ARTIFICIAL INTELLIGENCE AT WORK: AN OVERVIEW OF THE LITERATURE

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Abstract

This paper provides an overview of the actual and likely labour market transformations caused by increasing use of Artificial Intelligence (AI) technologies across the advanced economies, with a special focus on Germany. The scholarly debates on these issues mainly revolve around the impact of AI on the number and structure of jobs, and around AI-enabled management tools' perpetuation and aggravation of work-related inequalities and discrimination. The study starts with a brief background of AI as a technology, with a focus on its definition, subfields, capabilities, and history. Following this, it reviews the discussions on the implications of AI use in the world of work and its ethical and political repercussions and continues with a summary of AI use and its impacts in German labour markets. It then discusses the current gaps in the relevant scholarly literature and identifies numerous opportunities for further research.

The investigation concludes by addressing two far-reaching implications of increasing utilisation of AI-enabled tools in labour markets. First, in the case that the current trends remain unchanged, the AI-driven future of work is likely to perpetuate and aggravate work-related inequalities and discrimination, diminishing further the prospects of decent work, fair remuneration and adequate social protection for all. Second, predictions provided by current studies only point out one possibility amongst many. Thus, we still have choices as to the advancement, adoption, and utilisation of workplace AI technologies in a way that brings benefit to all.

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Executive Summary

Artificial intelligence (AI) is an emerging automation technology which builds upon successes, lessons, and experiences of the previous advances in digital technology. The digital technologies preceding AI were routine-biased. Thus, they replaced routine mental and physical tasks mainly performed by mid-skilled, mid-income workers. On the contrary, AI technologies are predominantly skill-biased, meaning they automate human skills such as matching, prediction, perception, and cognition. Compared to previous digital workplace technologies, skill-biased AI applications can displace labour in a wider set of jobs and tasks, across most of the skill and wage spectrum, in such a way as to make workers' bodies as well as their brains obsolete. Nevertheless, AI's labour markets effects remain largely unclear, mostly stemming from the fact that AI workplace technologies are nascent and have not yet been adopted on a large scale. As a result, while the research evidence as to how many jobs have so far been replaced by AI-enabled machines is still inconclusive, the forward-looking studies have different opinions as to whether workers in lower-paid/lower skilled, mid-paid/mid-skilled or high-paid/high-skilled jobs will be the ones most affected by AI-led automation.

Despite this ambiguousness, many experts agree that AI-enabled automation will not bring the end of jobs. Rather it will require re-allocation of skills and tasks between humans and machines, triggering two opposite changes in the skills and tasks composition of jobs. The first shift creates a new division of labour, where humans are allocated to the tasks that are uniquely human and difficult to automate, while machines take over repetitive and dangerous tasks requiring constant attention and stamina. In this scenario, AI-powered technologies augment workers' capabilities and add more value to the tasks performed by human labour. The second shift is related to the division of labour where the machines perform complex tasks involving comprehensive thinking and learning, while the workers are relegated to mundane tasks and/or carry out machine-generated directives. In this scenario, workers are likely to be deprived of opportunities to use their skills, as well as their possibilities to upgrade their skillsets.

As the utilisation of AI in standard business processes is increasing by almost 25 percent annually, these future scenarios are likely to come true. This is expected to create winners and losers, perpetuating, and exacerbating inequalities and discrimination at work along the lines of wages and working conditions. Winners are thought to be the already privileged young male workforce with AI skills. These workers are in the upper end of the wage spectrum, compete with machines and have individual power in negotiating their wages and working conditions. The losers are predicted to be the already vulnerable groups such as women, younger, older workers, and workers of certain ethnic and minority backgrounds holding jobs that are at high risk of automation. These workers compete against machines, and have very weak, if any, bargaining power on their wages and working conditions.

Some AI-enabled workplace applications also carry important implications for employment relations. Commonly referred to as algorithmic management tools, these systems are designed to automate or semi-automate managerial decisions related to working conditions and workers' control. Algorithmic management systems are likely to maintain and worsen a range of prevailing issues related to labour-capital relations, such as: (i) reproduction of biases based on gender, sexuality, race, nationality, or other categories; (ii) wider utilisation of precarious work arrangements, depriving workers of some of their fundamental rights and protection; (iii) blurring of boundaries between work and private lives; and (iv) diminishing possibilities of workers' collective resistance.

The transformation of labour markets towards an AI-driven world is expected to be slow and painful, as this process requires reskilling and relocation of many workers, as well as complementary innovations and socioeconomic and political adjustments. To ensure smooth progress into the labour markets with high AI penetration, the workplace implications of AI technologies need to be dealt with through decisive actions that consider democracy, accountability, transparency, human dignity, and the fundamental rights of workers as the main principles to follow. Yet, as of now, most of the ethical principles and guidelines for the invention and introduction of AI technologies lack enforceable mechanisms. As a result, they are rarely taken into consideration by developers and consumers of workplace AI technologies.

As currently more than 80 percent of the German workforce uses digital information and communication technologies, digital transformation also has important repercussions for Germany's world of work. However, international comparisons indicate that Germany has a long way to go in realising a comprehensive digital transformation. Germany's digital performance becomes even more concerning when it comes to AI workplace utilisation rates: at present only 6 percent of companies are using AI tools and technologies, and only 28 percent of them have plans to invest soon. Notwithstanding its sluggish digitalisation progress, the state, workers' organisations, and employers' associations in Germany consider digital transformation of the world of work a crucial topic to address. In their tripartite relationship, the German state aims to strike the right balance between the interests of the labour and the capital. German employers mostly favour of a *laissez-faire* approach in the digital transformation of labour markets. Workers' organisations come out as 'agenda setters' and assume a proactive role in dealing with workplace issues related to digitalisation.

Although issues around AI's workplace utilisation and its repercussions for workers and the workplace are currently attracting growing interest, the extant literature leaves significant gaps in our understanding of the subject on empirical, methodological, and theoretical levels. This is the case both in general and in the context of Germany. New and serious shortcomings will continue to emerge as AI-driven technology progresses further and the subject is further scrutinised. Adequately addressing and overcoming these limitations is crucial, for this will significantly help us attain a clear vision of the future world of work.

Notwithstanding the gaps in the current literature, a critical overview suggests that the increasing utilisation of AI-enabled tools in labour markets carries at least two policy implications. First, in the case that the current trends remain unchanged, the AI-driven future of work likely to perpetuate and aggravate work-related inequalities and discrimination, diminishing further the prospects of decent work, fair remuneration and adequate social protection for all. Second, predictions provided by current studies only point out one possibility amongst many. Thus, we still have choices as to the advancement, adoption, and utilisation of workplace AI technologies in a way that brings benefit to all.

1. Introduction[1]

Recent decades have witnessed some impressive advances in artificial intelligence (AI) technologies. AI has now become part of our daily lives, helping us book holidays, hail a cab, capture great photos, and discover new media contents to our liking. Yet, uses of AI extend far beyond our everyday activities. To name a few, thanks to AI's high competence in image recognition, health care professionals can now more accurately diagnose certain diseases. AI-powered augmented reality helps people with hearing and visual disabilities to manage their

[1] This research is conducted as a part of the 'Governing Work in the Digital Age' project based at the Hertie School of Governance, Berlin. The project is funded by the German Federal Ministry of Labour and Social Affairs (BMAS).

daily lives. AI-based prediction technology can scan hundreds of legal documents, find the most relevant content, summarise texts, and envisage possible decisions based on previous legal judgments. AI-enhanced matching systems help companies and jobseekers to connect and share information. AI-based digital career advisers help jobseekers create attractive CVs and cover letters.

The recent advances made in AI and their implications have aroused heated debate in global academic, business, technology, and policy circles. These discussions highlight different aspects of AI, ranging from its ethical repercussions to its profitable use in the economy, from AI-related productivity challenges to its potential to replace human labour (Brynjolfsson *et al.*, 2017, Rao and Verweij, 2017, Daugherty and Wilson, 2018a, Agrawal *et al.*, 2019, AI HLEG, 2019b, Moore, 2019b). Despite such variety of concerns, two recurring ideas from these discussions often come to the surface. First, AI has the potential to contribute to the wellbeing of individuals and populations in diverse ways, including but not limited to supporting research activities, enhancing the lives of people with disabilities, and assisting the fight with climate change (IBM *et al.*, 2020, Marr, 2020). Second, AI technologies need to be responsibly and ethically developed and utilised, as some of them may raise unprecedented challenges for individuals and societies in the future. For instance, observers maintain that AI-enabled algorithms might restrict our freedom to seek, receive and impart information and ideas of all kinds, as they have the power to select what we see, read, and hear on digital media platforms (van Est and Gerritsen, 2017, Craglia *et al.*, 2018, EPSC, 2018). It is widely argued that if AI's potential is used to replace labour rather than creating demand for it, this may aggravate existing income inequalities (Ernst *et al.*, 2018, Acemoglu and Restrepo, 2019b, Felten *et al.*, 2019, Servoz, 2019). Experts also warn that AI algorithms are likely to reflect the bias of the humans and data involved in their programming process (Dickson, 2017a, De Stefano, 2018, EPSC, 2018, Crawford *et al.*, 2019): an inbuilt flaw that would exacerbate social inequalities and reinforce existing discrimination, including but not limited to those based on race, ethnic and gender issues (O'Neil, 2016, Whittaker *et al.*, 2018).

It is against this background of tremendous AI capabilities that many experts regard AI as a distinctive technology, and not simply the latest in the line of information and communications technologies (ICT). Its fundamental difference lies in the fact that AI algorithms can learn from example and improve their performance by using structured human feedback. Such progress represents an important break from software-based digital technologies that relied on detailed descriptions of rules and procedures to perform tasks (Brynjolffson and McAfee, 2017, Frey, 2019a, Jarrahi, 2019). Experts hold that the traditional way of codifying knowledge into machines comes with a significant shortcoming, in that 'we can know more than we can tell' (Polanyi, 1966: 4). Our acquisition of such tacit knowledge becomes visible when, for instance, we can easily recognise a face, ride a bike, or speak our native language, but cannot explain how we carry out these tasks in a step-by-step fashion. This situation, also known as Polanyi's paradox, has long constituted a major impediment to machine intelligence. It is now gradually being overcome thanks to AI-based systems' competence to learn outside prescribed configurations and commands (Brynjolffson and McAfee, 2017, Brynjolfsson *et al.*, 2017).

Despite AI-driven technologies' marked difference from the digital technologies preceding them, experts consider AI to be an emerging automation technology, building upon successes, lessons and experiences of previous technological advances (Brynjolfsson and Mitchell, 2017, Manyika *et al.*, 2017, Acemoglu and Restrepo, 2018a, Brock and von Wangenheim, 2019, Frey, 2019a, Servoz, 2019). Thus, AI-driven automation technologies share an important feature with the previous digital automation technologies in their potential to displace, complement and augment human labour. However, according to experts, even in this commonality AI is still distinctive, as it 'has taken automation into new and unexpected areas that were previously safe havens for human labour' (Frey, 2019a: 8).

This study provides an overview of the actual and likely labour market transformations led by increasing use of AI technologies across the advanced economies. In undertaking this task, it largely and intentionally leaves out the profound shifts which occurred in the world of work under the impact of previous waves of digital automation, as this mission has already been accomplished by a good number of studies (Arntz *et al.*, 2016b, Eurofound, 2017, Goos *et al.*, 2019, MIT, 2019, Özkiziltan and Hassel, 2020). Our investigation addresses two policy implications. First, in the case that the current trends remain unchanged, the AI-driven future of work is likely to fail to offer prospects of decent work, fair remuneration and adequate social protection for all. Second, forward-looking predictions provided by current studies only point out one possibility amongst many. Thus, we still have choices as to the advancement, adoption, and utilisation of workplace AI technologies in a way that brings benefit to all.

The study starts with a brief background of AI as a technology, with a focus on its definition, techniques, capabilities, and history. Following this, it reviews the extant literature on the implications of AI use in the world of work and its ethical and political repercussions and continues with a summary of AI use and its impacts in German labour markets. The study then discusses the current gaps in the relevant scholarly literature and concludes by addressing the policy implications of AI utilisation in labour markets.

2. AI in a nutshell: Its definition, capabilities, and history

Notwithstanding the recent promising AI applications making our lives easier and the concerns some AI technologies cause, AI is not a new subject. In fact, since humans invented digital electronic computers during the Second World War, the idea of AI intrigued humanity. Starting from Isaac Asimov's robot-based short story 'Runaround', published in 1942, the enormous potential of AI has inspired numerous movies and novels over the years to engage their audience in thought-provoking future scenarios, from intelligent machines enslaving humanity to anthropomorphic robots acting as servants to mankind. At least as of now, it is only in the movies that AI exceeds human intelligence. In reality, AI does not even have a precise definition ascertaining its boundaries and features. What is more, AI has much narrower uses and less intimidating appearances, owing to its historical development path and current capabilities, all of which will be scrutinised below.

2.1. AI as a concept

A careful overview of the definitions of AI indicates that AI as a concept has remained a contested terrain since its first use in the mid-1950s. In fact, as John McCarthy, an early pioneer of AI who coined the very term in 1955, once famously stated: 'As soon as it works, no one calls it AI anymore' (Vardi, 2012). According to observers, this uncertainty is underpinned by the difficulties in identifying what intelligence embodies in humans, despite the vast availability of studies in various fields of research on this topic, ranging from psychology to neuroscience (Miailhe and Hode, 2017, AI HLEG, 2019a, Samoili *et al.*, 2020).

An important repercussion of this lack of definition appears to be the emergence of multiple descriptions of AI. For instance, in the European Commission's Joint Research Centre Flagship report on AI, the concept was defined as:

'AI is a generic term that refers to any machine or algorithm that is capable of observing its environment, learning, and based on the knowledge and experience gained, taking intelligent action or proposing decisions' (Craglia et al., 2018: 18).

OECD's AI Experts Group explains an AI system as:

'a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments. It uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models (in an automated manner e.g. with ML [machine learning] or manually); and use model inference to formulate options for information or action. AI systems are designed to operate with varying levels of autonomy. (OECD, 2019a: 15, brackets added).

IBM, on the other hand, favours the concept of 'augmented intelligence' over that of AI, for according to them AI 'brings to mind to the notion of replacing human intelligence with something synthetic' (Rossi, 2016: 1). According to IBM, AI is defined as:

'the capability of a computer program to perform tasks or reasoning processes that we usually associate to intelligence in a human being. Often it has to do with the ability to make a good decision even when there is uncertainty or vagueness, or too much information to handle' (Rossi, 2016: 1).

In order to address this inherent ambiguity surrounding the concept of AI and lay the foundations of an operational definition, Samoili *et al.* (2020) conducted a review of definitions from 55 highly relevant documents, covering AI policy and institutional reports, research publications and market reports that were published between 1955 and 2019. Drawing on these studies, the authors identified four features frequently attributed to AI. These are: (i) perception of the environment and real-world complexity; (ii) information processing: collecting and interpreting inputs; (iii) decision making, including reasoning, learning and taking actions; and iv) achievement of pre-defined goals (Samoili *et al.*, 2020: 4). Although the authors did not directly propose an operational definition for AI, in their research they highlighted the definition proposed by the European Commission's High-Level

Expert Group on Artificial Intelligence as a point of departure in developing one. According to this definition AI systems refer to:

> *'software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions.'* (AI HLEG, 2019a: 6).

Although AI lacks an official, standard definition, according to the prevailing consensus, current AI applications are 'narrow' systems. Commonly known as 'narrow AI', 'applied AI' or 'weak AI', these applications can compete with or even surpass human intelligence in the areas they were designed for, be it chess games, speech or image recognition. However, having been programmed to perform precisely specified tasks in one domain, these systems are neither capable of transferring their skills out of their natural habitat, nor can they genuinely learn some human skills such as emotional intelligence (Brynjolffson and McAfee, 2017, Dickson, 2017b, Miailhe and Hode, 2017, Pettersen, 2019, Zysman and Nitzberg, 2020).

In order for current AI systems to overcome these challenges, they would need to be equipped with 'general AI', also known as 'strong AI' or 'human-level AI', which refers to the level of intelligence exhibited by humans in understanding, reasoning and acting in a diverse range of domains (Dickson, 2017b). At this imaginary level of AI, machines would be able to transfer their learning experience from one domain to another without any human interference, learn and remember associations between unrelated items, understand complex situations and come up with well-thought-out, creative and effective decisions (OECD, 2019a).

What is more, achieving general AI is seen as the path towards creating super-intelligent machines surpassing humans in every cognitive and physical function. This is because autonomous machines would likely be working on their own progress once they possess human-level intelligence (Chalmers, Bostrom, 2014). Such self-evolution, according to many observers, would ultimately threaten the existence of humanity (Joy, 2000, Bostrom, 2014, Smith, 2015, Russell and Norvig, 2020, Turchin and Denkenberger, 2020). Nevertheless, despite the potentially catastrophic risks superintelligence poses to human existence, in the view of most experts, humanity is still far from designing machines demonstrating human-level intelligence (Brynjolffson and McAfee, 2017, Dickson, 2017b, Craglia *et al.*, 2018).

2.2. The subfields of AI

AI is an umbrella term including a wide array of techniques rooted in engineering and science, such as expert systems, robotics, and machine learning. Expert systems model the way human experts make decisions in complex situations, by making use of large bodies of accessible expert knowledge. These systems work on if-then rules and have been successfully in use since the 1980s, for instance in mineral and oil exploration, chemical and biological synthesis and medical diagnosis (Hunt, 1986). Robotics, on the other hand, is not entirely an AI field. However current progress achieved in robotics has much to do with AI, be it in self-driving cars or humanoid robots, as these machines successfully combine motor functions with state-of-the-art cognitive capabilities. This way, they become capable of handling intricate, dynamic, and unpredictable aspects of the physical environment (Dickson, 2017b, Miailhe and Hode, 2017, AI HLEG, 2019a).

Machine Learning (ML) is currently the most widely utilised AI technique, enabling computer systems to learn from data, to solve problems that cannot be precisely quantified and to improve performance on the task for which the machine was designed (Dickson, 2017a, AI HLEG, 2019a). ML draws on computational statistical inference, utilises large datasets, and produces successful outcomes in well-defined, narrow problem areas (Eldred, 2019, Zysman and Nitzberg, 2020). ML has different approaches, the most widely used being supervised learning, unsupervised learning, deep learning, and reinforcement learning.

In supervised machine learning, the computer is provided with examples of correct answers to a particular problem. For instance, if the problem to be solved is correctly identifying animals from photographs, the machine is fed with thousands, sometimes millions of photographs of accurately labelled animals. After a period of training, the system is expected to correctly identify animals in new and untagged photographs that were not present in the training data (Brynjolffson and McAfee, 2017, Zande *et al.*, 2020).

Unsupervised learning systems, on the other hand, are designed to learn from unlabelled data with no or very little human involvement. In doing so, the computer is expected to make inferences and find patterns previously unknown to humans (Brynjolffson and McAfee, 2017, Dickson, 2017a, Zande *et al.*, 2020). A common example of unsupervised learning is data clustering, which is used extensively in market research to target suitable customer groups for a product or a service in accordance with their age, education, income level etc.

Deep learning (DL) also known as 'deep artificial neural networks', is built from artificial neural networks simulating the configuration and functionality of the human brain. A DL system processes data by passing it through its several layers of neural networks, sometimes more than once, each time producing different layers of information for the final output (Dickson, 2017a, AI HLEG, 2019a). According to the experts, DL algorithms make better use of large data sets, for they continually improve as the data grows bigger. This feature gives them an advantage over older learning algorithms such as supervised and unsupervised learning, as these systems get better with additional data only up to a point, after which growing datasets do not lead to more accurate predictions (Brynjolffson and McAfee, 2017, Dickson, 2017a). DL has a wide array of commercial applications such as voice recognition, language translation and image labelling.

Reinforcement learning (RL) is another ML tool, designed to learn from experience. In this approach, the programmers describe the situation, goal to be achieved, permissible actions and restraints. The system is then allowed to freely experiment with various combinations of permissible actions to reach the goal. The RL algorithm receives a positive reward signal when it reaches its goal, and a negative signal when it fails. The system aims to maximise the positive rewards by following the provided rules (Brynjolffson and McAfee, 2017, Dickson, 2017a). RL is embedded in complex computer games as well as in a variety of applications, such as self-driving vehicles, drones, stock market trading tools, and defence technologies (Craglia *et al.*, 2018).

Currently ML systems outperform humans in their speed and scale in pattern recognition, be it in lipreading (Hodson, 2016), diagnosing rare diseases (Schaefer *et al.*, 2020) or strategy games (Brynjolfsson and Mitchell, 2017). However, at least as of now, ML algorithms do not outmatch humans in every single area, for according to observers, they suffer from two important shortcomings. The first is ML's limitations with respect to its native environment. That is, ML is a form of statistical inference, thus, its outputs will make little sense, if any, when the ML algorithm is asked to work with data that have little or no resemblance to its training data (Eldred, 2019, Zysman and Nitzberg, 2020). According to Eldred (2019), this restrains ML's use to non-dynamic, narrow problem domains, where the environment for analysis is strictly defined and stable.

Nonetheless, even when similar datasets are available, ML algorithms may fail to meet their accuracy target. This leads to ML's second limitation: lack of flexibility. According to observers, most AI solutions and/or AI expertise are unique to a specific sector or an operation in a work environment and extrapolating these across a wider ecosystem is beset with difficulties (Couzin-Frankel, 2019, Eldred, 2019, Szabo, 2019, Heavenarchive, 2020, Neff *et al.*, 2020). For instance, in identifying signs of diabetic retinopathy from an eye scan, Google's Health AI scanner achieved a 90 percent accuracy rate in the lab environment and generally produced results in under 10 minutes. Nevertheless, it failed to fulfil its promise in real-world settings, especially when the internet speed was slow, and the images were of lower quality than the training data (Heavenarchive, 2020). In another instance, a successful AI system developed in one hospital to predict patients' risk of pneumonia failed to make accurate predictions when it was fed with the scans from another hospital. A careful inspection revealed that, when used in a different hospital, instead of scanning patterns for disease, the AI system learned to distinguish between the hospitals' method of X-ray production (Szabo, 2019).

In short, it would be safe to argue that ML systems have still a long way to go, as currently they are 'unable to draw common-sense conclusions based on modelling physics, causality, or human norms and preferences' (Zysman and Nitzberg, 2020: 6). The range of tasks AI can currently undertake is the subject of the next subsection.

2.3. Capabilities and applications of AI

AI technologies carry considerable creative potential for our societies and economies. In the view of observers such tremendous capability of AI indicates that it is a general-purpose technology, in the same way as the steam engine, electricity, and the internal combustion engine (Brynjolffson and McAfee, 2017, Brynjolfsson *et al.*, 2017, Agrawal *et al.*, 2019, Frey, 2019a, Goldfarb *et al.*, 2019, Alekseeva *et al.*, 2020). According to Bresnahan and Trajtenberg (1995: 84), general purpose technologies (hereafter GPTs) are 'characterised by the potential for pervasive use in a wide range of sectors and by their technological dynamism'. Thus, GPTs are not final products. Rather, they facilitate surges of economic possibilities and innovations, and in this way significantly contribute to economic growth (Bresnahan and Trajtenberg, 1995, Brynjolffson and McAfee, 2017, Goldfarb *et al.*, 2019). GPTs also have a significant impact on labour markets, as they restructure companies' decision-making process (Goldfarb *et al.*, 2019, OECD, 2019a), including in relation to the number and skill-levels of workers to be used in production processes (Acemoglu and Restrepo, 2018a, Craglia *et al.*, 2018, Frey, 2019a).

AI, being a GPT, therefore inspires and opens up possibilities for further technical progress. In particularly, it accelerates innovation by equipping people with a series of 'innovational complementarities' (see Bresnahan and Trajtenberg, 1995) that include but are not limited to AI-powered vision systems, speech recognition technologies, image sensors and intelligent robots (Brynjolffson and McAfee, 2017). All these advancements augment the capabilities of humans for constant innovations, providing humanity with the prospect of further cutting-edge technologies. In doing so, AI as a GPT spreads its effects in a wide variety of sectors, with the potential to gradually transform economies and societies (Trajtenberg, 2018, Frey, 2019a).

Currently AI as a GPT has permeated into a broad spectrum of sectors, displaying a set of skills that were previously thought to be acquired and utilised only by humans. For instance, AI-powered algorithms specialised in prediction, perception and matching skills assist an increasing number of companies in monitoring and managing their employees (Ajunwa *et al.*, 2017, De Stefano, 2018, Aloisi and Gramano, 2019, Moore, 2019a). AI-supported chatbots with perception skills take our orders, help us track them, and register our complaints (Ganz *et al.*, 2019, Zande *et al.*, 2020). Robots equipped with matching, perceptive and cognitive AI technologies autonomously map out the best route in between different parts of warehouses and sort, pick, weigh, shelve, and, transfer items without human intervention (LogisticsIQ, 2019). Expert opinion ascertains that, amongst the skills displayed by AI technologies, the most commercialised are matching, prediction, perception, and cognition.

AI applications demonstrating matching skills are commonly used to pair supply and demand in competitive markets where varied products and services are offered to a large number of buyers. In recent years, AI-powered matching services have become popular thanks to platforms such as Uber and Lyft for transportation, Amazon and eBay for retail, Airbnb and booking.com for accommodation and hotel services, and LinkedIn and Indeed for professional networking and career development. The matching services provided by AI technologies are thought to have a distinct advantage over those offered by humans, for machines utilised in these tasks have proved to be much faster and more cost-efficient for buyers, sellers and users (Ernst *et al.*, 2018). AI prediction skills, on the other hand, are widely utilised to complete missing information in decision tasks requiring high levels of certainty. Observers point out that AI-based prediction systems outperform human prediction. as they are capable of providing faster, less expensive and more precise forecasts in a wide range of areas, be it credit applications, bail decisions, surgical operations, medical treatments or language translation (Agrawal *et al.*, 2019, OECD, 2019a).

Some AI-enabled machines also display a set of perception skills, mostly related to image and speech recognition. Many of us are familiar with these technologies thanks to social media applications like Facebook and Instagram, and digital voice agents like Alexa, Siri, and Cortana. Owing to recent improvements, AI-powered object detection and image classification technologies have accomplished an error rate of 2.3 percent in 2017 in the rendering these applications twice as successful as classifications made by humans (Liu, 2019). Similarly, in 2017, Microsoft's speech recognition system became able to transcribe human speech as accurately as humans, with the same 5.1 percent error rate (Price, 2017).

Last but not least, some AI technologies are designed to mimic human cognitive skills to independently recognise relationships in large amounts of data. Having attracted a great deal of public attention through applications like Google's AlphaGo for the Go game and IBM's Deep Blue for chess, AI's cognitive skills are put to use in gathering and evaluation of information (IBM *et al.*, 2020) and for complex problem-solving tasks in areas requiring human-like thinking (Brynjolffson and McAfee, 2017). Commercially, cognitive AI is utilised to detect malware and to prevent money laundering (Brynjolffson and McAfee, 2017).

2.4. History of AI

Historical accounts of AI point to the early 1940s as the years when intriguing possibilities offered by the idea of an artificial human-like mind inspired science and technology circles to discover new ways of thinking and problem solving in computational science. In this regard, two historic events are widely considered to have heralded the emergence of AI technologies. The first is the 'Turing test', devised by English mathematician Alan Turing in a seminal article in 1950. This method of inquiry aimed to determine whether a computer uses human-like thinking in completing tasks. Accordingly, if a human interacts with both a machine and a human, and cannot determine which one is the machine, the machine possesses intelligence (Turing, 1950). The Turing test still retains its relevance today and is used to evaluate artificial intelligence (Collins, 2019, Haenlein and Kaplan, 2019). The second is the 1956 Dartmouth Summer Research Project on Artificial Intelligence, where the invited scientists laid the foundations of AI. This workshop was the first gathering to use the term AI and to discuss the possibilities AI has to offer (Hunt, 1986, Moor, 2006, Haenlein and Kaplan, 2019, Mitchell, 2019). In the meeting, the participants placed a special emphasis on finding out 'how to make machines use language, form abstractions and concepts, solve kinds of problems now reserved for humans, and improve themselves' (McCarthy *et al.*, 1955: 1).

The Dartmouth workshop ushered in a two-decade 'AI spring', during which a series of remarkable achievements were made. For instance, in 1959 the 'General Problem Solver' was invented to function as an all-embracing machine to solve various kinds of problems, and in the mid-1960s 'ELIZA', the forerunner of natural language processing computer programmes, was devised. During these years, AI researchers often made bold claims about AI reaching human levels of cognitive and physical capabilities in the very near future (Brynjolffson and McAfee, 2017, Acemoglu and Restrepo, 2018a, 2019b). Indeed, for example 'within a generation' stated Marvin Minsky (1967: 2), an AI pioneer and a computer science professor, 'I am convinced, few compartments of intellect will remain outside the machine's realm'. Such heightened expectations, and a handful of successful outcomes like those mentioned above, stirred a wave of optimism among research and funding circles, leading to generous provision of financial support for the increasing number of ambitious AI projects. However, many of these projects failed to fulfil their promises, leading to disappointments regarding the advancement and forecasts of AI research. As a result, the mid-1970s marked the beginning of an 'AI winter' during which much of the funding allocated to this field of study was cut, public interest in promises of AI diminished, and AI research decelerated (Haenlein and Kaplan, 2019, Mitchell, 2019).

The decades of the 1980s and 1990s witnessed successive cycles of similar AI winters and AI springs (Mitchell, 2019). Towards the end of the 1990s, AI started to stir a renewed public enthusiasm and optimism, signalling the start of a new AI spring. This new AI season, however, has made its appearance with much humbler technologies, aiming to mirror and enhance human intelligence in prediction and pattern recognition (Acemoglu and Restrepo, 2019b). In this regard, many commentators consider the defeat of the world chess champion Garry Kasparov by IBM's Deep Blue in 1997 to be the beginning of the latest AI spring. AI technologies' comeback has continued with a series of innovations over recent years. To name a few, in 2006, Google launched its online translation tool, which, despite never having been perfect, provided the online community with a free global platform for language translation. In the 2010s, self-driving cars turned into a tangible reality. In 2016, Google's AlphaGo, a computer program using reinforcement learning, beat the 18-times world Go champion Lee Sedol: a victory marking AI's increasing capability for human-like intellect.

A review of extant literature suggests that this leap forward in AI technologies has been underpinned by exponential increases in computing power, and widespread usage of the internet (Craglia *et al.*, 2018, EPSC, 2018, Ernst *et al.*, 2018). These advances in digital technologies, as observers point out, led to two important and related developments. First, they consistently expanded digital storage capacity, which in turn facilitated creation and storage of massive amounts of digital data (Craglia *et al.*, 2018, Ernst *et al.*, 2018, OECD, 2019a). Second, the availability of ever-increasing digital data created a favourable environment for ML to discover previously unrevealed patterns from data and draw insights from them (Bughin *et al.*, 2017, Craglia *et al.*, 2018, Frey, 2019a). These developments in the digital field subsequently augmented the cognitive capabilities of computers to the point of matching and even outperforming those of humans in some skills, opening up exciting possibilities for further innovation in AI tools and methods (Ernst *et al.*, 2018, Furman and Seamans, 2018, Nowak *et al.*, 2018). With their capability to simulate some core human competencies, AI technologies hold potential to cause serious repercussions for the world of work. This is the subject of the next section.

3. AI in labour markets: Workers, machines, and the future of work

Observers insist that AI technologies are likely to have a different and more deep-seated impact on the labour force and labour markets compared to previous waves of digitalisation (Makridakis, 2017, Blit *et al.*, 2018, Craglia *et al.*, 2018, Frey, 2019a). Nevertheless, in reflecting on AI's repercussions for working life, one should also acknowledge that real life may not always unfold in a way that mirrors theory. Indeed, although in theory AI-driven technologies differ from other digital automation technologies, in practice the boundaries between these two are considered to be highly blurred, making it difficult to differentiate their particular effects on labour markets (Servoz, 2019). Bearing this in mind, the following subsections aim to provide an overview of the impacts of AI on the labour markets of advanced economies, as reflected in the recent literature.

3.1. AI in labour markets: An unknown terrain

Expert opinion asserts that AI technologies can automate an increasing number of tasks and jobs which it was previously thought could be performed only by human labour (Brynjolfsson and Mitchell, 2017, Blit *et al.*, 2018, Ernst *et al.*, 2018, Frank *et al.*, 2019). Despite this widespread consensus, the extent to which jobs and tasks could be automated has ignited an ongoing controversy in the extant literature. Spearheading such scholarly disagreement has been the Frey and Osborne (2013) (hereafter, FO) study. The authors claimed that, except for occupations requiring use of 'creative intelligence', 'social intelligence' and 'perception and manipulation tasks', which they termed 'three engineering bottlenecks', automation of almost any job is technologically achievable, as long as adequate data are collected for pattern recognition. Using data on 702 occupations from the 2010 US O*NET database, FO estimated that 47 percent of total US employment faces a high risk of disappearing by 2033. Researchers have applied FO's approach to various regional and country cases in the following years and come up with comparable numbers. For example, utilising ILO data, which is based on the 2012 EU Labour Force Survey, Bowles (2014) estimated that between 45 and 60 percent of jobs in Europe are of high risk of disappearing within the next 20 years. Similarly, using the data from Classification of Occupations (KldB) from 2010, provided by the Federal Employment Agency, Brzeski and Burk (2015) found out that 59 percent of jobs in Germany are at high risk of being replaced by automation by 2033.

Such future forecasts pioneered by FO spurred a fierce debate on whether advancing technologies have the power to make human labour redundant (Autor, 2015, Arntz *et al.*, 2016a, Brynjolffson and McAfee, 2016, MGI, 2017, Nedelkoska and Quintini, 2018). A group of authors challenged FO's approach on the grounds that automation replaces tasks rather than jobs/occupations (Autor and Handel, 2013, Arntz *et al.*, 2016a, Nedelkoska and Quintini, 2018). Building on this argument and utilising OECD's 2012 PIACC database (Programme for the International Assessment of Adult Competencies), Arntz et al. (2016a) re-estimated the proportion of jobs that are at risk of automation for 21 OECD countries. The authors concluded that on average 9 percent of jobs across the 21 OECD countries are highly automatable, with the shares varying somewhat between individual countries: for instance, 6 percent in Korea, 12 percent in Germany and 9 percent in the US.

Another study with the aim of analysing the risk of job losses through automation was conducted by Nedelkoska and Quintini (2018) using the PIACC database for the years 2011/2012 and 2014/2015. The authors calculated that around 14 percent of jobs in OECD countries are highly automatable, amounting to over 66 million workers in the 32 countries covered by the study. Nedelkoska and Quintini (2018) ascertained that the actual risk of automation varies significantly across the countries, from 33 percent of all jobs in Slovakia, to 18 percent in Germany and 6 percent of jobs in Norway. In the German context, a recent study by Dengler and Matthes (2018) also confirmed that the automation potential of jobs is much lower than what was calculated by those utilising FO's methodology. Using data by the German Federal Employment Agency (BERUFNET database), they observed that 25 percent of workers were employed in an occupation with high risk of automation in 2016, with the risk being highest in the transport and logistics professions.

So far, no consensus has been reached in the academic debate on the extent of human labour likely to be replaced by AI technologies in the near future. However, this ongoing discussion seemed to have contributed to the general scholarly agreement that the available literature is currently incapable of providing a satisfactory understanding of how AI technologies influence labour markets (Acemoglu and Restrepo, 2018a, Craglia *et al.*, 2018, Ernst *et al.*, 2018, Agrawal *et al.*, 2019, Muro *et al.*, 2019b, Servoz, 2019). Underlying this shortcoming, in the first place, is the fact that AI applications have not yet been adopted and understood by business on a large scale (Bughin *et al.*, 2017, Ransbotham *et al.*, 2019), thus, 'it is mostly too soon to see the impact of AI on labour markets' (Acemoglu *et al.*, 2020: 21). Indeed, notwithstanding the ongoing public and scholarly interest on AI, recent research findings indicate that on a global scale, only 19 percent of organisations are classified as AI 'pioneers'. These companies have complete understanding of AI in that they are aware of the costs of developing AI-based products, and the data required to train AI algorithms. They have also incorporated AI into both their services and products and their internal processes. Globally, 32 percent of organisations fall into the 'investigators' category, as they display understanding of AI and are at a pilot stage of AI utilisation. The rest are either 'experimenters'(13 percent), adopting or piloting AI without deep understanding, or 'passives' (36 percent) with no AI adoption and little understanding of the technology (Ransbotham *et al.*, 2019).

Second, even in the companies where AI is adopted, these technologies are nascent, thus their labour market impacts fall short of generating systematic evidence for conclusions (Ernst *et al.*, 2018, Agrawal *et al.*, 2019, Felten *et al.*, 2019, Frank *et al.*, 2019). Indeed, as was pointed out by Muro *et al.* (2019b) because AI technologies have not yet diffused widely, studies aiming to find out how AI automation is affecting labour markets have to utilise either case studies or subjective assessments by experts (see e.g. Frey and Osborne, 2013, Arntz *et al.*, 2016a, Daheim and Wintermann, 2016, Ransbotham *et al.*, 2017, Ransbotham *et al.*, 2019). Findings from such studies, as expert opinion maintains, blur the boundaries between AI- and other digital technologies, rendering it more challenging to measure the particular labour market effects of AI (Felten *et al.*, 2019, Frank *et al.*, 2019, Muro *et al.*, 2019b).

Third, it is reported that many AI initiatives yield disappointing outcomes for business (Ransbotham *et al.*, 2019, Szabo, 2019, Heavenarchive, 2020) implying that AI's impact on work and workplace might be insignificant in many cases. Indeed, according to a recent global survey, seven out of 10 establishments reported negligible or no impact from AI so far, and 40 percent of companies significantly investing in AI did not reap any business gain from these investments (Ransbotham *et al.*, 2019).

Notwithstanding the shortcomings of the literature in drawing a clear picture of AI-driven future labour markets, the available research provides us with some useful clues to understand the contours of the ongoing transformation in the world of work, which will be outlined below.

3.2. AI and the future of work: Tasks, jobs, wages, and skills reimagined

Across the extant literature, AI applications are commonly depicted as smart machines designed to imitate the ways humans learn, think, and adapt. Thanks to these capabilities, machines can now recognise images, understand speech, acquire knowledge, and inform high-stakes decisions. In turn, machines' acquisition of skills that were previously thought to be possessed and utilised only by humans spurs more technological dynamism and innovation, gradually removing the limits of what machines can automate. It is against this backdrop of technological breakthroughs that a series of profound shifts are expected to take place in the world of work, along the lines of tasks, jobs, wages, working conditions and skills.

3.2.1. AI and automation of tasks

Many researchers share the view that, in the labour markets of the future, AI will replace a much larger number of workers compared to previous digital technologies. This is underpinned by the argument that (pre-AI) digital automation is routine-biased, replacing routine tasks that follow a well-defined practice which can be codified and performed automatically based on algorithms (Autor *et al.*, 2003, Autor and Price, 2013, Arntz *et al.*, 2016a, Nedelkoska and Quintini, 2018). According to this argument, owing to the routine-biased nature of digital automation technologies, it has predominantly been the mid-skilled, mid-income workers performing routine mental and physical tasks (such as those related to bookkeeping, clerical work, and assembly line production) who faced a higher risk of losing their jobs to machines. Consequently, in economies where such labour-displacing technologies have been in use, a large number of tasks in the higher and lower end of the wage and skill distribution (such as those related to engineering, design, science or law and to catering, cleaning or security services respectively) have remained out of the technology's reach and continued to be predominantly carried out by humans (Autor *et al.*, 2003, Spitz-Oener, 2006, Goos *et al.*, 2014, Eurofound, 2016).

In contrast, expert opinion asserts that AI technologies are designed to be skill-biased, meaning they demonstrate human skills such as matching, prediction, perception, and cognition, which were, only recently, widely thought to be non-automatable (Manyika *et al.*, 2017, Ernst *et al.*, 2018, Bode *et al.*, 2019, Zysman *et al.*, 2019). In this way, AI-powered applications become capable of displacing labour in a much wider set of jobs and tasks, across most of the skill and wage spectrum, in such a way as to make workers' bodies as well as their brains obsolete (Makridakis, 2017, Manyika *et al.*, 2017, Blit *et al.*, 2018, Moore, 2019b). However, in saying so, it should be noted that there seems to be no consensus amongst observers as to whether the workers in lower-paid, lower-skilled (Ford, 2013, Manyika *et al.*, 2017, Hawksworth *et al.*, 2018, Frey, 2019a), or mid-paid, mid-skilled (De Stefano, 2018, Hawksworth *et al.*, 2018, Agrawal *et al.*, 2019) or high-paid, high-skilled (Ford, 2013, Manyika *et al.*, 2017, Brynjolfsson *et al.*, 2018, Ernst *et al.*, 2018, Fossen and Sorgner, 2019, Frank *et al.*, 2019, Haenlein and Kaplan, 2019, Muro *et al.*, 2019b, Webb, 2020) jobs will be most affected by AI-led automation.

This lack of scholarly consensus appears to mostly stem from variation in the methodologies employed by the authors. Indeed, each study comes with a scholarly preference as to the type of technological innovations and technical capabilities to be considered, directing researchers' focus either towards machine learning or towards a wider set of technological developments, including AI, robotics and various other digital automation technologies (Lane and Saint-Martin, 2021). Thus, according to Lane and Saint-Martin (2021) the body of research exclusively focusing on the technical competences of ML could miss the labour market implications of older AI applications, especially in the cases where previous automation technologies are updated to include AI or where they are completely replaced by AI, rendering their deployment more practical and/or cheaper (Lane and Saint-Martin, 2021: 24). 'To the extent that AI could make older automation technologies more attractive' says Lane and Saint-Martin (2021: 24), 'the impact of AI along skill lines could be more similar to previous waves of automation'.

Commentators maintain that, at the lower end of the wage/skill spectrum, AI-led technologies are more likely to reduce demand for physical and manual skills used in highly organised and predictable surroundings. These skills are commonly sought in construction, extraction, repair, maintenance, transportation, production, sewage and waste management, agriculture, retail, storage, and food preparation jobs (Ford, 2013, Manyika *et al.*, 2017, Hawksworth *et al.*, 2018, Muro *et al.*, 2019a). In the middle of the wage/skill distribution, AI-powered technologies are likely to threaten workers employed for their matching, prediction, perception, and cognition skills that are related to information collection and processing tasks (Manyika *et al.*, 2017, Muro *et al.*, 2019a). These tasks are traditionally bundled within office-administration jobs, including middle-managerial roles (De Stefano, 2018, Agrawal *et al.*, 2019), human resources (De Stefano, 2018, Agrawal *et al.*, 2019, Ganz *et al.*, 2019) customer services (Algorithm Watch, 2019, Ganz *et al.*, 2019, Moore, 2019b) and personal assistance (Pat Research, 2020).

In the high-skill/high-wage category, on the other hand, AI-based technologies are more likely to replace experts whose main task is information processing to inform high-stakes decisions. In fact, according to Webb (2020) those with university and master's degrees will be the workers most exposed to the labour-replacing impact of AI. Amongst these, the most commonly mentioned are lawyers and paralegals examining documents for court cases (Ford, 2013, Korinek and Stiglitz, 2017, Haenlein and Kaplan, 2019); medical doctors performing diagnostics tasks (Frey, 2019a, Haenlein and Kaplan, 2019); finance professionals forecasting stock exchange variations (Korinek and Stiglitz, 2017, Frank *et al.*, 2019, OECD, 2019a); market research analysts preparing reports and recommendations by drawing data from various sources (Muro *et al.*, 2019b); and clinical laboratory technicians, chemical engineers, optometrists and power plant operators performing tasks related to identifying patterns, making decisions, and optimisation (Webb, 2020).

Although AI technologies have an impact on a wider set of jobs and tasks across most of the skill and wage distribution, it appears that the occupations/jobs in the sectors which are the pioneers of AI deployment are more at risk of automation. According to the existing research, these sectors are: finance, insurance, professional and technical services (Hawksworth *et al.*, 2018, Muro *et al.*, 2019b); travel, transport and logistics (PEW, 2014, McKinsey&Company, 2019); high-tech, automotive and assembly, telecom, consumer packaged goods, retail (McKinsey&Company, 2019); and agriculture, natural resource extraction and manufacturing (Muro *et al.*, 2019b).

AI technologies' replacement of labour in an ever-growing number of tasks across various industries is also expected to render some jobs out of human reach. This is because smart machines are likely to perform some tasks, such as delivery, checkout operation, and driving, at much cheaper costs compared to human labour (Brougham and Haar, 2017, Blit *et al.*, 2018). Moreover, AI may also have disruptive effects on a set of jobs that are not directly at risk of AI automation. For instance, with the introduction of driverless cars on public roads, the need for driving instructors and licence testing officers could significantly decrease (Brougham and Haar, 2017).

3.2.2. The new structure of jobs

Backward-looking calculations suggest that AI deployment has so far generated modest overall effects on employment levels (McKinsey&Company, 2019, Acemoglu *et al.*, 2020). Looking forward, although the scholarly consensus holds that an increasing number of jobs and occupations are likely to be exposed to AI-based automation in the future, various economic, social, and political issues create obstacles in the everyday use of new technologies. For instance, according to Acemoglu and Restrepo (2018b), despite the theoretical possibility that all tasks can be automated, in real life, tasks are automated when their allocation to machines generates more profit. What is more, according to the authors, by bringing down the cost of labour in the tasks that are easy to perform, automation restrains its own speed of diffusion, as this way it 'generat[es] a self-correcting force toward stability' (Acemoglu and Restrepo, 2018b: 1526). Another economic issue appears to be the additional investment expenses, as, according to Brynjolfsson *et al.* (2019), the adoption of new technologies requires organisational restructuring, new skills, and new employees, all of which incur extra costs for companies.

When it comes to social and political issues, for example, minimum wage mechanisms, collective bargaining, and other wage-setting institutions, as highlighted by Arntz *et al.* (2019), play an important role in companies' decisions to automate tasks, for these might exert a noticeable impact on labour costs. Furthermore, the utilisation of some new technologies, as in the case of driverless cars, requires the consideration of various ethical and legal dilemmas that are yet to be resolved (Bonnefon et al., 2016; Lee, 2017). It is also pointed out that, people might prefer human labour over machines in the performance of some tasks, even if they are fully automatable, as in the cases of music production or artisan baking (Pratt, 2015).

Against this background, according to many observers, the risk of AI-enabled automation does not necessarily bring the end of the world of work. Rather, higher AI exposure rates imply that in the future, many jobs and occupations will be reshaped in such a way as to re-allocate skills and tasks between humans and machines. On the skills front, AI is likely to trigger a change in the skills composition of jobs, where humans are allocated to the tasks that are uniquely human and difficult to automate (Brown *et al.*, 2018, Muro *et al.*, 2019a, Servoz, 2019). Among others, these skills include empathy, social intelligence, social interaction, imagination, creativity, judgment, critical thinking, coaching, planning, communication and complex problem-solving (PEW, 2014, Brown *et al.*, 2018, Shook and Knickrehm, 2018, WEF, 2018a, Servoz, 2019).

A review of available resources suggests that these difficult-to-automate human skills are concentrated in several tasks across the wage/skill spectrum. For instance, in the lower and middle parts of the skill distribution, tasks which take place in unpredictable physical environments and/or require social interaction skills, such as child and elderly care, cleaning, gardening, plumbing, building maintenance (Muro *et al.*, 2019a, Servoz, 2019), teaching, training, social and community services and healthcare (Muro *et al.*, 2019a), are seen as more likely to be allocated to humans. Across the high-skill/high-wage spectrum, the least AI-exposed tasks are thought to be those involving skills such as critical thinking, coaching, planning, complex problem-solving, and social interaction (Brynjolffson and McAfee, 2017, Muro *et al.*, 2019a, Servoz, 2019) in a variety of fields such as business and finance, engineering, management, law, science and technology, education, arts, media and entertainment (Muro *et al.*, 2019a). As Brynjolffson and McAfee (2017: 18) point out, '[t]hat means entrepreneurs, innovators, scientists, creators, and other kinds of people who figure out what problem or opportunity to tackle next, or what new territory to explore, will continue to be essential'.

When it comes to the task composition of jobs, it appears that humanity is 'heading toward a future where work is different, rather than an evolution of what we have today' (Evans-Greenwood *et al.*, 2017: 131). Accordingly, jobs will be redesigned by re-bundling automated and non-automated tasks, to place the workers 'in this assemblage of humans and non-humans' (Del Castillo, 2018: 4). With AI taking over an increasing number of repetitive and dangerous tasks, workers are more likely to take on tasks related to supervising and troubleshooting AI systems (Manyika, 2018). For instance, it is reported that radiologists using AI-embedded reading systems already have more time to focus on diagnosis of diseases and actions to take, as machines can perform the task of highlighting abnormal patterns on scans with high accuracy rates (Agrawal *et al.*, 2019). Against this background of increasing human-machine partnership at work, experts believe AI's impact will be more visible in the task composition of jobs rather than the number of jobs/tasks created or eliminated by the smart machines (Brynjolfsson *et al.*, 2018, Manyika, 2018, Shook and Knickrehm, 2018).

However, this re-allocation of skills and tasks between humans and machines is likely to pose challenges to some workers. Indeed, on the one hand, as indicated by Ernst *et al.* (2018), many AI-powered systems are designed to provide specialist skills/knowledge to non-experts. For instance, generative design software can design lighter aircrafts, stronger buildings, or more comfortable shoes without human intervention (Howarth, 2017). Ridesharing services provide dedicated GPS systems for drivers, helping them to navigate their ways in intricate city streets without prior knowledge (Agrawal *et al.*, 2019). Expert system applications in agriculture help farmers to choose and plant the seed that is most appropriate for their land and the time of year (Ernst *et al.*, 2018). All these, according to Ernst *et al.* (2018), enhance the productivity of lower-skilled workers while reducing the demand for those in the middle and higher skill-wage spectrum.

Observers also point out the new division of labour between AI-based systems and workers seen in some cases, where the machines perform complex tasks involving comprehensive thinking and learning, while the workers are relegated to mundane tasks and/or carry out machine-generated directives. For example, on-the-spot training devices provide live coaching to unskilled workers in variety of environments, largely eliminating these workers' chances of specialising on specific tasks (Moore, 2019b). Similarly, with their competence to recognise faces and licence plates, analyse social media to identify threats, and carry out security surveillance, AI-powered systems threaten policing, by taking over the core skills associated with this occupation (Joh, 2019). As a result, as various human skills and tasks are rendered mechanical by AI technology, some workers are thought to be deprived of the chance to use their capabilities, as well as their possibilities of upgrading their skillsets (Jarrahi, 2019, Joh, 2019, Moore, 2019b).

Human-machine cooperation appears to present further challenges in work environments where humans collaborate with AI-powered robots. Widely known as 'cobots', these smart machines are designed to ease the work process and enhance workers' capabilities. They facilitate integration of advantages of robots, such as strength and precision, with those of humans, including flexibility and creative thinking (Daugherty and Wilson, 2018a, Villani *et al.*, 2018). However, research evidence shows that cobots raise safety, trust and stress issues (Jansen *et al.*, 2018, Villani *et al.*, 2018) that are yet to be dealt with. Furthermore, those coworking with robots appear to find themselves in a work environment where they constantly need to acquire new qualifications, and technical and organisational capabilities. As pointed out by Moniz and Krings (2016), this constant need for change occurs mostly because system integrators and robot manufacturers rarely consider the social impact of new technologies on working environments. Perhaps such an awareness on the part of system designers and producers might provide a partial solution to the human-robot interaction puzzle, for, as was aptly put by Sheridan (2016: 531), '[w]hereas the human race is changing very slowly, computers and robots are evolving at a very rapid pace'.

3.2.3. Socio-economic inequalities in labour markets with high AI penetration

Even before the introduction of AI technologies, inequalities were already widespread in the labour markets of advanced economies (ILO, 2008, UN, 2013, Dustmann *et al.*, 2014). Scholarly opinion maintains that AI-induced re-allocation of tasks and skills between man and machine is likely to exacerbate socioeconomic inequalities, primarily along the lines of wages and working conditions.

According to one strand of the literature, wages of workers competing against machines are likely to decrease (Korinek and Stiglitz, 2017, Makridakis, 2017, Acemoglu and Restrepo, 2018a, 2019b). At the heart of this bleak forecast lies the scholarly observation that, across the advanced economies, productivity growth has been rather slow over the past decade compared to previous decades, despite their increasing adoption of automation technologies (Brynjolfsson *et al.*, 2017, Evans-Greenwood *et al.*, 2017, Furman and Seamans, 2018, Manyika, 2018, Acemoglu and Restrepo, 2019b, Frey, 2019a, Servoz, 2019). According to Acemoglu and Restrepo (2018a, 2019b) an important factor contributing to this stagnation in productivity gains is the ‘so-so’ nature of current AI technologies. That is, these technologies replace workers without creating a noticeable improvement in productivity, and thus they fail in generating new jobs/tasks. For instance, robotic process automation used in call centres, automated chat programs integrated in online customer support services, and self-checkout kiosks at supermarkets often do not enhance service quality and productivity (MIT, 2019). On the contrary, these automation technologies are often publicly criticised for confusing and frustrating costumers (Gagliordi, 2013, Mumbrella, 2016, Elliott, 2018). Despite their downsides, however, as observed by Acemoglu and Restrepo (2019b), so-so technologies are just good enough for employers to replace human labour. This squeezes workers into a continuously decreasing set of tasks, creating a downward pressure on wages.

In contrast to this wage drop predicted for workers at risk of being replaced by smart machines, AI literature suggests that there is already a sizeable wage premium for those working with machines. More specifically, workers who design and engineer AI systems and those whose labour is augmented by AI (Felten *et al.*, 2019), as well as those in charge of steering their companies towards productive deployment of AI (Alekseeva *et al.*, 2020), have already started to experience a marked increase in their wages. For instance Alekseeva *et al.* (2020) calculated that wage offers increase by 51 percent in job postings where both AI skills and other comparable skills are required. On the other hand, by linking specific applications of AI to different occupation-level abilities, Felten *et al.* (2019) devised a new measure which they labelled as ‘AI Occupational Impact’ (AIOI). The authors found out that while an increase of one standard deviation in the AIOI is associated with a 0.41 percentage point increase in wage growth, the same deviation is associated with a 0.61 percentage point increase in wage growth among occupations requiring high level of familiarity with AI software.

Besides the worsening wage gap, labour markets with high AI penetration are also likely to aggravate existing inequalities in working conditions. Indeed, as expert opinion asserts, many workers who will lose their jobs to smart machines will have to accept jobs located on the lower end of the wage/skill spectrum (Crawford *et al.*, 2019, OECD, 2019b). As it is widely reported, lower-skilled and lower-paying jobs often come with poor working conditions, job insecurity, and excessive or inadequate working hours. What is more, workers in these jobs often experience difficulties in accessing occupational training to gain new skills and/or upgrade their skillsets (Bassanini and Ok, 2004, Albert *et al.*, 2010), and they have too little, if any, bargaining power to improve their working conditions (Evans and Gibb, 2009, ILO, 2016, OECD, 2019b).

In contrast, high-skilled workers have greater access to skill upgrading opportunities (Lane and Saint-Martin, 2021), and more individual bargaining power in negotiating their wages and working conditions (Servoz, 2019). Furthermore, according to Fossen and Sorgner (2019), if faced with a risk of losing their jobs, this group of workers has more possibilities to change their occupation or become an entrepreneur compared to lower-skilled workers. However, a careful look at the literature also suggests that even those working in occupations with higher skill requirements are not totally safe from losing their jobs to smart machines. Underlying this is the rapid progression of AI-led technologies, demanding an equally swift response from workers regarding their skillsets (Brown *et al.*, 2018, Furman and Seamans, 2018, Frey, 2019a).

A review of extant literature reveals that these rising inequalities in labour markets where AI is heavily used are likely to create winners and losers. Winners are thought to be the already privileged young male workforce with AI skills. According to a 2018 report prepared by the World Economic Forum in cooperation with LinkedIn, globally around 78 percent of AI jobs are held by men. What is more, the report suggests that AI-related senior roles are more likely to be filled by men, and men are more likely to gain expertise in a number of high-profile and emerging AI skills (WEF, 2018b). The losers, on the other hand, are predicted to be the already vulnerable groups (Muro *et al.*, 2019b) who represent a larger proportion of the workforce in lower-wage, lower-skilled jobs that are under high risk of automation. The available research suggests that these are women (WEF, 2018b, OECD, 2019b), young (PwC, 2017b, OECD, 2019b) and older workers (Basu *et al.*, 2018) as well as those without tertiary degrees (Green, 2019, OECD, 2019b) and certain racial and ethnic groups (Lund *et al.*, 2019, Muro *et al.*, 2019a) such as Hispanic, American Indian, and black workers in the U.S. (Muro *et al.*, 2019a).

3.2.4. The new opportunities in the labour market

AI-driven labour market transformation is expected to create some favourable opportunities for certain workers. At the core of this lies the augmentation of some workers' capabilities using AI-powered technologies, in such a way as to add more value to the tasks performed by human labour. Indeed, a good number of commentators insist that smart machines often complement human labour rather than totally replacing it (Brynjolffson and McAfee, 2017, Evans-Greenwood *et al.*, 2017, Ransbotham *et al.*, 2017, EPSC, 2018, Agrawal *et al.*, 2019, Fossen and Sorgner, 2019, Jarrahi, 2019, Servoz, 2019). For instance, a pen-like AI-powered camera used in brain surgeries has the capacity to improve the predictions of brain surgeons as to which particular areas of the brain needs to be removed, with more than 90 percent accuracy (Agrawal *et al.*, 2019). Wearable AI-powered mobile machines, also known as 'passive exoskeletons', are increasingly adopted by auto manufacturers to reduce worker injuries, as well as human errors associated with worker fatigue (Marinov, 2019). Personal Interactive Assistants help customer advisors to more quickly and easily resolve issues with customers contacting the company (IBM *et al.*, 2020) As a result, observers agree that when AI is used to augment human labour, the collaborative outcome achieved becomes particularly valuable for humans (Brynjolffson and McAfee, 2017, Evans-Greenwood *et al.*, 2017, Agrawal *et al.*, 2019) as this way workers can specialise in more complicated and/or pleasant tasks (OECD, 2019a, Servoz, 2019) leaving repetitive, mundane and dangerous tasks to machines.

AI-led technologies are also widely expected to increase demand for a set of existing jobs and tasks (Makridakis, 2017, Manyika, 2018, Agrawal *et al.*, 2019, OECD, 2019a, Servoz, 2019). For instance, those related to ICT, marketing, product design, engineering, science, data analysis, education, healthcare (Servoz, 2019) childcare, and personal care (Makridakis, 2017) are forecast to be in high demand, thanks to the decreasing price of automated tasks boosting the economy (Acemoglu and Restrepo, 2019a). In fact, Gartner (2017) estimated that by the year 2025, AI-related job creation will reach up to two million net-new jobs, divided between high-skilled and low-skilled jobs.

Besides AI's positive impact on the future demand for some jobs and tasks, experts point to a remarkable current upsurge in the demand for AI skills (Makridakis, 2017, Del Castillo, 2018, OECD, 2019a, Alekseeva *et al.*, 2020). 'AI skills', otherwise known as 'AI literacy', involve general knowledge of computers, high familiarity with particular software and hardware, ability to interpret and manipulate data, high levels of logical and computational reasoning, and aptitude for recognising and resolving AI-related complications (Del Castillo, 2018). According to Alekseeva *et al.* (2020), while the number of positions asking for AI skills rose ten-fold from 2010 to 2019, their share in all job postings saw a four-fold increase. Alekseeva *et al.* (2020) also point out that AI skills are most sought after in IT jobs, closely followed by architecture, engineering, life, physical and social sciences, and management.

Observers also maintain that increasing AI deployment is likely to create entirely new tasks and jobs for the labour markets of advanced economies (Stone *et al.*, 2016, Brynjolfsson and Mitchell, 2017, Acemoglu and Restrepo, 2018a, Bessen, 2018, Shook and Knickrehm, 2018, Acemoglu and Restrepo, 2019b, Agrawal *et al.*, 2019, Muro *et al.*, 2019b, OECD, 2019a, Servoz, 2019). This forecast is backed by historical evidence demonstrating that in previous waves of automation humanity witnessed the creation of new tasks requiring human labour (PEW, 2014, Brynjolfsson and Mitchell, 2017, Acemoglu and Restrepo, 2018a, Manyika, 2018). Ultimately, this boosted productivity and labour demand across the advanced capitalist states (Acemoglu and Restrepo, 2018a, 2019b). However, observers agree that it is difficult to predict straightforward examples, due to the limited diffusion of current AI technologies (Manyika, 2018, Agrawal *et al.*, 2019, Muro *et al.*, 2019b, Servoz, 2019). Despite this, one can still find examples from the extant AI literature, such as 'AI and Machine Learning Specialists', 'New Technology Specialists', 'User Experience and Human-Machine Interaction Designers', 'Training and Development Specialists' (WEF, 2018a: 9), 'Translator for human-machine & machine-human', 'Algorithm insurer', and 'Algorithmic ethics expert' (Daheim and Wintermann, 2016: 21).

A further look at the available literature suggests that most of these job titles reflect new types of human-machine relationships, in which humans and machines work as a team (Daugherty and Wilson, 2018b, EC, 2019, Saenz *et al.*, 2020). Indeed, for instance, according to Daugherty and Wilson (2018b), in the age of AI, three new categories of jobs requiring human-robot collaboration will be of paramount importance. These are: 'trainers', improving AI algorithm's performance; 'explainers', clarifying complex algorithms to non-specialists;

and 'sustainers' ensuring AI systems operate ethically and responsibly. A study by Manyika (2018) suggests that the new types of occupations that we cannot yet imagine may make up to 10 percent of jobs created by 2030. In fact, according to Servoz (2019), with the increasing deployment AI-systems at work and workplace, it is possible that there will be more jobs in Europe's future labour markets, although we do not yet know which sectors will benefit most from this positive outcome or when these jobs will enter the picture. The way the AI-led transformation in labour markets is expected to happen is scrutinised next.

3.3. Slow and painful: Transformation explained

Besides the extant literature's suggestion that labour markets where AI is heavily used are expected to undergo a remarkable transformation along the lines of tasks, jobs, skills, and wages, it also seems to have a definite answer for the question as to how this shift is likely to happen: slow and painful (Brynjolfsson *et al.*, 2017, Korinek and Stiglitz, 2017, Acemoglu and Restrepo, 2018a, Blit *et al.*, 2018, IMF, 2018, Frey, 2019b, 2019a). In substantiating this argument, observers point out to the example of the first Industrial Revolution, which began in Britain in the mid-eighteenth century. As the historical accounts portray, for more than half a century following the first automation of production processes, many workers in the then industrialising countries experienced a dramatic decline in their wages and living conditions. In contrast, those owning the capital saw a massive boost in their profits (Acemoglu and Restrepo, 2018a, Frey, 2019b, 2019a). Following Allen (2009), authors refer to this era as 'Engel's Pause': a historically short period, yet stretching over a lifetime of many individuals, in which the adjustment costs of rapid technological progress were borne by workers. This rendered their lives, in the way depicted by Thomas Hobbes (1651 [1965]: 97): 'nasty, brutish, and short'. According to these historical accounts, it was only starting from the mid-nineteenth century that the workers in industrialising Western societies began to enjoy the benefits of technological advancements in their earnings and living standards.

Scholarly literature offers three reasons as to why labour markets with high AI penetration are likely to undergo a slow and painful adjustment process, in a similar way to the labour markets of the first Industrial Revolution. The first reason concerns workers' skills. It is widely argued that AI-powered technologies require and will continue to require many workers to upgrade/update their skill sets. However, scholars point to a slow and costly reskilling process. This calls not only for individual responsibility for lifelong learning (Brown *et al.*, 2018, Hawksworth *et al.*, 2018) but also for a profound transformation in companies' professional development schemes, as well as in national educational and vocational training systems (Bughin *et al.*, 2017, Arntz *et al.*, 2018, Brown *et al.*, 2018, OECD, 2019c, Servoz, 2019). The second reason is the location of work. According to experts, jobs created in labour markets where AI is heavily used are highly likely to be in new sectors and geographical areas (Acemoglu and Restrepo, 2018a, Manyika, 2018, Servoz, 2019). This would, in turn, require workers to migrate to new sectors and locations to match their skillsets with the available jobs, adding to the bitterness and sluggishness of the adjustment process (Korinek and Stiglitz, 2017, Acemoglu and Restrepo, 2018a, Servoz, 2019).

The third reason is AI's categorisation as a general-purpose technology. As mentioned above, being a GPT, AI enables waves of economic possibilities and innovations which widen its applicability to a broad range of sectors. According to observers, socio-economic benefits of AI will eventually be experienced by the wider society (Brynjolfsson *et al.*, 2017, Frey, 2019a). However, 'the more profound and far-reaching the potential restructuring from transformative technology, the longer it will take to see the full impact on the economy and society (Brynjolfsson *et al.*, 2017: 10). Indeed, Brynjolfsson *et al.* (2017: 10) state that 'while the fundamental importance of the core invention and its potential for society might be clearly recognizable at the outset, the myriad necessary co-inventions, obstacles, and adjustments needed along the way await discovery over time'. Thus, according to Brynjolfsson *et al.* (2017: 10), 'the required path may be lengthy and arduous'. The repercussions of AI for the future of employment relations will be scrutinised next.

3.4. Algorithmic management and employment relations: The invisible boss

In the past few years, observers of working life have witnessed employers' growing deployment of smart machines in employment relationships. To name but a few examples, currently 40 percent of international companies, mostly US based, are deploying AI solutions for HR management, including for their recruitment and hiring processes (PwC, 2017a). In some cases, candidates are not only pre-selected, but also interviewed by an intelligent machine before a real person decides, based on a machine-produced detailed report, whether they are a good fit for the company (Agrawal *et al.*, 2019, Algorithm Watch, 2019, Harwell, 2019).

Humanyze, a technology company providing people analytics for large corporations around the world, developed an ID badge with a microphone, Bluetooth and infrared sensors, and an accelerometer embedded in it. Employers using this system can have insight into a wide range of worker activities, such as how much time they spend with people of the same/opposite gender, how active they are during the workday, and how much they speak and remain silent. It is reported that when the information derived from these badges is integrated with the data from workers' emails and calendars, the generated outcome provides the management with a detailed overview of employees' performance (The Economist, 2018b).

Similarly, in 2018, Amazon was granted patents for a wristband, devised to track employees and their hand movements in real-time. This gadget uses vibrations to nudge employees' hands to the right shelves and bins in Amazon warehouses (The Guardian, 2018). Although there is no available information about whether Amazon has started to utilise this tracking device, its employees are no strangers to algorithmic management. Indeed, as was recently revealed by Lecher (2019), the employee tracking system, that was widely used in Amazon warehouses until at least mid-2019, measured employees' performance at work, and automatically warned or even fired employees in the case of underperformance without any involvement of human decision-makers.

Another example comes from the ride-hailing company Uber. As reported by the company itself, Uber monitors its drivers' driving behaviour through their smartphones, with harsh braking and acceleration habits used as indicators of unsafe driving (Beinstein and Sumers, 2016). Yet this is not all, for as Scheiber (2017) described, Uber also uses a range of psychological incentives, such as video game techniques, graphics and rewards of little monetary value, to influence its drivers over the time, duration and location of work. For instance, to make sure Uber drivers do not log off, the ride-hailing company notifies them how close they are to the earnings goal they previously set in the system or provides them another ride opportunity even before they complete the current one.

Commonly referred to as 'algorithmic management', such HR practices automate or semi-automate managerial decisions related to working conditions and workers' control. To achieve this, algorithmic management utilises AI, big data, and ML (De Stefano, 2018, Mateescu and Nguyen, 2019, Prassl, 2019, Kellogg *et al.*, 2020). An overview of the extant resources suggests that algorithmic management has the potential to offer some tangible benefits to both sides of the employment relationship. These include better health and safety precautions and increased productivity at the workplace (The Economist, 2018b), shift schedule optimisation reconciling the needs of the workers with workplace requirements (Rogers, 2020), and more accurate personality judgements (Youyou *et al.*, 2015) leading to more objective hiring, firing and promotion decisions and more commitment to diversity at work (Bodie *et al.*, 2016, The Economist, 2018a, Weisbeck, 2020).

Yet it should be noted that these advantages are often pushed forward by technology companies in marketing their products, with the argument that algorithm-based decision-making in employment relations is superior to the judgement of human managers as it is based on evidence and impersonal, neutral data (The Economist, 2018b, Leicht-Deobald *et al.*, 2019, Mateescu and Nguyen, 2019). However, critics note that utilisation of AI-powered HR decision support tools often perpetuates and aggravates a range of prevailing issues in employment relations. These are scrutinised below.

3.4.1. Exacerbation of inequality and discrimination

Companies' use of algorithmic management to control workers and work processes is commonly reported to maintain and even exacerbate inequalities and discrimination at work. For many, biases embedded in AI systems and the technology's facilitation of non-standard work practices are important sources of this problem.

Regarding biases, observers insist that the prejudices of the human programmers, who are predominantly young, white, highly educated, and male (European Economic and Social Committee, 2017, De Stefano, 2018, EPSC, 2018), are an important matter of concern. This is because this group of workers, as the critics point out, build their work ethos around high work performance-related ideas, such as productivity maximisation, competence development, success assurance and cultural fitness (De Stefano, 2018, Crawford *et al.*, 2019). Thus, for instance, when companies opt for pre-recorded video interviews, which are then analysed by AI-powered algorithms, the employers could end up discarding immigrants, nervous interviewees or those who do not correspond to the stereotype built within the algorithm by its human developers (De Stefano, 2018, Harwell, 2019). According to Meredith Whittaker, a co-founder of the AI Now Institute, this is 'a license to discriminate… [a]nd the people whose lives and opportunities are literally being shaped by these systems don't have any chance to weigh in' (Harwell, 2019).

Another point of concern is patterns of bias rooted in data (Brynjolffson and McAfee, 2017, Bughin *et al.*, 2017, Dickson, 2017a, Haenlein and Kaplan, 2019, Moore, 2019b). According to the European Economic and Social Committee (2017: 6), data embedded in AI systems are hardly ever neutral, given that they are 'easy to manipulate, may be biased, may reflect cultural, gender and other prejudices and preferences and may contain errors'. Algorithms using biased data are thus highly likely to shape their outcomes by building on the trends and preferences embedded in data, which might perpetuate previous discriminatory practices (Dickson, 2017a, De Stefano, 2018, Haenlein and Kaplan, 2019). For instance, even before it was put into actual use, Amazon had to discard its AI recruiting tool project as the algorithms were found to favour male against female applicants. Amazon's machine-learning specialists revealed that this discriminatory practice occurred because the system was fed with the company's own recruitment data of the previous ten years, from which the system learnt that male candidates were more desirable (Dastin, 2018). Similarly, a team of researchers uncovered that while Google showed male jobseekers adverts for a career coaching service for higher-paid executive jobs 1,852 times, this number plunged to 318 for female jobseekers (Gibbs, 2015).

The extant literature suggests that consumer-sourced rating and review systems could also perpetuate and intensify inequalities and discrimination at work. Currently consumer ratings are widely used by digital platform companies such as Uber, Upwork and Amazon, and by traditional service businesses such as hotels, restaurants, and retailers. According to observers, consumer biases based on gender, sexuality, race, nationality, or other categories may be the cause of poor ratings for workers' performance (Rosenblat *et al.*, 2016, Ticona and Mateescu, 2018, Mateescu and Nguyen, 2019). It is also reported that, in the case of platform work, workers might receive low ratings even when they did not undertake the 'gig': a punishment inflicted by clients on the workers for not accepting their job offer (Ticona and Mateescu, 2018). Critics point out that poor consumer ratings put workers at risk of seeing their livelihoods destroyed, for based on these assessments their payments might be cut, their working hours might be reduced, or their contracts might be terminated (O'Donovan, 2018, Mateescu and Nguyen, 2019). Consequently, as indicated by Rosenblat *et al.* (2016), by making use of consumer-sourced rating systems, companies may pave the way for employment discrimination and evade the responsibility of their unfair practices.

What is more, according to experts, self-learning systems have the capability to find new methods to disseminate and exacerbate inequality and discrimination (Dickson, 2017a, De Stefano, 2018, Beck et. al, 2019, Moradi and Levy, 2020). Thus, even if programmers want to eliminate biases associated with data, this may not always be as easy as retraining algorithms to discount sensitive information such as race, gender, and disability. According to De Stefano (2018), the remaining information embedded in data, for instance parental leaves, names, surnames and postcodes, can act as proxies for sensitive data. This way, the algorithms might still punish certain groups of applicants - in particular women and minorities that are not represented enough in past hiring decisions - by scoring them lower based on machine learning predictions.

Besides biases embedded in AI systems and in the data utilised by AI tools, the rise of platform work is also seen as an important source of inequality and discrimination in the world of work with high AI penetration. Platform work is an umbrella term denoting a variety of non-standard work arrangements utilised for value creation by digital platform companies such as Uber, Airbnb, Amazon, eBay, Upwork and YouTube (Bearson et al., 2019; Kenney et al., 2019b). Providing a comprehensive discussion of platform work is outside the scope of this study and has been already done by others (Eurofound, 2018, ILO, 2018a, Rosenblat, 2018, Bearson *et al.*, 2019, Kenney *et al.*, 2019a). However, it is important to highlight that platform work extends beyond the scope of what is commonly known as ‘gig work’, to include all types of platform-dependent compensated labour intermediated by platforms - for instance, online merchants, in-person service and remote service providers and consignment content creators (Bearson *et al.*, 2019).

In principle, work performed within the ecosystem of digital platforms is based on self-employment, whereby independent contractors provide services for digital companies (ILO, 2018b). Yet scholarly opinion maintains that self-employed people on many digital platforms are working in hierarchical structures, where companies exert power to subordinate them in a similar way as it occurs in traditional employment relationship (Rosenblat, 2018, Servoz, 2019, Rogers, 2020). What is more, many platform service providers are dependent upon the platforms for their livelihoods in the same way that those in traditional employment relationships are dependent on their jobs (Kenney *et al.*, 2019a).

Platform companies’ non-acknowledgement of traditional employment relations by redefining workers as independent service providers exacerbates existing unfairness in the world of work. Indeed, having been legally classified as independent contractors, self-employed people do not enjoy the rights granted to workers by national labour legislations, including but not limited to minimum wage, pensions, national insurance contributions, parental leave, and collective interest representation and bargaining (Moore, 2019b, 2019a, Servoz, 2019). Instead, in many countries platform workers as service providers are subjected to the rules of commercial law (ILO, 2018b), which shift the cost and administrative burden of employment on to the independent contractors, reducing labour costs and economic risks for the digital platforms (Wisskirchen *et al.*, 2017, ILO, 2018b, Rogers, 2020). This way, the platform companies refashion the world of work for a group of workers 'in ways that are unexpected and potentially irreversible'(Rosenblat, 2018: 206).

3.4.2. Invasion of workers' privacy

Besides maintaining and worsening inequalities and discrimination at work, companies' utilisation of algorithmic management tools raises two serious privacy concerns. The first is the blurring of boundaries between work and private lives. This is because AI-powered technologies facilitate employers' monitoring of activities outside the physical workplace. Thus, for instance, when workers opt for remote working arrangements or when they are travelling for business, they constantly remain under the watchful eyes of the monitoring systems. While this kind of surveillance might provide benefits regarding safety and security (Ajunwa *et al.*, 2017, Article 29 Data Protection Working Party, 2017), critics point out that it might constitute a serious interference with workers' right of privacy, as the technology extends workplace surveillance towards workers' domestic sphere (Ajunwa *et al.*, 2017, Article 29 Data Protection Working Party, 2017, Moore, 2019a, Prassl, 2019).

The second privacy concern pertains to use of collected data. It is widely reported that current technologies allow for the collection of individual data from numerous sources, such as keyboard and mouse movements, call logs, screenshots, webcams, application logging activities, wearable devices, and wellness programmes (Ajunwa *et al.*, 2017, Article 29 Data Protection Working Party, 2017, De Stefano, 2018, Aloisi and Gramano, 2019, Prassl, 2019). Expert opinion maintains that HR algorithms' accessing and processing of such a broad range of data might result in unfair workplace practices, as in the cases of firings based on pregnancy or genetic inclination to certain diseases (Ajunwa *et al.*, 2017). What is more, according to observers, even if the data gathered from employees are anonymised, or the content of communications/activities such as conversations or texts are not analysed, individuals could still be identified and sensitive personal information can be used against them (Article 29 Data Protection Working Party, 2017, De Stefano, 2018, Prassl, 2019). As a result, by 'revealing previously unmeasured aspects of the labour process' (Moore, 2019a: 126), algorithmic management tools constitute a serious challenge to workers' 'human right to privacy and personal liberty in domains that have been traditionally considered separate from work and the workplace'(Ajunwa *et al.*, 2017: 142).

3.4.3. Workers' further disempowerment

The shifting balance of power in the world of work against the interests of workers is not a new phenomenon but is a continuation of a series of trends including, but not limited to neoliberal ideology, and globalisation observed across the advanced economies since the 1970s (Standing, 2002, Brynjolffson and McAfee, 2016, ILO, 2018a, Nedelkoska and Quintini, 2018, Özkiziltan, 2020). Expert opinion maintains that companies' deployment of algorithmic management in employment relations has further tipped the balance of power between capital and labour in favour of the former (Crawford *et al.*, 2019, Mateescu and Nguyen, 2019, Moore, 2019a, Prassl, 2019, Servoz, 2019, Kellogg *et al.*, 2020, O'Brien and Lawrence, 2020).

Indeed, scholars point out that many algorithmic management systems are designed to serve employers' interests, such as productivity and cost effectiveness. Thus, their outcomes hardly, if at all, respond to workers' needs and perspectives (Crawford *et al.*, 2019, Mateescu and Nguyen, 2019, Kellogg *et al.*, 2020, Moradi and Levy, 2020, O'Brien and Lawrence, 2020). What is more, some algorithmic decisions are produced by highly complex neural network systems. This renders them opaque: that is to say, they are hard to understand even for their human creators (Brynjolffson and McAfee, 2017, Craglia *et al.*, 2018, Moore, 2019b, OECD, 2019a) let alone the workers whose livelihoods are dependent on them (Crawford *et al.*, 2019, Mateescu and Nguyen, 2019, Kellogg *et al.*, 2020). Thus, according to critics, in companies where complex algorithmic managements tools are used, it is this opacity managing the workforce, enabling the managers to shift the responsibility for managerial decisions onto the machines (Crawford *et al.*, 2019, Mateescu and Nguyen, 2019, Prassl, 2019, Kellogg *et al.*, 2020). In some cases, this leaves workers with no one to appeal to when they face disciplinary measures or lose their jobs (Bearson *et al.*, 2019, Kellogg *et al.*, 2020).

By increasing the capabilities of employers to supervise, control and rate the performance of workers (De Stefano, 2018, EPSC, 2018, Crawford *et al.*, 2019, Servoz, 2019, Kellogg *et al.*, 2020, Rogers, 2020) algorithmic management also diminishes the workers' possibilities of resistance (Moore, 2019a, Kellogg *et al.*, 2020). True, for one thing, by placing workers under the constant watch of management, these systems render 'the sites of everyday resistance facilitated by worker-to-worker communication penetrable by management' (Moore, 2019a: 126). Yet this is not all, for employers using new worker monitoring tools can now measure previously unmeasurable aspects of work such as attitudes, tiredness, mental wellbeing, and stress (Moore, 2019a). In doing so, algorithmic control enables management to individualise its surveillance over workers through custom-made nudges, rewards, and penalties (Kellogg *et al.*, 2020). 'This, in turn, can transform the modalities of worker resistance,' argue Kellogg *et al.* (2020: 386), for according to them '[w]hereas previous systems of control allowed collectives of workers to organize and share resistance tactics over time, especially regarding shared rewards and penalties, algorithmic control can make such initiatives and contestations harder to achieve'.

Available literature also suggests that these power asymmetries become even more pronounced in the case of platform work. Indeed, the platform companies have sole discretion both to determine how their algorithms function and to alter the rules and regulations governing the platforms. This power, in turn, endows the platform owners with a tight control over the platform users, as it creates information asymmetries, enabling the companies to shape the behaviours of platform workers towards desired directions (Bearson *et al.*, 2019, Kenney *et al.*, 2019b, Mateescu and Nguyen, 2019). For instance, ride hailing drivers might feel obliged to accept unprofitable trips for fear that algorithms might lock them out of the system (Mateescu and Nguyen, 2019). Similarly, a YouTuber might suddenly find her account and all her content deleted, or domestic workers and ride hail drivers might find out that their service contracts were abruptly terminated as a result of partial changes in digital platforms' terms and conditions.

What is more, Kenney *et al.* (2019a) point out that as platforms become more successful, their dependence on individual users decreases. This condition creates further power imbalances between digital platform companies and platform workers. This is because, with their growing power, platforms also increase their capability to extract more value from the work done within the platform ecosystem. Meanwhile, the workers feel obliged to enter and stay in the platforms for the continued compensation of their work: a situation potentially depriving workers of their livelihoods and bargaining power.

In addition, as pointed out by Servoz (2019), working as independent contractors may also hinder the service providers' construction of identity as platform workers. This lack of awareness would challenge the future possibilities of solidarity between the service providers, giving the upper hand to digital platforms in their dealing with the independent contractors.

According to the critics, all these factors reduce the bargaining power of platform workers and violate their rights, placing them in a highly disadvantageous position in their relations with digital platforms (IMF, 2018, Manyika, 2018, Moore, 2019b, Servoz, 2019, Rogers, 2020). The ethical and political implications of the use of AI in the world of work will be scrutinised next.

4. AI in a human world: The ethical and political repercussions

As discussed above, current AI deployment rates are low. Nevertheless, a recent global survey found that the utilisation of AI in standard business processes is increasing by almost 25 percent annually (McKinsey&Company, 2019), implying that AI technologies are increasingly becoming an integral part of business and labour markets. According to observers, AI's turning into an everyday reality brings with it many advantages, such as increased productivity, further innovations (Brynjolfsson and Mitchell, 2017, Hawksworth *et al.*, 2018) and growing income levels (EPSC, 2018). However, critics also point out the risks of the 'wrong kind of AI' (Acemoglu and Restrepo, 2019b), which is poised to exacerbate prevailing socio-economic problems in society in general and in labour markets in particular. These include but are not limited to inequalities, discrimination (Spencer, 2017, Blit *et al.*, 2018, EPSC, 2018, Crawford *et al.*, 2019) violation of human and labour rights (De Stefano, 2018) and undermining of democratic values (O'Neil, 2016, Stone *et al.*, 2016, Craglia *et al.*, 2018, OECD, 2019a, Bernhardtz, 2020). Therefore, according to a growing scholarly consensus, the outcomes produced by AI are rarely, if ever neutral and apolitical (Beck et. al, 2019, Jarrahi, 2019, Pettersen, 2019, Servoz, 2019, Rogers, 2020), and they need to be addressed and challenged from ethical and political perspectives (Stone *et al.*, 2016, Blit *et al.*, 2018, De Stefano, 2018, Servoz, 2019, Rogers, 2020). The ethical and political repercussions of the use of AI in the world of work are the subjects of the following subsections.

4.1. AI at work with human values: An ethical perspective

As described in the above sections, AI technologies' potential to be disruptive in labour markets - from replacing labour with machines to intruding on workers' privacy, from ramping up discrimination at work to exacerbating power asymmetries between employers and workers - was well documented in the extant literature. Yet the world of work is only one part of the story. As reported by Whittaker *et al.* (2018), there appear to be numerous incidents illustrating AI's detrimental impacts in various domains of life, from driverless cars killing passengers and their drivers (Wakabayashi, 2018) to unfair deportation of international students (Baynes, 2019), from recommendations of unsafe and incorrect cancer treatments (Ross and Swetlitz, 2018) to enabling police to search surveillance video footage for skin colour (Joseph and Lipp, 2018).

It is against this background that recent years witnessed the emergence of a body of different ethical guidelines, providing those developing AI tools with a set of rules, principles, and directions to curb the harmful effects of new AI technologies (Hagendorff, 2020). Reviewing these guidelines is outside the scope of this research. However, it is important to note that, having analysed and compared 22 of the major guidelines of AI ethics published during the last five years, Hagendorff (2020) found out that in about 80 percent of all guidelines, the issues of accountability, privacy and fairness were regarded as laying the foundations of ethically robust AI systems. However, critics point out that most ethical principles and guidelines for the invention and introduction of AI technologies lack enforceable mechanisms. Thus, they are rarely, if ever, taken into consideration by developers of AI technologies (Whittaker *et al.*, 2018, Crawford *et al.*, 2019, Hagendorff, 2020).

Furthermore, it appears that a heedless or at best sluggish response towards the ethical implications of AI is not limited to those producing AI technologies. According to Deloitte's recent global survey polling nearly 9,000 business and HR leaders in 119 countries, only 14 percent of the respondents stated that they were very ready to address ethical challenges related to the future of work including the rapid adoption of AI in the workplace, and only 27 percent reported that they had clear policies and leaders in place to manage these challenges. On a closer look, the survey reveals that in addressing ethical issues the organisations are least prepared in relation to matters where humans and technology intersect. 20 percent of the respondents declared that their organisations were not ready to manage the impact of automation on the workforce. Organisational unreadiness levels soared to 31 percent and 37 percent respectively in issues related to the 'use of AI and data to monitor individuals' and the 'workplace use of algorithms to influence decision making' (Volini *et al.*, 2020).

It is somewhat surprising that the respondents disclosed such low organisational readiness levels, even though 85 percent of them believed that the future of work raises ethical challenges, and 75 percent of them said that ethics related to the future of work was important or very important for the success of their organisations over the next 12 to 18 months (Volini *et al.*, 2020). According to Volini *et al.* (2020: 102) this readiness gap 'has much to do with the broader tendency for organizations to treat technology and humanity as distinct paths with their own programs, processes, and solutions'. Volini *et al.* (2020: 106) insist that the ethical challenges associated with the future of work, including those related to the adoption of AI in the workplace, require 'focus[ing] on how to operationalize and govern the combination of humans, machines, and algorithms working as a team'. According to them, it is this holistic approach that 'can enable organizations to harness the power of humans and technology together to truly operate as a social enterprise' (Volini *et al.*, 2020: 106).

4.2. AI, society, and the workplace: A political perspective

Some experts believe that AI technologies' diffusion into various spheres of our daily lives has the power to change the socioeconomic fabric on a scale that was never witnessed before (Makridakis, 2017, Blit *et al.*, 2018, Craglia *et al.*, 2018, EPSC, 2018, AI HLEG, 2019b). Thus, according to a prevailing consensus, coping with the transformative nature of AI technologies requires societies to put in place new policies. These policies, as the critics point out, need to be designed vigilantly because the widespread adoption of AI tools carries political implications not only for the further development of societies but also for the progression of AI technology itself.

Regarding AI's societal repercussions, many observers hold the opinion that, if the distribution of outcomes of AI is left to market forces alone, certain parts of society will thrive while others will suffer (Stone *et al.*, 2016, Spencer, 2017, Blit *et al.*, 2018, EPSC, 2018, Acemoglu and Restrepo, 2019b, Crawford *et al.*, 2019). 'That is', as aptly put by Blit *et al.* (2018: 3) 'while in the past, economists may have viewed technological change as being largely factor-neutral and, thus, a tide that lifts all boats, this will not be true with the current revolution, which is certain to benefit some factors of production while harming others'. This is what Acemoglu and Restrepo (2019b: 5) refers to as 'the wrong kind of AI', which, 'rather than undergirding productivity growth, employment and shared prosperity … would contribute to anaemic growth and inequality’. It is at this point that, as critics maintain, workplace and wider societal implications of AI technologies could be best dealt with through decisive political actions (Stone *et al.*, 2016, Brown *et al.*, 2018, EPSC, 2018, Ernst *et al.*, 2018, Kenney *et al.*, 2019b, Prassl, 2019, Servoz, 2019, Zysman and Nitzberg, 2020) These steps, according to observers, need to be taken with the involvement of all stakeholders (IBM *et al.*, 2020, Stowasser and Oliver Suchy et al., 2020) and consider democracy, accountability, transparency (Craglia *et al.*, 2018), human dignity and the fundamental rights of workers (De Stefano, 2018) as the main principles to follow.

Observers also regard politics as a vital factor in the further advancement of AI technologies, particularly in relation to the AI innovations devised to control, replace and/or augment human labour (Manyika *et al.*, 2017, Brown *et al.*, 2018, Ernst *et al.*, 2018, Acemoglu and Restrepo, 2019b, Servoz, 2019, IBM *et al.*, 2020). Underpinning this lies the utilisation of AI workplace technologies as an important source of power to increase profitability and productivity levels (Spencer, 2017, O’Brien and Lawrence, 2020, Rogers, 2020). ‘This means that,’ as Spencer (2017: 145) puts it, ‘what kinds of digital technologies get produced, how they are used and what outcomes they yield, are at least partly dependent on the interests of capital and its representatives’. Thus, according to Acemoglu and Restrepo (2019b), societies should not expect that political non-interference will eventually lead to ‘the right types of AI’ being constructed and deployed. Instead, as observers insist, the further development of AI towards socio-economically desirable directions requires political actions designed to strike the right balance between continued innovation, on the one hand, and the fair distribution of prosperity created by the development and adoption of AI technologies, on the other (Korinek and Stiglitz, 2017, Acemoglu and Restrepo, 2018a, EPSC, 2018, IBM *et al.*, 2020). ‘A society that is not willing to engage in such actions’, according to Korinek and Stiglitz (2017: 39) ‘should expect resistance to innovation, with uncertain political and economic consequences.’ The implications of the use of the AI technologies in the context of Germany will be scrutinised next.

5. AI in German labour markets: Re-imagining the future of work

With more than 80 percent of the German workforce using digital information and communication technologies, digitalisation affects almost every worker in Germany (DGB, 2016a, BMWi *et al.*, 2017). As a result, from polarisation of jobs and income levels to conflict between humans and machines and between work and leisure, the deep-seated repercussions of digital transformation on the world of work have recently received considerable attention in the German public debate (Rahner and Schönstein, 2018). As a part of its response to these debates, the German government adopted the Artificial Intelligence Strategy in 2018, with the main aim of making Germany and Europe the leaders in the advancement and utilisation of AI technologies (Bundesregierung, 2018). This section provides an overview of the current state of AI utilisation in Germany's world of work, and the literature on German social partners' concerns related to digital transformation of the work and workplace. In doing so, this overview also reflects an important shortcoming of the extant literature, in that the majority of the studies investigate digital transformation in the country under the rubric of 'digitalisation', without distinguishing between previous digital and AI-based technologies.

5.1. Jobs, companies, and workers: AI in numbers

As mentioned above, the extent to which AI-powered machines will replace human labour in future labour markets is a contentious topic in the academic debate. This lack of scholarly consensus also extends to discussions on German labour markets, rendering the forecasts on risk of job automation in Germany highly inconsistent. Indeed, an overview of the available research reveals that these calculations fluctuate significantly, with the current highest figure 59 percent (Brzeski and Burk, 2015) diminishing to 25 percent (Dengler and Matthes, 2018), 18 percent (Nedelkoska and Quintini, 2018), and 12 percent (Arntz *et al.*, 2016a) depending on the preferred data and methodology (see section 3.1 for a detailed overview of these discrepancies).

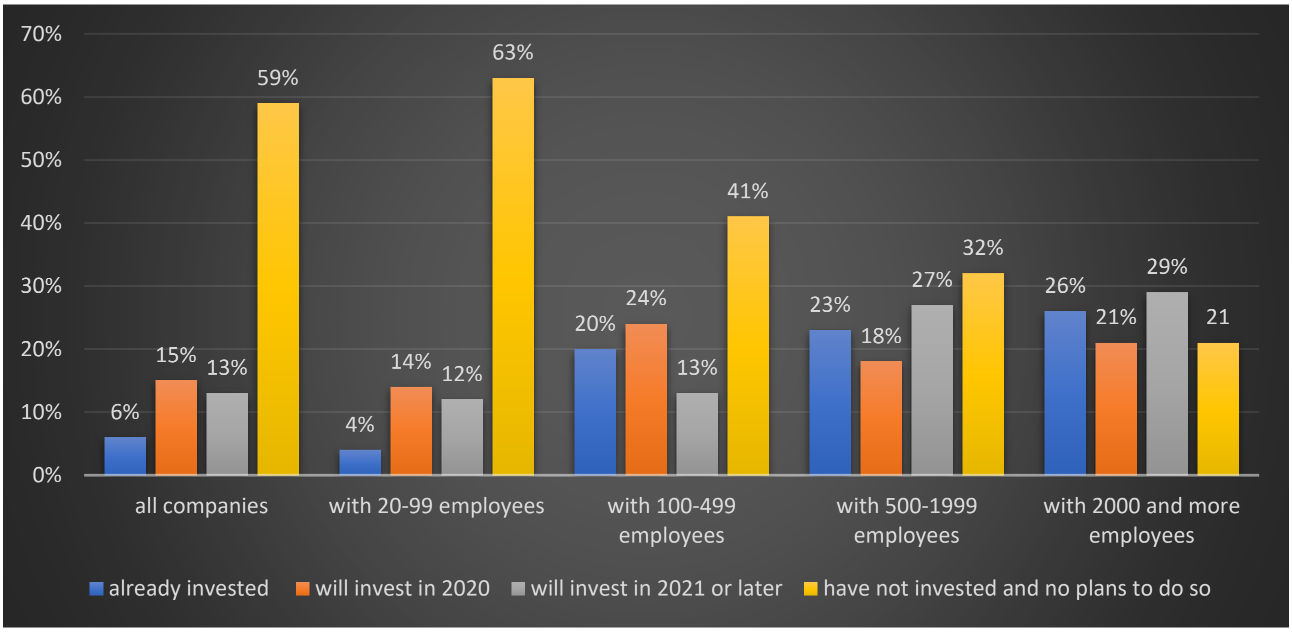
This existing inconsistency was also addressed by a recent expert report on the socio-economic impacts of AI, commissioned by the German Federal Parliament, with the argument that studies drawing up econometric calculation models and possible scenario analyses paint a more realistic picture (Deutscher Bundestag, 2020). Two such studies come to the forefront in this regard. The first is the research conducted by Kriechel *et al.* (2016), as a part of which the authors forecast the changes in the number of jobs becoming available in German labour markets under an accelerated digitalisation scenario by the year 2030. Accordingly, in the case that Germany opts for a development strategy that relies on the intensive use of digital technology in all domains of socio-economic life, one million new jobs will be created in 13 industries, including mechanical engineering, vehicle construction, electronics, IT services, corporate services, and research and development. However, it is also estimated that, by the year 2030, digital technology will replace human labour in around 750,000 jobs in Germany across 27 industries, including retail, paper and printing, and public administration.

The second study was undertaken by Zika *et al.* (2018), with the aim of forecasting the labour market effects of digitalisation in Germany. The research results suggest that, even if German labour markets undergo an extensive digital transformation by 2035, the overall level of employment would not be affected by digitalisation. However, the findings indicate that an all-embracing digitalisation of the German economy would lead to noteworthy structural changes in individual regions, and re-allocation of labour across industries. Accordingly, the biggest changes are expected to take place in Baden-Württemberg, with 6.7 percent of all jobs in the region set to be affected by digitalisation. The digital transformation is forecast to decrease the number of jobs in some industries, including agriculture, metal, and vehicle construction, and to create new jobs in others, including information and communication, education, and domestic work in private households.

Although the available studies predict a future for German labour markets where AI and other state-of-the-art digital technologies are in extensive use, Germany's current performance in digital transformation suggests that the country has a long way to go in realising this scenario. Indeed, currently Germany ranks 12th out of 28 EU countries in the Digital Economy and Society Index (EC, 2020), which compares the performance of member states in digital public services, digital skills, digital connectivity, and online activity. The country is also the 18th out of 63 in the Institute for Management Development's World Digital Competitiveness Ranking for the year 2020, an international comparison which uses 52 criteria to measure countries' capacity and readiness to adopt and explore digital technologies as a key driver for economic transformation in business, government, and wider society (IMD, 2020)

Germany's digital performance becomes even more concerning with respect to current AI utilisation rates. The latest representative Bitkom (2020) survey of 603 companies from all industries with 20 or more employees shows that only 6 percent of companies are using AI tools and technologies, and only 28 percent of them have plans to invest soon. On the other hand, the vast majority, 59 percent, have never invested in AI and have no plans to do so. Figure 1, below, displays German companies' approach to AI investment. Accordingly, as a company's employee numbers increase, so does its likelihood of investing in AI technologies. The survey results also indicate that companies' current AI utilisation is largely limited to less-advanced applications designed to deliver quick and concrete benefits, such as targeted advertising (69 percent), automated payments booking and automated answering of inquiries/complaints (40 percent), price optimisation (32 percent), predictive maintenance (25 percent), planning transport routes (19 percent), and automated forecasts (17 percent). According to the survey results, the use of AI in more complicated work-related issues such as recruitment processes and product development is highly insignificant, with their proportion being 2 percent and 1 percent, respectively.

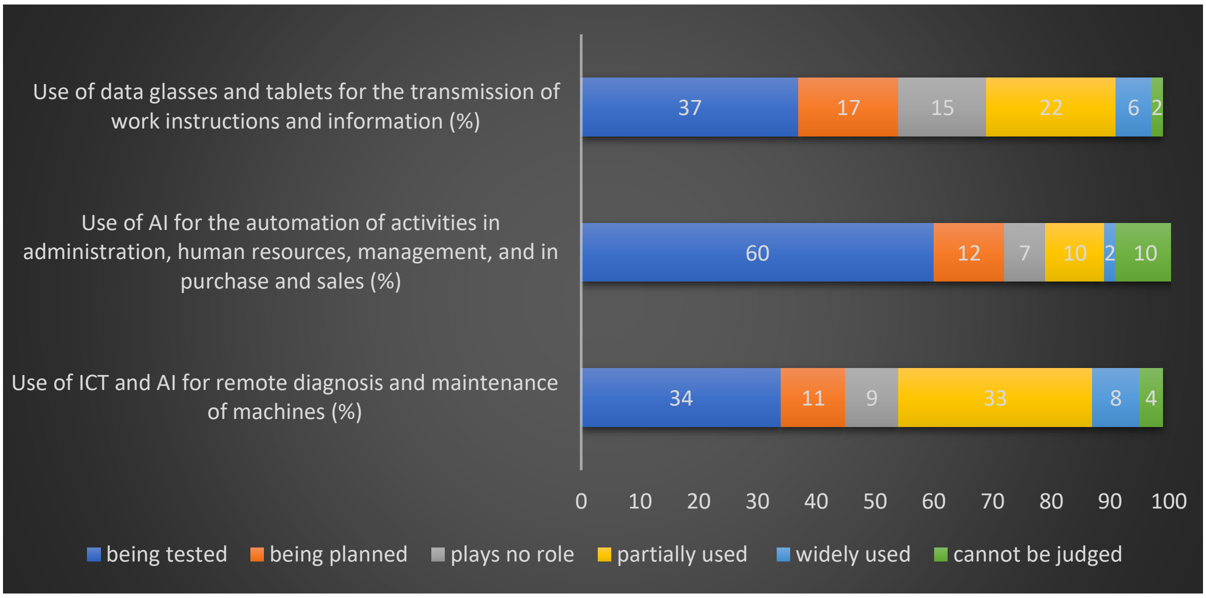
Figure 1: German companies' approach to AI investment



Source: Bitkom (2020).

Data from the 'Transformation Atlas Survey' conducted by IG Metall (*Industriegewerkschaft Metall*, Industrial Union of Metalworkers) reveal that AI tools and technologies are relatively widely used across Germany's metal industry. The survey is based on information provided by works councils and shop stewards from 1,964 companies employing, in total, more than 1,700,000 people. The respondents represent all sectors of the organisational area of IG Metall, including but not limited to mechanical engineering, the automotive industry, electricity, metalware, metal production and processing. According to the survey results, 41 percent of the companies in Germany's metal industry use information technology and artificial intelligence, either partially or widely, for remote diagnosis and maintenance of machines. Furthermore, the findings show that while 12 percent of the companies partially or widely use AI solutions for the automation of activities in administration, human resources management, and purchasing and sales, 28 percent of them partially or widely utilise data glasses and tablets for the transmission of work instructions and information (IG Metall, 2019b). Figure 2 below summarises the relevant findings from the survey.

Figure 2: Use of AI in administration and maintenance across the metal industry in Germany (in percent)



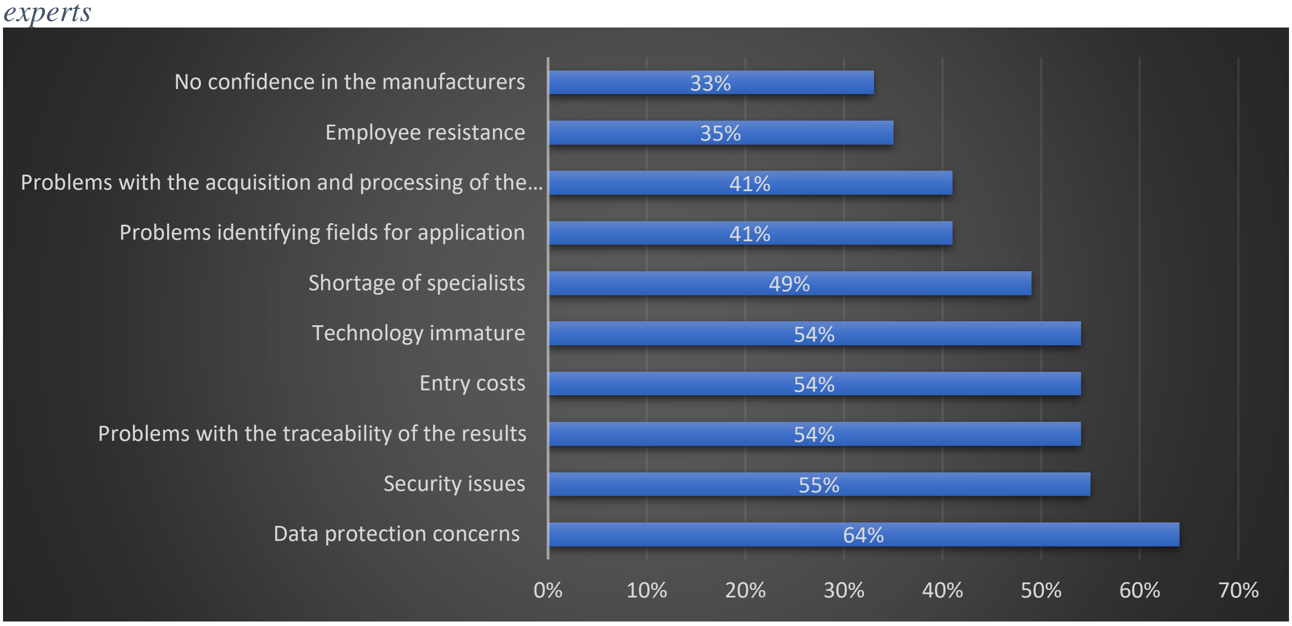
Source: IG Metall (2019b: 9)

A recent survey of AI experts[2] from around 265 German companies of various sizes and from different sectors offers various explanations as to why German companies are demonstrating sluggish progress in digital transformation. Accordingly, as illustrated by Figure 3 below, data protection concerns (64 percent), security issues (55 percent) and inadequate traceability of the results of AI systems (54 percent) are the most important challenges for companies' adoption of AI in business processes and models. These obstacles were followed by high entry costs (54 percent), insufficiently developed technical solutions (54 percent), shortage of specialists (49 percent), problems identifying fields for application (41 percent), problems

[2] This survey included high-ranking decision-makers at 1,061 German companies of various sizes and from different sectors. As BMWi (2018: 16) notes, at the time of the survey, around a quarter of these companies (hence around 265) were 'already using AI, investigating it, planning to do so in the near future or at least consider it important'. BMWi (2018) refers to this group as 'AI experts', and characterises them by their keen interest, high level of information, and high expectations for AI and its solutions.

with the acquisition and processing of the required data (41 percent), employee resistance (35 percent), and lack of confidence in the manufacturers (33 percent) (BMWi, 2018). Similar obstacles, such as high costs of digitalisation (59 percent), lack of qualified IT specialists (55 percent), lack of know-how (44 percent) and lack of technical solutions (35 percent), were also observed in a survey of 155 medium-sized German companies (Sames and Diener, 2018).

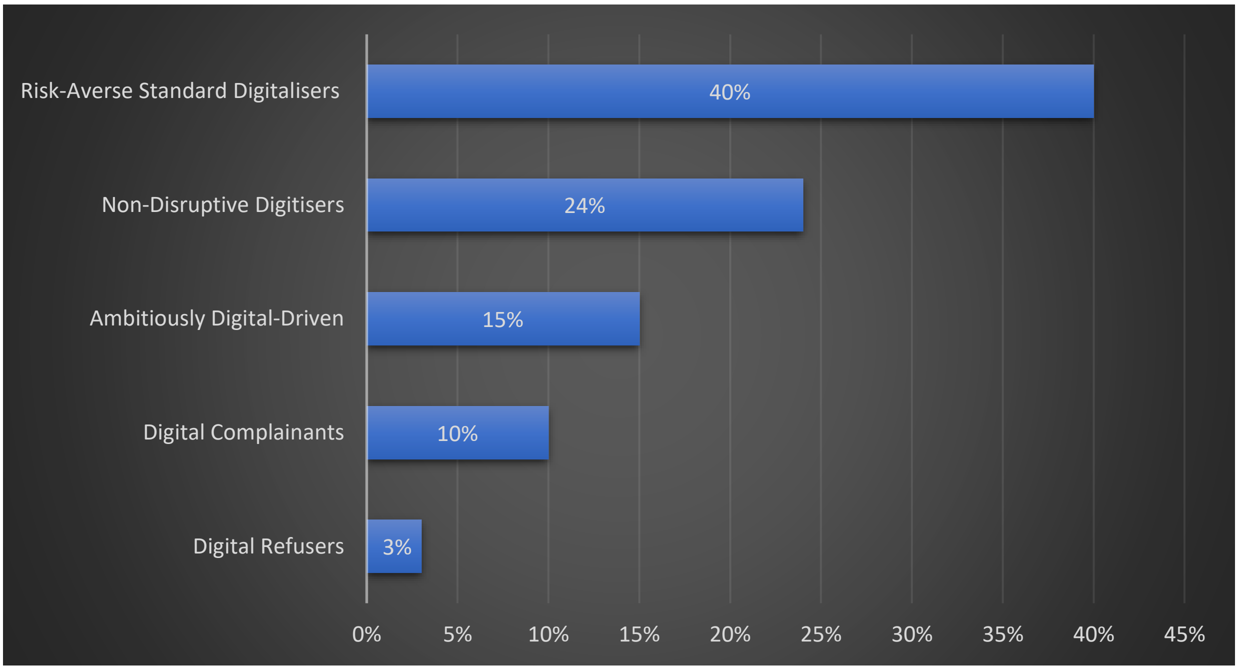
Figure 3: Obstacles hindering German companies' digital transformation according to the AI experts



Source: BMWi (2018: 18).

Besides the existence of various challenges which hold back German companies' AI-driven digitalisation journey, a recent survey of 165 board members of large German companies also suggests that company managers' approaches to digital transformation significantly shape and drive their digitalisation agendas. Figure 4 below summarises the results from this survey, which was carried out by the management consultancy Kearney. According to the survey, there are five different types of German companies when it comes to digital modernisation. The first, representing 3 percent, are the 'digital refusers' deeming digitalisation as hype, mostly because digital products are not yet in great demand among their customers or in their respective industries. 10 percent of German companies belong to the second type, the 'digital complainants'. These companies are aware of the benefits to be brought by digitalisation, but on their own, they are not capable of overcoming the hurdles related to digital transformation. 15 percent of German companies belong to the 'ambitiously digital-driven' category, with impatience, high expectations and frequent changes in the digital business solutions they utilise characterising their digital transformation. Because these companies lack a clear digitalisation strategy, their implementation of new technologies does not always yield successful results. The study portrays 24 percent of German companies as the 'non-disruptive digitisers'. The companies belonging to this group, despite having an established digital culture and being on the way to digital transformation, carry the fear that being overambitious would harm their traditional, profitable core business. Finally, 40 percent of German companies are categorised as the 'risk-averse standard digitalisers' type. This group of companies do not have clear strategic goals, and they do not know the extent to which digitalisation will benefit their business. They also lack an established digital culture, owing to their old, centrally oriented structures (Meyer, 2020).

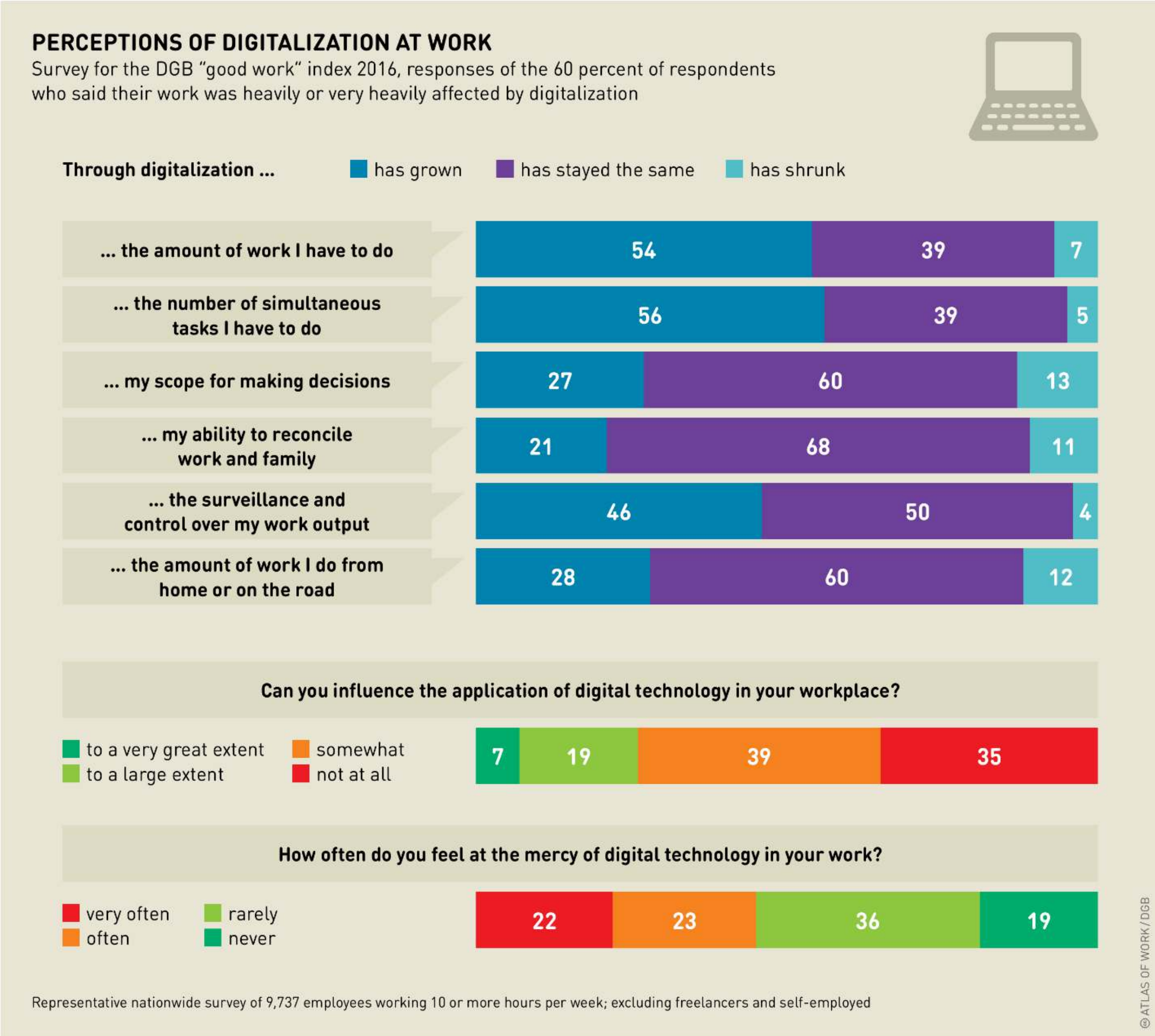
Figure 4: Types of digital modernisation in Germany companies



Source: Meyer (2020)

Notwithstanding the German economy's slow progress in digital transformation and German companies' hesitant steps into the digital realm, research results reveal that the impacts of digitalisation have already become a part of working life in the country. At this point, however, it is important to note that, in the same way as the extant literature, existing surveys on the repercussions of digitalisation on the Germany's world of work also largely fail to distinguish between non-AI digital and AI-based technologies. Therefore, these surveys need to be interpreted keeping in mind that their results might significantly differ from those of future surveys exclusively designed to uncover the effects of AI on the German workforce.

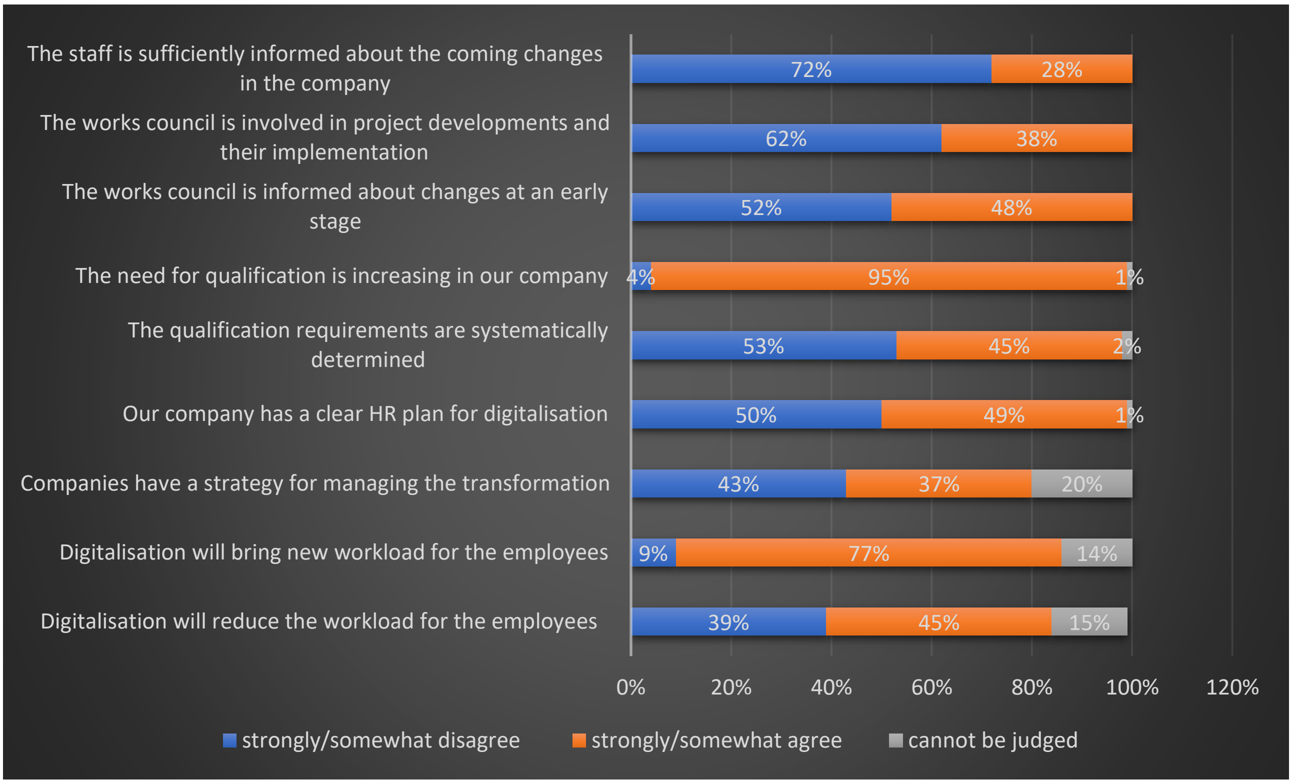
Figure 5: Digitalisation at work according to the DGB Good Work Index



Source: Bartz/Stockmar, CC BY 4.0, imported from DGB and HBS (2018: 35)

According to Good Work Index produced by the DGB (*Deutscher Gewerkschaftsbund,* German Trade Union Confederation), which is based on a representative nationwide survey of 9,737 employees, 82 percent of employees in Germany are being affected by digitalisation at their workplace (DGB, 2016a). What is more, 60 percent of workers think that their work has been heavily or very heavily affected by digitalisation. Figure 5 above summarises the responses of this 60 percent as a whole. It shows that, within this group, 54 percent of these workers think the amount of work they had to do has grown, 56 percent consider the number of simultaneous tasks they have to do has increased, and 45 percent of them feel that they are at the mercy of digital technology. However, the numbers also suggest that increasing workplace digitalisation does not always produce unfavourable or out-of-the-ordinary outcomes for workers. For instance, workplace digitalisation has not changed the scope of decision-making for 60 percent of workers, while 27 percent of workers found themselves in a position to make more decisions. According to the survey, increasing workplace digitalisation has decreased only 13 percent of the workers' control of decision-making processes. Workers' ability to balance work and family life has increased in 21 percent of cases, decreased in 11 percent, and stayed the same in 68 percent of the cases. For 46 percent of workers, surveillance and control over their work output has grown, while for 50 percent it stayed the same, and for 4 percent this has shrunk. The amount of work that the workers are doing from home or on the road has grown for 28 percent of the workers, while staying the same for 60 percent and even shrinking for 12 percent of them.

Figure 6: Digital transformation of work in Germany's metal industry



Source: IG Metall (2019b: 14-22)

Further insights into the repercussions of workplace digitalisation on work and working life in Germany in the context of the country's metal sector are provided by IG Metall's (2019b) abovementioned ‘Transformation Atlas Survey’. Accordingly, as displayed by Figure 6 above, while 77 percent of respondents believe that digitalisation is prone to bring new workloads for the employees, 45 percent trust digital transformation’s capability to reduce workers’ current workload. The survey results suggest that, in almost all companies across the metal sector, the need for a qualified workforce is increasing. What is more, almost half of the companies either partially or fully develop HR strategies for digitalisation, determine qualification requirements for digital transformation, and inform works councils about upcoming projects at an early stage. However, companies’ performance in digitalisation turns out to be less impressive when it comes to management of digital transformation and workers’ participation in this process. Indeed, according to the survey, only 37 percent of the companies have a strategy in place to manage the challenges arising from the transformation. To add to this, in 72 percent of the workplaces, the workers are not sufficiently informed about upcoming projects on digital transformation, while in 62 percent of the cases, works councils are not involved in transformation-related project developments and their implementation. The social partners’ interests regarding the digital transformation of work in Germany are the subject of the next subsection.

5.2. The state, workers, and employers in the process of digital transformation: Shaping the future of work in Germany

The workers’ and employers’ organisations in Germany consider digital transformation of the world of work a crucial topic to address. In response to the growing concerns of workers and employers, the German Federal Ministry of Labour and Social Affairs (BMAS) launched its ‘Work 4.0’ initiative in 2015: an open dialogue process on the future of work involving academic experts, trade unions, employers’ associations, companies and other stakeholders. These efforts resulted in the publication of a White Paper: ‘Work 4.0’ (BMAS, 2017). According to the White Paper, the main challenges presented by the digital transformation of the work and the workplace are striking the right balance between work-related flexibility and workers’ security, and between automation and employment security, as well as unbiased utilisation of big data and coping with the repercussions of the platform work and of machine-human interaction. The White Paper also highlighted the importance of fair wages, social protection, and workers’ self-determination in shaping the future world of work. It insisted that workers’ participation in the workplace digitalisation process and the provision of decent work and quality jobs are crucial in overcoming the obstacles posed by the digitalisation of work and the workplace (BMAS, 2017).

To achieve these, the White Paper identified a series of policy options. These are: adoption of the country's skills development programs and continuing vocational education and training to changing needs; re-organisation of working time in such a way as to better suit the requirements of workers and employers; improvement of conditions for safe and healthy work in digitalised workplaces; adequate protection of employee data; facilitation of workers' participation in the issues related to workplace digitalisation; and provision of adequate social protection for self-employed people, in order to address their income levels, pension insurance and participation in workplace decision-making processes (BMAS, 2017).

As the main points of the White Paper outlined above indicate, in the Work 4.0 initiative the main emphasis was placed on the ongoing digital transformation in the world of work. In contrast, AI's possible and specific impacts on the labour market received very limited attention. What is more, as aptly pointed out by Byhovskaya (2018), despite being the product of a broad consensus among social partners, the White Paper has so far failed to yield tangible political outcomes. Yet this should not be taken to mean that the White Paper was a futile effort by social partners to shape the future world of work in labour markets with high AI penetration. Indeed, for one thing, it acknowledges the growing public attention towards AI's presence in Germany's working life. For another, according to Byhovskaya (2018: 17) 'the relevance of the dialogue process is that it was the first on such a scale and with multi-stakeholder engagement'.

BMAS' 2015 Work 4.0 initiative has elicited mixed reactions from the social partners in Germany. It received backlash from employers' representatives, as German employers mostly favour *laissez-faire* policies in labour markets' transformation towards a digital world (BDA, 2015, DGB, 2015, Gesamtmetall, 2015). This approach becomes most visible in the position paper on digitalisation produced by the BDA (*Bundesvereinigung der Deutschen Arbeitgeberverbände*, Confederation of German Employers' Associations) in 2015, in which the employers opposed any further regulations of the flexible organisation of work and working time, as well as the extension of statutory occupational health and safety measures and minimum wage regulations to crowd-workers. Furthermore, they demanded the implementation of new communication practices between employers and workers, in order to speed up the co-determination process in companies, and the promotion of digital literacy through adequate education and lifelong learning. These measures, as the BDA (2015) contended, are critical in remaining competitive and in successfully managing the digital transformation of work.

BDA's approach to the digital transformation of work and the workplace received severe criticism from DGB (2015) on the grounds that the employers' organisation expects market forces to take care of the digital transformation rather than coming up with a clear digitalisation strategy on its own. DGB (2016b) welcomed the goals and priorities set by BMAS White Paper, acknowledging that promoting greater scope for professional mobility, facilitating workers' participation and co-determination in issues related to workplace digitalisation, strengthening collective bargaining institutions, and enabling self-determination for flexible work arrangements are vital steps in preparing workers for the future world of work. In achieving all these, DGB (2016b) highlighted the importance of political commitment for swift reforms.

DGB's response to the White Paper could be regarded as a manifestation of organised labour's stance on workplace digitalisation issues in Germany. Indeed, in contrast to employers' *laissez-faire* attitude, workers' organisations, particularly those representing larger numbers of workers such as IG Metall, ver.di (*Vereinte Dienstleistungsgewerkschaft* – United Services Trade Union) and DGB, have come out as 'agenda setters' and assumed a proactive role in dealing with workplace issues related to digitalisation (Harbecke and Filipiak, 2018, Armaroli, 2019, Haipeter, 2020, IBM *et al.*, 2020). In doing so, organised labour in Germany has on the one hand affirmed its confidence that digital transformation of the workplace will bring benefit to all (Harbecke and Filipiak, 2018, Hoffmann, 2019, IG Metall, 2019a, ver.di, 2019b, 2020a). On the other, it has asserted that the change needs to be human-centred, with the concept of 'good work' (INQA, 2007) accorded the highest priority by all parties in shaping the future of work (DGB, 2015, ver.di, 2016b, DGB, 2017, 2019, IG Metall, 2019b, ver.di, 2019b, 2020a).

An examination of the extant resources indicates that workers organisations champion four main interests for the promotion of good work in the process of digital transformation. The first is the extension of statutory social protection measures to the new flexible work practices facilitated by digital technologies (DGB, 2015, ver.di, 2016b, DGB, 2017). These forms of work arrangements are broadly classified under the rubric of platform work (see above section 3.4), and have been highly praised and eagerly accepted by employers in Germany (BDA, 2015). Nevertheless, DGB (2015, 2016c, 2017) insists that flexibility at work will only bring benefit to all if it is regulated to ensure that workers in all kinds of flexible work arrangements have adequate access to social protection measures, including but not limited to minimum wage regulations, social security coverage, health and safety procedures and co-determination.

Second, the labour movement in Germany maintains that digital transformation necessitates further extension and strengthening of workers' participation in workplace decision-making process on issues related to technological change (ver.di, 2016a, DGB, 2017, Harbecke and Filipiak, 2018, Hoffmann, 2019, IG Metall, 2019b, ver.di, 2019b). Ensuring this, as DGB (2017) argues, is crucial in unlocking the full potential of digitalisation for sustainable economic and social innovations. Additionally, labour organisations assert that introduction and utilisation of AI require further action to ensure effective workers' participation, for AI's acceptance and safe usage are closely related to definition of its objectives and application areas as well as assessment of its impacts. These, as the workers' organisations contend, needs to be mutually determined by workers' and employers' representatives at the workplace (ver.di, 2019b, DGB, 2020).

Digital competence of workers in the process of digitalisation is the third interest pursued by labour organisations in Germany. According to them, the country's successful transformation into the digital world requires reform and adjustment of its education and vocational training system in accordance with the needs and opportunities of the digital economy (DGB, 2015, 2017, Hoffmann, 2019). In achieving this, trade union representatives emphasise the importance of workers' continued involvement in lifelong learning programmes, employers' acceptance of more responsibility in skills training, and the state's commitment to provide necessary support to all parties involved in transformation processes (DGB, 2017, Hoffmann, 2019, ver.di, 2019b).

The fourth interest pursued by the German labour movement pertains to employee data protection. In the view of trade unions, data protection in the workplace needs to be ensured to prevent digital worker surveillance and monitoring (DGB, 2015, ver.di, 2016b, DGB, 2017, 2019, ver.di, 2020b). Efficient protection of employee data, as DGB (2015) maintains, is necessary if the aim is completing the German economy's successful transition into the digital realm.

Labour organisations in Germany pursue their interests in workplace digital transformation, as Haipeter (2020) points out, through three main strategies: they launch campaigns to increase their membership, activate works councils, and promote workers' participation in workplace decision-making processes. To achieve particularly the latter two, trade unions have launched numerous initiatives during the recent years. To name but a few: in 2016, three trade unions from different sectors (IG Metall from metalworking, IG BCE from mining, chemicals and energy, and NGG from food, drink, tobacco and hospitality) jointly initiated the project 'Work 2020' – *Arbeit 2020* – in North Rhine-Westphalia. Thirty workplaces were involved in the project's first phase, with its second phase already in progress in summer 2019 (Haipeter, 2020). The Work 2020 project aimed to increase the capabilities of works councils in small and medium enterprises to reap the benefits of digital transformation through negotiation of workplace agreements (Harbecke and Filipiak, 2018, Armaroli, 2019, Haipeter, 2020).

Also in 2016, IG Metall launched the project 'Work and Innovation' – *Arbeit und Innovation* – with the involvement of more than a hundred companies from different sectors across the country. The Work and Innovation project was designed to provide tailored training to workers' representatives and skilled workers, with the aim of increasing their capabilities to actively assist and shape the digital transformation projects in their workplaces (Harbecke and Filipiak, 2018, Armaroli, 2019).

Another example comes from the service sector labour organisation ver.di, in the form of further training activities. In its aim of fostering workers' participation in workplace digitalisation issues, ver.di offers numerous training opportunities for workers' representatives, including but not limited to issues related to organisation of work, employee data protection, project management, personnel planning, and reconciliation of work and private life (ver.di, 2019a, 2020c).

As this overview of the available sources reveals, organised labour in Germany is determined to ensure that workers catch up with the changes in the world of work and receive a fair share of the wealth created by the new technologies. It appears that the extent to which they will achieve this, hinges not only on the state and social partners' arrival at a mutual agreement on digitalisation of work and the workplace, but also on the findings from robust research revealing the impacts of digitalisation in the world of work. The next section scrutinises the gaps in the literature.

6. Gaps in AI literature

Issues around AI's workplace utilisation and its repercussions for workers and the workplace are currently attracting growing interest. Indeed, it is not unusual for researchers studying the subject to find numerous recently published studies nearly every day with the same keyword search on the same bibliographic databases. Despite this, many researchers scrutinising the impacts of AI on the world of work would agree that the extant literature leaves significant gaps in our understanding of the subject on the empirical, methodological, and theoretical levels, both in general and in the context of Germany.

At the empirical level, as the experts note, notwithstanding the increasing number of studies, our grasp of some important matters is still very limited (Craglia *et al.*, 2018, Kenney *et al.*, 2019b, Deutscher Bundestag, 2020), and as a matter of fact hardly moves beyond scenarios and speculations (Zysman *et al.*, 2019). This shortcoming means we have only a foggy view of upcoming qualitative and quantitative AI-related changes in the world of work (Deutscher Bundestag, 2020). It also renders the findings from various studies difficult to generalise (Zysman *et al.*, 2019, Deutscher Bundestag, 2020). Among the subjects for which a more accurate and deeper empirical understanding is needed, the most conspicuous seem to be those regarding the ways AI tools and technologies impact work and employment relations (Craglia *et al.*, 2018, Zysman *et al.*, 2019, IBM *et al.*, 2020), especially when it comes to:

- How do workers perceive the use of AI-enabled tools and what influence do AI systems have on work quality and job satisfaction (IBM *et al.*, 2020)?
- To what extent will workers accept using AI-related technologies at work (Deutscher Bundestag, 2020)?
- How can we identify and quantify causal effects of the use of AI on productivity and work quality (IBM *et al.*, 2020)?
- Does AI deployment render workers' performance better and faster (IBM *et al.*, 2020)?
- To what extent do workplace AI technologies help to reduce workloads by supporting human activities (Deutscher Bundestag, 2020)?
- What will the division of labour between humans and smart machines in labour markets where AI is heavily used look like (Zysman *et al.*, 2019, Deutscher Bundestag, 2020, IBM *et al.*, 2020)? More specifically: What kind of new activities

and tasks will be created for humans in workplaces where AI technologies are utilised, and which ones will be assigned to machines (IBM *et al.*, 2020)?

- How do the skills profiles of available jobs/occupations change in the presence of AI deployment (IBM *et al.*, 2020)?
- What types of skills will be lost to, required, and complemented by AI technologies (Acemoglu and Restrepo, 2018a, Zysman *et al.*, 2019)?
- Do companies implementing workplace AI technologies consider workers as their assets, and therefore invest to improve their skillsets, or do they merely see workers as a cost to be controlled and reduced (Zysman *et al.*, 2019)?
- Where will the new jobs created by AI technologies be located (Zysman *et al.*, 2019)?
- When and how fast will the changes occur (Zysman *et al.*, 2019, IBM *et al.*, 2020)?
- What are the examples of good jobs strategies across AI-driven sectors? What were the factors leading to their adoption? How could these strategies be politically promoted (Zysman *et al.*, 2019)?

A critical overview of the extant literature suggests that the following topics are also in need of further empirical scrutiny:

- Do non-AI digital and AI-powered automation technologies complement and enhance each other? If so, how; if not, why? Are their implications on the world of work separate from or complementary to each other? How can we understand and explain these disparities/similarities?
- How does the utilisation of AI in the workplace impact different groups of workers, including low-, middle-, and higher-skilled, as well as women, younger, disabled, older and migrant workers, and workers of different ethnic origins? This line of inquiry could be further detailed as:
    - What kind of advantages do workers draw from workplace AI tools and technologies and which groups of workers benefit from these the most?
    - What kind of disadvantages do workers experience in relation to the adoption of AI tools and technologies at the workplace and which groups of workers suffer from these the most?
- How do workers, individually and collectively, cope with the pressures of AI-driven workplace technological change? This line of inquiry could be further detailed as:

  - Do workers from different sectors, of different skill levels and different socioeconomic backgrounds (e.g., women, older, younger, migrant workers) exercise their agency in different ways to contribute to better working conditions? If so, how can we understand and explain these differences?
  - Are there examples of workers' resistance from around the world in which their efforts led to fairer and better working conditions in workplaces where AI-enabled tools are utilised? If so, how can these positive examples be used to enrich the repertoire of actions of workers around the world in their efforts towards achieving fairer and better working conditions in an AI-driven world of work?
- How do legal, regulatory, and political environments impact the utilisation of AI in the world of work across the advanced capitalist states? This line of inquiry could be further detailed as:
  - What is the role of current labour legislation and collective bargaining institutions in the adoption and utilisation of AI-driven workplace technologies? What do they imply for the future policymaking process, from the perspective of respect for human dignity and the fundamental rights of workers (De Stefano, 2018)?
  - How far does institutional context in Germany regarding skills adjustment and development, labour market regulations and programmes, and social dialogue help in addressing challenges arising from digitalisation (Walwei, 2016) in general, and AI utilisation in particular?
  - To what extent can suitable criteria and regulations be created for vulnerable workers in AI-driven sectors under social security law (Deutscher Bundestag, 2020)?
  - What are the roles of employers, workers' organisations, and states in creating favourable conditions for sustainable and fair utilisation of AI at work and in the workplace?
  - Are trade unions and works councils involved in the introduction of AI and identification of solutions to AI-related problems, and if so in what ways (Ohlert *et al.*, 2020)?
  - Do workers in general, and in particular more vulnerable groups of workers (i.e. women, older, younger, migrant workers), receive support to update their

skillsets from their employers and the state during periods of intense technological change? If so, how do these different groups of workers utilise vocational training and lifelong learning opportunities? Are there differences between different groups of workers as to how they receive and make use of training opportunities?

- What are the reasons behind workers' decisions to upgrade their skillsets, or to switch to other occupations/sectors when their skills become out-of-date due to the introduction of AI-based technologies?
- How do German social partners and the German state compare to other advanced market economies in their efforts to achieve a comprehensive, fair, and sustainable digital transformation at work and in the workplace, against the background of increasing competition from international markets?

An overview of the available studies suggests that our understanding of the subjects related to AI's impacts in the workplace is also challenged by the methodological shortcomings in the literature. Underlying this, in the first place, is AI technologies' distinct differences from those based on previous non-AI digital automation, rendering inference from past trends deceptive (Brynjolfsson and Mitchell, 2017). Second, as asserted by a recent expert report, the data on AI's workplace utilisation are very scarce, as AI technologies are currently deployed in only a small number of companies (Deutscher Bundestag, 2020). This situation compels researchers either to use indirect measures for AI automation (Frey and Osborne, 2013, see e.g. Arntz *et al.*, 2016a, Daheim and Wintermann, 2016, Ransbotham *et al.*, 2017, Ransbotham *et al.*, 2019) or to focus on more specific and easier-to-measure technologies, such as industrial robots. What is more, the existing data are mostly available at an aggregated or industrial level, making it difficult for researchers to measure, understand and explain how companies and individuals adjust to technological shifts in the context of work organisation, further training and education and future work and employment prospects (Deutscher Bundestag, 2020). Nevertheless, although data resources are limited, the majority of research studying AI's workplace impacts utilises quantitative methods. Thus, the third methodological shortcoming of extant literature is the lack of qualitative inquiries. Greater availability of qualitative research would enable a deeper understanding of how workers and employers in labour markets with high AI penetration perceive the changes, interact with each other, and cope with the challenges associated with the new world of work. The fourth shortcoming pertains to the scope of the existing studies, which are currently largely limited to small research projects. This makes it more difficult to deal with challenges related to the future of work, as a comprehensive understanding of these issues requires a broad, systematic and data-based examination of AI applications from both qualitative and qualitative perspectives (Deutscher Bundestag, 2020).

Besides its empirical and methodological shortcomings, the literature on AI's repercussions on work and the workplace also offers us highly limited social theoretical perspectives. Thus, in its current state, it does not help us much in exploring and enhancing our understanding of the future world of work in a more insightful and critical fashion. Indeed, currently only a few studies analyse AI's utilisation in the workplace from theoretical viewpoints drawn from previous sociological studies, the most noticeable exceptions being Kellogg *et al.*'s (2020) application of labour process theory on algorithms at work, Spencer's (2017) use of Marxian theory of surplus value to analyse the reproduction of power imbalances between capital and labour in AI-driven economies, and Kenney *et al.'s* (2020) introduction of Polanyi's double movement argument to the discussions on the platform economy.

Two factors seem to underpin this theoretical limitation. The first is the abovementioned shortcomings at the empirical and methodological levels, which render any type of theoretical analysis difficult to formulate and advance. The second, as asserted by Zysman *et al.* (2019), is the lack of new vocabulary to account for the novel ways income is generated and distributed, as in the case of categorisation of people earning substantial sums of money using social media channels. Overcoming these theoretical challenges appears to be important, for theoretical insights would help researchers to 'shape the narrative, the story and interpretation of events' in their efforts to contribute to the formulation of good jobs and good livelihood strategies (Zysman *et al.*, 2019: 15). Against this background, among the issues awaiting further theoretical scrutiny in the extant literature, the most conspicuous seem to be:

- How is power reproduced and distributed between labour and capital in workplaces and sectors where AI technologies are utilised?
- What is the new division of labour between man and machine in the world of work, and what is the role of the state, capital and labour in this process? How do available social theories understand and explain these issues? What are the limitations of available social theories and how can we improve our theoretical understanding of this subject?

- What are the new sources of power for labour and capital, and how do actors utilise these resources? What are their consequences?
- How do people working in AI-led economic sectors construct their work identity? How do they reformulate their interests in the context of these novel worker identities?
- Are there new types of working and capitalist classes in the making in AI-led sectors, and if so, what are the main characteristics and attributes of these new classes? How do these differ from the working and capitalist classes as we know them, and what does this imply?
- Does work-related precarity appear in different ways in labour markets with high AI penetration, and if so, what does this imply for the political economies of the advanced market economies?
- How can we understand and explain the contradictions between increasing workplace surveillance and increasing societal demand for freedom and self-determination in the advanced market economies?
- What are the work-related assumptions, values, and beliefs embedded in AI-led economies/sectors? What are the discourses formed and produced to meet the demands arising from the new values at work? Through which channels are these expressed?
- Are voices and interests represented in novel ways in AI-led economies/sectors? If so, how can we understand and explain these? How and why do they differ from previous ones?

It is important to note that the limitations in the extant literature highlighted above represent a non-exhaustive list. New and serious shortcomings will emerge as AI-driven technology progresses further and the subject is scrutinised more. We are of the opinion that adequately addressing and overcoming these limitations are crucial, for these will significantly contribute to our attainment of a clear vision of the future world of work.

7. Conclusion

AI technologies continue to spread through our societies, transforming many aspects of daily life at an incredible pace. From environmental conservation to medical imaging and to supporting people with disabilities, most of these hold great promise in advancing societies and addressing existing problems. The utilisation of AI-driven tools and techniques at work and in the workplace also offers several advantages to workers and employers, be it better health and safety precautions, increased productivity, or optimisation of shift schedules. However, experts warn us that AI-driven technologies are also poised to perpetuate and exacerbate prevailing socio-economic problems, including but not limited to inequalities, discrimination, human rights violations, and undermining of democratic values. Projected into the world of work, these issues take the form of -among many others - replacement of human labour by machines, workers' relegation to mundane tasks, aggravation of disparities in wages and working conditions, invasion of workers' privacy, erosion of workers' traditional power resources, and intensification of power asymmetries between capital and labour. Taken from this perspective, the AI-driven future of work, as reflected by the scholarly work, is likely to perpetuate and aggravate work-related inequalities and discrimination, diminishing further the prospects of decent work, fair remuneration and adequate social protection for all.

What needs to be emphasised here is that the forward-looking predictions provided by current studies only point to one possibility amongst many. Indeed, the future is not decided yet, and the research findings so far have failed to take us beyond the hazy realm of speculation (Zysman *et al.*, 2019). As Zysman *et al.* (2019: 12) note, '[t]he ambiguity suggested by the various studies points to choices and options before us. We have choices about how to develop, deploy and use these technologies.' Expert opinion insists that these choices need to be made in such a way as to bring mutual benefit to capital owners and working people. Otherwise, as Acemoglu and Restrepo (2018a: 34) duly warn us, 'the development and adoption of productivity enhancing AI technologies cannot be taken for granted', for according to them, '[i]f we do not find a way of creating shared prosperity from the productivity gains generated by AI, there is a danger that the political reaction to these new technologies may slow down or even completely stop their adoption and development'. As Acemoglu and Restrepo (2018a: 34) continue, this 'underscores the importance of studying the distributional implications of AI, the political economy reactions to it, and the design of new and improved institutions for creating more broadly shared gains from these new technologies.'

As a result, a great deal of responsibility lies on the shoulders of researchers and research funding bodies in the creation of a better future for all parties related to the world of work.

This is because, as we believe, a fair and inclusive future of work will rest on robust and reliable research findings, social partners' acknowledgment of these findings, and policy-makers' translation of research results into tangible political outcomes.

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