

Artificial Intelligence (AI): Explaining, Querying, Demystifying



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Abstract Artificial intelligence (AI) is a buzzword today, reminding us of the concept of “globalization” and the relating debate two decades ago. As with globalization then, for the greater part of society, AI remains a concept poorly understood, vague, and approached with fear of the unknown. While AI is hailed as the panacea to all the ills of the prevailing socio-economic model and a source of unimaginable opportunities, it is also seen as a source of substantial risks and threats to safety, security, and the operation of the markets. The objective of this chapter is to explain, query and demystify AI and by so doing to highlight the areas and domains that are crucial for AI to develop and serve society at large. To this end, the “dry”, i.e., quite technical, facets of AI are discussed, and a case for an AI ecosystem is made. Technology-related limitations of AI, as well as possibilities, are outlined briefly. An overview of AI’s implications for the (global) economy and selected policies follows. The ethical concerns are discussed in the concluding section.

Keywords Artificial intelligence (AI) · AI ecosystem · International economy

1 Introduction

Artificial intelligence (AI) has become a buzzword of today, reminiscent of the concept of “globalization” and the relating debate on globalization two decades or so earlier (cf. James & Steger, 2014; Rosamond, 2003; Turenne Slojander, 1996). As in the case of globalization and the discourse surrounding it (however defined!), AI remains a concept both powerful and yet insufficiently explained, explored or understood by large sectors of society. AI is hailed by many as the panacea to all the ills of the current socio-economic model as well as a source of unimaginable opportunities (cf. Zhuang et al., 2017; Eager et al., 2020; Floridi, 2020). However, AI, especially in popular discourse, is also seen as a source of risks and threats. Clearly, it is too early to

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imagine and understand all the possible implications, positive and negative, that the use of AI-enhanced solutions may trigger for our societies, including their politics, economics, business sectors, competition, and innovation, as well as education and healthcare provision etc. Therefore, a thorough and unbiased conversation, including academics, researchers, and practitioners, on AI and AI-related topics is necessary. This chapter and thus the entire volume respond to this plea by offering an insight into diverse aspects of AI and its use across wide-ranging issues and domains, including security and military affairs, the decision-making process, and public administration. Interestingly, amidst the frequently alarming media accounts of AI and the alleged existential risks and threats to humanity that it bears, AI-based solutions, including services and applications, have been present in our lives for some time. Consider the autocorrect feature in smart phones, and how it picks the key language you use daily, and how it learns throughout the process to recognize which language you are using at a given moment when sending your messages or typing your emails. However, AI is much more than language and speech recognition applications in the smart phone. AI and AI-based techniques and applications, and, for example, AI-based solutions, have relevance across very many issues and domains. At present, when advances in AI and related technologies have been transferred from the field of research to application, the challenge is to create appropriate, resilient and flexible regulatory frameworks to ensure that the risks and threats that AI holds for our societies can be preempted and addressed, whilst ensuring that the development of AI and, thus, innovation centered on AI and its ecosystem are not suppressed. To address these complex issues, a thorough understanding of the nature of AI, its limitations and potential is necessary. This chapter aims to provide this.

The discussion in this chapter is structured as follows. In the next two sections, the “dry” i.e., quite technical, facets of AI are discussed. Here a case for an AI ecosystem is made and the notions of artificial neural networks and unsupervised machine learning are discussed. In what follows, technology-related limitations of AI as well as possibilities are outlined briefly. An overview of AI’s implications for the (global) economy and selected policies follows. The ethical concerns are discussed in the concluding section.

2 AI and Its Ecosystem

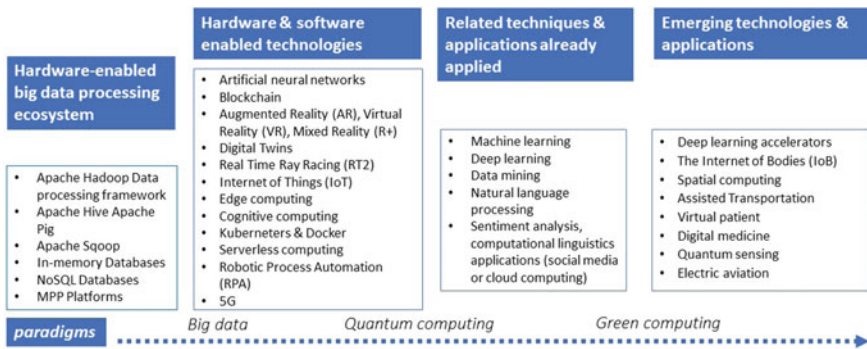
The popular understanding of AI and, for that matter, the key lines of the popular narrative on AI portray AI as a sort of crystal ball capable of foreseeing the future, a super-computer capable of resolving the most complex problems, a super-weapon of total destruction, and perhaps also as a super-machine waiting to replace human beings. This conception of AI, characterized by fear of the unknown, has been famously captured in Lem’s (1964, 1990) visionary robots’ fables, the thrust of which concerned the big question of the human–computer (aka robot) interaction. The onset of AI and, perhaps most importantly, the machine-learning-mediated possibility for people to enter a form of interaction with a computer/machine revives the basic

question of how to conceive of the absolutely new form of communication, i.e., with a non-human. To be clear, the objective of this chapter and thus, also of the entire volume, is to showcase that, regardless of the potential inherent in AI and related technologies, AI should not be reified or, in other words, considered as ontologically distinct from the human being, even if valid fears exist that AI might replace the human (Archer, 2021; Rakowski et al., 2021; Sætra, 2020; Fiske et al., 2019). To understand why, it is necessary to shed light on the very essence of AI.

Contrary to popular (mis)understanding, AI is best conceived as an ecosystem of sophisticated technologies, techniques, and applications. Their emergence is a function, first and foremost, of the development of ever more efficient processors capable of handling ever more complex calculations in an ever-shorter time span, and thus delivering greater power necessary for our computers to operate and perform the tasks we require (cf. Khan et al., 2021). Central to the emergence of AI is the development of neural networks, i.e., several layers of interconnected processors that, similarly to neurons in a human brain, have the capacity to share impulses and, thus, data.

The emergence of AI is directly related to the onset of the big data paradigm in computer science, and thus the ability to process huge data sets in a short period of time, a task impossible before (Farami et al., 2021; Visvizi et al., 2021). The emergence of the big data paradigm changed the way data is conceived and valued. That is, now, huge datasets become a source of invaluable information across domains (Lytras et al., 2021). Yet the capacity to process the phenomenally huge and complex sets of data is only possible due to the emergence and application of such software technologies as Apache Hadoop and other. These technologies enable, on the one hand, a different and a more efficient way of processing data, and, on the other hand, distributed processing of large data sets across clusters of computers by means of simple programming models.

In other words, as Fig. 1 outlines, any discussion on AI needs to be based on the recognition that it is an AI ecosystem rather than a single super-technology. Specifically, the emergence, development and utilization of AI are driven by three



Source: The author.

Fig. 1 AI and its ecosystem. Source The Author

major paradigms that shape the debate in the discipline of computer science, i.e., the big data paradigm, the quantum computing research, and green computing (Hu et al., 2021; Piattini et al., 2020; Lytras et al., 2021). These three broad debates, representing interconnected but paradigmatic shifts, shape the developments in the discipline and in the field. As such, they are consequential for the remaining items in the AI ecosystem, such as the (i) hardware-enabled big data processing frameworks and open-source software utilities, (ii) hardware- and software enabled technologies; (iii) related techniques and applications already in application; (iv) emerging technologies and applications. Notably, the landscape of techniques, technologies, and applications, all fostered by advances in the three basic paradigms that shape advances in information and communication technology (ICT) today, changes rapidly. Thus, stories that hold truth today, are subject to contestation and revalidation tomorrow. Knowledge is emancipatory after all (Archer, 1998; Bhaskar, 1975).

3 AI and the Neural Networks: From Supervised to Unsupervised Learning

To put it simply, AI is the—enhanced by super-processors—process of grouping, structuring and analyzing huge sets of data, especially of unstructured data, i.e., the kind of data that has not been previously “tagged”. Notably, AI is not a new term. Already in the 1950s, attempts were made to utilize the learning potential of computers of that period. At that time, however, the focus of the activity was directed at so-called supervised machine learning. The latter employs algorithms that require structured or tagged data. The machine learning process consists in this case of the classification of data based on a key, i.e., a key included in the algorithm, and drawing conclusions based on the classic probability tree. Even if supervised machine learning is still in use in some domains today (cf. Jiang et al., 2020), it displays fundamental weaknesses. Its efficiency is directly related to the possibility and ability of the human, in this case the system manager, to label or tag the data. Considering that the data sets are huge and that the supply of data is massive and continuous, tagging (or labelling) data is time-consuming, requires a lot of skill and thus is very expensive.

In contrast to supervised machine learning, unsupervised learning—and it is the essence of the concept of AI—allows unstructured data to be fed into the system and subsequently examined (cf. Alloghani et al, 2020; Rajoub, 2020). To explain the meaning of unsupervised learning, it is necessary to highlight three basic terms, i.e., artificial neural networks, algorithms, and deep learning. The artificial neural networks consist of an immense number of connected processors operating at the same time, which as per the design—are supposed to mirror the functioning of the human brain. Each of the processors that builds a part of each of the neural networks has access to the local memory and is fed by, on the one hand, huge data sets and, on the other hand, information about the relationships among the data. The neural

networks work as a system, i.e., they may overlap—thus the talk of layers of the artificial neural networks—and co-operate.

The content and quality of the algorithms define the ways in which the neural networks and the layers operate and co-operate. A given algorithm defining the functioning of a neural network is responsible for the process of (i) recognizing the characteristics of data available in the system, a process called feature introspection; (ii) identifying similarities among chunks of data, a process called similarities detection; and (iii) grouping these unstructured data into clusters. In other words, algorithms establish the relationships between and among data, e.g., vanilla ice-cream (taste), and not, say, red ice-cream (color) (Strickland, 2019). Taking into account that neural networks can overlap, i.e. it is possible to use several layers of neural networks, and an algorithm enables the exchange of data/information among them, it is possible to talk about the learning process of a neural network. However, for a neural network to learn, the algorithm and the software that operationalize it must demonstrate to the neural network how it has to respond to external cues, e.g., to data introduced by the user.

AI is based on the utilization of the outcomes of this kind of multilayered co-operation of complex neural networks. Precisely this feature of unsupervised learning, consisting of the multilayered co-operation among neural networks, defines the thrust of what is otherwise referred to as “deep learning”. Viewed in this way, the process of deep learning is feasible due to specific algorithms and advanced processors. Under these conditions, in a complex multilayered neural network, based on co-operation among specific layers of the neural network, the following processes take place: introspection, similarities’ detection, clusters’ grouping, and, finally, delivering an answer to a question included in the algorithm.

Considering that the number of data available in the system increases, the artificial neural networks have to expand, the power/capacity of processors has to increase, the number of relationships between and among chunks of data becomes denser, and thus the learning capacity of a given neural network increases, always in line with the logic defined in the algorithm that defines its operation. It remains to be seen how and in which direction artificial neural networks will develop. Now, irrespective of the fact that AI tends to be viewed as an embodiment of unsupervised learning, and therefore also as a form of deep learning, the classic rules deriving from the science of probability are also at play in the process of the functioning of neural networks. Having said that, it is necessary to dwell on the limitations, possibilities and risks inherent in neural networks.

4 Limitations, Possibilities and Risks Inherent in Neural Networks

AI is directly correlated with the processing power of respective processors as well as with the quality of the algorithms that define a neural network’s operation and

co-operation. From a different angle, regardless of arguments suggesting that neural networks can do everything, neural networks are not intelligent enough. In other words, a neural network cannot make decisions about and create the logic of thinking that subsequently will allow it to connect data in line with certain rules. The latter are quintessential for the processes of introspection, similarities detection, and clustering, i.e., for the process of building a logical whole out of a myriad of pieces. Notably, attempts to teach neural networks, e.g., by means of generating cookbooks led to quite anecdotal combinations such as “Take 250 gr of bones or fresh bread . . .”, etc. In other words, the problem, or a challenge, rests in the fact that a neural network repeatedly committed mistakes suggesting it did not have any memory at all (Strickland, 2019). To put it differently, artificial neural networks can only work forward, i.e. in a range from T_0 to T_1 . They cannot predict the future. Artificial neural networks can support real-time tasks and commands.

Another, by now classic, example that was meant to hail the success of AI relates to AlphaGo, i.e. the software and a game from the company DeepMind (cf. Granter et al., 2017; Li & Du, 2018; Holcomb et al., 2018). Go is a traditional, highly complex, Chinese board game, and its history goes back 3000 years. Attempts to utilize supervised machine learning to develop a software version of the game allowed for an amateur-level version of the game (cf. Lu et al., 2020). This is because the number of possible moves, the number of their combinations, and the evaluation of their relative values for the follow-up of the game were far more than the possibilities inherent in the traditional probability “trees”. The advent of neural networks and so, also, the onset of unsupervised learning made it possible to bypass this problem. That is, the software AlphaGo, developed by Deepmind (and purchased by Google for USD 500 m in 2014, (cf. Shu, 2014), employs an advanced probability equation to filter the layers of the neural network that is structured according to such values/functions as “politics”, “values” etc., i.e., items specific for the game (cf. Binder, 2021).

An interesting discovery relating to the AlphaGo is that the software was unable to define what “human being” is. Even more so, the software was unable to discern whether it was competing with a machine or with a human being. To put it differently, at present, the algorithms underpinning the functioning of neural networks demonstrate great precision whenever the problem/task at hand is narrow and very well defined. Thus, the more specific a given problem, the smarter AI appears to be. The opposite is also true. For instance, should a given algorithm be designed to generate pictures and, more specifically, pictures of birds, it will not be able to generate a picture of any other animal.

Discussion of possibilities inherent in AI needs to take into account the parallel advances in sophisticated technologies, applications, and techniques related to the process of the handling of big data. This includes the highly technical issues already at the level of the processor and its speed, as well as exchange of information between and among processors, etc. These factors, as mentioned earlier, directly influence the possibilities relating to deep learning, and especially the pace of deep learning and the condensation of information that it may lead to. Possibly, if only the processors’ capacity would increase as fast as the increasing quantity of data they are fed with, one could argue that the potential inherent in AI was unlimited. At this point, it is worth

mentioning the case of deep learning accelerators (see also Fig. 1), i.e., a technology that seeks to mitigate some of the technical limitations specific to the limited overall speed of the existing processors. In this context, it is also important to highlight the case of quantum computing, i.e. an emerging paradigm that revolutionizes the way in which the very process of computing is conducted and that, at the same time and for precisely this reason, a myriad of possibilities and applications across fields and domains open up (Hassija et al., 2020; Lee, 2020; Outeiral et al., 2021).

With regards to AI's limitations, several barriers exist that limit the feasibility of its utilization. These barriers can be identified at diverse levels and in several overlapping domains and issues specific to contemporary politics, society, and the economy. These barriers may include: digital illiteracy; lack of awareness and expertise regarding the use of AI-enhanced tools; lack of resources to purchase AI-based tools and solutions; and a lack of, or insufficient, infrastructure that would enable rightful access to data and their efficient use. The poor quality of data, i.e. data in an improper format, constitutes another obstacle to efficient AI utilization (cf. OECD, 2015; Hatani, 2020). As shall be discussed in the following section, obstacles and limitations to the use of AI-based solutions rest also in the regulatory field, including questions of privacy, personal data protection, safety and security, grey areas of regulations, as well as regulatory barriers, insufficient complementarity of regulation in the field of AI in the international context and many others. Considering the breadth of the discussion focused on contentious issues pertaining to the emergence, development and application of AI in modern world, the following section will merely outline the key areas of concern. The content of the volume (cf. Visvizi & Bodziany, 2021) will serve as a necessary addition to the brief introduction included in this chapter.

5 AI and the Society: Focus on the (Global) Economy and Selected Policies

From the perspective of what is technically feasible, the onset of AI and AI-based solutions, applications and techniques is a source of a great number of opportunities. These opportunities may be seen through several interpretive lenses. For example, viewed from the perspective of the global economy, it may be assumed that further automation and digitalization of production, this time employing AI-based solutions, would allow an aggregate global productivity increase. This would be due to the work substitution effect: the rise in innovativeness and innovation and the adoption of new technologies; increased competition; diversification of products; optimization of supply-chains as well as of global value chains, etc. From a different point of view, AI is a source of great hope in the field of healthcare in that the inroads of AI-based techniques and applications, always in connection with other technologies, revolutionize the way in which data is handled for the purposes of early detection and diagnosis of diseases, treatment, medicine development, the analysis of archived patients' records, surgery and so much more (Lytras et al., 2021). AI, as the content of

this volume amply demonstrates, is employed in public administration, the services sector, marketing (Huang & Rust, 2021; van Veenstra et al., 2020; Loukis et al., 2020) and, of course, in the field of the military. Viewed in this way, the hopes, prospects, and opportunities that AI-based solutions bring to our society are immense. However, as is the case with any new technology or an ecosystem of technologies, tools, techniques and applications, downsides always exist, and a period of adjustment is necessary. Consider the case of the automobile in the late nineteenth century (Berger, 2001), and the regulatory frameworks that we continue to put in place to strike a sound balance between the benefits of using a car and the externalities that the aggregate use of vehicles creates for the environment.

The case of AI proves that, even if its value added and its potential are immense, our societies, but perhaps more precisely the regulatory frameworks and the governance structures in place, are not fit enough to accommodate not only the plethora of regulatory challenges ahead but also the variety of resulting, and yet still unaccounted for, policy-making considerations that will have to be addressed (cf. Ulnicane et al., 2021). Substantial effort has been undertaken at the global (G20), international (United Nations, the Organization for Economic Co-operation and Development), regional (the European Union (EU)), and national levels to address the challenge (e.g., Chatterjee, 2020). In some ways, as more critical voices outline, the “race to AI” has turned into a global “race to AI regulation” (Smuha, 2021), in which a country’s capacity to influence international standards and regulations in the field of AI turns into competitive advantage (Dexe & Franke, 2020). Consider the case of the EU, a global player after all. 290 AI policy initiatives devised by the EU member states exist. The EU, especially the European Commission, makes an explicit attempt to promote a broad approach to AI (European Commission, 2020; European Commission, 2021). AI is thus seen as a tool, on the one hand, to help the EU compete globally and, on the other hand, to—even if this notion is quite implicit—allow the EU to reclaim its position as the “normative power of Europe” (Manners, 2002). In relation to the first objective, the European Commission places emphasis on innovative capacity at large, and in this context on the use of data and developing “critical computer capacity”. In relation to the second objective, the European Commission’s narrative is filled with references to “AI for the people”, “AI as a source of good”, and to “trustworthy AI” (European Commission, 2018).

It is difficult not to be critical of the approach to AI that the European Commission promotes. It seems like too little, too late, and not comprehensive enough. In other words, the Commission’s approach to AI and to the prospect of reaping the benefits of AI, resembles hand-steering rather than anything else. The point is that too much emphasis is placed on direct-support measures for, say, research and investment in AI, at the expense of letting the market mechanisms play their due part as well. This is certainly a nod to all those who deal with economic policy in specific EU member states and with economic policy coordination at the euro-area level. The notions of the EU competition policy and industrial policy complete the picture. Full stop. The point is that hand-steering alone will not allow small- and medium-sized enterprises (SMEs) in the EU, or elsewhere in the world, to pick up and adopt AI-based tools and solutions in their daily activities (cf. Troisi et al., 2021). For this, tax incentives

and flexible labor markets are needed to enable SMEs to acquire talent, which is rare and highly expensive, and invest in AI-based solutions.

The downside of this story, as many observers note (cf. Naudé, 2021), is that, since AI-based tools are key to digital platforms and digital platform economy, and data is the key source of advantage, as the case of Google, Apple, Facebook, Amazon, and Alibaba (GAFAA) illustrates, we witness a major distortion of competition these days. The thrust of the problem is that the barriers to entry are so high that companies like GAFAA lack natural competitors. From a different perspective, though, the case of Microsoft and the way it was dealt with in the context of the EU competition policy more than a decade ago demonstrates that a thin line divides attempts to defend fair competition from those to create disincentives for innovation (Larouche, 2009; Manne & Wright, 2010). In brief, the case of the EU is illustrative of the scale of the challenge that the inroads of AI create for the economy and for the regulators.

Looking at this issue from a different perspective, it is necessary to mention the “first-mover advantage”, i.e., a situation when companies that were first in the field are capable of maintaining their dominant position, at the expense of other market players (cf. Park, 2021). This is already happening, cf. GAFAA. Consider, however, the global implications of the same process. That is, how will the inroads of AI shape and reshape the Global North-Global South relationship? In the context of the debate on the Global South, the “first-mover advantage” thesis suggests that companies from the Global North, i.e., current leaders, might be able to capture the opportunities first, effectively denying them to actors in the Global South. This might lead to exclusion and reproduction of the old global dependency patterns. Of course, the case of China adds to the complexity of the issue. In brief, with reference to AI and its impact on the global economy, time and coordination are crucial. It remains to be seen whether a consensus on these issues will be reached at G20 any time soon.

6 By Means of Conclusion

While the economy has been centrally featured in the discussion in the previous section, this chapter would be incomplete if some of the ethical considerations pertaining to the development and adoption of AI-based solutions were not mentioned. Several exist. The thrust of the concern is twofold, i.e., to what extent will the computer, the machine, be able to operate independently of the human being and regardless of the human being’s express consent, and how can it be ensured that it will be a force for good? There is a growing body of literature that deals with the question of ethics and AI (Jobin et al., 2019; Coeckelbergh, 2020; Vesnic-Alujevic et al., 2020; Roberts et al., 2021; Ryan & Stahl, 2021; Rakowski et al., 2021; Neubert & Montañez, 2020). International organizations, such as the UN, the EU, the World Health Organization, as well as national governments (Dexe & Franke, 2020) are central in shaping and developing the debate. A very useful typology of ethical considerations that the debate on AI and ethics revolves around has been introduced by Jobin et al. (2019) and further elaborated by Ryan and Stahl (2021,

p. 65). In brief, the following ethical considerations are key for the debate in AI in our societies: transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust and trustworthiness, sustainability, dignity, and solidarity. What are the practical implications thereof? As the chapters included in this volume demonstrate, the use of AI-enhanced tools in the battlefield is one of the most contentious issues in this respect. This certainly applies to unmanned aerial vehicles (UAVs), or simply drones, and warfare. Consider non-maleficence. The case of facial features' recognition in China raised very serious ethical concerns. Consider justice and fairness, privacy, freedom and autonomy and so on. The question of who, under which conditions and for what purpose, has the right to collect, or who gains access to, our personal data is another case that highlights sensitive issues surrounding AI-based tools and techniques. The General Data Protection Regulation (GDPR) implemented in the EU since 2018 is one of the strictest regulatory responses to this issue in the world.

The conversation on AI and ethics leads to another question, i.e., prospective directions of growth and development of AI and AI-based tools. In this context, it is necessary to return to the initial point that AI is bound to fundamentally change the relationship between the human being and the machine. This time, it is not a literary question. This is because current and future users of technology will have to learn a form of interaction with a non-human. Consider the case of education and technology-enhanced learning based on AI and cognitive computing. By means of enhancing the user's experience, and thus amplifying the teaching and learning process (Lytras et al., 2018; Visvizi et al., 2020), already today, young students should acquire the necessary skills and ethical stance that would allow them to shape the future human-computer relationship in a responsible manner.

Another issue that should be mentioned here relates to the question of the impact of AI on inequality, exclusion, and, from a different perspective, non-growth. It is possible to imagine that the emerging economic system, to a large extent based on digital platforms (Alahmadi et al., 2020; Malik et al., 2021), will also lead to the consolidation of a new system of social relations, of wealth, and wellbeing, both locally and globally. Depending on the way of reading it, this scenario may be devastatingly daunting. To prevent it from happening, transparency understood as explainability, explicability, understandability, interpretability, communication, disclosure, and showing, is the key issue in the debate on AI. This chapter has sought to do just that.

References

- Alahmadi, D., Babour, A., Saeedi, K., & Visvizi, A. (2020). Ensuring inclusion and diversity in research and research output: A case for a language-sensitive NLP crowdsourcing platform. *Applied Sciences*, 10, 6216. <https://doi.org/10.3390/app10186216>
- Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussain, A., & Aljaaf, A. J. (2020). A systematic review on supervised and unsupervised machine learning algorithms for data science. In M. Berry, A.

- Mohamed, & B. Yap (Eds.), *Supervised and unsupervised learning for data science. Unsupervised and semi-supervised learning*. Springer. https://doi.org/10.1007/978-3-030-22475-2_1.
- Archer, M. S. (2021). Friendship between human beings and AI Robots? In J. von Braun, M. S. Archer, G. M. Reichberg, & M. S. Sorondo (Eds.), *Robotics, AI, and humanity*. Springer. https://doi.org/10.1007/978-3-030-54173-6_15
- Archer, M. S. (1998). *Critical realism: Essential readings*. Routledge.
- Berger, M. I. (2001). *The automobile in American history and culture: A reference guide*. Greenwood Publishing Group. ISBN 978-0313245589.
- Bhaskar, R. (1975). *A realist theory of science*. Books.
- Binder, W. (2021). AlphaGo's deep play: Technological breakthrough as social drama. In J. Roberge, & M. Castelle (Eds.), *The cultural life of machine learning*. Palgrave Macmillan. https://doi.org/10.1007/978-3-030-56286-1_6.
- Park, C. (2021). Different determinants affecting first mover advantage and late mover advantage in a smartphone market: A comparative analysis of Apple iPhone and Samsung Galaxy. *Technology Analysis and Strategic Management*. <https://doi.org/10.1080/09537325.2021.1895104>
- Chatterjee, S. (2020). AI strategy of India: Policy framework, adoption challenges and actions for government. *Transforming Government: People, Process and Policy*, 14(5), 757–775. <https://doi.org/10.1108/TG-05-2019-0031>
- Coeckelbergh, M. (2020). *AI ethics*. MIT Press.
- Dexe, J., & Franke, U. (2020). Nordic lights? National AI policies for doing well by doing good. *Journal of Cyber Policy*, 5(3), 332–349. <https://doi.org/10.1080/23738871.2020.1856160>
- Eager, J., Whittle, M., Smit, J., Cacciaguerra, G., & Lale-Demoz, E. (2020). Opportunities of artificial intelligence, report, policy department for economic, scientific and quality of life policies, directorate-general for internal policies, PE 652 713—June 2020. European Parliament.
- Eskak, E., & Salma, I. R. (2021). Utilization of artificial intelligence for the industry of craft (November 5, 2020). In *Proceedings of the 4th International Symposium of Arts, Crafts & Design in South East Asia (ARCADESA)*. Available at SSRN <https://ssrn.com/abstract=3807689> or <https://doi.org/10.2139/ssrn.3807689>.
- European Commission. (2018). Draft ethics guidelines for trustworthy AI, working document for stakeholders' consultation. In *The European Commission's High-level Expert Group on Artificial Intelligence*. European Commission. <https://digital-strategy.ec.europa.eu/en/library/draft-ethics-guidelines-trustworthy-ai>
- European Commission. (2020). White paper on artificial intelligence—A European approach to excellence and trust. Brussels, 19.2.2020, COM(2020) 65 final.
- European Commission. (2021). Coordinated plan on artificial intelligence 2021 review, annexes to the communication from the commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee and the Committee of the Regions, Fostering a European approach to Artificial Intelligence, Brussels, 21.4.2021, COM(2021) 205 final.
- Farami, K. A., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. *Big Data Mining and Analytics*, 4(1), 47–55. <https://doi.org/10.26599/BDMA.2020.9020015>
- Fiske, A., Henningsen, P., & Buyx, A. (2019). Your robot therapist will see you now: Ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy. *Journal of Medical Internet Research*, 21(5), e13216. <https://doi.org/10.2196/13216>. PMID:31094356; PMCID:PMC6532335
- Floridi, L. (2020). AI and its new winter: From myths to realities. *Philosophy and Technology*, 33, 1–3. <https://doi.org/10.1007/s13347-020-00396-6>
- Floridi, L., Cows, J., Beltrametti, M., et al. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28, 689–707. <https://doi.org/10.1007/s11023-018-9482-5>

- Granter, S. R., Beck, A. H., Papke, & D. J. (2017). AlphaGo, deep learning, and the future of the human microscopist. *Archives of Pathology & Laboratory Medicine*, 141(5), 619–621. <https://doi.org/10.5858/arpa.2016-0471-ED>
- Hassija, V., Chamola, V., Saxena, V., Chanana, V., Parashari, P., Mumtaz, S., & Guizani, M. (2020). Present landscape of quantum computing. *IET Quantum Communication*, 1, 42–48. <https://doi.org/10.1049/iet-qtc.2020.0027>
- Hatani, F. (2020). Artificial Intelligence in Japan: Policy, prospects, and obstacles in the automotive industry. In A. Khare, H. Ishikura, & W. Baber (Eds.), *Transforming Japanese business. Future of business and finance*. Springer. https://doi.org/10.1007/978-981-15-0327-6_15.
- Holcomb, S. D., Porter, W. K., Ault, S. V., Mao, G., & Wang, J. (2018). Overview on deep mind and its AlphaGo Zero AI. In *Proceedings of the 2018 International Conference on Big Data and Education (ICBDE'18)* (pp. 67–71). Association for Computing Machinery. <https://doi.org/10.1145/3206157.3206174>
- Hu, N., Tian, Z., Du, X., Guizani, N., & Zhu, Z. (2021). Deep-Green: A dispersed energy-efficiency computing paradigm for green industrial IoT. *IEEE Transactions on Green Communications and Networking*, 5(2), 750–764. <https://doi.org/10.1109/TGCN.2021.3064683>
- Huang, M.-H., & Rust, R. T. (2021). Engaged to a robot? The role of AI in service. *Journal of Service Research*, 24(1), 30–41. <https://doi.org/10.1177/1094670520902266>
- James, P., & Steger, M. B. (2014). A genealogy of ‘Globalization’: The career of a concept. *Globalizations*, 11(4), 417–434. <https://doi.org/10.1080/14747731.2014.951186>
- Jiang, T., Gradus, J. L., & Rosellini, A. J. (2020). Supervised machine learning: A brief primer. *Behavior Therapy*, 51(5), 675–687. <https://doi.org/10.1016/j.beth.2020.05.002>
- Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence*, 1(9), 389–399. Available at <https://doi.org/10.1038/s42256-019-0088-2>
- Kashef, M., Visvizi, A., & Troisi, O. (2021). Smart city as a smart service system: Human-computer interaction and smart city surveillance systems. *Computers in Human Behavior*, 2021, 106923. <https://doi.org/10.1016/j.chb.2021.106923>
- Khan, F. H., Pasha, M. A., & Masud, S. (2021). Advancements in microprocessor architecture for ubiquitous AI—An overview on history, evolution, and upcoming challenges in AI implementation. *Micromachines*, 12, 665. <https://doi.org/10.3390/mi12060665>
- Larouche, P. (2009). The European microsoft case at the crossroads of competition policy and innovation: Comment on Ahlborn and Evans. *Antitrust Law Journal*, 75(3), 933–963.
- Lee, R. S. T. (2020). Future trends in quantum finance. In *Quantum finance*. Springer. https://doi.org/10.1007/978-981-32-9796-8_14
- Lem, S. (1964). *Bajki Robotów [Robot Fables]*. Wydawnictwo Literackie.
- Lem, S. (1990). *The cyberiad: Fables for the cybernetic age, masterpieces of science fiction*. Easton Press, reprint edition.
- Li, F., & Du, Y. (2018). From AlphaGo to power system AI: What engineers can learn from solving the most complex board game. *IEEE Power and Energy Magazine*, 16(2), 76–84. <https://doi.org/10.1109/MPE.2017.2779554>.
- Loukis, E. N., Maragoudakis, M., & Kyriakou, N. (2020). Artificial intelligence-based public sector data analytics for economic crisis policymaking. *Transforming Government: People, Process and Policy*, 14(4), 639–662. <https://doi.org/10.1108/TG-11-2019-0113>
- Lu, M., Chen, Q., Chen, Y., & Sun, W. (2020). Micromanagement in StarCraft Game AI: A case study. *Procedia Computer Science*, 174(2020), 518–523. <https://doi.org/10.1016/j.procs.2020.06.119>
- Lytras, M. D., Sarirete, A., Visvizi, A., & Chui, K. W. (2021). *Artificial intelligence and big data analytics for smart healthcare*. Academic Press.
- Lytras, M. D., Visvizi, A., Damiani, D., & Mthkour, H. (2018). The cognitive computing turn in education: Prospects and application. *Computers in Human Behavior*. <https://doi.org/10.1016/j.chb.2018.11.011>

- Malik, R., Visvizi, A., & Skrzek-Lubasińska, M. (2021). The gig economy: Current issues, the debate, and the new avenues of research. *Sustainability*, *13*, 5023. <https://doi.org/10.3390/su13095023>
- Manne, G. A., & Wright, J. D. (2010). Innovation and the limits of antitrust. *Journal of Competition Law & Economics*, *6*(1), 153–202. <https://doi.org/10.1093/joclec/nhp032>
- Manners, I. (2002). Normative power Europe: A contradiction in terms? *JCMS: Journal of Common Market Studies*, *40*, 235–258. <https://doi.org/10.1111/1468-5965.00353>.
- Naudé, W. (2021). Artificial intelligence against COVID-19: An early review. IZA Discussion Paper, 13110. <https://covid-19.iza.org/publications/dp13110/>.
- Neubert, M. J., & Montañez, G. D. (2020). Virtue as a framework for the design and use of artificial intelligence. *Business Horizons*, *63*(2), 195–204. <https://doi.org/10.1016/j.bushor.2019.11.001>
- Niebel, C. (2021). The impact of the general data protection regulation on innovation and the global political economy. *Computer Law & Security Review*, *40*. <https://doi.org/10.1016/j.clsr.2020.105523>.
- Nitzberg, M., & Zysman, J. (2021). Algorithms, data, and platforms: The diverse challenges of governing AI (March 10, 2021). *Journal of European Public Policy*. Available at SSRN <https://ssrn.com/abstract=3802088> or <https://doi.org/10.2139/ssrn.3802088>.
- OECD. (2015). *Frascati manual 2015: Guidelines for collecting and reporting data on research and experimental development, the measurement of scientific, technological and innovation activities*. OECD Publishing. <https://doi.org/10.1787/9789264239012-en>
- Outeiral, C., Strahm, M., Shi, J., Morris, G. M., Benjamin, S. C., & Deane, C. M. (2021). The prospects of quantum computing in computational molecular biology. *WIREs Computational Molecular Science*, *11*, e1481. <https://doi.org/10.1002/wcms.1481>
- Piattini, M., Peterssen, G., & Pérez-Castillo, R. (2020). Quantum computing: A new software engineering golden age. *SIGSOFT Software Engineering Notes*, *45*(3), 12–14. <https://doi.org/10.1145/3402127.3402131>
- PWC. (2017). *Artificial intelligence study*. Price Waterhouse Coopers (PWC). <https://www.pwc.com/gx/en/issues/data-and-analytics/publications/artificial-intelligence-study.html>.
- Rajoub, B. (2020). Supervised and unsupervised learning. In W. Zgallai (Ed.), *Developments in biomedical engineering and bioelectronics, biomedical signal processing and artificial intelligence in healthcare* (pp. 51–89). Academic Press. <https://doi.org/10.1016/B978-0-12-818946-7.00003-2>
- Rakowski, R., Polak, P., & Kowalikova, P. (2021). Ethical aspects of the impact of AI: The status of humans in the Era of artificial intelligence. *Society*. <https://doi.org/10.1007/s12115-021-00586-8>
- Roberts, H., Cows, J., Morley, J., et al. (2021). The Chinese approach to artificial intelligence: An analysis of policy, ethics, and regulation. *AI & Society*, *36*, 59–77. <https://doi.org/10.1007/s00146-020-00992-2>
- Rosamond, B. (2003). Babylon and on? Globalization and international political economy. *Review of International Political Economy*, *10*(4), 661–671. <https://doi.org/10.1080/09692290310001601920>
- Ryan, M., & Stahl, B. C. (2021). Artificial intelligence ethics guidelines for developers and users: Clarifying their content and normative implications. *Journal of Information, Communication and Ethics in Society*, *19*(1), 61–86. <https://doi.org/10.1108/JICES-12-2019-0138>
- Sætra, H. S. (2020). Correction to: The parasitic nature of social AI: Sharing minds with the mindless. *Integrative Psychological & Behavioral Science*, *54*(2), 327. <https://doi.org/10.1007/s12124-020-09536-1>
- Sarirete, A., Balfagih, Z., Brahimi, T., Lytras, M. D., & Visvizi, A. (2021). Artificial intelligence and machine learning research: Towards digital transformation at a global scale. *Journal of Ambient Intelligence and Humanized Computing*. <https://doi.org/10.1007/s12652-021-03168-y>
- Shu, C. (2014). *Google acquires artificial intelligence startup DeepMind for more than \$500M*. Techcrunch, 27 January 2014. <https://techcrunch.com/2014/01/26/google-deepmind/>.
- Sikos, L. F., & Choo, K. -K. R. (Eds.) (2020). *Data science in cybersecurity and cyberthreat intelligence*. Springer. <https://www.springer.com/gp/book/9783030387877>.

- Smuha, N. A. (2021). From a 'race to AI' to a 'race to AI regulation': Regulatory competition for artificial intelligence. *Law, Innovation and Technology*, 13(1), 57–84. <https://doi.org/10.1080/17579961.2021.1898300>
- Strickland, E. (2019). How smart is artificial intelligence? *IEEE Spectrum*, 19 April 2019. <https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8678419>.
- Russell, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach* (3rd Ed.). Pearson. <https://www.amazon.com/Artificial-Intelligence-Modern-Approach-3rd/dp/0136042597>.
- Troisi, O., Visvizi, A., & Grimaldi, M. (2021). The different shades of innovation emergence in smart service systems: The case of Italian cluster for aerospace technology. *Journal of Business & Industrial Marketing, ahead-of-print*. <https://doi.org/10.1108/JBIM-02-2020-0091>.
- Turenne Slojander, C. (1996). The rhetoric of globalization: What's in a Wor(1)d? *International Journal*, 51(4), 603–616. Globalization, <https://doi.org/10.2307/40203150>.
- Ulnicane, I., Knight, W., Leach, T., Carsten Stahl, B., & Wanjiku, W.-G. (2021). Framing governance for a contested emerging technology: Insights from AI policy. *Policy and Society*, 40(2), 158–177. <https://doi.org/10.1080/14494035.2020.1855800>
- van Veenstra, A. F., Grommé, F., & Djafari, S. (2020). The use of public sector data analytics in the Netherlands. *Transforming Government: People, Process and Policy, ahead-of-print*(ahead-of-print). <https://doi.org/10.1108/TG-09-2019-0095>.
- Vesnic-Alujevic, L., Nascimento, S., & Pólvara, A. (2020). Societal and ethical impacts of artificial intelligence: Critical notes on European policy frameworks. *Telecommunications Policy*, 44(6), 2020. <https://doi.org/10.1016/j.telpol.2020.101961>
- Visvizi, A., & Bodziany, M. (Eds.). (2021). *Artificial intelligence and its context—Security*. Springer.
- Visvizi, A., Daniela, L., & Chen, Ch. W. (2020). Beyond the ICT- and sustainability hypes: A case for quality education. *Computers in Human Behavior*, 107. <https://doi.org/10.1016/j.chb.2020.106304>.
- Visvizi, A., Lytras, M. D., & Aljohani, N. (2021). Big data research for politics: Human centric big data research for policy making, politics, governance and democracy. *Journal of Ambient Intelligence and Humanized Computing*, 12(4), 4303–4304. <https://doi.org/10.1007/s12652-021-03171-3>
- Xu, L. (2020). The Dilemma and countermeasures of AI in educational application. In *2020 4th International Conference on Computer Science and Artificial Intelligence* (pp. 289–294). Association for Computing Machinery. <https://doi.org/10.1145/3445815.3445863>.
- Zhuang, Yt., Wu, F., Chen, C., & Pan, Y. (2017). Challenges and opportunities: From big data to knowledge in AI 2.0. *Frontiers of Information Technology & Electronic Engineering*, 18, 3–14. <https://doi.org/10.1631/FITEE.1601883>.

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