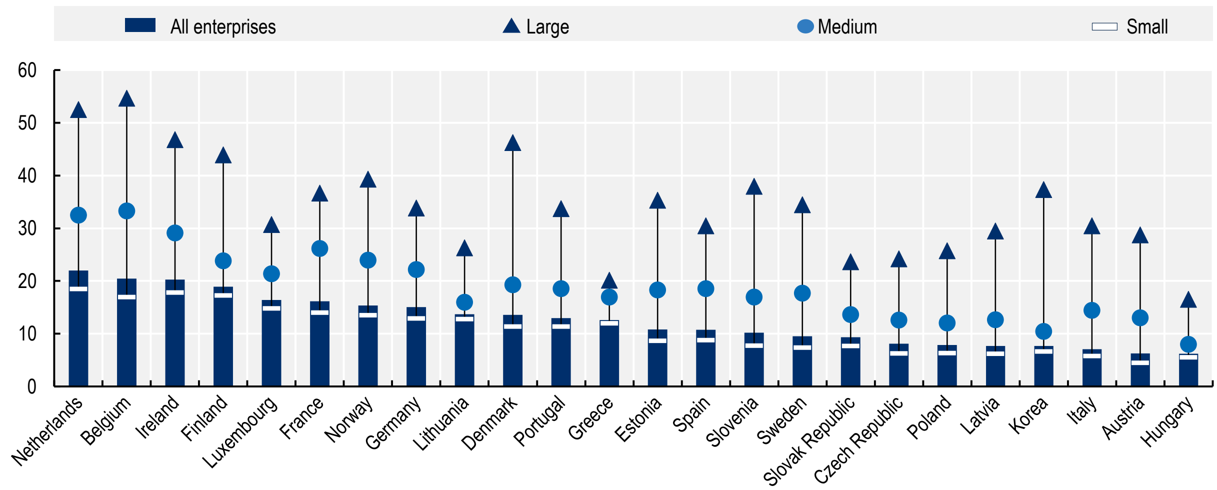
AI diffusion, barriers and modalities

AI diffusion and the SME gap

Evidence suggest different degrees of AI diffusion in the business sector across countries, sectors and firm sizes. This is not without consequence on the capacity of governments to reduce the inequalities that already exist across industries, firms and places, and that could further enlarge with the diffusion of AI. Brynjolfsson and McElheran (2016[70]) estimate that the timing of diffusion is actually essential, in the case of data analytics, as leading adopters are receiving the biggest gains, while laggards that reach the frontier later tend to have lower net benefits, or not at all.

Figure 5.6. Businesses having performed big data analysis

As a percentage of enterprises in each business size class, 2018



Note: Business size classes are defined based on employment. Small enterprises (10-49 persons employed), medium-sized enterprises (50-249) and large enterprises (250 or more).
Source: OECD (2020[71]), OECD Database on ICT Access and Usage by Businesses, http://stats.oecd.org/Index.aspx?DataSetCode=ICT_BUS (accessed on 19 September 2020).

StatLink https://doi.org/10.1787/888934227849

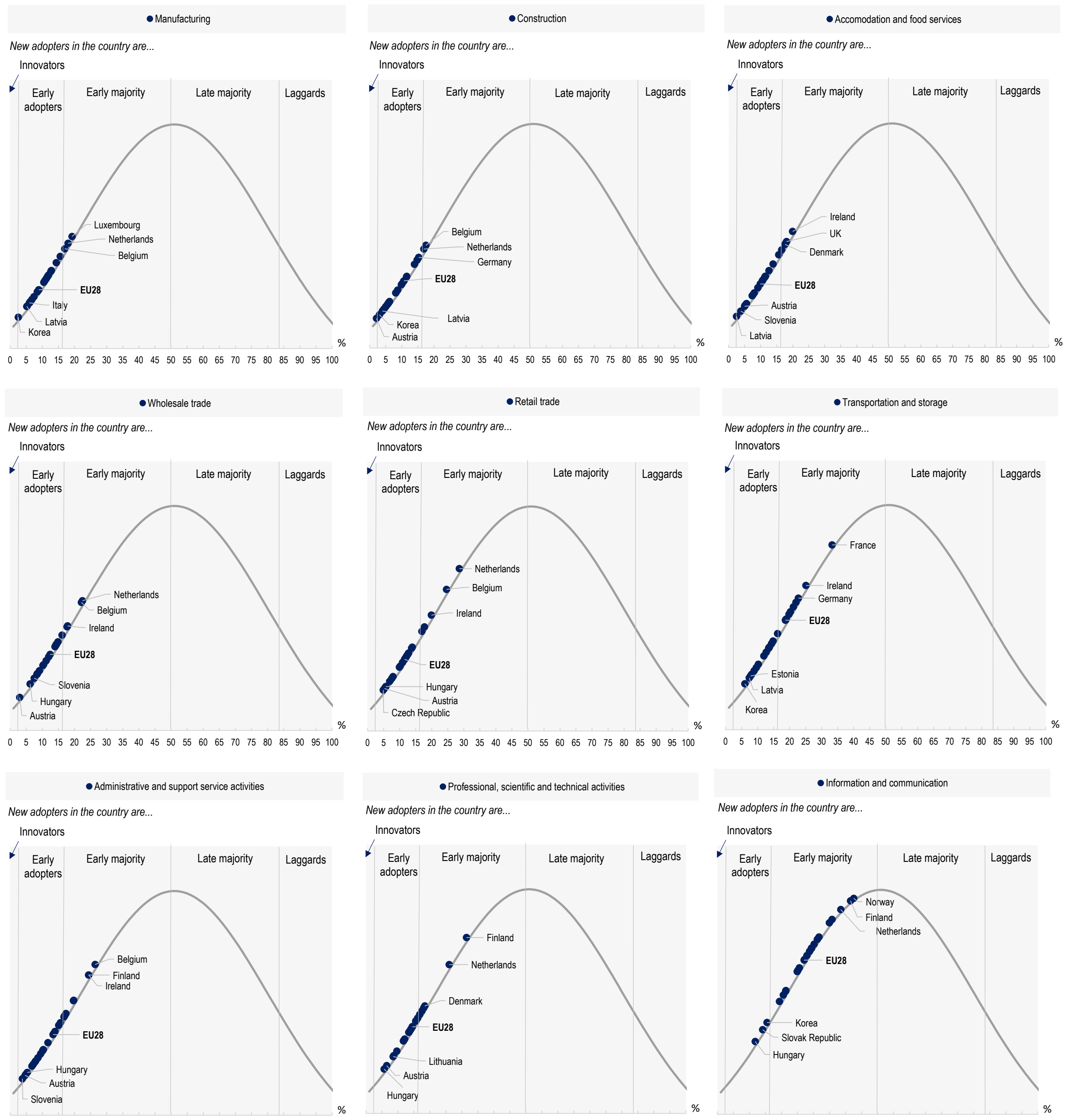
Overall, business population in most countries show low level of adoption of data analytics but some countries have taken the lead. OECD statistics on business use of ICT[3] show that the Netherlands, Belgium and Ireland are AI champions, as per the relative share of domestic firms performing big data analysis (Figure 5.6). In these countries, more than 20% of enterprises (enterprises employing 10 employees or more) have performed big data analysis in 2018. Hungary, Austria and Italy close the ranking, where enterprises are three times less likely to be engaged in such activities (6-7% only). Eastern European countries tend to lag behind, with few enterprises engaging in these new practices, while innovation leaders (such as Finland and Luxembourg) and big players such as France, the United Kingdom or Germany are more advanced in the transformation process.

New AI practices are diffusing across all sectors, with services adapting faster than manufacturing or construction (Figure 5.7). Especially in the knowledge- and technology-intensive information and communication services, there is already an early majority of enterprises across most countries (i.e. between 16% and 50% of total business population) that have moved to these new practices. However, AI is also deployed in less knowledge-intensive and SME-dominated sectors, such as retail trade, and transportation and storage services. As a matter of fact, leading countries in the AI transformation process tend to head the ranking in all sectors, while lagging countries tend to lag in all of them. This recalls the pervasive and generic nature of AI.

As compared to large firms, SMEs lag in adopting data analytics. The same OECD statistics on businesses performing big data analysis illustrate a gap across firm sizes (Figure 5.6). On average, businesses that perform big data analytics account respectively for 34.1%, 18.8%, and 10.6% of large, medium-sized and small enterprises across OECD countries in 2018. The spread between large and small firms is especially large in Belgium, Denmark, the Netherlands and Slovenia, where large firms are more often engaged in data analytics than elsewhere, and new large adopters tend to be rather a late majority (see Chapter 2 on digital access and uptake).

Figure 5.7. Diffusion of data analytics in manufacturing and SME-dominated sectors: A stylised approach

Diffusion rate, as a percentage of enterprises with 10 or more employees in the sector, 2019 or latest year available



Note: The diffusion rates of each country are plotted along a stylised diffusion curve that features higher potential benefits in adoption by earlier adopters. The thresholds between different categories of adopters are drawn from (Rogers, 1962[72]). Innovators are technology adopters that account for 2.5% of total business population. Early adopters account for an additional 13.5% of the total population, the early majority for additional 34%, the late majority for additional 34% and the latest 16% of adopters are laggards. See Chapter 2 on digital access and uptake for more information.

Source: Data are drawn from the OECD database on business ICT use (OECD, 2020[71]).

StatLink https://doi.org/10.1787/888934227868

National studies and statistics also stress an SME gap in implementing AI solutions. In Korea, around 50% of small enterprises surveyed in 2018 responded that they were not aware of work-related AI application or services, which was higher than for large businesses (29%) (MSIT and NIA, 2020[73]). According to Denmark's ICT Use in Enterprises Survey, 24% of large enterprises used machine learning or Artificial Intelligence in 2019, compared to 5% of small enterprises (Statistics Denmark, 2019[74]). In the case of Canada, large companies are 7.5 times more likely to use automated systems for inspection (e.g. vision- or sensor-based) than SMEs (Galindo-Rueda, Verger and Ouellet, 2020[75]). However, these statistics do not allow for an international comparison because the definition of AI and its applications used by national statistical institutions differ across countries.

Barriers and challenges for SMEs

SMEs face barriers in adopting AI, some of which are common to other digital technologies, such as lack of awareness and readiness, and some that largely stem from the very characteristics of machine learning techniques.

High costs and uncertainty about AI benefits

Building and maintaining an AI system remain a costly investment. Training AI systems requires large amount of data, as well as human intervention to process the data and make them machine-readable. For example, labelling an hour of video typically takes eight hours (Murgia, 2019[76]). Despite the availability of open-source AI tools and declining training costs of AI algorithms (Coleman et al., 2020[77]), SMEs may lack cash flow and finance to bear these capital expenses, especially since calculating the cost of developing AI system and its benefits are often challenging (Accenture, 2019[78]). Furthermore, uncertainty and the lack of clear evidence and business plans can raise the cost of accessing credit (OECD, 2019[56]).

An effective implementation of AI solutions requires developing and adopting complementary technologies, whereas SMEs lag behind large firms in all technological areas (see Chapter 2 on digital access and uptake). Investments in 5G and high-speed internet infrastructure are needed to increase digital connectivity and to facilitate data transfer. Further diffusion of cloud computing services could help increase data storage and computing power capacity, making AI applications more accessible and affordable. Technologies closely related to generating and maintaining reliable data, e.g. IoT and blockchain, or technologies enabling AI systems to interact with the real-world environment, such as 3D printing, augmented reality and robotics, are few examples of complementary technologies that can support AI deployment and enhance its transformative potential.

A broader AI diffusion requires investments in adapting the technology to business processes and skills structure. Reconfiguring business practices means going beyond a simple replacement of current systems with AI solutions in order to optimise the usage of AI systems. Adapting to AI-enhanced working environment also calls for a retraining of the workforce, in order to provide workers with the skills for training AI algorithms and interpreting predictions. In some sectors or business functions, the skills gap could be substantial. In addition, reconfiguring business activities for accommodating AI solutions include organisational changes and reskilling to integrate complementary technologies.

However, the AI transformation may not deliver immediate benefits and productivity gains, which raises sunk costs for SMEs before a growth potential could be achieved. As observed with the adoption of electric motors in production (Box 5.4), it is expected that it would take time to build a sufficient stock of AI subfields before seeing effect (Brynjolfsson, Rock and Syverson, 2017[38]). Gartner (2019[79]), a consultancy with a specialty in technology, anticipates that most advanced AI technologies will require at least 2 years to become mainstream. In addition, how AI will be effectively applied in businesses will vary and depend on the purpose of adoption and the combination of technologies (Table 5.1). In fact, apart from innovative start-ups, firms in general, with SMEs in particular, may be reluctant to uptake innovations that could result in losses on a short run due to their limited revenues and cash flow (Holmes, Levine and Schmitz, 2012[80]).

Reputational and legal risks

The lack of explainability of AI systems that use machine learning has been one of the obstacles to further adoption, and could raise a series of challenges for users and producers of AI solutions (Michael Chui, 2018[81]). While this is also true for large tech firms (Vincent, 2018[82]), SMEs are particularly more at disadvantage, even those that are using AI without knowing it. For instance, when an issue occurs with an AI solution provided by a third party, it is highly likely that SMEs may not be able to react in a timely manner, and may not have the authority or capacity to audit the algorithm. SMEs using AI-enhanced tools to interact with customers could face reputation issues and legal liability especially if the AI model used is perceived as unethical (Capgemini Research Institute, 2019[83]), and shows discriminative behaviour, such as in product pricing and recruitment.

The human factor

Unclear understanding of potential and risks of using AI, from managers to workers

There is a need to raise awareness among SME owners, managers and entrepreneurs about what AI could bring to their business, and to demystify the technology. Managers need to see AI as an option in pursuing their digital journey. As an example, entrepreneurs could have misconceptions of AI, possibly confounding current developments in AI with AGI (Roffel and Evans, 2018[84]). It is therefore important for them to access information about AI solutions, their capabilities, as well as their constraints, with concrete business use cases. Understanding how different subfields of AI could apply to different industries, different business functions and different business models is critical for further diffusion (McKinsey, 2018[58]). Likewise, greater clarity on the Return on Investment (RoI) that AI adoption could generate is needed (Mannar, 2019[85]).

Awareness raising among the workforce, including better information about the complementary role AI play with workers in new AI-enhanced systems, is key for effective implementation. Concerns regarding AI, the risk of losing human knowledge and expertise at the expense of AI systems, and the threat of job replacement by machines are key obstacles to the transformation of workplaces and processes. These concerns should be addressed upstream in the transition. A clear communication on the complementary aspect of AI systems with the workforce should be made, while leveraging insiders' opinion and knowledge on how best to manage the transition (Tabrizi et al., 2019[86]).

Raising the skillset for an effective implementation of AI solutions

The implementation of AI in the business process may require different skillsets from managers and workers.

Decision makers and managers have to be trained in order to rethink their business processes and to reconfigure tasks and organisational structures accordingly. Managers need to nurture understanding of what AI systems can or cannot do, as well as what decisions can be automated by AI. They need to learn how to create sound models and manage algorithms, by setting clear objectives and stating soft goals in training and using AI (Luca, Kleinberg and Mullainathan, 2016[87]).

More workers will be called to exercise their judgement to guide algorithms. AI enables reducing the cost of prediction while increasing its frequency (Agrawal, Gans and Goldfarb, 2019[88]), making it possible to apply data-driven prediction methods more extensively. An increase in the number of predictions produced requires in turn more decisions to be taken, which necessitates some human interpretation and intervention. Early researches on workforce's use of AI emphasise the importance of enabling employees to learn from their own work (OECD, 2019[53]; Beane, 2019[89]). It further suggests that workers using AI should be provided with incentives to experiment new ways of working with the technology and adjust their work process, as well as opportunities to recover from mistakes, given that there is no playbook in using AI.

In this new landscape, the value of human judgement is likely to increase with the availability of predictions (McKinsey & Company, 2018[90]). Human intervention in decision making remains important because all options cannot be fully codified in advance (Agrawal, Gans and Goldfarb, 2019[88]), the AI systems can find patterns and correlation in existing data but cannot explain causality, and their forecasting ability remains limited when circumstances change drastically, as observed during the COVID-19 pandemic (Heaven, 2020[91]). Furthermore, human judgement is needed to reassess the predictions in different settings (Luca, Kleinberg and Mullainathan, 2016[87]).

Lack of data culture and weak data management practices

SMEs are less well prepared to valorise their data. Although SMEs produce and handle a great volume and variety of data, from the back office to the front office, small businesses often lack the ability to collate, manage and protect them. In addition to the data that are not captured, data collected and stored may not be of adequate quantity or quality to derive meaningful insight (Bianchini and Michalkova, 2019[92]). Inconsistencies in data format and collection method, data duplication, or incorrect manual input are some of the examples undermining data integrity (see also Chapter 3 on cybersecurity).

SMEs need to raise data readiness with appropriate data management practices. As a start, SMEs can aim to break data siloes between different business functions within the enterprise in order to form a consolidated data pool. Small businesses can begin building structured and time-series datasets based on their data, such as consumer, user, production, or administrative data, which could be used to derive value with use of AI (McKinsey, 2018[58]). Enhancing SME data readiness today could allow them to anticipate and prepare before deploying machine learning techniques in their workstreams when such techniques become affordable.

The enhanced volume and granularity of data collected and managed can expose SMEs to more data breaches. Data privacy issues concern personal, credentials, or financial data of SMEs' customers and workers, as well as internal data to the firm, and in some sectors medical records as well. Although the providers of AI solutions offer in general applications that are compliant with privacy regulations such as the EU's General Data Protection Regulation (GDPR), SMEs could be deemed liable for the consequences of data breaches if the process of data collection does not meet legal requirements.

AI solution markets for SMEs

SMEs can source external knowledge and technology solutions from knowledge markets (Hayek, 1945[93]). Knowledge-intensive business services (KIBS), including software, information and technology (IT) services, are key enablers of knowledge diffusion (Den Hertog, 2000[94]; Muller and Zenker, 2001[95]) and their use is conducive to more business innovation, including radical innovation (Burger-Helmchen, 2012[96]; Cao, Shuo and Nagahiraagahira, 2010[97]; Doloreux and Shearmur, 2012[98]; OECD, 2017[66]).

Typically, KIBS compensate for a lack of internal capacities of a firm and complement the knowledge transfer capacities of universities and public research institutes. KIBS have been more and more in use in SMEs for overcoming size-related barriers in accessing strategic resources (OECD, 2019[56]), e.g. developing innovation-related skills (Zhou, Kautonen and Wei, 2015[99]), or outsourcing knowledge and R&D (García-Quevedo, Mas-Verdú and Montolio, 2013[100]). KIBS have therefore emerged as a dynamic industry, increasingly important for firms to adapt processes and commercialise new products and services. New technologies have been instrumental in this expansion, reducing substantially the cost of copying, storing and sharing data and information, and enabling new models of knowledge sourcing.

Digital platforms increasingly allow to centralise software, technology or databases (e.g. through cloud computing services), ideas and solutions (e.g. through crowdsourcing and collaborative platforms on specialised software solutions), and user and client data (e.g. through e-commerce platforms), giving the firm greater access to a larger portfolio of innovation assets at a reduced cost.

Software as a Service

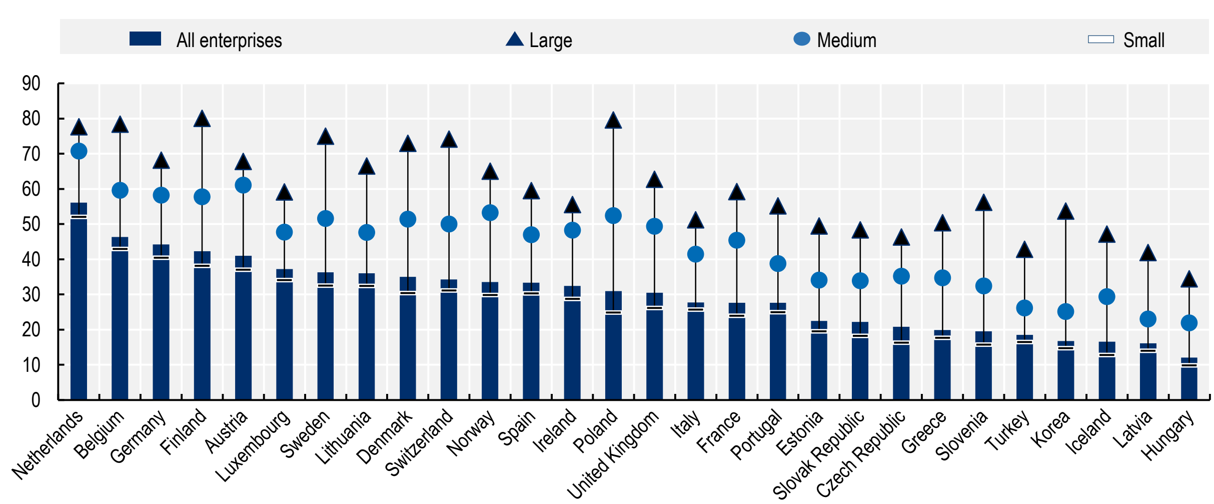
Instead of developing costly and complex AI systems, SMEs can rely on external AI application providers. Between the autonomous development of AI models and non-adoption at all, there is a range of degrees of intensity and maturity in the SME transformation.

Software as a Service (SaaS) is the typical model of cloud computing services, whereby an IT application running on a cloud computing infrastructure is provided to consumers, usually in the forms of subscription plans. SaaS offers a pre-coded data structure for SMEs to use. Examples of SaaS for enterprises include cloud enterprise resource planning (ERP), cloud consumer relationship management (CRM), cloud office suite, e.g. email systems offering auto-completion functions for writing or graphic software integrating machine learning framework to increase workflow efficiency. Beyond cloud ERP and CRM, there is also a variety of SaaS that use and provide access to pre-trained AI models, such as real-time conversation transcription, 3D prototype design, or online fraud detection.

SMEs could access AI-embedded features by upgrading their software or by switching to higher price offerings. Usually provided by large IT companies such as Salesforce, SAP and Microsoft (IDC, 2019[101]; Gartner, 2019[102]), business SaaS are increasingly incorporating AI techniques, making the technology accessible to many (OECD, 2019[53]). Figure 5.8 presents the share of businesses adopting cloud-based CRM software. On average, 13.5% and 8.6% of the medium-sized and small enterprises are purchasing SaaS respectively. The gap in adoption between large and small companies is smaller than for data analytics (Figure 5.6).

Figure 5.8. Businesses purchasing cloud CRM software

As a percentage of enterprises in each employment size class, 2019 or latest year available



Note: Small enterprises (10-49 persons employed), Medium enterprises (50-249 persons employed) and Large enterprises (250 persons employed or more).
Source: OECD (2020[71]), OECD Database on ICT Access and Usage by Businesses, http://stats.oecd.org/Index.aspx?DataSetCode=ICT_BUS (accessed on 19 September 2020).

StatLink https://doi.org/10.1787/888934227887

Compared to conventional software, SaaS offers a number of advantages to SMEs. First, SMEs can receive constant upgrades and maintenance support without the need to internalise these functions and related costs. The use of SaaS solutions does not require any technical knowledge on AI from end users, which could help SMEs overcome the limitations of their skills in the first instance. Actually, users may not even be aware of using AI, as they receive results from the data that the AI algorithm processed. For example, the customer sentiment analysis that is embedded in CRM software uses natural language processing techniques, to determine the tonality of customers, which is then labelled as positive, neutral and negative. Finally, SMEs could also benefit from secured data storage, as SaaS are generally based on cloud computing infrastructure, such as Amazon Web Services and Microsoft Azure that integrate data security measures.

However, the use of AI-integrated SaaS could present some challenges for SMEs with regard to data ownership and portability. Businesses using SaaS are mainly responsible for managing their identity and access, as well as protecting the data they have stored off-line (McAfee, 2020[103]; AWS, 2020[104]). In the case of SaaS, issues can arise about data ownership and data control, as user data are often hosted remotely for the purpose of training AI systems (Steenstrup and Foust, 2018[105]). There is also an issue of data portability, when data generated from one SaaS provider are not transferable and reusable by another provider of similar software.

In that vein, SaaS solutions could expose SMEs to lock-in effects, and make it difficult for them to reconsider their subscription plans and switch to other (eventually more competitive or appropriate) solutions and providers (Seethamraju, 2014[106]). As the performance of machine learning algorithms improve with the volume of data processed, the lack of data portability could increase switching cost further. Dependency on SaaS is also exposing SMEs to external risks, as their business activities rely on the continuity of the software provision and they may not be able to access their data and software anymore if their SaaS providers discontinue their services.

Machine Learning as a Service

SMEs have the possibilities to train AI models themselves, purchase algorithms or rent the infrastructure needed to use AI systems. Commonly referred to as Machine Learning as a Service (MLaaS), these platforms provide automated or semi-automated machine learning services using various data sources, and allowing for greater customisation than SaaS can offer. MLaaS providers generally adopt a “pay-as-you-go” model, whereby users are charged according to their usage. To illustrate, a MLaaS for natural language processing charges USD 1.5 per 1 000 pages of document uploaded, USD 3 per hour for algorithm training and USD 0.05 per hour for deployment, along with USD 25 per prediction of 1 000 pages. MLaaS offers similar advantages as SaaS, in terms of flexibility and the scalability of subscription plans with SMEs’ needs. It requires, however, a higher level of expert skills and digital maturity.

The use of SaaS and MLaaS, since they are cloud based, require access to the Internet in order to transfer data and run software applications. There is a minimum speed and quality connection needed to support the exchange of large volumes of information, with low latency for ensuring real-time predictions. Although digital network infrastructure has gained in reach, speed and sophistication in recent years, smaller firms remain less likely connected (OECD, 2019[56]). The SMEs’ lag in connecting to high-speed broadband has even increased across all OECD countries in recent years. In 2018, 23% of European firms with 10 or more employees had high-speed connection, up from 7% in 2011, but smaller firms have lost ground in the transition, with twice less connections than large firms on average. In addition, special challenges affect the deployment of digital infrastructure that are often geographically distributed, and administratively and financially decentralised. In that respect, subnational governments at regional and municipal level play a vital role in the infrastructure landscape, and their infrastructural policies are likely to grow further in relevance.

Conclusion

Recent developments in machine learning, greater data availability for training AI models, and increased computing storage and processing capacity have created a new generation of AI statistical systems that constantly adjust, while processing input data, with little (or no) human supervision.

The new generation of AI systems can affect and benefit SMEs in two ways: by altering their business environment, or by enabling them to change their business practices, and increase productivity and outreach. The main business applications of AI relate to automation, image/face recognition, natural language processing, data analytics and decision making, the latter including enhanced information management and predictive capacity.

By identifying patterns in datasets and learning from tacit knowledge, new AI systems make automating non-routine tasks possible and free workers from repetitive lower value-added tasks, provided their jobs could be re-organised and their skillset upgraded. These new waves of automation could help SMEs increase productivity, e.g. by refocusing activities on higher value-added functions, by reducing human and economic costs associated with accidents or injuries, or improving work environment. The implementation of such systems could also help small businesses overcome administrative bottlenecks and increase reactivity at lower costs, for instance by enabling customer interaction 24/7.

AI allows a significant drop in prediction price and facilitates decision making. SMEs can execute predictive analytics to map uncertainties and lower their exposure to risks, automate business projections such as sales and budget forecasts, or increase efficiency in asset maintenance and management. Enhanced prediction capability allows for greater market segmentation and price differentiation and give SMEs a possibility to innovate, as they can predict customer behaviour and price sensitivity better, and can anticipate shifts in demand.

AI can be applied to most sectors, with a few number of sectors likely to see greater gains. AI can also bring changes to the internal value chain of the firm and be applied to multiple business functions. Marketing and sales, supply chain management and production are seen as the business functions where AI could have the greatest impact.

Moreover, AI can substantially affect SME business environment, and in various ways. Machine learning can enhance the efficiency of public administration, reducing red tape. AI adoption can help tax authorities implement a “tax compliance by design” approach for SMEs. Language processing and AI ability to mine documents could make case examination more efficient and cheaper, reducing the amount of internal resources SMEs divert for solving commercial disputes. AI systems are also increasingly relevant for securing the ICT infrastructure, and addressing the rising number of cyber-attacks and the skills shortage in the digital security industry. Neural network techniques enable the analysis of credit report data, lowering default risk and the cost of lending, and making it more profitable for credit institutions to serve some segments of the SME population. The use of AI and “people analytics” in the workplace can support the evaluation of work performance and hiring and firing decisions. The automation of science can reduce the costs of experimentation and improve data sharing and reproducibility, putting scientific research at the reach of more (and likely smaller) firms. At the same time, algorithms increase the risk of tacit collusion on product and labour markets, and of sustaining profits and prices above a fair competitive level, at the detriment of smaller businesses.

Evidence suggest different degrees of AI diffusion across countries, sectors and firms. Overall, business population in most countries show low level of adoption of data analytics but some countries have taken the lead. Among OECD countries, the Netherlands, Belgium or Ireland are AI champions in performing big data analysis (20-22% of firms). Austria, Italy and Eastern European countries tend to lag behind.

New AI practices are diffusing across all sectors, with services adapting faster than manufacturing or construction. Especially in information and communication services, there is already an early majority of enterprises across most countries (up to 50% of total business population) that moved to data analytics.

There are also converging evidence of an SME gap in using data analytics or implementing AI solutions. SMEs face a series of barriers in adopting AI. They incur high sunk costs for training and maintaining AI systems. This combines with the need for investing in new business processes, skillset and complementary technologies in order to implement AI, whereas the transformation may not deliver immediate benefits, future productivity gains are difficult to anticipate, and the return on investment is difficult to assess, and therefore the investments to finance.

There is a need to raise awareness among SME owners, managers and entrepreneurs about the opportunities and challenges AI could bring to their business, and how different subfields of AI could apply to different industries, business functions and business models. There is also a need to raise awareness among SME workers on the real impact of AI on job replacement, and the complementarity of AI systems with the workforce.

Training is required. The implementation of AI in business processes may imply different skillsets from managers and workers. Decision makers have to train in order to rethink their processes and to reconfigure tasks and organisational structures. More workers would need to exercise their judgement to guide and interpret algorithms, and experiment new ways of working with the technology. In this new landscape, the value of human judgement is likely to increase with the availability of predictions.

SMEs are less well prepared to valorise their data. Although they produce and handle a great volume and variety of data, small businesses often lack ability to collate, manage and protect them, and those collected may not be of adequate quality or inadequate quantity to derive pertinent analysis. In addition, the increased volume and granularity of data can expose SMEs to more data breaches. Data privacy issues concern personal, credentials, or financial data of SME customers and workers, as well as internal and external data to the firm, for which SMEs could be deemed liable.

The lack of explainability of statistical algorithms also raises a series of challenges for SMEs using AI solutions, if they are not able to react in a timely manner, cannot audit the algorithm, or incur reputational risks, etc.

SMEs can source external AI expertise and technology solutions from knowledge markets that typically compensate for a lack of internal capacity. Instead of developing costly and complex AI systems, SMEs can rely on external providers of SaaS and MLaaS. SaaS offers access to pre-coded data structure and pre-trained AI models for SMEs to use, such as cloud ERP, or cloud CRM. MLaaS platforms provide automated or semi-automated machine learning services using various data sources, and allowing for greater customisation than SaaS.

Compared to conventional software, SaaS offers a number of advantages to SMEs, e.g. scalability of AI solutions and costs, no prior technical knowledge required, digital security features directly embedded in the software, etc., but they also raise some challenges related to data ownership and portability, and lock-ins effects. MLaaS offers similar advantages as SaaS, in terms of flexibility and the scalability of subscription plans, but it requires a higher level of expert skills and digital maturity.

Last but not least, the use of SaaS and MLaaS, since they are cloud-based, require access to the Internet in order to transfer data and run software applications. There is a minimum speed and quality connection needed to support the exchange of large volumes of information, with low latency for ensuring real-time predictions. Although digital network infrastructure has gained in reach, speed and sophistication in recent years, smaller firms remain less likely and less well connected.

This range of issues calls for enhanced policy attention to be given to:

- Supporting SMEs in building a culture of data, from collection, to management, to protection and analysis, and ensuring the AI transition takes place with improved digital risk management practices in SMEs.
- Raising awareness among SME managers and workers on the benefits of AI, the conditions of a transition and how the risks could be best managed.
- Reskilling SME managers and workers and ensuring a participatory approach for redesigning work processes and training AI models.
- Collecting and building more evidence on the return on investment of moving to AI business models and practices, in order to inform SME managers and business owners, as well as investors and financial institutions.
- Identifying mechanisms to bridge the financing gap until AI can deliver its full promises.
- Enabling SMEs leapfrog to AI-enhanced models through cloud solutions by ensuring the well functioning of knowledge markets that provide cloud solutions embedding AI technologies, and the transfer of knowledge that could enable SMEs scale up their capacity before being eventually able to develop their own AI solutions.
- Building differentiated evidence about the industry-wide or function-wide specificities of the AI transition(s), to account for the low transferability of AI knowledge across environments, including analysing the sectoral impact of AI on SME business activities, with concrete business use cases, and informing relevant stakeholders.
- Better understanding the role large firms, business associations, chambers of commerce, academia, national and local governments, international organisations, and SMEs as well, could play to advance on these different dimensions, and supporting knowledge sharing and mutual learning, through international platforms such as the OECD Digital for SMEs Initiative and the OECD.AI Policy Observatory.

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Notes

[1] However, there is no universally accepted threshold as to when data can be considered "big". It is suggested that such data sets, whether structured or unstructured, require the capacity beyond conventional tools and methods to process and analyse (Kitchin and McArdle, 2016[107]; Gobble, 2013[108]).

[2] For example, attributes of a person could include name, age and nationality.

[3] Other studies provide higher diffusion rates but also adopt a broader definition of what AI adoption could embed and cover rather large corporations. For example, MIT Sloan School of Management, in collaboration with BCG, suggests categorising businesses as pioneers, investigators, experimenters and passives based on the degree of AI maturity in businesses, with 20% of the businesses surveyed as "pioneers" that both understand and have implemented AI (Ransbotham et al., 2019[109]). Another similar survey conducted by McKinsey & Company (2019[110]) presents comparable results where firms representing 20% of the workforce have operationalised AI-related technology in their core business, and 9% having adopted machine learning approach.

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