

Artificial Intelligence and the Future of Work

Intelligence Artificielle et Avenir du Travail

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Electronic version

URL: <https://journals.openedition.org/rei/8727>

DOI: 10.4000/rei.8727

ISSN: 1773-0198

Publisher

De Boeck Supérieur

Printed version

Date of publication: September 1, 2020

Number of pages: 57-88

ISBN: 978-2-8073-9397-4

ISSN: 0154-3229

Electronic reference


Salima Benhamou, "Artificial Intelligence and the Future of Work", *Revue d'économie industrielle* [Online], 169 | 1er trimestre 2020, Online since 05 January 2023, connection on 27 June 2024. URL: <http://journals.openedition.org/rei/8727> ; DOI: <https://doi.org/10.4000/rei.8727>




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ARTIFICIAL INTELLIGENCE AND THE FUTURE OF WORK

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 **Keywords:** Artificial Intelligence, future of work, learning organisations, healthcare sector, transport sector, banking sector

 **Mots-clés :** Intelligence artificielle, avenir du travail, organisation du travail apprenante, compétences, conditions de travail, secteur de la santé, secteur des transports, secteur bancaire

1. INTRODUCTION

Artificial intelligence—meaning the group of technologies that carry out computationally tasks traditionally assigned to human beings—is central to current debates around the world on social and technological changes. About ten years ago, Artificial Intelligence (AI) technologies started to achieve remarkable progress in a surprising variety of applications. This is due to three interconnected technological advances: increases in processing power that allowed for larger models to be trained with machine learning algorithms; the availability of large amounts of annotated data for purposes of training these large models; and progress in machine learning theory resulting in improvements in learning algorithms.¹ In the near future, technological progress may well enable AI to carry out increasingly complex tasks, coming ever closer to rivalling human cognitive capacities.

¹ For a discussion of the factors driving recent advances in AI, see Chollet, 2018, pp. 20-23.

The machine's victory in the game of Go, the first autonomous vehicles, and the successful use of computer-aided medical diagnosis software are all emblematic of the advances made thus far. There are an impressive number of areas where AI can be applied, including healthcare, transport, banking and insurance, retail, science. This broad scope of application has led to the view that AI is a "general-purpose technology" that potentially will disrupt all aspects of life, economy and society (Brynjolfsson, E. and McAfee, A., 2014).

Some observers see AI as an economic opportunity due to the productivity gains it may generate (lower costs as a result of automation of operations, improvement of coordination processes, production flow optimisation, etc.) and the new markets it may create. AI is also perceived as a social opportunity thanks to the processing of big data generated by connected systems which may well give rise to new professions (data scientists, AI programmers, etc.) and improve working conditions by taking over repetitive routine tasks. Others, however, see AI as a threat to employment and as a technology that will aggravate inequalities and social polarisation, with the almost certain disappearance of whole realms of activity in many sectors, and various professions, some requiring few qualifications but others that are highly skilled (lawyers, auditors, physicians, etc.).

But how real is the risk for substitution of human tasks with AI? A number of researchers have put forward the hypothesis of massive automation of existing jobs by new digital technologies including artificial intelligence. The famous study by Frey and Osborne (2013), from the University of Oxford, predicted that 47% of total employment in the United States was at a high risk (70% chance or higher) of vanishing over the next two decades. Other studies adopting the same methodology predicted similarly alarming impacts in other industrialized nations (Bowles, 2014). The studies adopting the methodology of Frey and Osborne (2013) are carried out at the occupational level and assume that the same occupational category will be impacted in the same way regardless of the size of the firm and the country of location. However, Arntz *et al.*, (2016), in a study carried out at the task level and taking into account country-specific differences in the job content of the same occupations, estimated that only between 10% and 15% of occupations are at high risk of being automated.² Furthermore,

² See Le Ru (2016) for a critical assessment of the literature.

it is important to appreciate that such studies only focus on the technical potential for job elimination without taking account the fact that new jobs will be created by technical change.³

Given the uncertainty in recent studies concerning the impact of AI on jobs and employment, we turn to recent history in order to imagine what work will be like in tomorrow's world and the consequences of the adoption of artificial intelligence on employment. History shows us that technological advances have never led to abrupt changes leading to massive destruction of jobs. On the contrary, their effects have been progressive and have always resulted in the emergence of new forms of work. But are we not confronted with an altogether new phenomenon? Artificial intelligence may not only impact the volume of employment but also its content, as it is no longer a matter of automating tasks depending primarily on physical strength, agility and speed, as was the case in previous industrial revolutions, but rather one of automating cognitive tasks.

It is difficult to know what will be happening in fifteen or twenty years from now as regards technological advances and their dissemination and appropriation in the world of work. Technology and how much it is used are certainly factors of change, but they are far from being the only determinants of the transformation of work organisation and practices. Other factors also contribute to "shaping" work, including the legal environment, the economic context (competition in particular) and the social environment as regards the level of education, access to training, individual aspirations or demography. If we want to project ourselves into the future in order to identify the benefits and risks connected with AI, we must also incorporate these contextual factors which combined with future advances in AI may well transform work and employment.

The objective of this article is to clarify the debate on the impact of AI on work by starting from a consideration of what we know today about AI, both in terms of its limits and its potential. Defining artificial intelligence is the first step in providing the keys to understanding future transformations (Section 2). The uncertainties regarding its longer-term potential serve to "inflare" the ongoing debate, given that AI raises questions that

3 For the various limitations of the forward-looking literature seeking to predict the future impact of AI on employment, see Muro *et al.*, 2019, p. 20.

go far beyond the world of work including fundamental questions connected with ethics and social acceptability, personal data protection, AI designers' and users' responsibility and transparency of human/machine interactions. This article does not seek to supply exact answers on what work will be like in tomorrow's world. Its main goal is to examine how AI is being used today and, on that basis, to identify plausible possibilities for its future use in particular fields of application and selected sectors of activity. The sectoral approach is useful for identifying potential opportunities and risks in detail, including task evolution, learning dynamics, increases in technical and social skills, changes in working conditions, managerial practices and gains in or loss of autonomy (Section 3). The article focuses on three sectors in which AI has already started to spread: health, retail banking and transport. They are also regarded as sectors with the potential for creating jobs and are therefore important focuses of public policies. Finally, once the risks and benefits of AI on work have been analyzed, the concluding section will consider what forms of work organisation are best adapted to promoting human-machine complementarity, while enabling organisations to reconcile a high level of innovation with a high level of quality of work and employment (section 4).

2. THE REALITY OF AI

2.1. The potential of AI

Artificial intelligence is a scientific discipline that is by no means new with its foundations dating back to the beginnings of computer science in the 1940s and 1950s, with numerous different methods whose purpose is to reproduce cognitive functions by computers. The term "artificial intelligence" itself was coined in 1956 by John McCarthy, one of the founding fathers of the field along with Allen Newell and Herbert Simon.

One branch of AI, known as machine learning or statistical learning, has made spectacular progress over the past few years due to the remarkable efficiency of multilayer deep neural networks in performing classification tasks, of images in particular, following a learning phase based on a large number of examples. Pattern recognition seemed to require human intelligence, given the almost infinite dimensions of the problem to be solved

(the number of parameters characterising an image). Advances in neural network design, however, show that this is not the case and this is what sparked off the recent AI revolution that is raising new questions about the transformations of work.

AI brings together a range of fields including logical reasoning, knowledge representation, and natural language perception and processing. Its main applications at present are connected with advances in machine-learning techniques, deep learning in particular, which usually requires the availability of big data. A first type of application consists of radically simplifying human/machine interaction. Voice recognition and synthesis and natural language processing (NLP), whether to engage in simple conversations between people and machines or for automatic translation, are just a few examples of this initial group of generic applications usable in a whole range of activity fields. A second type of application is recognition of specific patterns in big data, resulting from multiplication of sensors or organised collection. Examples include image and video analysis, facial recognition and detection of breakdown precursor signals. These two major use categories, both of which are closely connected with the degree to which the activities concerned are digitised, are already possible.⁴

Without going into the details of these technologies, suffice it to say that they reproduce existing classifications or achieve well-defined objectives such as winning a game. Even though the exact mechanisms that result in such efficiency are not yet fully understood from a theoretical point of view, the technology is nonetheless deterministic and controlled. It is the AI programmer that chooses the software architecture he or she wishes to use (type of neural network, number of layers, etc.), the learning method (initialisation algorithm and updating of weights for each neuron) and the training data to be used. We are therefore a long way off from an autonomous system operating independently of its designer.

Such systems can possess a real capacity for learning in the sense of the automatic exploration of a solution space much deal larger than the algorithm's designer would have been able to imagine. This is how AlphaGo software, which was initially trained to play Go on the basis of millions of recorded matches, was subsequently able improve its strategies by playing

4 For an overview of machine learning applications, see Alpaydin, 2016, Ch. 1.

against itself until it ultimately succeeded in winning against a human being. This example does not serve to demonstrate any intelligence or consciousness on the machine's part, but rather an ability to solve complicated problems characterised by a high configuration space.

2.2. The limits of AI

Although AI has made considerable progress in recent years, there are several limitations to this technology that prevent it from competing with humans on complex tasks or activities. These limitations are mainly related to the access and quality of big data and the inability to understand and explain complex mechanisms that are not based on deterministic laws.

First, with respect to its use of big data, AI requires colossal computing capacity to train algorithms for the exploitation of deep learning. For example, according to Jangqing Jia, director of engineering for Facebook's AI platform, "to train one typical ImageNet model takes about one exaflop of computing"⁵. Achieving human brain capability would require several orders of magnitude of increase in computational power that is out of reach today, which is a severe limitation of AI.

Secondly, training algorithms requires data properly annotated by humans, which may require considerable effort, particularly for training large neural networks. The work consists in putting the data in a form appropriate for training the algorithms by cleaning them, annotating them and converting them into a usable format for the users. For example, ImageNet, an image database, required nine years of work and its contributors manually annotated more than 14 million images⁶. The data must also be sufficiently representative of the problem to be solved.

Furthermore, the quality of AI systems also depends on the training base on which the algorithm was built. If the training data contain biases in terms of such factors as gender or location the algorithm will naturally

5 See: <https://www.techrepublic.com/article/four-ways-machine-learning-is-evolving-according-to-facebooks-ai-engineering-chief>.

6 See: <https://www.kdnuggets.com/2018/05/data-labeling-machine-learning.html>.

reproduce these biases in its recommendations. The biases may come from the very modelling of the system architecture and in particular from the categorization of the possible decisions and the nature of the performance criterion or the family of decision rules accessible by the algorithm. The data used to train the algorithms may also be non-representativeness of the population concerned or simply reflect the structural biases of society. These biases can then lead to inequities in the treatment of individuals and raise the question of the value to be given to the choices made by the algorithms. For example, a recent study has shown that a risk prediction algorithm used to define the amount of financial aid for health care gave a lower score to blacks than to whites (Obermeyer and al., 2019). After eliminating the discriminatory feature of the algorithms, the percentage of black patients considered to be sick rose from 17.7% to 46.5%. This bias was due to the fact that the algorithm predicts health care costs rather than illness. Inequality in access to care means that black patients spend on average less money on medical treatment than white patients. Thus, while health care costs can be an effective indicator of population health, significant racial biases can occur. This risk can also arise when AI is used to quickly screen and select job applicants based on their characteristics or career paths, as was the case with the system used by Amazon.⁷ Thus, ensuring the absence of bias in the data can require considerable human and financial effort, both in terms of data collection and the subsequent “on-the-ground” verification testing necessary for both learning and final performance verification.

Finally, AI is capable of performing not only simple tasks but also complicated tasks as long as these tasks are based on predetermined rules or standards that are highly standardized in a mass of codifiable data. It is therefore difficult for AI-based systems to deviate from standards or to think for themselves. The learning dynamic is based on a routine mechanism and limited to a very specific context. This limitation makes it difficult for AI to solve complex problems such as managing unpredictable human behaviours, understanding people in all their complexity, showing empathy, or performing several complex tasks at the same time. It is no coincidence that the most important successes of AI operate mainly on images that are very standardized in terms of digital content. In fact, it

7 See: <https://www.theguardian.com/technology/2018/oct/10/amazon-hiring-ai-gender-bias-recruiting-engine>.

would be more appropriate to talk about artificial learning than artificial intelligence. Finally, even if the current output of AI is based on the availability of a large number of events (often several thousand) and on significant computing power for learning, the results are not very generalizable to other situations. Advances are still a long way from portending the advent of so called “strong” AI, which would actually be comparable to human intelligence in its ability to understand context and make use of “common sense” in its ongoing capacity to learn. Such an achievement seems well out of reach at the present time, as the researcher Yann LeCun⁸ has emphasised, even if the generic character of the technologies developed so far is enough to give us a foretaste of future impacts on all sectors of the economy.

Most of the literature in economics, including the substantial body of research following the methodology of the seminal study by Frey and Osborne (2013), has focused on how AI will substitute for different tasks and in some cases for entire occupations. In what follows, we show based on empirical evidence at the level of organisations and sectors, that the effects are more complex and that the creation of new tasks and competences is as important as the elimination of old. This also varies across sectors. This article, therefore, aims to make explicit the missing “complementarity” dimension in the analysis of the impact of AI on work transformation.

To realistically illustrate the current and potential impacts of the diffusion of AI, this section focuses on the diffusion of existing AI technologies or the potential for their diffusion in the near future with a high degree of certainty. It leaves unaddressed the question of the possible impact of radical advances in technology, including the ability to achieve “strong AI”. In order to provide concrete examples of the possibilities being opened up by artificial intelligence and its impacts on work, the analysis of three sectors of activity—transport, banking and health—all of which provide useful examples of the trends underway. Together, the three sectors cover

8 “As long as the problem of unsupervised learning has not been solved, we will not have a truly intelligent machine. This is a fundamental scientific and mathematical question, not a question of technology. Solving this problem may take many years, even several decades. Truth to tell, we know nothing about it”, Yann LeCun, Computer Science and Digital Sciences Chair, 2016-2017, class at the Collège de France.

a range of realities in terms of types of production in both industry and services as well as types of actors coming from both the private and public sectors and from various institutional and regulatory contexts.

3. THE IMPACT OF AI ON WORK: A SECTORAL APPROACH

The three sectors analysed are generally considered to be ones that are highly exposed to AI. Transport has attracted attention due to the development of the autonomous vehicle, which has been much publicised since Google, followed by Waymo, Uber, Tesla, General Motors, Navya, and other corporations announced their intention or started to test vehicles. The already advanced degree of digitisation in the banking sector as well as the intangible nature of the “matter” it handles involving the exchange of information on transactions, has lent itself perfectly to exploitation by AI. The health sector is one that everybody is concerned with and there is great interest in the scope for AI to be used as a support in processing data connected to highly complex life science-based mechanisms. These three sectors are regularly referred to in France’s national AI strategy (Villani, 2018) and in the AI strategies of others advanced countries (OECD, 2019). In addition, in terms of entrepreneurship, they are often leaders in the ranking of sectors in terms of investment in start-ups (OECD, 2019).

The discussion focuses in on whether the use of AI in certain fields of activity could replace human work or, on the contrary, will prove to be complementary to human work. For each sector, the analysis identifies first the main areas of AI application and then focuses in on how AI substitutes and complements for skills of different occupations or professions. In relation to this it assesses how the transformation of work affects skills and working conditions. The analysis of these three sectors is based in part on the results of case studies and surveys conducted in the framework of hearings with AI experts and professionals (company directors, managers, engineers, doctors, start-ups etc.) for France Stratégie, and described in more detail in Benhamou *et al.* (2018).⁹

9 See: <https://www.strategie.gouv.fr/publications/intelligence-artificielle-travail>.

3.1. Work Transformations in the Health Sector

Health is often presented as one of the sectors where artificial intelligence could produce major transformations in the workplace. Medico-technical robotics is already important in biology, pharmacology and surgery. Some observers go so far as to envision a “medicine without a doctor” that could fundamentally transform medical practice and the organization of our health care system (Vallancien, 2015).

3.1.1. *Several fields of application are concerned by AI*

Nearly all fields of artificial intelligence that have been developed, including image and video recognition, natural language processing, automatic learning, and robotics find applications in health care. This is true for diagnosis and therapeutic recommendations, surgery with smart robots, personalized follow-up, the medical-social field, rehabilitation but also prevention and clinical research.

For example, in the field of medical diagnostics, there are many AI tools on the healthcare market and the scope of their applications is impressive. They can be found in medical specialties such as oncology, which covers all medical specialties, studies, diagnosis and treatment of cancer, cardiology, ophthalmology, radiology and the detection of neurological disorders (e.g. Alzheimer and Parkinson). Whatever the field, the principle is always the same. Algorithms fed and trained by massive data (medical image recognition, medical research results, etc.) are self-programmed to detect pathologies. The emblematic tool is the Watson computer software from the IBM industrial group, which was introduced to the healthcare market in 2005. Watson has been used in particular at the Memorial Sloan Kettering Cancer Centre, an American institute specializing in medical research and cancer treatment, to assist in diagnosis and therapeutic proposals. This type of software, presented as an “intelligent” medical decision support tool, synthesizes a mass of information from millions of medical reports, patient records, clinical tests and knowledge (updates) from medical research. Some software may soon be able to diagnose cancer as well as, or even better than, specialists. According to a recent study (Wang *et al.*, 2016), artificial intelligence has been able to automatically detect breast cancer with a 92% success rate, almost equivalent to that of

specialists (96%). When the doctor's analyses and the diagnostic methods from the automated software are combined, the success rate is 99.5%, with a greatly reduced risk of error.

Other medical specialties use image recognition to diagnose, for example, patients with eye diseases. This is the case of the robot developed by Google's DeepMind Health (AI) division, which by looking at thousands of photos of retinas, has been able to establish a more reliable diagnosis than that of a human ophthalmologist (Knight, 2016). Other Ultromics systems use AI to diagnose heart disease¹⁰ or neurological disorders such as Parkinson's disease.¹¹ In the field of surgery, new generations of surgical robots are emerging that are moving towards greater autonomy from the surgeon (Azad *et al.*, 2016).

Although there are numerous examples of AI applications in the health field, the promises remain unclear at this stage. There is no health system or health organization in the world that has been completely transformed and actual health applications are very limited. No large-scale deployment closely or remotely related to AI exists except for a few very isolated cases such as IBM's Watson, Google's Deepmind or smart robots. There is also little scientific evidence today on the effectiveness of AI in the different fields of application mentioned above. The most highly recognized international academic journals in the medical field have published few articles on the evaluation of AI.¹² There is also very little medico-economic evaluation of AI applications that measures their economic and social returns. The information we have today on the impact of AI on diagnosis is mostly limited to subfields of a very specific discipline, such as oncology.

¹⁰ See: <http://www.ultromics.com/technology/>.

¹¹ See: IBM Research (5 January 2017): <http://www.research.ibm.com/5-in-5/mental-health/>.

¹² See, notably, *Journal of the America Medical Association*, *Delanceit*, *New England Journal of Medicine* and *Annales of Internal Medicine*.

3.1.2. Medicine is characterized by a high level of complexity that AI only imperfectly integrates

The hypothesis of a total substitution between health professionals and the machine is at present more fiction than science. Medicine is characterized by a high level of complexity that AI can only imperfectly integrate. Indeed, the quality of a patient's care (disease detection, therapeutic proposal, patient follow-up, etc.) is a highly complex process which is directly linked to the existence of a strongly "mediated" relationship between the medical team and the patient. In this field, the existence of a standard patient model is generally not sufficient to develop and implement a management strategy that is totally adapted to the individual patient. It is also known that AI feeds on a large mass of data via algorithms that aim to establish correlations to explain phenomena as a basis for deriving clinical recommendations. The robustness of correlations between several phenomena depends in AI on the mass of data collected. The more important the data, the more robust the correlations are. It is therefore the big data that allows AI to function and compete with humans through its ability to process data from a mass of continuously updated information. However, correlation does not necessarily mean causality. The causal mechanisms that "explain" the occurrence of a disease and its evolution are often more complex than "mechanical" correlations. The causes may be multiple, some of which are difficult to codify, such as those related to the patient's socio-demographic environment or the feeling of symptoms, or even their total absence as has been the case with Covid-19. Moreover, there may be a very high variance between patients. The complexity of the health-care professional's work is to take into account all these specificities from detection to the therapeutic proposal to be delivered to patients. In the clinical field, correlations are not sufficient. Even evidence-based medicine, which should be based on the most up-to-date evaluation results in the medical field, can only provide knowledge and clinical recommendations based on an "average" modelled patient. However, the "real" patient who is diagnosed during a consultation with a doctor does not necessarily correspond to the "average" patient who has been modelled. This is also true for therapeutic proposals. The doctor (specialist or general practitioner) has to take into account the specific characteristics of the patient to define the best treatment, or even to "negotiate" with the patient for his or her adherence to the treatment. Research has shown, that the patient's

commitment to the treatment prescribed for a disease influences the healing process (Institute of Medicine, 2013). However, only dialogue and trust between a doctor and a patient make it possible to negotiate the best “cost-benefit” trade-offs and to ensure the involvement of a family carer (Institute of Medicine, 2013).

At the current stage, AI developments are often concentrated on a single pathology—for example Watson on cancer—as are the clinical guidelines that are the foundation of evidence-based medicine. But what happens when a patient presents several pathologies, which occurs with increasing frequency. For the moment, according to the Director of Foresight and Research of the French Hospital Federation, Antoine Malone, this central question remains unanswered, while the performance of health systems in the future will largely depend on the ability to “manage” polypathological patients over time ¹³.

In short, the quality of a diagnosis depends not only on the volume of information available but on the quality of interpretation of complex mechanisms that are not based on fixed natural laws and therefore are not deterministic. Big data works well on simple and mechanical explanatory phenomena. But humans are constantly evolving with their environment and this dynamic process means that in the field of medicine and patient care, Artificial Intelligence will not be able to replace health professionals. The engine of a car or an airplane is as complicated as its design, and one can predictably know how an engine reacts in a given context. This is not the case for a human being who has the ability to adapt to changing environments and can respond in various ways to unpredictable events. The mere availability of information is not enough to influence behaviour. Obesity, for example, has become a major public health issue in many Western countries despite the access to preventive health applications via a smartphone, (Malone *et al.*, 2020). Another difference concerns social acceptability and responsibility. Unlike the use of AI for predictive models in marketing and advertising, if there is a mistake in medical diagnosis and treatment there may be human injury or death, which raises major issues of social accountability.

¹³ Interview with Antoine Malone for France Strategie, 2018.

The discourse to the effect that AI will lead to the disappearance of the human practitioners in the field of health is not credible when one takes into account all the complexity that the field of medicine covers. However, this does not mean that AI is a “non-subject” in the field of health, nor does it mean that certain professions—some of which are highly qualified (e.g. radiologists)—are not threatened. We can say, however, that in the coming decades AI will not replace the work of doctors and nurses and there is little risk that that they will become mere algorithm executors.

What could be AI’s role if we are moving, as seems likely, towards a system dedicated to the management/prevention of polypathologies with a very strong psychological and behavioural component. What the system will aim for will be long-term behavioural changes and this type of action requires close and “human” interaction with patients (Alderwick *et al.*, 2015). What AI could bring is a better management of patients and identification of costs and adapted structures for global management (Malone *et al.*, 2020). Let us take the example of Kaiser Permanent Washington (2018) in the USA, recognized as an efficient health system in achieving the triple aim of assuring quality of patient care, improvements of the population’s health and these at the lowest possible cost (Foley *et al.*, 2015). These systems invest heavily in AI-based tools. But they also recruit a lot of doctors, nurses, orderlies and even social workers to improve the management and prevention of complex pathologies, such as obesity or diabetes because these pathologies are of socio-economic origin. They are also developing local hospital structures within regions to be closer to patients in order to influence their behaviour and minimize unnecessary interventions. So, it is likely that we will still have doctors and nurses’ assistants in the future because the tasks that make up their jobs will not all be open to automation. Indeed, it is more likely that there will be an even greater need for healthcare professionals with the deployment of Artificial Intelligence, if, thanks to big data and information gathering techniques, prevention strategies adapted to each specific population can be improved (Malone, 2018 and Malone *et al.*, 2020).

3.1.3. AI will transform the way we work and interact with patients

This section focuses on work transformation in a concrete way by identifying the benefits but also the potential risks for medical workers themselves in several identified fields of application. One benefit is that AI has the capacity to process millions of items of up-to-date data, thus generating gains in completeness, timeliness and the development of several possible hypotheses for disease detection. The physician will then have better access to the information necessary for his decision-making including a complete histology of the patient providing access to the best therapeutic protocols based on evidence-based medicine.

If such “intelligent” expert systems gain the confidence of physicians and the general public, the impact on the physician’s profession can be multifaceted. Physicians will be able to benefit from assistance in the management of complex case diagnoses, with greater security in decision-making. It will also lead to a strengthening of the doctor-patient relationship and dialogue in order to provide the information necessary to understand the diagnoses. The use of artificial intelligence will continuously increase the level of “technical” competence of the physician as he or she is able to fully exploit the most up-to-date clinical knowledge and medical practices. This could result in a cognitive enrichment of the physician’s work, with less time spent interpreting “routine” data that intelligent systems can handle leaving the most complex expert cases to the physician. An increase in skills will be all the more necessary as the doctor will also need to be able to “challenge” the software and to explain the diagnosis and therapeutic management responsibly.

These advantages, if they were to become widespread in the daily practice of physicians, would make it possible to combine human intelligence and artificial intelligence in a complementary way in the service of better decision-making, combining speed of decision-making and better optimization of patient care expenses. This is also the case in the field of surgery with Star (for Smart Tissue Autonomous Robot), a robot that does not completely replace specialized surgeons but provides them with a tool capable of greater precision in performing certain procedures such as suturing (Shademan et al., 2016).

3.1.4. *The evolution of professions*

Medical imaging professionals are particularly affected by the foreseeable widespread use of automated image reading. If AI makes it possible to automate a part of conventional radiology for a specific field and clinical situations, this will reduce the radiologist's activity, despite the growth in needs due to the aging of the population and the pervasiveness of chronic diseases. Ultimately, the question may arise as to the need for the intervention of the radiologist in the establishment of the diagnosis. This automated step could be carried out by radio manipulators trained in the development of diagnoses. It could also be carried out by a non-radiologist equipped with tools for interpreting medical images. Such developments presuppose an adaptation of the current regulatory framework. Radiologists in such a scenario would reserve their time for the interpretation of complex cases. In interventional imaging, on the other hand, the need for their expertise will increase in almost all medical specialties. The profession of radiologist could evolve towards increased specialisation in interventional radiology for diagnostic purposes (punctures, biopsies, etc.) for complex cases or for therapeutic purposes guided by medical imaging. This evolution towards interventional radiology has already been recognized by the profession, according to the National Federation of Medical Radiologists¹⁴.

In cardiology, new electrocardiogram (ECG) interpretation services are being developed that rely on software rather than on the expertise of the cardiologists. The software is capable of detecting rare or silent cardiac abnormalities such as mitral leakage or cardiac arrhythmias which a specialist sometimes finds difficult to detect. This can provide the doctor, whatever his or her speciality, with a gain in the quality of the diagnosis. Such a service may transform the practice of the ECG by making its use more frequent for more medical specialties (emergency physicians, general practitioners, geriatricians, etc.) but perhaps also by opening it up to non-physicians (nurses, firemen, etc.). It should free up the cardiologist's time, if only through its ability to manage simple cases that will be treated upstream without being referred to the physician. This could

¹⁴ Interview with Jean-Michel Masson, President of the Fédération nationale des médecins radiologues (FNMR) as reported in Benhamou and Janin (2018).

refocus the physician's activity on the most complex cases and lead to benefits from continuous learning thanks to the software program's capacity to exploit the most up-to-date clinical knowledge and medical practices. AI could accentuate the trend towards over-specialisation of professions (coronographies, arithmology, cardio-paediatrics, etc.) by the increasing digitalisation of certain medical devices. In cardiology, as in all fields, the extent of the impact will depend on the quality of the tool. At the same time, AI makes it possible to develop another type of service which consists in interpreting ECG data collected over a long period (several days), whereas these data were previously rarely collected. For the cardiologist, it opens up the prospect of a new type of follow-up for his or her patients¹⁵.

3.1.5. An intensification of work related to cognitive exhaustion

AI has contradictory effects depending on its use in the same way as other technologies do. If the gains made thanks to AI (speed of data processing) result in an increase in the same proportions in the time devoted to cognitive tasks (expertise, decision-making, solving complex problems, etc.), this will leave little time for the doctor's brain to "breathe" through alternating between "stakeholder" and "little or no stakeholder" activities. If the time "freed up" is only allocated to this type of task, we can thus identify a potential risk linked to what neuroscientists describe as professional cognitive exhaustion to which healthcare professionals, and in particular the youngest and least experienced ones, would be exposed.

a. Improvement of working conditions in the "care" professions

The care and monitoring of elderly patients suffering from one or more chronic pathologies, particularly Alzheimer's, is an extremely burdensome task for the nursing staff. The management of these behavioural disorders leads the staff to devote a great deal of time to them and makes their working conditions particularly difficult (stress, feelings of professional inefficiency, burnout, etc.). These conditions often lead to the discouragement of the health care team, even those that are experienced. This is a field where intelligent social robots could intervene. Modern robotics incorporating AI, whether in the management of sensors or in the

¹⁵ Interview with Yann Fleureau, CEO of Cardiologs for France Stratégie, 2018.

programming of movements, is being developed in order to provide domestic assistance for elderly or frail people. In Japan, robots are already being experimented with to assist people in their daily activities, helping them to move around, to move from chair to bed and vice versa. Residential institutions for elderly dependents could be equipped with this type of robot in a few years. There are already robots that provide solutions to the problems of caring for elderly patients with cognitive and behavioural disorders (Alzheimer's, autism, etc.). These robots are equipped with artificial intelligence through numerous sensors and microphones that enable them both to interact with the caregivers who handle them and to respond to the requests of elderly patients. Their physical presence and their ability to interact socially through speech, facial expression and gestures makes them ideal for working with people who have difficulty communicating verbally. Several international literature reviews in the field identify enough acceptability of these robots, especially animal robots, with show there are positive effects on the well-being of patients. The Paro robot, which reacts to its name, compliments and touch, is the most widely used robot in geriatric wards around the world. A study has shown that the integration of these machines has reduced the physical and mental strain on nurses and care assistants¹⁶.

3.2. Work Transformations in transport sector

The major innovation brought about by the development of AI in the field of transport will undoubtedly be the autonomous vehicle, even though the timeline for its deployment remains uncertain. Of course, it all depends on the degree of autonomy we are talking about, as automation of driving is divided up into six levels from the international classification of the SAE (Society of Automotive Engineers). This classification defines what human drivers and/or autonomous systems can and cannot do. It starts from level 0 which corresponds to no automation because all driving is done by the driver up to level 5 which corresponds to the fully autonomous driving of the vehicle in any situation (dense urban traffic, country roads, winding roads, etc.) which completely dispenses with a human driver. Level 5

¹⁶ See: <http://www.mutualite-loire.com/index.php/nos-actualites/799-l-etude-inedite-sur-les-usages-du-robot-paro-pour-des-residents-atteints-de-la-maladie-d-alzheimer-ou-apparentee-en-ehpad-mutualiste>.

has not yet been announced by any manufacturer, even though experiments on open road traffic without a driver have been carried out since 2017 and in particular by two of the main manufacturers of autonomous vehicles, Waymo, the Google subsidiary, and the French company Navya. But according to John Krafcik, boss of Waymo, it will take decades before level 5 is reached. Autonomous vehicles may still need a driver¹⁷.

The technological maturity of the different levels and their subsequent diffusion will therefore be decisive in the transformation of the transport sector and the transformations of work and the level of employment in this sector. Within 5 or 10 years, the degree of vehicle autonomy could reach level 4, which corresponds to total autonomy but in very specific contexts and where the surroundings are perfectly simplified and marked out (moving and parking in a car park, driving on motorways). The discussion here, therefore, is limited to the impact of the diffusion of the level 4 autonomous vehicle in a horizon of 10 years and only considers the impact that artificial intelligence may have on road and rail transport, which will be the segments most affected by the development of autonomous vehicles.

3.2.1. Application fields in transport sector

Other than the autonomous vehicle, AI applications in the sector mainly concern the development of predictive equipment maintenance, logistics and flow optimization. The use of industrial sensors is already widespread to measure machinery wear points and equip production-chain control points. Reduction in the cost of such sensors enables the collection of big data. Artificial intelligence can process such data on a greater scale than human processing can manage, so enabling the addition of more control points and refining the diagnoses resulting from the analysis of such data. This being so, companies can have smart diagnostic tools available that facilitate maintenance operations and develop indicators prior to the appearance of anomalies, which opens the way to predictive rather than preventive maintenance (McKinsey Global Institute, 2015). Maintenance and control operations are only carried out when required, before any

17 <https://www.cnet.com/news/alphabet-google-waymo-ceo-john-krafcik-autonomous-cars-wont-ever-be-able-to-drive-in-all-conditions/>

anomaly occurs that might hold up a production chain, or before a piece of equipment wears out. Predictive maintenance is of major interest to all (rail and road) network and vehicle (aircraft, trains, heavy goods vehicles, etc.) operators, as it optimises operations, limits downtime due to maintenance and reduces servicing costs. According to the Mobility and Transport Department of the General Commissariat for the Environment and Sustainable Development, maintenance services may also be able to anticipate and even avoid peaks of activity¹⁸.

Artificial intelligence also enables optimisation of logistics in the event of crises. When an incident occurs, mainline and metro train operations can be seriously disrupted. When preventive maintenance has been unable to avoid a crisis, its resolution may still be speeded up by artificial intelligence. These days, crisis-scenario responses are standardised, with information processing and coordination of required action as the two main stumbling-blocks: two obstacles that AI can help remove. AI may well be able to bring more specific and appropriate responses to crises by taking more information into account. For example, in the event of a breakdown on a metro line it will be able to take into consideration the number of passengers, which determine optimal speed for relieving congestion on the line, the availability of replacement trains and the workforce required to put them into service and the available alternative routes. Such optimisation of logistics and flows is only possible if AI is provided with real-time data on a wide range of parameters, with all the risks of blockage that the diversity of actors involved may generate¹⁹.

It would seem possible for the applications described above to reach a level of technological maturity enabling their deployment within the next five to ten years. However, such maturity must also be able to respond to various parameters affecting the dissemination of artificial intelligence including the availability of massive data for the large-scale operation of autonomous vehicles and respect for the privacy of individual owners with the development of connected vehicles²⁰.

18 Interview with Marie-Anne Bacot for France Stratégie, 2018.

19 Interview with Hoang Bui, Head of Bureau of Transport Equipment, Mechanics and Production Machinery, General Directorate of Enterprises for France Stratégie, 2018.

20 The CNIL has published a sector-specific reference framework enabling manufacturers to comply with the European regulation on data protection. This reference

In any future deployment of artificial intelligence in transport, issues of data collection and exploitation will essentially be raised between companies, and consequently will not concern the question of respect for privacy but rather that of sharing value. For optimal use of AI's possibilities, data on vehicle navigation and maintenance and on infrastructures will have to be shared between several types of actors including, railway (SNCF network and RATP in France) and road (Vinci, Bouygues, etc.) infrastructure managers and vehicle operators (Ouigo, RATP, road hauliers, etc.). Economic and technical conditions with regard to harmonisation, quality, interoperability, real time, etc. will therefore have to be clearly defined.

a. Impacts on jobs in the transport industry

The impact of AI on the transport professions will depend on the prospects for the deployment of autonomous vehicles, which will themselves vary according to the transport activity. As far as road freight transport is concerned, the development of autonomous vehicles could threaten lorry drivers.

Several reasons can be put forward. In Europe, the labour force in this sector represents between 35% and 45% of total costs (International Transport Forum, 2017), which can be a strong incentive for companies to invest in technologies that promise savings. In addition, the sector is subject to strong international competition, which is an additional factor in the penetration of innovations. The advent of level 4 autonomous vehicles would allow automated driving in convoys on motorways, which is an environment particularly suited to this type of vehicle. Also, on major roads where many lorries travel, the formation of convoys makes it possible to reduce fuel costs while at the same time increasing safety through the interconnection of vehicles²¹. This automated traffic in convoys would initially make it possible to increase truck driving times by modifying the regulations on rest periods for drivers who would no longer be in a driving situation throughout the journey. Eventually, the presence of a driver could even be required only at the head of the convoy. A human

framework provides in particular for a scenario where “data collected in the vehicle is transmitted to the outside to trigger an automatic action in the vehicle”. See: CNIL (2017).

²¹ See: www.eutruckplatooning.com/About/default.aspx.

presence would still be necessary to take over tasks that are not yet automated (e.g. refuelling).

Local drivers could be used to take the trucks to the highway or provide local services. A new logistics system for transporting the trucks could then be put in place as is already the case with the rail transport. Trucks would be driven by drivers to an interface area at the entrance to the highways before joining a self-contained convoy, and picked up at the exit for delivery at the final point. Thus, the reduction in the need for long-distance drivers would be accompanied by an increase in the demand for local drivers, who would benefit from better working conditions (shorter journeys in a restricted geographical area). If the number of lorry drivers' jobs were to be threatened, jobs as controllers could be created to supervise vehicle fleets from a distance (Benhamou *et al.*, 2018).

In France, as in Europe, transport of private individuals is mostly by personal vehicles. Autonomous vehicles are unlikely to have any major impact on this segment as the advent of level-5 automatic driving is still difficult to predict. However, level 4 should already enable the development of new public transport services that might replace a percentage of individual journeys. Initial experiments underway focus on shuttle services travelling routes in delimited areas. Navya, a world leader in this area, has already deployed over 50 vehicles across the world on short-distance routes (up to two kilometres). We may therefore imagine that the coming years will see increasing numbers of autonomous shuttles providing new public transport services on local routes with fewer potential passengers and not covered by present-day services such as night services. The Rouen Normandy Autonomous Lab experiment on mobility-on-demand services on the open road is in this direction (Transdev, 2017).

Such autonomous shared shuttles ensuring local services could complement the existing public transport offer, competing with mass public transport and the transport of individuals by taxi or chauffeur-driven cars, in which case there may well be an impact on drivers' jobs in these areas. However, as long as level-5 autonomous vehicles only remains on the drawing-board, taxis and chauffeur-driven cars will remain the leading means of transport for door-to-door journeys. Moreover, the circulation capacities of autonomous vehicles that take to the road will not be able to rival classical means of public transport on the most frequented routes:

that would lead to unacceptable over-congestion of highways. These developments will also be accompanied by the creation of jobs for supervision of fleets, as well as customer-relations positions responsible for passenger reception and safety.

New work organisation for maintenance staff could also emerge. The smart maintenance tools that will form part of the standard equipment for new vehicles and infrastructures could also be installed on existing vehicles. People responsible for service and maintenance will consequently be faced with a need for new competences, both as regards the tasks being carried out and the tools being used.

Smart tools will provide help and even “instructions” in both the diagnosis and performance of maintenance tasks. It is hard to contradict a machine on the origins of a breakdown, especially if it has not happened yet as will be the case with predictive maintenance. Artificial intelligence will not just indicate the component that needs repairing, it will also indicate how the repair is to be carried out. To borrow an image from the medical sector, it will provide both diagnosis and treatment, implying the risk of staff losing an overall vision of how a vehicle functions and the maintenance operations to be carried out. This could lead to deskilling of maintenance work, with humans being responsible for their performance without necessarily any deep understanding. At present, such a risk seems limited by a general determination to preserve employees’ autonomy with regard to a vehicle’s overall maintenance and not focus on specialising on specific tasks which may later be automated. Increasing skills is therefore essential if this overall approach is to be maintained, despite vehicles growing complexity and dissemination of new smart tools. Lastly, work pace at a maintenance centre is likely to be affected by predictive maintenance, which will enable better forecasting of workloads as well as limiting activity peaks (Benhamou *et al.*, 2018).

3.3. Impacts in the banking sector

The banking sector has been a pioneer in the adoption of IT tools to manage customer databases and to set up networks for online banking. The banking sector was also one of the first to implement “expert systems”, computer programs designed to process technical transactions. In fact, the

AI solutions employed in the banking sector cover a wide variety of functions and technologies, which can be divided into four categories: applications oriented towards customer relations, back office operations, trading and wealth management applications, and applications oriented towards regulatory use. Thus, the strong presence of structured data and the dematerialised nature of the vast majority of transactions make the banking sector a fertile ground for the development of artificial intelligence solutions (DGE, 2019).

With regard to customer relations, the most developed artificial intelligence applications are to be found in the field of credit risk rating. Banks have historically developed an ability to analyse the risk associated with any loan applicant using statistical models. These models are now enriched by additional data sources that may require artificial intelligence processing. Similarly, AI is used by insurers to improve the granularity of their offers and recommendations (IAIS, 2017).

But the main field of application and the one with the greatest potential to transform work in the banking sector is that of conversational assistants or chatbots (Athling, 2017). A number of “back office” operations can be related to the financial activities of banks, including risk modelling and optimising the use of capital. As for applications in the field of wealth management, they are gradually focusing on the analysis of weak signals that can provide useful information for investments. Finally, in the regulatory field, AI applications are linked to the detection of irregular transactions and can also be used to optimise customer knowledge mechanisms, for example by using image recognition to automatically extract useful information from the scanned image of an identity document.

3.3.1. Evolution of the advisor's profession

The changes brought about by AI could profoundly transform the profession of bank advisor. In its study for the Observatoire des métiers de la banque, Athling (2017) highlights as the most impacted activities those relating to compliance with regulatory, legal and tax changes specific to the banking sector. These activities will be improved thanks to more relevant monitoring and more advanced and personalised recommendation tools, such as that provided by the legal search engine *Doctrine.fr*, which

will allow “on-demand” access to this information. The construction of client profiles using AI tools will also enable advisers to process credit applications more quickly, or to identify financial risks such as tax fraud or money laundering more effectively.

Independently of the development of AI, the announcement of its advent combined with new consumer expectations are pushing banks to transform their activities to reorient themselves around a service available 24 hours a day, 7 days a week. They intend to respond to the dual promise of instantaneous and quality service by combining an AI-based service for the request sorting and management phase of the most frequently asked questions with a remote human service, available at all times. A form of low-cost service could also emerge where the consumer would only have access to automated help, even if it means paying an additional fee to interact with a human. At Orange Bank, the solution set up to filter customer service requests has achieved a recognition and comprehension rate of around 80%.²² Artificial intelligence is not always able to provide a relevant response, which means that customer service agents process about one out of every two requests in the end. The agents mainly assigned to the operation of the platform or to solving technical problems encountered during its use could gradually see a double effect on their job: a reduction in the number of dedicated employees and an increase in the complexity of the tasks remaining to be processed.

The increasing efficiency of AI in answering questions related to the online banking platform, which is already the priority means of interaction between customers and their bank, will in fact free up time and facilitate the work of these agents by filtering the number of requests. The bank could then choose to train these customer service agents to respond to requests that traditionally fall under the responsibility of the bank advisor. This development corresponds to the expectations of the customer, who increasingly sees his adviser not as the one who shares responsibility for managing his portfolio, but as an assistant who must help him navigate through the complexities of the banking system, making himself available to unblock a situation.

22 Interview with Emeric Chaize, Chief Digital Officer of Orange Bank, for France Stratégie, 2018.

This field is also seeing the emergence of new players who have one of the key resources for setting up an AI-based system. Integrated services groups specialising in customer relations, which have access to considerable amounts of data as part of customer service operations on behalf of third-party companies, will be led to set up a replacement offer managed solely by a robot—“bot-shoring”—which could drastically reduce their costs.

The availability of AI technologies that facilitate the banking advisor’s job and reduce the volume of knowledge required by making them more available may also be an incentive for bank advisors to evolve towards greater customer knowledge. Advisors could then take on more responsibility for managing their clients, spending more time recommending investments or sources of financing. In this scenario, social and decision-making skills will be enhanced, and bank branches may be encouraged to focus on training in dialogue or negotiation skills.

Depending on the choices made by companies in the sector, artificial intelligence may help to optimise the service and further the trend towards dematerialisation, or it may reinforce the importance of the adviser by giving him or her greater autonomy.

3.3.2. Transformation of support functions

The transformation of support functions within the banking sector is in line with previous developments observed with the advent of the digital environment. With artificial intelligence, certain tasks, including the most repetitive ones, are bound to disappear, particularly those related to data collection, which will be optimised or accelerated. New working modalities will emerge, where actors will have to learn how to interact with the new AI-based system to help it progress (Benhamou *et al.*, 2018).

As far as information systems are concerned, the arrival of methods derived from artificial intelligence will not disrupt the organization. The advances will be in line with the processes set up with “RPA” or Robotic Process Automation—IT automation projects based on non-learning algorithms, implemented since the 1990s and continuously developed. For other activities, such as compliance activities, AI tools can lead to an upgrading

of transferable skills identified for example in the work of France Stratégie where the bank's employees demonstrate responsiveness, adaptability, as well as office automation and IT skills (Lainé, 2018). Highlighting these skills could increase their employability.

3.3.3. Evolution of skills specific to artificial intelligence

The needs specifically related to the IT development of AI in the banking sector do not represent a particular stake in the total volume of employment in the sector. Nevertheless, they do require special adaptations that deserve to be highlighted. The scarcity of skills pushes companies wishing to implement solutions based on artificial intelligence to turn to specialized external organizations²³. Those who want to create these skills internally will be forced to make major changes to their working environment as AI projects require an extended phase of experimentation and preparation which is similar to advanced research projects, requiring scientific rigour and patience. Rather than focusing on internal skills development, the major digital groups have chosen to open their research departments to the outside world and to form partnerships with universities or research organisations. These transformations are a prerequisite for the deployment of artificial intelligence.

4. CONCLUSIONS: LEARNING ORGANISATIONS AND THE FUTURE OF AI

The objective of this article has been to use sectoral examples as a basis for drawing more general lessons concerning the effects of AI on work. The analysis has shown that not all tasks that make up the core jobs in the three sectors analysed can be automated. Trades that draw their strength from their human and social activities and mobilize skills that call for creativity and complex problem solving will be preserved. This is the case in particular for certain highly skilled occupations, such as doctors, or low-skilled occupations such as care assistants or social workers. While

²³ According to a survey carried out by EY in December 2017 among 200 AI professionals, 56% of whom estimated that a shortage of trained profiles was the main obstacle to development of AI.

in the transport sector the activity of driving may disappear in the long run with the further development of the autonomous vehicle, more and more supervisory tasks may also appear, thus transforming certain professions. This phenomenon is not new. Robotization in the automotive industry is an old phenomenon which has led to the repositioning of workers on supervisory tasks. This is also the case for the banking sector with the digitisation of a large number of activities is leading to the evolution of the professions providing advice to individuals. The article also points out that AI has made it possible to carry out tasks that previously weren't carried out, either because they were too time consuming and tedious for humans or because they were economically unprofitable. In the health sector, for example, the analysis of electrocardiograms is a case in point or in the banking sector the detection of anomalies in transactions using AI-based devices.

In many cases AI-based devices appear to be used in ways that are complementary to the tasks performed by humans. Here, the human element in the task is not eliminated and the person relies on a tool that helps him or her: a tool to assist in diagnosis or therapeutic proposals in the medical field or a tool to support the customer advisor in the banking sector. At the same time, alongside this process of complementing human skills, AI can substitute for certain routine cognitive tasks. With technological progress, the scope for this sort of substitution is likely to increase, with AI competing directly with a wider range of human cognitive abilities. The skills associated with any task that follows pre-determined rules—simple or complicated—risk being downgraded by future advances in AI.

For this reason, in order future-proof one's position in tomorrow's labour market a major challenge will be to have the ability to learn continuously and to develop new skills, especially those that are transversal to the labour market (Benhamou, 2018). The sectoral examples point out in particular that cross-cutting competencies—the ability to communicate with others and influence decisions, the ability to transfer organizational skills and know-how and the ability to manage hazards—will become more important with AI.

In this light, learning forms of work organization that are based on a logic of continuous learning could be particularly well suited to the challenges posed by the integration of artificial intelligence. As the recent study by

Benhamou and Lorenz (2020a ; 2020b) shows, learning organizations are based on the use of forms of work organisation that develop cross-cutting competencies and support continuous employee learning. Adopting these forms of work organization could be a relevant lever to ensure that AI is used to enhance complementarity between machines and humans and not simply to substitute for humans.

Another factor that argues in favour of the model of learning forms of work organization concerns the innovation diffusion process itself. Indeed, the principle of AI is to discover statistical regularities while remaining “encapsulated” in an “expert” decision-making system that uses historical data. Paradoxically, this can favour a certain conservatism in human decision-making. However, progress is not a matter of the past, but of creativity and risk-taking. This also speaks in favour of adopting a learning organization design that encourages risk-taking and the development of “systems thinking” to increase the organization’s ability to move beyond “predetermined frameworks and norms” resulting from standardized production processes. If, to the contrary, companies adopt more traditional hierarchical forms of organisation there is an increased risk that AI will be used mainly for purposes of substituting for human labour because the production process in these organizational forms are based on a very high degree of standardization and compliance with predetermined rules.

Thus, independently of the impact of AI on the level of employment, the deployment of AI points to the need for a profound rethinking of work organisation to support continuous learning capacities and the evolution of skills. Much will depend on the competitive market strategy of the enterprise and on the organisation of work that is adopted in its support. While the use of learning forms of work organization contributes to the competitive advantage of firms seeking competitiveness based on innovation, the use of low-skilled employees with limited training and a low capacity for learning contributes to the pursuit of competitive advantage through cost-cutting. If AI is used in support of a logic of cost rationalisation, the virtues of training will be limited because human-machine complementarity will not be sought.

The organisational challenges posed by the advent of AI are immense and must be considered in a manner consistent with a nation’s education and training system. In order to protect the labour market against the risks

of skills downgrading and obsolescence, it will be necessary to invest in cross-cutting skills and to increase the capacity of individuals and firms to continuously learn. While these forms of skills development can be supported through innovative policies at the level of the formal educational and training system, they will also depend on the choices made by employers. Skills emerge in part from employees' daily work experience and this speaks to the need for complementary policies and frameworks designed to promote the adoption of learning forms of work organization.

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