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The development of AI and its impact on business models, organization and work

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The development of AI and its impact on business models, organization and work[*]

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Abstract

This project explores the development of Artificial Intelligence (AI) and its impact on business models, market structure, organization and work. By adopting a *history-friendly* perspective, the present contribution traces a stylized history of the AI technological domain in order to highlight moments in time, places and sectoral domains that fostered its diffusion and transformative potential. Some descriptive analyses are also provided to investigate the diffusion of AI technologies and, at the same time, the underlying industrial and market dynamics.

Keywords: Artificial intelligence, industrial dynamics, work organization

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1. Introduction

During the last few decades, the diffusion of smart devices able to 'learn' and - thanks to this learning - adapt to changing environments has been dramatically transforming the functioning of capitalistic systems. Machine (artificial) intelligence is based on a combination of different advanced technologies capable of reproducing and/or enhancing different human tasks and cognitive capabilities, such as planning, learning or speech and image recognition (Martínez-Plumed et al. 2020). More precisely, we can define AI as a technological domain whose core components can be traced to *Machine Learning* (ML), *Deep Learning*, *Natural Language Processing* (NLP) platforms, predictive *Application Programming Interfaces* (APIs), and *image* and *speech recognition* tools (Martinelli et al. 2019). This combination of knowledge, materials and technologies allows machines and electronic devices to cross boundaries hitherto considered 'exclusively human'. Indeed, the major transformative element lies in the growing ability of AI-equipped machines to adapt their behavior and modify their objectives on the basis of past experience and in response of changing environments (Brynjolfsson and Mitchell, 2017; Teddy, 2018).

Looking at the industrial dynamics, the development of AI has been accompanied with a fast and dramatic process of market concentration. This is particularly true in the case of companies selling web-services and controlling key digital platforms, such as Amazon, Alphabet and Facebook, among others. The increasing monopolistic power of such Internet giants, however, also affects the functioning of other related markets by favoring the spread of new business models based on the intensive exploitation of information (e.g., as in the case of Uber-type firms reshaping the transport sector or food-delivery platforms, dramatically stepping up their operations in times of pandemic). This often crowds out existing businesses, again paving the way for further market concentration dynamics. Moreover, for 'traditional' companies adopting a business model not based on AI and Big Data, accessing services provided by platforms epitomizing the spreading of AI, such as Amazon, becomes increasingly vital. AI-based platforms are in fact key to entering virtual markets that are continuously growing in size *vis-à-*

vis the physical ones, and indeed to accessing crucial information on consumers' preferences and behavior. As a result, the spread of AI coincides with the diffusion of dependency relationships involving, on the one hand, companies that need to access these virtual platform-controlled markets in order to grow and, on the other hand, AI-based platforms enforcing a dominant position as gatekeepers, and thereby capturing significant shares of value added along both the demand and the supply sides. The more a company is dependent on platform-controlled markets, the higher is the risk of becoming in practice a dependent supplier involved in an asymmetric relationship with the platform. As for the labor market, the development of business models based on data, platforms and AI technologies drives yet further the process of outsourcing (i.e. with a continuously increasing number of tasks than can be performed remotely and/or controlled by platforms), fragmentation (leading, in some cases, to the extreme of 'human as a service') and 'casualization' of work (on this point, see Codagnone et al. 2016).

The socio-economic impact of AI is attracting increasing attention in both academic and political debate. Two organizationally and economically relevant counterparts of AI – automation and robotization – are now at the center of many analyses focusing on their potential impact on jobs, with particular regard to the risk of a new wave of technological unemployment (Autor, 2015; Brynjolfsson and McAfee, 2016; Frey and Osborne, 2017; IFR, 2017; Montobbio et al., 2020; Webb, 2020). On the other hand, the scientific literature dealing with the organizational by-product of AI – i.e. the 'platform economy' – is extensively exploring the impact of the latter on market concentration and inequalities (on this point, see Codagnone et al. 2016). The aim of this contribution is to carry out further investigation into the development of AI. Working on a history-friendly theoretical basis, we will explore and describe the recent technological and economic developments of AI with a specific focus on industrial dynamics. First, starting from the historical origins of AI as a technological domain, we seek to identify some of the key factors that have fostered its diffusion and transformative potential along specific *evolutionary trajectories* (Nelson and Winter, 1977, 1982, 2002). As a reference point, we rely on the recent arguments advanced by Dosi and Virgillito (2019) discussing the impact of '*intelligence automation*' on the socio-economic fabric. Indeed, far from being neutral, the new technologies interact with the specific socio-economic structures characterizing the complex systems in which they are nested. What might substantially affect the development (and impact) of new technologies are pre-existing macro-trends in terms of income distribution, labor relations, market structures and, more broadly speaking, institutional characteristics. These trends could be inverted or reinforced by the diffusion of '*intelligence automation*' technologies. The latter, on the other hand, may take on peculiar forms and trajectories given the heterogeneous nature that those trends assume across sectors and countries.

In the first part, we follow the theoretical guidance provided by scholars like Freeman, Dosi and Perez (Dosi, 1982, 1988; Freeman and Perez, 1988; Perez, 2009) to speculate on the nowadays popular but still challenging questions. For example, are we facing a 'technological revolution'? Does AI represent a new techno-economic paradigm? We do not expect to arrive at definitive answers to such complex questions. However, we rely extensively on the theoretical categories provided by the evolutionary literature to better understand the characteristics of the process of change triggered by the development of AI technologies. Moreover, adopting a '*history-friendly*' approach (Malerba et al. 2016), we propose a '*stylized history*' of AI with the aim of identifying possible *discontinuities* in terms of economic, industrial and organizational structure and dynamics, as well as mechanisms reinforcing pre-existing capitalistic trends, which may have fostered its massive diffusion among sectors and economies. In particular, we focus on factors that may have triggered (or allowed for) the development of AI, such as the availability of technologies (*machine learning* and *deep learning* tools) capable of *enabling* the full exploitation of an increasingly huge amount of data, also combined with a vast constellation of ICT technologies (e.g., the *Internet* infrastructure). These factors are then interpreted in the light of pre-existing macro-trends intrinsically characterizing capitalistic development. Among these patterns we find the slowdown of productivity and economic growth, the increasing *rentification* of the economy at the global level and the long-term trend towards monopolistic or oligopolistic market configurations (Dosi and Virgillito, 2019).

Having traced out the theoretical framework and retraced the historical evolution of this technological domain, we attempt to provide a descriptive overview on the market and the technological dynamics shaping the development of AI. On this basis, we analyze the evolution of key economic variables (such as revenues and market shares) by focusing on companies and markets related to the production and commercialization of AI. On the technology side, we explore the patent data, concentrating on fields that are directly related to AI components. In line with Martinelli et al. (2019), we discuss the dynamics of patenting, providing evidence on the direction of technological efforts and the interaction among technological domains as well as the process of concentration/fragmentation.

2. The advent of intelligent machines

The evolution of capitalism as a mode of production and accumulation has been punctuated by the emergence and diffusion of different *General Purpose Technologies* (GPTs): first, steam power, then electricity and ultimately the development of Information and Communication Technologies (ICTs). The introduction of each GPT represents a structural break (Bresnahan and Trajtenberg 1995; Helpman 1998; Teece 2018). Consolidated economic, social, institutional and cultural configurations start to wane, opening the way for the emergence of new power structures, new markets, new needs and products, and new technologies. Each break coincides with the emergence of a new *techno-economic paradigm* (Freeman and Perez, 1988), associated with the diffusion of a constellation of different innovations whose pervasiveness affects both the technological and the economic domains that have been transforming our economic systems and societies, as well as an increasing number of economic sectors and industries (Perez, 2009; Dosi and Virgillito, 2019).

Discussion as to whether AI represents the new GPT (Trajtenberg, 2018; Varian, 2018), giving rise to the 'Fourth Industrial Revolution', or should, rather, be analyzed in the light of the convergence of different pre-existing *technological paradigms* (Dosi, 1982) and hence within the long tail of the previous ICT *techno-economic paradigm* (Freeman and Perez, 1988; Perez, 2009), involves complex and much debated questions.

Even though the answers to these questions are beyond our scope, the evolutionary literature may help to define a theoretical framework as well as identify some key elements characterizing the development of AI viewed as a broad process of change. Dosi and Virgillito (2019) stressed that this analysis should entail assessment of possible discontinuities in firms' knowledge bases and interaction between organizational capabilities and skills dynamics (Dosi et al., 2000; Zollo and Winter, 2002) within and among firms and sectors, as well as the localization of the main actors driving these new processes. On a similar basis, Cetrulo and Nuvolari (2019) ascribe the recent improvements in AI and automation-related technologies to the development of the ICT techno-economic paradigm and its macro-trajectories by highlighting the incremental nature of such 'new' technologies as well as the long time-span over which a different paradigm has completed its life-cycle from a historical perspective (Nuvolari, 2019).

Moreover, Martinelli et al. (2019) provide a patent data analysis with the aim of tracing the perimeter of what is called 'Industry 4.0' as a composite cluster of *enabling* technologies (Teece, 2018), including AI. The transformative potential of the latter is significantly emphasized, foreseeing the potential for a paradigm change due to the development of current digitalization and automation trends as well as recombination or convergence among different existing technologies.

Thus, by relying on these theoretical reference points, we will now seek to trace the *historical* patterns of AI in the light of possible factors driving its adoption and diffusion (Malerba et al. 1996a, 1996b, 1997; Dosi and Nelson, 2010) along specific *evolutionary technological trajectories* (Dosi, 1982; Nelson and Winter, 1977, 1982, 2002; Dosi and Nelson, 2016). This approach also relies on the well-established '*history-friendly*' tradition (Malerba et al. 1999; Malerba et al., 2016; Capone et al. 2019) with the aim of analyzing and simulating the evolution of industries on the basis of their '*stylized history*'. The fundamental purpose is to identify crucial dimensions such as the industrial *demography*, *structural dynamics*, and *structural evolution* of specific industrial sectors (Garavaglia, 2010) in order to replicate their historical patterns and trajectories. Although we do not intend to simulate the evolution and dynamics of AI industry, by adopting these theoretical lenses we can embark upon an '*appreciative*' exploration (Malerba et al., 2016) of AI adoption and diffusion as the result of the convergence of different technological trajectories. This may also help us to investigate whether AI has peculiar characteristics or represents an incremental pattern related to the last ICT wave and its possible future developments, as well as the foreseeable impact on business models, market structure, organization and work.

On this ground, Table 1 (in Appendix) summarizes the timeline of the stylized history of AI which we discuss in the next Section. As can be seen, the evolution pattern of this complex and composite technological domain arises from the convergence of different technological advances developed along specific *technological paradigms* (Dosi, 1982) and evolutionary *technological trajectories* (Dosi and Nelson, 2010, 2016). In particular, we identify three different trajectories whose interaction has enabled the development and diffusion of AI as a technological domain: i) developments in statistical and computational theory and specific algorithmic techniques; ii) data availability, strictly linked to the Internet trajectory (Cernobbio e Moggi, 2020); improvements in computational power and data storage capacities. These trajectories are punctuated by technological advances, in terms of knowledge, techniques and applications. Thus, in the course of this stylized history we can shed light on the key technological components, complementary innovations and supply and demand conditions of AI that have enabled the fast and ubiquitous diffusion observed so far, also interacting in turns with changes in organizational routines and labor-related dynamics. In particular, we identify: i) *technological factors*, such as the diffusion of *Big Data*, improvements in *Machine Learning* (ML) and *Deep Neural Networks* (DNNs) *tools* and the pervasive *connectivity* allowed for by the *Internet* infrastructure (Section 2.1.1); ii) *organizational factors* related to the growing knowledge and fragmentation of tasks in the course of production processes and the possibility of overcoming space and time constraints on work provided by AI technologies combined with other digital and automation tools (Section 2.1.2); iii) factors related to *market* and *industrial dynamics*, such as the quasi-monopolistic position gained by big-tech companies (e.g. Amazon or Google) due to their comparative advantages and lock-in positions in exploiting AI-related technologies.

2.1. A '*stylized history*' of AI.

The origins of AI have often been traced back to the first attempts at creating rudimental automata in history, like those invented by Heron of Alexandria in the 1st century BC, or mechanical calculators able to 'automize' human computation abilities, like the logical machine invented by R. Lullo drawing on his "*Ars Magna*" (1308) which inspired Leibniz's "*Dissertatio De Arte Combinatoria*" (1666), identified as one of the ancestors of the building blocks of modern 'computational thinking', or even the project of an analytical engine developed[1] by C. Babbage (1837).

Between the 19th and the early 20th century, major achievements were also seen in statistical and probabilistic theory, ranging from Legendre's Least Square method (1805), thereafter widely used for data fitting problems, Bayes' studies and the formalization of 'Bayes theorem' proposed

[1] The machine was never constructed by Babbage, but it interestingly represented a source of inspiration for a certain literary imagery during the 1990s, as in the dystopic novel "*The Difference Engine*" (1990) by W. Gibson and B. Sterling.

by Laplace (1802), to the introduction of the 'Markov chains' (1913), still representing a pivotal probabilistic theoretical tool to analyze stochastic processes.

Nevertheless, besides the seminal contribution of those brilliant minds to the statistical, computational, philosophical and epistemological roots of this complex technological domain, the first step towards modern informatics and then AI as we know it were certainly taken by Alan Turing. Turing's contribution ranges from algorithmic and computational theory, as his famous '*Turing machine*' represents the direct ancestor of the modern computer[2], to logical thought and investigation into machine '*intelligence*' (the well-known *Turing test*). After some innovative advances in the field of Artificial Neural Networks (ANNs) between the 1940s and 1950s, such as the Threshold Logic Unit (TLU) in 1943 and the first neural network machine, i.e. the Stochastic Neural Analog Reinforcement Calculator (SNARC) in 1951, another major breakthrough came in 1956, during a famous workshop organized by J. McCarthy and other brilliant computer scientists including the future Nobel Prize H. Simon, at the Dartmouth College in New Hampshire.

Building upon the Dartmouth discussions, Newell and Simon created a program, *Logic Theorist* (or LT), capable of imitating some kind of 'reasoning' by proving theorems starting from mathematical principles. This was the first step towards the implementation of programs and algorithms aiming at ever finer imitation of human heuristics and cognitive processes. Then in 1958 F. Rosenblatt, working at the Cornell Aeronautical Laboratory, introduced the 'perceptron', which is an ML algorithm originally implemented as an ANN machine for image recognition (the 'Mark I perceptron'), also causing a considerable stir among the US media, and thus paving the way for a potential first 'hype' of AI.

Indeed, during the 1960s probabilistic theory was extensively applied to advances and developments of ML algorithms. Nevertheless, the 1970s have been defined as the 'AI winter' due to a slowdown in the related research projects and the limitations of ML applications highlighted in 1969 by Minsky and Papert in their book "Perceptrons".

Besides the rate of the evolution in AI technologies in those years, the nature and the right definition of AI has also given rise to much debate since its inception as a specific research area,

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[2] In 1936, A. Turing in his "*On Computable Numbers, with an Application to the Entscheidungsproblem*" introduced an algorithmic computational model, based on his famous theoretical *machine*, capable of solving the 'decision problem' proposed by D. Hilbert (the *Entscheidungsproblem*) and laying the foundations of modern informatics and computational theory.

even among scientists working in the field. In his book "*The Science of the Artificial*" (1996) H. Simon wrote «*The phrase "artificial intelligence", […] was coined, I think, right on the Charles River, at MIT. Our own research group […] have preferred phrases like "complex information processing" and "simulation of cognitive processing". But then we run into new terminological difficulties […]. At any rate, "artificial intelligence" seems to be here to stay.*». This passage about the naming, and thus definition, of this new technology, may provide insights into the divide between what AI really was (and is) and what computer scientists and researchers would like it to be (i.e. the soul of a 'truly' intelligent machine).

Indeed, we know how bounded human capabilities and rationality are by the limited amount of information that our brain can simultaneously process in order to compute decisions or undertake specific tasks (Simon, 1985, 1996). However, replicating or simulating human interaction in *real-world* changing environments entails simulation of complex cognitive abilities not only involving data collection or combinatorial solutions to (complex) problems. Actually, AI has evolved rapidly over the last few decades thanks to the huge improvements in computational and processing capacities of related technologies, mainly ML algorithms using *Deep Neural Networks* (DNNs). In fact, after the 'AI winter', during the 1980s research on ANNs saw a new momentum thanks to some major advances including the implementation of Recurrent Neural Network (RNN) models (1982), backpropagation techniques to train ANNs (1986), and Convolutional Neural Networks (CNNs) intensively applied to shape and image recognition and classification, and built on the pioneering work of K. Fukushita on the 'neocognitron' (1979).

Between the 1990s and the early 2000s, ML-driven AI technologies were increasingly applied to a progressively wider range of knowledge domains and application fields, also shifting research efforts from theory-driven to data-driven ML and AI developments. In those years, the first work on Support Vector Machines (SVM) was presented by C. Cortes and V. Vapnik (1995), representing a pivotal tool to solve Natural Language Processing (NLP) problems, and S. Hochreiter and J. Schmidhuber introduced the Long Short-Term Memory (LSTM) Recurrent Neural Network (RNN) architecture (1997), extensively contributing to deep learning algorithmic developments.

At the same time, the development of AI systems went through a crucial and rapid transition from experiments in building computational machines (programs) able to explore high-dimensional but still finite combinatorial problems better and faster than humans, such as IMB's

Deep Blue (1997), to machines (programs) capable of imitating typical and complex human cognitive abilities, such as IBM's *Watson* (2011) (Dosi and Virgillito, 2019).

On this basis, contemporary AI technologies are, on the one hand, capable of *enabling* and enhancing: i) human tasks, by performing cognitive abilities such as *deep learning* or *language processing* (Quintarelli, 2019); ii) old available technologies belonging to the wide '*constellation' of technologies* characterizing the ICT revolution[3], such as electronic components, computer (e.g. GPUs or hardware), software and networking equipment (Cetrulo and Nuvolari, 2019); iii) exploitation of both structured and unstructured *data*. On the other hand, these new technologies also potentially threaten to substitute many human *routine* and even *non-routine* tasks by affecting, in turn, an increasing number of occupations in both the manufacturing and service sectors (Dosi and Virgillito, 2019; Montobbio et al., 2020).

Thus, in the light of the stylized history we are tracing (Tab. 1), the AI domain can be described as consisting of *incremental* technologies combining through the convergence of different technological paradigms and trajectories (Dosi and Nelson, 2016), along the unfolding of the ICT *techno-economic paradigm*, with potentially *radical* and pervasive impact on the whole socio-economic system (Perez, 2009). Moreover, in evolutionary terms, the spread of AI in production processes as well as its key role in shaping business models, organization and work represents a crucial 'passage' in the long-lasting, complex interplay between humans and machines, and between *natural* and *artificial* worlds (Simon, 1996).

However, the diffusion of AI has not followed a linear pattern. In its early stages, AI represented an academic niche, especially in Europe, with few industrial and business applications. Its development, as illustrated above, was mostly fueled by scientific research (involving various research fields and benefiting from international cooperation amongst researchers) aiming at replicating something that was to be – according to the scientists who worked most intensively on this aspect – 'as close to human intelligence as possible'. As the new millennium was about to dawn, the interplay of *technological*, *market* and *institutional* conditions paved the way for a 'great leap', which took the form of a *discontinuity point* along the pattern of adoption and diffusion of AI systems. Starting in the ICT and high-tech sectors, AI technologies rapidly became ubiquitous across industries. For example, by embedding Machine Learning (ML)-based

[3] Following the discussion proposed by Perez (2009), we can insert AI diffusion within the convergence of different industries evolution within the ICT paradigm: that is, semiconductors as *motive branch*; computer, software and smartphone producers as *carrier branch*; Internet as the main *infrastructure*.

technologies in artefacts that are at the heart of almost all production and consumption activities (e.g., electronic payment systems, customer-care services, ID-recognition services, etc.), AI is *de facto* penetrating all the economy's interstices. In other words, while systematic industrial investments in AI technologies are still concentrated in sectors like manufacturing, retail, banking and finance (Lee et al. 2018; Martinelli et al. 2019), AI is becoming a key component of consumers', producers' and public operators' lives.

2.1.1. Technological factors

The availability of an increasingly large amount of digitized information is one of the key factors contributing to accelerating the development and diffusion of AI technologies. In fact, data constitute the 'nourishment' of machine intelligence. The more digitized information is available, the greater will be the opportunity for machines to learn and become 'smarter'. From an infrastructural point of view, the rapid diffusion of grids enabling widespread connectivity throughout the economy amplifies the opportunities for data generation, storage and transmission. Similarly, the massive diffusion of connected objects (e.g., smartphones and, more broadly speaking, smart devices) multiply the 'events' that can be transformed into inputs that can be understood by AI-enhanced devices. Of course, an important role is also played by parallel developments in the domain of materials with the pivotal advances in the field of semi-conductors and super-conductors, such as the introduction during the 1980s of the Complementary Metal-Oxide-Semiconductors (CMOS) technology, allowing for practical developments and applications of ANNs.

Moreover, the increasing amount of data made available first by the rise of the Internet technological trajectory (Cernobbio and Moggi, 2020), and then by the diffusion of *Big Data*, enhanced the development of new technological instruments *enabling* the exploitation of huge amounts of information in a non-linear and not exclusively deterministic way by means of complex *data processing* tools and structures. On the other hand, the availability of new technological tools, such as *ML algorithms* and *Reinforcement Learning* (RL) mechanisms, as well as the introduction of new Database Management Systems (DBMSs), such as the *In-Memory Databases* (IMDB), and then the development of Non-Structured Query Language (NSQL) and powerful tools such as the 'Spark Apache' open source framework, specifically designed to manage big data, boosted the speed of usage and exploitation of this trove of *structured* and *unstructured data*. Relatedly, as we have seen, the rapid improvement in *Deep Neural Networks* (DNNs) abilities enhanced the use of ML-driven AI systems[4], not only in performing specific-task games but also in *real-world* interactions (e.g. with customers or clients).

Some interesting examples, among others, are Google's *AlphaGo* (2016), an AI system implemented to play the ancient Chinese game Go, or the highly modular AI system implemented by Maluuba (Microsoft) to play Atari's Pacman game (2017). The latter, by adopting RL instead of *Supervised Learning* (SL) mechanisms, is able to break down the entire game into different composite tasks each of which is performed by a parallel DNN routine within a *Hybrid Reward Architecture*.

However, *game-solver* ML algorithms still follow highly codified rules requiring codified knowledge, whereas ML algorithms applied to *real-world* interactions require both codified rules and specific knowledge of the theories governing the specific knowledge domain wherein they are expected to operate. Thus, the development of AI industrial technologies has been increasingly focusing on the combination of such ML and DNNs tools with other complementary innovations.

Focusing on this matter, Martinelli et al. (2019) stress the key importance of improvement in ML and DL and the introduction of low energy consumption sensors, also becoming increasingly cheaper, together with *cloud connectivity* tools and new ways to connect monitoring and management systems for the future prospects of industrial AI.

2.1.2. Organizational and labor-related factors

As pointed out by Perez (2009), techno-economic paradigms are characterized by the introduction and/or reinforcement of peculiar organizational practices. In fact, organizational and technological change often tend to represent two sides of the same coin. Such is the case, for example, of the 'Tayloristic' workplace organization that became dominant during the era of 'Fordist' mass production (for discussion of which, see Braverman, 1974). As the development

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[4] Teddy (2018) describes AI systems as consisting of three main building blocks: i) domain structure; ii) data generation tools; iii) General Purpose Machine Learning (GPML).

of Taylorism has shown, the introduction of a specific organizational set-up (e.g., the fragmentation and codification of work tasks envisaged by Taylor) can be a fundamental pre-condition for technological change and innovation to occur. In turn, the diffusion of new technologies is likely to facilitate organizational innovation and change in behaviors. From an evolutionary perspective, the adoption of new technologies also depends on firms' idiosyncratic dynamic (organizational) capabilities (Zollo and Winter, 2002; Dosi et al. 2010). The latter are heterogeneously distributed among firms, reflecting their specificities in terms of knowledge base, behavioral patterns, routines and hierarchical arrangements (Dosi and Marengo, 2015).

The interplay between companies' economic aims (e.g., increasing efficiency and reducing costs) and organizational innovations is also relevant to explaining the diffusion of AI technologies. In manufacturing, the introduction of smart machines that are able to 'learn' and recognize images and sounds represents a leap forward along the 'lean production' (Cirillo et al. 2018; Coriat, 1991a, b; Musso, 2013) organizational trajectory. At the plant level, AI technologies can enable efficiency gains of proportions unimaginable at the beginning of the trajectory (back in the 1970s) by reducing the amount of labor input required along the production process; maximizing the efficiency of both human and machines in performing their tasks; fixing bottlenecks and providing continuous feedback to improve quality. Outside the plant, AI enhances the effectiveness of the technical and managerial means that companies put in place to control supply chains and interact with competitors, suppliers and customers. By facilitating the performance and monitoring of productive tasks, regardless of where the latter are carried out, AI is also contributing to driving further the process of flexibilization, fragmentation and externalization of production, in both manufacturing and services. In the case of services, some authors (see, among others, Dosi and Virgillito, 2019) are envisaging transposition of 'lean logic' to the production and provision of a large array of services. A paradigmatic example is that of labor platforms (see the discussion above and Codagnone et al. 2016). Thanks also to AI technologies, these platforms organize and control service providers even if they are located miles apart while continuously improving the efficiency of the whole process relying on Big Data and ML algorithms. In Dosi and Virgillito's words, this type of techno-organizational arrangement can be defined as 'Digital Taylorism'.

In this context, the tendency towards an increasing fragmentation of production processes is likely to stimulate the design, adoption and use of AI tools capable of reproducing *routine* tasks (blue collar) based on highly codified knowledge and specific rules. However, the capacity to use and interpret 'unstructured' data (i.e. data referring to the types of complex environments that humans normally address to perform their cognitive-intensive tasks) could also allow AI technologies to replicate *non-routine* and more specialized tasks (e.g. white-collar tasks) based on non-codified rules, experience and complex knowledge. Martínez-Plumed et al. (2020) recently proposed an interesting system of mapping between AI (benchmarks), labor tasks and cognitive abilities. With this kind of task-based approach it is possible to piece together (and in some respects to foresee) a fine-grained picture of the human cognitive abilities that AI may reproduce, enhance or substitute. In particular, these authors show that jobs traditionally considered non-substitutable, given the significant amount of cognitive abilities they entail, are in fact at risk of being substituted due to the rapid advances in AI performance. Similar arguments, pointing to the fast improvements in ML-based AI systems are advanced, among others, by Brynjolfsson and Mitchell (2017), Brynjolfsson et al. (2018) and Webb (2020). From an empirical standpoint, these arguments seem to be confirmed through analysis of AI-related patents, like the analysis proposed by Montobbio et al. (2020). These authors have recently documented that a great many AI patents are concentrated in human-intensive industries, such as logistic or health and medical activities. Moreover, systematic textual analysis of AI patent descriptors brings out the growing importance of 'labor-saving heuristics' associated with the use of robots.

However, alongside the automation and robotization of human activities made possible by the advances in AI technologies, we also observe, in contrast, the increasing use of much (mostly unqualified) human work *behind* 'intelligent' machines. This is eloquently exemplified by the Amazon Mechanical Turk (AMT)[5], a crowdsourcing internet service used by coders (known as *requesters*) to perform specific microtasks (*Human Intelligence Tasks*, HITs) that machines cannot perform, on-demand by human workers (the so-called '*turkers*')[6] (Irani and Silberman,

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[5] The name refers to the (fake) chess-player automata invented by W. Von Kempelen as a homage to Maria Theresia von Österreich in 1769. The 'Turk' was, in fact, operated by a hidden human chess player.

[6] The Amazon MTurk's home page reads: "[…] *MTurk enables companies to harness the* collective intelligence*, skills, and insights from a global workforce to streamline business processes, augment data collection and analysis, and accelerate machine learning development.*" The reference to the *collective intelligence* may remind us of the well-known "*Fragment on Machines*" contained in K. Marx's *Grundrisse* (1857-58), one of the first brilliant prefiguration of the 'information society'. However, far from envisaging the development of *collective intelligence* in a Marxian perspective, the presentation provided by Amazon MTurk itself, provides some points of reflection on the critical current state of human-machine interaction.

2013). No less relevantly, as a result of the introduction of AI components into commonly used products – cars, for example (Tubaro and Casilli, 2019) - there seems to be an increase in the demand for unqualified labor, mostly operating remotely, required to 'support, maintain and train' the ML algorithms that allow such goods to be so 'smart'. Tubaro and Casilli (2019) report that in order to maintain and increase the efficiency of the AI devices included in their cars, French automotive companies rely on an 'army of turkers', largely located in African French-speaking countries. These workers, managed by platforms similar to AMT, perform micro-tasks with the aim of training French-speaking AI-based car assistants to avoid 'misunderstandings' between themselves and drivers. Thus, while, on the one hand, AI technologies may destroy jobs down the car assembly line (see the discussion above), on the other hand they boost the demand for micro-tasks performed by spatially dispersed platform workers that tend to be exposed to a high degree of exploitation (see De Stefano, 2016 for a detailed discussion on this point). This is also the case of the ML algorithms upon which the activities of key Internet platforms are based. Across the globe, every day thousands of workers are in fact required to 'solve problems' (which often include pressing ethical or socio-political issues, like the contents that need to be removed from the web) that cannot be solved by an ML algorithm, however 'smart' it. may be. It is worth noting that lively debate is mounting about the working and income conditions of this growing AI-related workforce, which is often localized in areas of the world where wages and social protection institutions are relatively weak.

Finally, the increasing adoption of AI systems has been also shaping the entire approach to business and work organization and the interaction with customers/clients in big-tech companies. A clear example is Amazon. In this case, AI and ML technologies are intensively used to improve both internal organization - the so-called *Flywheel* approach - as well as to offer new product such as Alexa, 'animated' by ML technologies as Amazon Echo, to suggest personalized lists of products according to consumers' preferences through the *Amazon recommendation engine*, or even to propose a fully 'automatized' shopping experience at Amazon *Go Stores*.

Thus, we observe a complex interplay between work content and organizational patterns and the development and diffusion of AI and automation technologies across different economic sectors, due also to the possibility of transcending space and time constraints on work offered by AI technologies combined with other digital and automation tools.

2.1.3. Industrial and market dynamics

During the 1980s, thanks also to renewed interest in ANNs and the availability of new human-machine interfaces, AI systems started to be adopted by large US companies, such as Digital Equipment and DuPont. Later on, *expert systems* programs (see above), the ancestors of the latest *intelligent systems*, started spreading among large companies, mostly located in the US, Japan and the UK. This was the beginning of the AI industry. In this phase, the diffusion of AI technologies was also facilitated by the development of *General Purpose Machine Learning* (GPML) (Teddy, 2018) opening the way to business activities such as 'Data Mining' and 'Predictive Analytics'.

At the beginning of the 1990s, in the midst of the ICT revolution, the main research efforts and developments in the field of AI came from few prominent innovative companies operating in the computer industry. The companies investing most were IBM, Hitachi and Toshiba, among others (Martinelli et al. 2019). In terms of market dynamics, this was a phase that saw a constellation of new entrant *start-up companies* rising, especially in the US and the UK, alongside emerging big-tech oligopolists - like Google and Amazon - and older incumbents like Microsoft and IBM. The peculiar nature of AI technologies favored the development of start-ups that, in some cases, simply building on the ideas of a few brilliant programmers and scientists, managed to penetrate major markets. On the other hand, with their economic and technological power, the big players were able to acquire the same start-ups whenever it might mean higher revenues and/or prevent a reduction in the market share. A paradigmatic example is offered by the acquisition of Deep Mind, a start-up company producing ML-driven AI system, founded in 2010 in UK and then acquired by Google in 2014 (currently subsidiary of Alphabet Inc.), or the acquisition of Maluuba, a Canadian AI developer start-up, by Microsoft in 2017.

What gives big-tech companies all that market power? What leads to such a concentrated structure? The characteristics of AI technologies and, in particular, of ML algorithms are part of the explanation. To allow devices to be smart and services to be so efficient (for example, compare the effectiveness of the Google's search engine with most of the others) that customers

can no longer do without them, ML algorithms need to be continuously fed with a huge amount of data. Controlling infrastructures and more broadly-speaking technologies that can offer comparative advantages in archiving, processing and profiting from data is key to gaining market power by means of AI. The big-tech companies that were among the first in pioneering such infrastructures and acquired a comparative advantage in owning and using Big Data for AI purposes now enjoy market positions that are indeed hard to challenge. Moreover, companies like Amazon, Google or Microsoft are also leaders in providing 'web-services' and platforms that, on the one hand, make it relatively easy for innovators and start-ups to design, test and market AI-related innovations. On the other hand, such platforms represent a 'panopticon' by means of which the big players can take over new initiatives with the aim of acquiring the more promising start-ups and/or using strategic patenting in order to minimize competitive threats.
This pattern of concentration is thus driven by a *winner-takes-all* strategy (Guellec and Paunov, 2017) and leads to quasi-monopolistic positions. These dynamics are substantially contributing to what the Nobel Prize winner Joseph Stiglitz defines as the *rentification* pattern of the global economy (Stiglitz, 2016). As pointed out by Dosi and Virgillito (2019), this macro trend has been characterized by an increase in market capitalization shares and a growing financialization of these non-financial companies (Lazonick, 2014; Stiglitz, 2016).

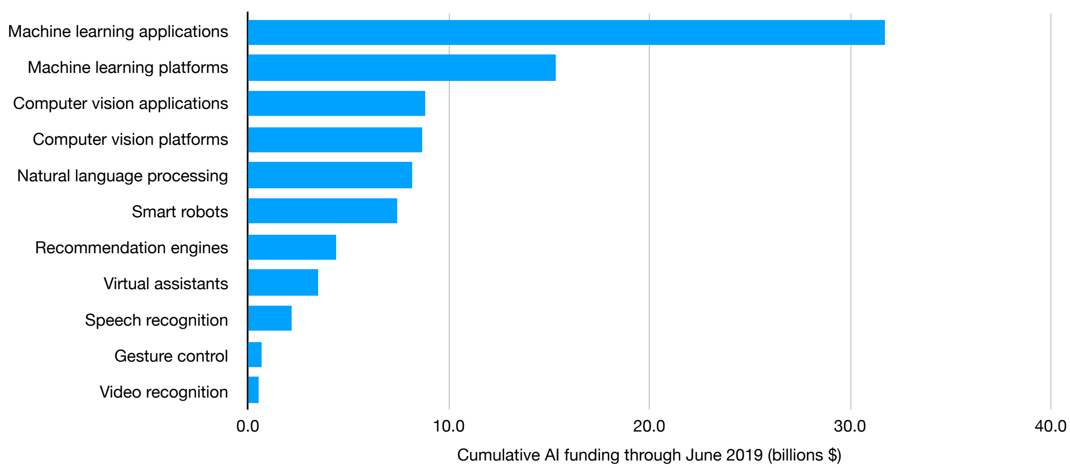
3 The development of AI: a descriptive analysis

In this Section, the spread of AI is analyzed focusing on: i) investments in AI technologies and diffusion by type of technology; ii) impact on companies' cost structure; iii) demand-side developments with specific reference to companies' market shares and revenues; iv) start-up demographic patterns and acquisitions; iv) AI-related patent dynamics.

Investments and diffusion

We start our descriptive exploration of AI dynamics by focusing on the recent trends in corporate AI investments. In this way, we shed light on the diffusion of AI technologies with respect to both the intensity of corporate investments and their qualitative composition (i.e. type of AI technology). Figure 1 shows the amount of worldwide spending on AI technologies between January and June 2019. A large amount of AI-related investments are concentrated in six technological areas. The lion's share goes to ML applications and platforms, amounting, respectively, to 31.7 and 15.3 billion U.S. dollars. However, a non-negligible share of the overall spending relates to computer vision and platforms as well as natural language processing (8.8, 8.7 and 8.2 billion of U.S. dollars) and smart robots. A significantly smaller amount of spending characterizes, in turn, domains such as virtual assistants, speech and video recognition and gesture control.

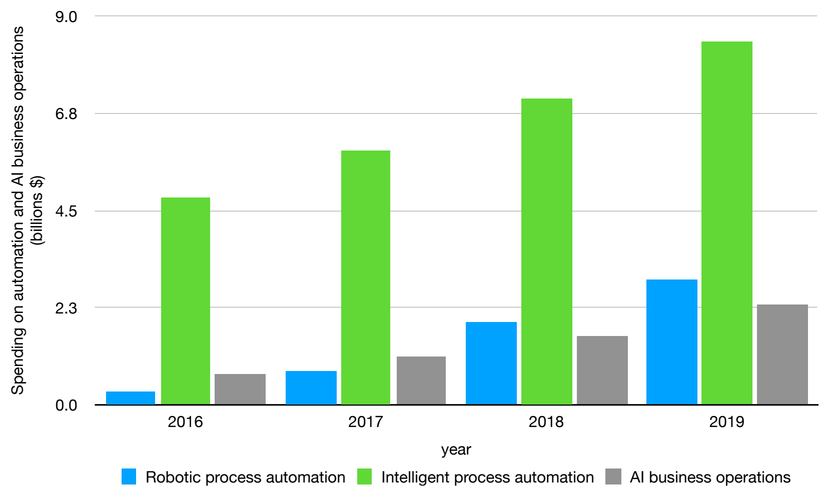
Figure 1. Worldwide AI cumulative funding (2019)
by technological category (billion U.S. dollars)



Source: Authors' elaboration on Statista data

In terms of dynamics, AI investment displays constant growth (Figure 2) in both Robots and Intelligent Process Automation (IPA) and AI business operations. Both RPA and IPA show a substantial increase in spending over a relatively short time-span (2016-2019). This seems to suggest that the diffusion of AI technologies is, at least in relation to corporate investments, driven to a considerable extent by process innovations aiming at increasing efficiency. By the same token, the significant share of investments directed to RPI points to an intensification in the diffusion of AI related technologies in manufacturing industries relying on smart robots to reduce costs and increase process efficiency.

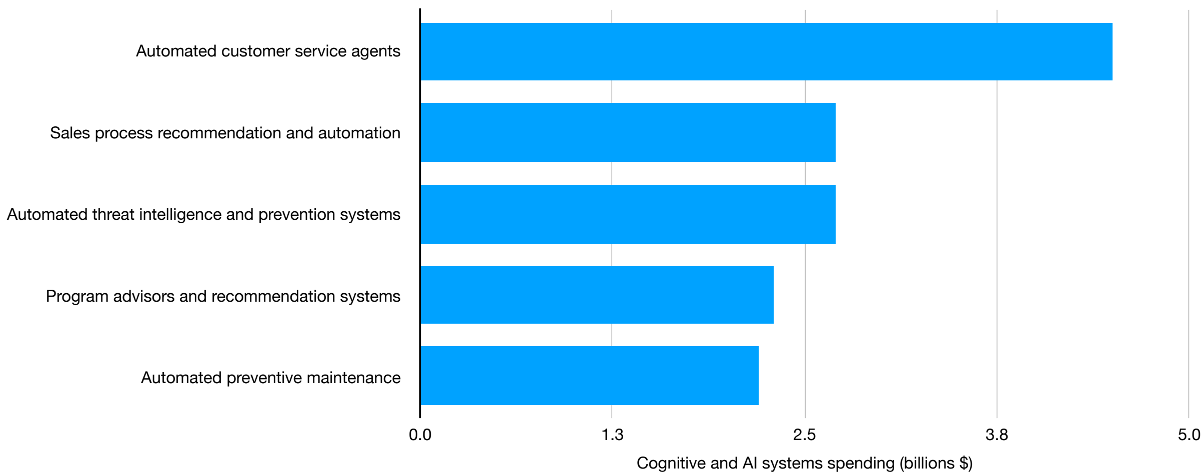
Figure 2. Worldwide spending in automation (RPA/IPA) and AI business operations (billions U.S. dollars) – 2016-2019



Source: Authors' elaboration on Statista data

Focusing on services, (automated) customer care is the area attracting the largest amount of investments (more than 4.0 billion dollars) followed by sales process recommendation (2.7 billion) (Figure 3). In both cases, AI might help automate cognitive tasks characterized by a medium-high degree of repetitiveness. In this respect, the introduction of AI technologies seems again to aim at reducing the amount of labor input in order to increase the efficiency of the production process. As emphasized by Dosi and Virgillito (2019), such developments (i.e. the intensive use of digitalization and automation technologies in the service sector) might be interpreted as a translation of the 'Tayloristic' organizational logic to the service sector – in other words, 'digital Taylorism'. As for the other use cases, most of the AI-related investments turn out to be concentrated in areas related to security, quality control and maintenance. The increase in investment related to security is linked to the data intensive nature of AI, requiring continuous upgrading in terms of cybersecurity and privacy standards. As for quality control and maintenance, these areas are again linked to process innovations designed to reduce inefficiencies and costs.

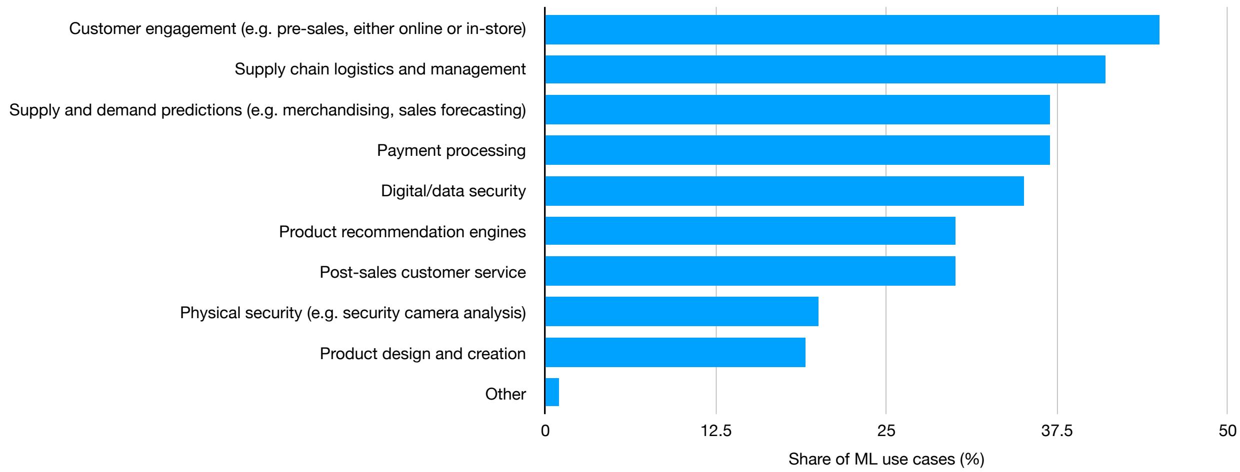
Figure 3. Worldwide cognitive and AI systems spending (billion U.S. dollars) by use case - 2019



Source: Authors' elaboration on Statista data

Partial confirmation of the Digital Taylorism hypothesis (Dosi and Virgillito, 2019) is provided in Figure 4, where AI investments are analyzed by focusing on the retail sector's use cases. In 2019, the largest share of use cases were related to customer engagement (45% of companies exploiting ML adoption for customer engagement). This reflects the huge improvements allowed for by AI technologies in terms of customer engagement, particularly during the phases of product design. In this respect, companies rely on AI technologies in order, on the one hand, to tailor products to the customers' needs and preferences and, on the other hand, to further improve the relative efficiency of processes, continuously adjusting them according to the changing market needs. The second ranked use case is directly related to process efficiency (supply chain logistics and management, with 41% of companies recording a use case) while the third is significantly related (supply and demand predictions). An important role is played also by payment services, customer care and data security services (confirming the previous evidence).

Figure 4. Worldwide Machine Learning use cases in the retail industry (%) - 2019

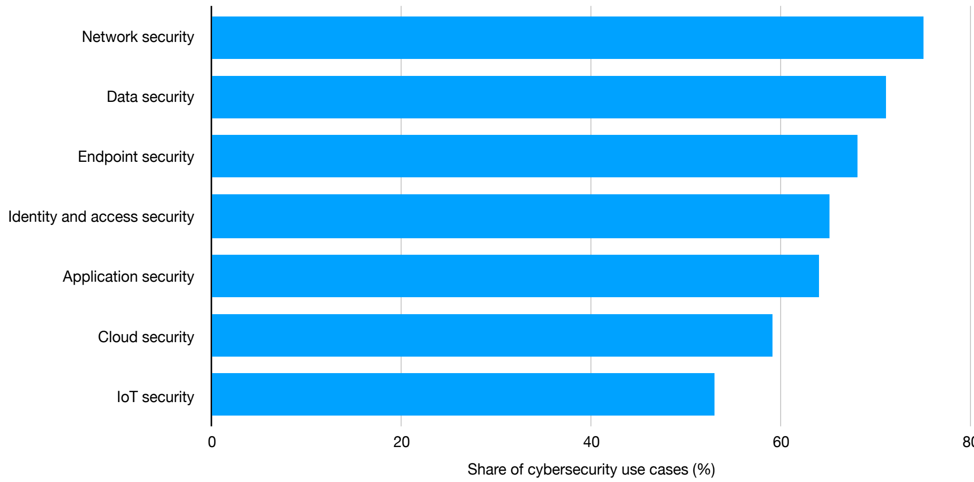


Source: Authors' elaboration on Statista data

Continuing our exploration of AI diffusion, Figure 5 shows the distribution of corporate use cases in cyber and data security in selected countries[7]. As argued, the use of AI-based technologies itself represents an activity requiring parallel investments (and organizational efforts) in terms of security. This is attested by the fact that use cases related to security are homogeneously distributed across the AI domains. The areas characterized by the largest number of use cases are network (75%) and data security (71%). With regard to these domains (as well as the others listed in Figure 5), such a high concentration of use cases could have to do with the fact that almost all AI technologies and devices imply the use of digitized information networks. Therefore, ensuring networks and data protection tend to represent a pre-condition for safe operation with all the AI technologies.

[7] The selected countries are: Australia, France, Germany, India, Italy, Netherlands, Spain, Sweden, United Kingdom, United States. For further details, see the Statista database (https://www.statista.com/).

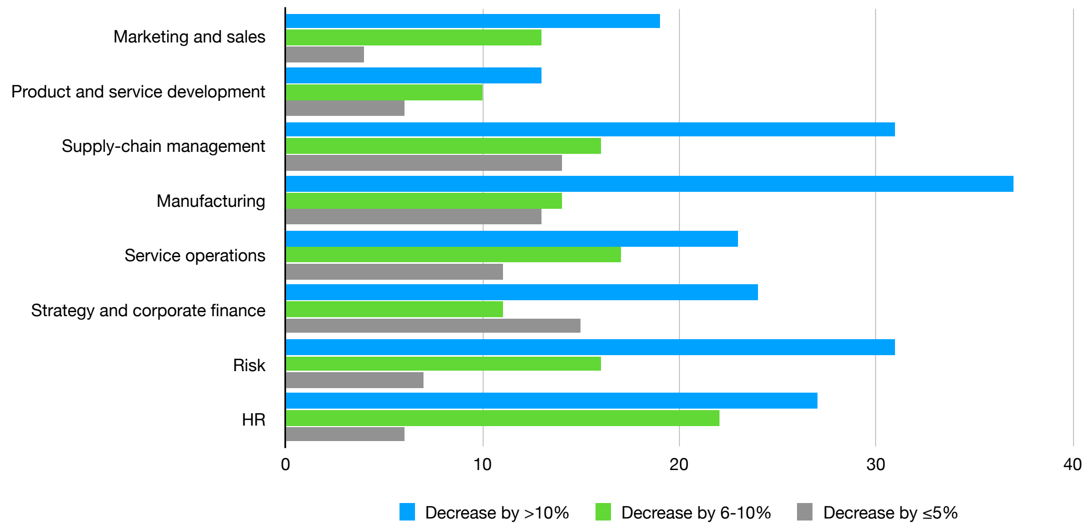
Figure 5. Top cybersecurity use cases in organizations (%) - 2019



Source: Authors' elaboration on Statista data

To conclude, we demonstrate the impact that adoption of AI technologies may have in terms of cost reduction by distinguishing by type of activity. Figure 6 shows that, in almost all the activities affected by the introduction of AI technologies, cost reduction is over 10% for the majority of companies included in the analysis. The most significant reductions are observed in manufacturing (37% of companies reporting a decrease in costs over 10%), supply chain management and risk management (31%). A considerable drop in costs is also registered in service-related activities like HR (27%), strategy and corporate finance (24%) and marketing (18%). Thus, the efficiency-enhancing effect of AI seems to be confirmed in both traditional manufacturing activities and more service-oriented ones.

Figure 6. Worldwide cost decreases from adopting AI in organizations
by function - 2019

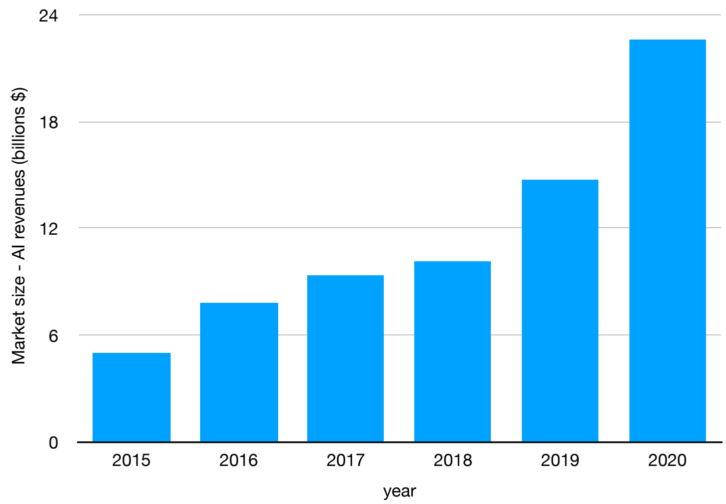


Source: Authors' elaboration on Statista data

Demand-side

The next step of the analysis consists in empirical exploration of the demand-side of AI industry. The time series of market revenues related to AI products and services (Figure 7) illustrates the evolution of the overall AI market in terms of size. Figure 7 shows that, in 2020, the AI market is four times larger than it was in 2015, rising from 5 to 22.6 billion U.S. dollars.

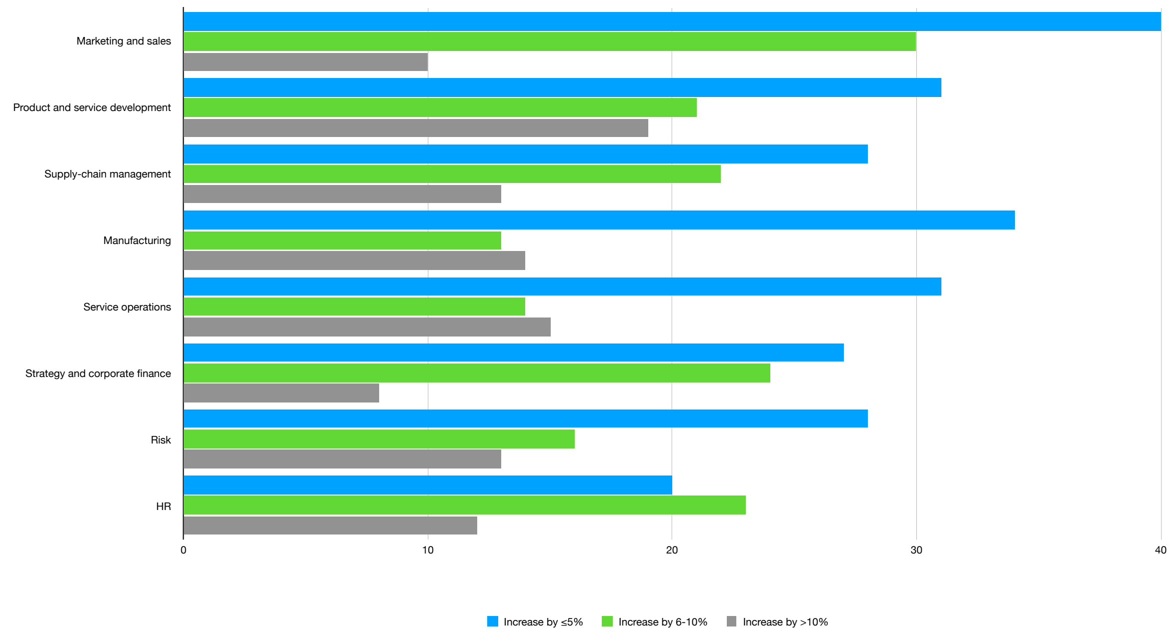
Figure 7. Worldwide AI market size in terms of revenues (billions U.S. dollars) – 2015-2020



Source: Authors' elaboration on Statista data

Reflecting the evidence reported on the decrease in relative costs associated with the use of AI technologies (see Figure 6), the relative increase in revenues associated with the use of AI in various corporate activities now comes under focus. Unlike the findings that emerged with respect to the cost-reduction and efficiency enhancing effects of AI, Figure 8 shows that, on average, the majority of adopters reported an increase in revenues of less than 5% (blue bars). This is particularly evident on turning to marketing and sales (40%), manufacturing (34%) and service operations (31%). An increase ranging between 6 and 10% (green bars), is in turn mostly associated with marketing and sales (30%), strategy and corporate finance (24%) and human resources (23%). On the other hand, the higher share of companies increasing their revenues by more than 10% through adoption of AI technologies is related to product and service development (19%), manufacturing (15%) and service operations (14%).

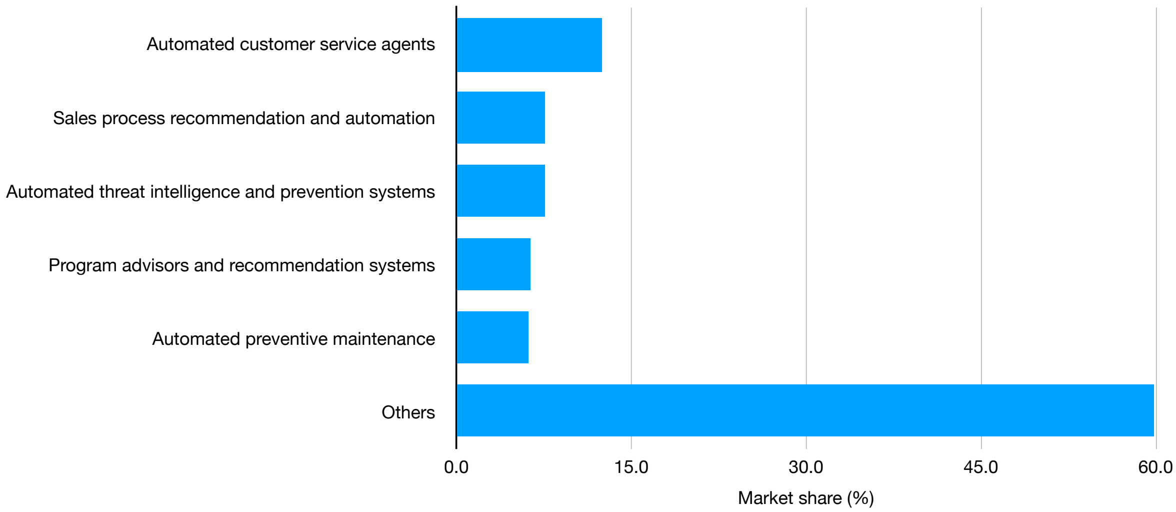
Figure 8. Worldwide revenue increase from adopting AI in organizations by function - 2019



Source: Authors' elaboration on Statista data

Finally, Figure 9 ranks AI use cases according to companies' market shares in 2019. As can be seen, automated customer service agents account for 12.5% of the use cases of AI and cognitive systems, followed by sales process recommendation and automation, and automated threat and prevention systems accounting for 7.5 and 7.6%, respectively.

Figure 9. Worldwide top use cases of cognitive and AI systems by market share - 2019



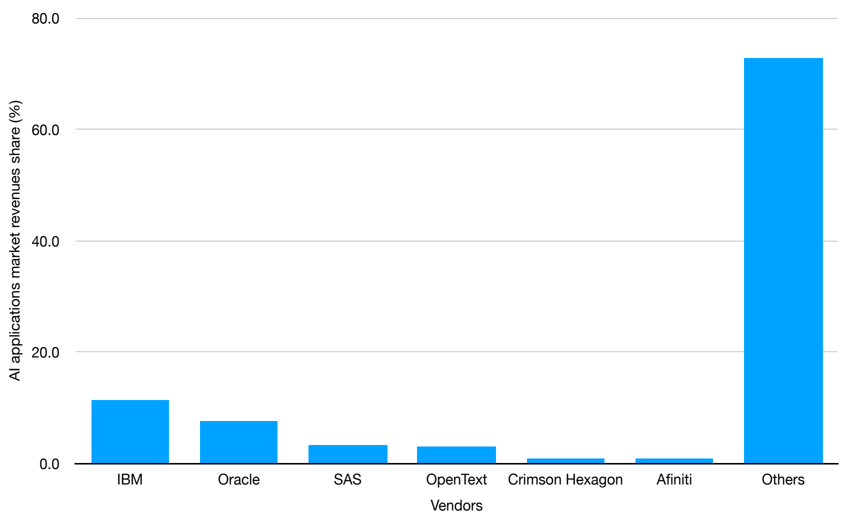
Source: Authors' elaboration on Statista data

Market concentration and AI-related patent dynamics

We will now provide some evidence on the structural evolution of AI markets. First of all, we must point out that we are still dealing with a relatively small market (around 10 billion US dollars) as compared to the overall IT (3.8 trillion US dollars) and software (450 billion US dollars) markets. However, given the increasing 'hype' around the diffusion of AI technologies and the consequent potential business opportunities and transformations following from its developments, it is crucial to investigate how this market is structured, who the key players are, and how it may evolve in the near future.

Thus, consistently with the history-friendly approach adopted for our theoretical discussion the development of AI (see Section 2), we now investigate, empirically, whether the spread of such data-intensive technologies is accompanied by an increasing degree of market concentration. Dynamics of increasing concentration might in fact be generated by the peculiar characteristics of AI technologies. In the AI domain, technological advances and innovations (in particular related to ML and Big Data) are characterized by a significant degree of *cumulativeness*. Companies having a comparative advantage with respect to technologies and competences that are relevant to the development of AI are likely to increase and consolidate market positions at the expense of existing and potential competitors. At the same time, AI markets leave room for start-ups developing new products that may find a gap in the market, opening the way for growth patterns and increasing market shares. Nevertheless, the very nature of AI technologies also leads to a contrary tendency for AI market dynamics. In fact, in order to develop their products, these start-ups or new actors in the AI industry may have to rely on the big players' technologies and services, such as developers' platforms or databases, increasing the probability of acquisitions leading to further concentration.

Figure 10. Worldwide AI applications market revenue share by vendor - in 2018



Source: Authors' elaboration on Statista data

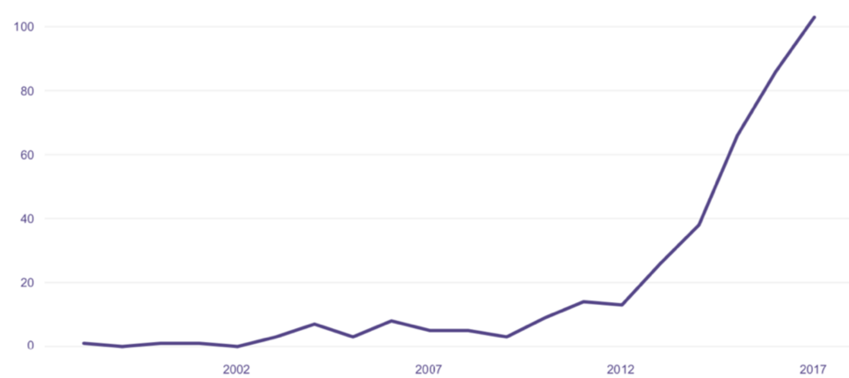
Figure 10 depicts the role of IBM as a leader in the AI applications market, with a global market share of 11.4%, but it also shows how the "others" category records a global market share of over 70%. This might reflect intense competitive dynamics, partly related to high levels of opportunities for new businesses and companies, especially start-up companies, to enter the market in the light of the rapid growth and diffusion of the AI technological domain.

However, to provide a complete picture, we also have to investigate the degree of appropriability and the acquisition dynamics on the part of the key players operating in the AI market.

Thus, Figures 11, 12 and 13 show the number of company (Fig. 11) and start-up (Fig. 12) acquisitions, including information on the key buyers (Fig. 13).

As can be seen in Figure 11, the number of acquisitions within the AI industry grew on average by 5% between 2000 and 2012 and then strikingly accelerated with an average growth of 33% between 2012 and 2017. Such a fast growth pattern of acquisitions provides an initial picture confirming the tendency towards an increasing concentration dynamics within the AI industry discussed above.

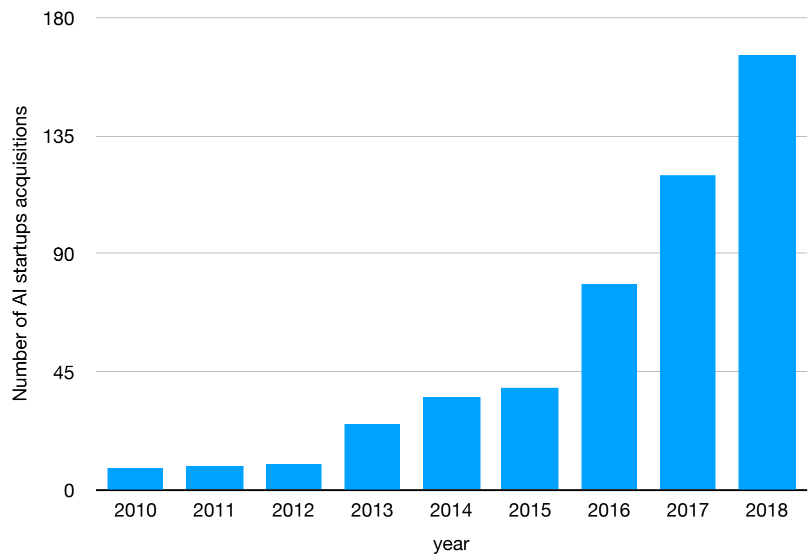
Figure 11. Number of acquisitions in the AI sector by the acquisition year – 1997-2017



Source: WIPO Technology Trends 2019

Despite the enthusiastic dynamism and ‘hype’ accompanying the diffusion of AI technologies and their applications across countries and industries has led to an increase of AI start-up initiatives at the same time, the number of AI start-up acquisitions has also been increasing. Between 2010 and 2018, the number of acquisitions of AI start-ups saw massive growth, rising from 39 acquisitions in 2015 to 166 acquisitions in 2018 (Figure 12).

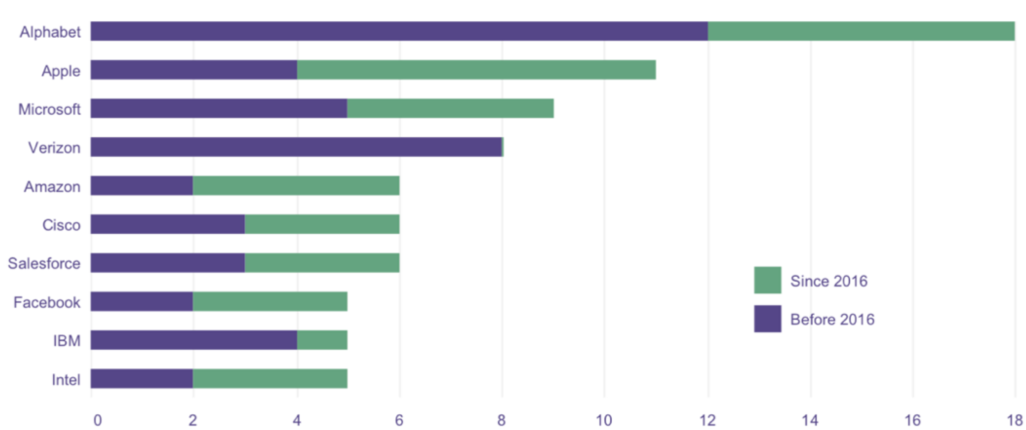
Figure 12. Worldwide number of AI startups acquisitions – 2010-2018



Source: Authors' elaboration on Statista data

As shown in Figure 13, the leading companies driving this market process are both consolidated incumbent multinational groups, such as Apple, Microsoft, IBM and Intel, and younger big-tech giants, such as Alphabet/Google (accounting for 4% of the overall acquisitions), Amazon or Facebook.

Figure 13. Number of companies acquired by top acquired companies



Source: WIPO Technology Trends 2019

This pattern offers three key messages: i) the trend to increasing market concentration continued to consolidate after 2016; ii) massive appropriation of AI-related technological and market advantages by a few U.S. multinational companies is detected; iii) Alphabet (Google) outperforms high-tech companies in terms of market acquisitions. Overall, strategic acquisitions by big-tech companies emerge as a pivotal channel through which they can conquer technological and market comparative advantages.

Once we have documented the degree of *indirect* appropriation of technological and market advantages related to AI-technologies *via* company acquisitions we can provide an assessment of the degree of *direct* appropriation *via* patent applications and ownerships at different levels of aggregation. To this end, we exploit the detailed information provided by the World Intellectual Property Organization (WIPO) in their recent Report on AI-related patent data (WIPO, 2019). As documented by the WIPO Report, nearly 340,000 patent families and more than 1.6 million scientific publications related to AI were registered and published between 1960 and 2018, and the number of AI-related annual patent registrations has been rapidly growing over the last ten years.

Table 2 – Top AI patents by technologies, application categories and fields, and top companies and countries by AI patents

Technology categories	Companies	Countries	Application categories	Companies	Countries	Application fields	Companies	Countries
Machine Learning	IBM - Microsoft	China - US	Computer Vision	Toshiba - Samsung	US - China	Telecommunications	Microsoft - Samsung	US - China
Logic Programming	IBM - Siemens	US - China	Speech Processing	Nuance Communications - Panasonic	US - Japan	Transportations	Toyota - Bosch	US - China
Fuzzy logic	Omron - Siemens	US - China	Natural Language Processing	IBM - Microsoft	US - China	Life and Medical Sciences	Siemens - Phillips	US - China

Source: WIPO Technology Trends 2019

With the information included in the WIPO Report we can identify the top AI-related technologies, their functional applications and the fields of application. In addition, it is possible to map the distribution of patents among key companies and countries for each technology, application category and application field.

Table 2 confirms the qualitative discussion we presented in Section 2. Machine Learning is indeed the dominant technological category within the AI domain, representing 89% of AI patent families, followed by Logic Programming and Fuzzy Logic. Computer Vision is the top AI functional application, representing 49% of the related patent families, followed by Speech Processing (14%) and NLP (13%), while Telecommunications (24%) and Transportations (24%) are the two top AI application fields in the AI patent families, with more than 50,000 patent filings each, followed by Life and Medical Sciences (19%).

Turning to the key players, IBM and Microsoft, with portfolios of 8,920 and 5,950 total AI patents, respectively, maintain leading positions, especially in ML technologies, with portfolios of 3,566 and 3,079 patents, and in a large number of ML subcategories, such as Probabilistic Graphical models, Rule Learning or Reinforcement Learning (IBM), Supervised Learning techniques (Alphabet), and Neural Networks (Siemens).

The picture changes slightly when it comes to identifying the top patent applicants related to AI functional applications. IBM and Microsoft confirm their leadership in NPL and Knowledge Representation and Reasoning, while Toshiba and Samsung dominate in Computer Vision, and Nuance Communications and Panasonic are the top applicants in Speech Processing.

As for the AI application fields, Transportations is dominated by Toyota and Bosch, being the leading Japanese and German automobile manufacturers or suppliers. The WIPO Report highlights the fact that Toyota also dominates crucial AI patent fields in Transportation sub-categories such as autonomous vehicles, transportation and traffic engineering, and vehicle recognition. In turn, Microsoft and IBM are leaders in AI applications related to Personal devices, computing and HCI, Document, management and publishing, and Business applications. Patents related to AI applications in Life and Medical Sciences are dominated by multinational companies operating in the medical equipment sector, such as Siemens, Phillips and Samsung, while AI patents in Telecommunications are dominated by Microsoft, leading in computer networks/internet and telephony, and Samsung, leading in radio and television.

From a geopolitical standpoint, China turns out to be the rising star with a prominent position in ML-related patent applications, followed by the US and Japan. The situation is more balanced in the field of Logic Programming patents. By contrast, more Fuzzy Logic application registrations are recorded in the US than in China.

China and the US also dominate for all the functional applications. Of the latter, the highest number of patent applications is recorded in Computer Vision, with Japan ranking third. Among the top registration offices in specific applications we find Australia (NLP), Germany (Computer Vision, Speech Recognition, Robotics, Planning and Scheduling and Control Methods), Canada (Predictive Analytics and Knowledge Representation and Reasoning) and India (Distributed AI).

Turning to the ranking of patent offices with respect to AI application fields, we found China and the US to be the two dominant actors, followed by Japan and the Republic of Korea, ranking second for AI Military applications. According to the WIPO Report, China seems to have acquired a leading position in AI applied to Industry and manufacturing, Networks, Energy management, Computing in government, Agriculture, Law, and social and behavioral sciences, whereas the US dominates in all the other fields.

As discussed in Section 2.1.3, behind the narrative describing AI industry and economic sectors as characterized by high levels of competition and market dynamism in terms of technological and business opportunities for new companies and start-ups, we actually find a high degree of appropriability of such opportunities by big-tech incumbents, such as Microsoft and IBM, and relatively younger big-tech giants, such as Google, Amazon or Facebook in terms of both massive acquisition of innovative start-ups and patent ownerships.

4 Conclusions

The present work contributes to the current discussion on the origins and evolution of AI. To this end, we have attempted to trace a theoretical framework to analyze the history of AI and the effect of its diffusion on business models, organization and work. In so doing, we have embraced a *history-friendly* perspective in order to trace out a '*stylized history*' of AI, thereby identifying possible *discontinuities* in terms of economic, industrial and organizational dynamics, as well as mechanisms reinforcing pre-existing capitalistic trends, which may have fostered its massive diffusion among sectors and economies.

Moreover, taking the evolutionary theoretical perspective, we define AI as a relatively complex technological domain shaped by *incremental* innovations. The latter are located at the intersection of different technological paradigms and trajectories, embedded in the ICT *techno-economic paradigm* with potentially *radical* and pervasive impact on the entire socio-economic system. In particular, we identify three different trajectories whose interaction has enabled the development and diffusion of AI as a technological domain: i) developments in statistical and computational theory and specific algorithmic techniques; ii) data availability, closely linked to the Internet trajectory; iii) improvements in computational power and data storage capacity. These trajectories are punctuated by technological advances, in terms of knowledge, techniques and applications. Thus, tracing back the stylized history of AI we can identify key technological components, complementary innovations and supply and demand conditions enabling fast and ubiquitous diffusion for it, also interacting with changes in organizational routines and labor-related dynamics. Among these key elements we find: i) *technological factors*, such as the diffusion of *Big Data*, the improvement of *Machine Learning* (ML) and *Deep Neural Networks* (DNNs) *tools*, and the pervasive *connectivity* allowed for by the *Internet* infrastructure; ii) *organizational factors* related to the growing fragmentation of knowledge and tasks along production processes and the possibility of overcoming space and time work constraints; iii) and factors related to *market* and *industrial dynamics*, such as the quasi-monopolistic position gained by big-tech companies (e.g. Amazon or Google) due to their comparative advantage in exploiting AI-related technologies.

The evolution of the AI technological domain should also be interpreted in the light of pre-existing macro-trends intrinsically characterizing capitalistic development, such as the increasing *rentification* of the economy at the global level and the long-term tendency towards oligopolistic market configurations. The diffusion of AI technologies is reinforcing the overall trend towards market concentration characterizing the ICT domain. By exploiting their technological comparative advantage and acquiring most of the more promising start ups, big tech players consolidate their dominant positions influencing both technological and market dynamics. This oligopolistic configuration is also reflected in the distribution of AI-related patents. A small group of companies owns a majority share of AI patents with a geographical distribution dominated by China and the US as the key global players.

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Appendix

Table 1 – A time line of the history of AI

Year	General Description	Theoretical and algorithmic developments	Data availability	Computational power and data storage
XIV-XIX sec.	Theoretical roots of computational and probabilistic thinking			
1308		R. Lullo "Ars Magna", theorization of logical machine		
1666		Leibniz "Dissertatio De Ars Combinatoria"		
1805		Legendre's Least Square method		
1812		Laplace works on Bayes' contributions formalizing the Bayes theorem		
1913		A. Markov introduces the Markov Chains		
1936	The rising of AI	Turing Machine to solve Hilbert's 'Entscheidungsproblem'		
1940-1950	First developments of ML algorithms and ANNs			
1943		Threashold Logic Unit (TLU), a formal design for Turing-complete artificial neurons		
1951		D. Edmons and M. Minsky, first neural network machine: Stochastic Neural Analog Reinforcement Calculator (SNARC)		
1951		A. Samuel (IBM), first machine playing checkers		
1956	AI as a proper research field	J. McCarthy coins the term 'AI' during the seminal workshop at Dartmouth College		
1956		A. Newell and H. Simon implement Logic Theorist (LT)		
1958		F. Rosenblatt working at the Cornell Aeronautical Laboratory		

		introduces his ANN: the perceptron		
1960s	Extensive application of probabilistic methods and developments of ML algorithms			C. Bachman designs the Integrated Database System (IDS), the first Database Management System (DBMS)
1963		D. Michie implements a machine able to play Tic-Tac-Toe via Reinforcement Learning (RL)		
1965				Moore's Law on exponential growth of the chip power. The number of transistors in a dense Integrated Circuit (IC) is expected to double every two years
1967		Nearest Neighbor algorithm as a first step towards pattern recognition		
1970s	The 'AI winter'	Limitations of ML applications and developments highlighted by Minsky and Papert's book "Perceptrons" (1969)		
1971				Bachman's Database Task Group presents the standard language Common Business Oriented Language (CBOL)
1973				M. Stonebraker and E. Wong (UC Berkley) start the Interactive Graphics and Retrieval System (INGRES) project on relational database systems using the query language QUEL
1974				IBM develops the Structured Query Language (SQL)

1979		K. Fukushita work on the neocognitron ANN laying the groundwork for Convolutional Neural Networks (CNNs)		
1980s	Revival of ML research projects and first commercial AI products	Diffusion of Expert Systems within US industries		Complementary Metal-Oxide-Semiconductors (CMOS) technology, as a Development of Metal-Oxide-Semiconductors (MOS) Very Large-Scale Integration (VLS): practical development of ANNs
1982		J. Hopfield introduces Recurrent Neural Networks (RNNs) as Content-Addressable Memory (CAM) systems		
1986		D. Rumelhart, G. Hinton and R. Williams introduce the backpropagation technique to train ANNs		
1989		C. Watkins develops Q-learning by improving RL methods		
1989		Axcelis, Inc. (US) commercializes Evolver, the first software package for PC using genetic algorithms		
1989		Convolutional Neural Networks (CNNs) to shape and image recognition and classification		
1990-2000	Exploitation of ML-AI for a wide and increasing range of knowledge domains and application fields. From theory-driven to data-driven ML research and			

	development			
1991			World Wide Web	
1992		G. Tesauro implements TD-Gammon, an ANN program playing Gammon		
1995		Introduction of random forest algorithms		
1995		C. Cortes and V. Vapnik first work on Support Vector Machines (SVMs), widely used to solve many Natural Language Processing (NLP) problems		
1997		S. Hochreiter and J. Schmidhuber introduce the Long Short-Term Memory (LSTM) Recurrent Neural Networks (RNNs)		
1997		IBM's Deep Blue vs chess champion G. Kasparov		
1998		S. Brin and L. Page (Stanford University) introduce PageRank algorithm	Release of the Modified National Institute of Standards and Technology (MNIST) Database to train image processing systems	
2000s			Web 2.0	Diffusion of Non-Structured Query Language (NSQL) and In-Memory Databases
2002				Amazon Web Services offers cloud-based storage and computing power to users
2004			Facebook	
2005			YouTube	
2007			Apple launches the first iPhone	

2009			ImageNet database	M. Zaharia (UC Berkley's AMPLab) develops the Apache Spark open source framework to exploit and update Big Data
2008-2015			Web 3.0 - S*emantic Web*	
2010				Microsoft and Google launch their cloud, Microsoft Azur and Google Cloud Storage
2011		IBM's Watson beats two human champions at *Jeopardy!* by using NLP ML and information retrieval techniques		
2012		Google Brain team creates an ANN capable of recognizing cats from unlabeled YouTube video frames		
2013		DeepMind implement a CNN able to play Atari via Deep Learning		
2014		Facebook researchers present DeepFace, a neural network system for face recognition		
2014		Google's researchers present Sibyl, a ML-driven platform for users' behavior prediction and recommendations		
2016		Google's AlphaGo plays Go		
2017		Maluuba (Microsoft) implements a RL algorithm able to play Pacman		