Received: 29 January 2023 | Revised: 17 July 2023 | Accepted: 18 July 2023 | Published online: 24 July 2023

Artificial Intelligence and Applications
2023, Vol. 1(4) 181–197
DOI: 10.47852/bonviewAIA3202689

REVIEW

A Critical Historic Overview of Artificial Intelligence: Issues, Challenges, Opportunities, and Threats

Peter P. Groumpos[1,*]

[1] *University of Patras, Greece*

Abstract: Artificial intelligence (AI) has been considered a revolutionary and world-changing science, although it is still a young field and has a long way to go before it can be established as a viable theory. Every day, new knowledge is created at an unthinkable speed, and the big data-driven world is already upon us. AI has developed a wide range of theories and software tools that have shown remarkable success in addressing difficult and challenging societal problems. However, the field also faces many challenges and drawbacks that have led some people to view AI with skepticism. One of the main challenges facing AI is the difference between correlation and causation, which plays an important role in AI studies. Additionally, although the term cybernetics should be a part of AI, it was ignored for many years in AI studies. To address these issues, the cybernetic artificial intelligence (CAI) field has been proposed and analyzed here for the first time. Despite the optimism and enthusiasm surrounding AI, its future may turn out to be a "catastrophic winter" for the whole world, depending on who controls its development. The only hope for the survival of the planet lies in the quick development of CAI and the wise anthropocentric revolution. The text proposes specific solutions for achieving these two goals. Furthermore, the importance of differentiating between professional/personal ethics and eternal values is highlighted, and their importance in future AI applications is emphasized for solving challenging societal problems. Ultimately, the future of AI heavily depends on accepting certain ethical values.

Keywords: artificial intelligence, machine learning, deep learning, cybernetics, fuzzy logic, fuzzy cognitive maps, cybernetic artificial intelligence

1. Introduction

Humankind today is confronted with several challenges, threats, risks, and problems that never had faced before (World Economic Forum, 2019). Furthermore, they are global and require cross-institutional solutions. These challenges include issues related to energy, environment, health, ecology, business, economics, international peace, stability, world famine, and spiritual decline just to mention a few. The world is experiencing several catastrophic physical phenomena which increase every year. Humans blame these phenomena on the environment disregarding that it is not the only reason. We share some responsibility for all this. The root causes of all these challenges must be determined carefully, analyzed, and then find sustainable solutions that are valuable and reasonable (Organization for Economic Cooperation and Development, 2007; World Economic Forum, 2019).

Today we are often hearing several news with statistics and updates on the problems and challenges of the world. However, in the last 10–15 years there too many issues been added to all these problems. From the recent COVID-19 pandemic and other major health problems to the recent major war in Ukraine and other smaller conflicts in different parts of the world, to climate change, economic crises, high rates of gender inequality, many people living without access to basic needs and medical care, energy shortages, environmental threats, food shortages, and many others. The World Health Organization (WHO), the United Nations, and other world organizations have conducted several studies and have listed numerous serious aspects that the world should be aware of (World Economic Forum, 2019). Which issues are the most important and urgent? Can people solve the problems just by themselves? Certainly not! Working to alleviate global issues does not have to be confusing or stressful. There are various organizations and other established infrastructures to help us see where there are human needs and what resources and services must be sought and been useful to humanity (Organization for Economic Cooperation and Development, 2007).

Everywhere, there is a feeling of insecurity. Some serious questions are frequently raised such as: "how our future life will be"? "How can we survive on a disturbing and uncertain world?" "Will new «technologies» leave us without a job?" "What will happen to our children?" (World Economic Forum, 2019). Whether we like it or not, we cannot live the same way as we used to. The life of each person, all structures of the society, the working situations, and the state affairs of governments must be replanned (Groumpos, 2022; World Economic Forum, 2019). The humankind every day, using already existing well-known

*Corresponding author: Peter P. Groumpos, University of Patras, Greece. Email: groumpos@ece.upatras.gr

© The Author(s) 2023. Published by BON VIEW PUBLISHING PTE. LTD. This is an open access article under the CC BY License (https://creativecommons.org/licenses/by/4.0/).

knowledge, evolves and progresses moving forward. In addition, the knowledge been generated everyday by the scientific and academic communities is also at the hands of all citizens of the world to be used for solving their problems and making better their everyday life.

Our main objective is to control and/or exploit natural phenomena or to create human-made "objects" using new and advanced theories and technologies while at the same time keeping in mind that all our efforts will naturally be useful to humankind. To face and solve all these difficult problems, new theories and methods have emerged during the last 100–120 years. Information theory (IT) one of the basic concepts of AI was founded by Claude Shannon (1948). Cybernetics emerged around the 1950s as a new scientific field (Ashby, 1956; Stafford, 1976). Norbert Wiener, considered the father of cybernetics, named the field after an example of circular causal feedback – that of steering a ship (Wiener, 1948). Cybernetics are embodied in several scientific fields and social issues (Pickering, 2011).

Another scientific field was developed at the end of the 1960s and in the 1970s that of robotics and mechatronics (Asimov, 1951; Merlet, 2000; Sajadi & Esfahani, 1960; Schilling, 1990; Spong et al., 2006). Robotics is an interdisciplinary branch of computer science and engineering with the main objective to create intelligent machines that can act like humans and assist them in a variety of ways. Since the 1950s first appearance of the term robotics, the field has evolved and covers a lot of other issues: probabilistic robotics (Thrun et al., 2005), the potential of robots for humankind (Moss, 2018), and robots and AI at work (Upchurch, 2018). It is of interest to mention studies on holism and chaotic systems: Early work on holism as early as 1926 (Smuts, 1926) and the Prigogine theory on chaotic evolution of dynamic systems (Prigogine, 1980).

In the 1950s, AI was also born (Buchanan, 2007; Luger, 2005; Nilsson, 2005; Warwick, 2011). Artificial intelligence (AI) is often regarded as a groundbreaking and transformative field, despite its relatively recent development. Many individuals held high expectations that AI would provide solutions to all global issues. In reality, various scientific disciplines have emerged since the 1950s to tackle societal challenges and problems. Regrettably, there is limited collaboration and integration among these diverse scientific approaches. The remarkable and somewhat unsettling aspect is that AI is assuming a dominant role in addressing global challenges, overshadowing other scientific disciplines. However, the complex issues of society have not been thoroughly examined thus far. It is widely recognized that no single scientific field can offer comprehensive solutions. Therefore, it is essential to adopt a holistic approach, encompassing diverse theories, methods, and techniques, in order to study and tackle these problems effectively. The journey ahead is lengthy and fraught with obstacles, which serves as the primary motivation and purpose of this introductory paper.

The unique features of this critical historical overview paper are:

(1) For the first time in the same historical overview paper for AI issues like: cybernetics, edge intelligence (EI), fuzzy cognitive maps (FCMs), correlation vs causation, and "AI Summers and Winters" are analyzed and discussed so thoroughly. The findings of this analysis reveal that AI has never till today pay the appropriate attention.
(2) For the first time the debate why, cybernetics is totally ignored by AI is analyzed.
(3) The importance of causality in AI is discussed in detail, and it is differentiated from correlation.
(4) The use of FCM theories on AI studies is explained.
(5) The new term cybernetics artificial intelligence (CAI) is introduced for the first time on an International Journal.

In Section 2, a historical review and some ancient myths of AI are presented, while a historical road map for AI is covered in Section 3. In Section 4, the AI "Summers and Winters" are analyzed also giving a graphical presentation of them over the last 70 years. Section 5 outlines all AI methods and technologies, including for first time the EI as part of AI. In Section 6, the confused meaning of the two extremely important parameters of AI, correlation vs causation, is carefully analyzed for the first time in an overview AI paper. Several challenges and opportunities for AI are provided in Section 7. In Section 8, the threats of AI are discussed but not extensively since it is not an easy task. In Section 9, for the first time in an overview AI paper, the touchy topic of cybernetics been totally ignored by AI architectures and methods is considered and carefully discussed. Section 10 is presenting the new and young scientific field of FCMs and analyze its usefulness in AI. In Section 11, the future of AI is discussed briefly. Conclusions and future research are provided in Section 12.

2. Some Historical Remarks and Myths for AI

In contrast to common perception, the origin of AI dates back much further than commonly thought. In fact, Greek mythology contains numerous myths and tales that allude to the early foundations of AI (Mayor, 2018). In ancient times, skilled artisans were believed to have created intelligent beings, as depicted in these myths and legends. Many regard Aristotle (384–322 B.C.) as the progenitor of AI, given his early formulation of a precise set of principles that elucidated the workings of the human mind, stating that "Logic is the novel and essential reasoning" (Aristotle, 1963; Robin, 2017).

The very first humanoid robot in history is attributed to the ancient Greeks, known as Talos (Mayor, 2018). Remarkably, even today, the myth of the bronze giant, Talos, who served as the guardian of Minoan Crete, remains relevant. Talos symbolizes the extraordinary technological accomplishments in metallurgy during the prehistoric Minoan era. The scientists of that time had achieved an impressive level of technological advancement, crafting a bronze superhero to safeguard their civilization. According to the myth, Talos was not born but rather created, either by Zeus himself or by Hephaestus, the god of metallurgy and iron, under Zeus's command (Mayor, 2018).

The depiction of Talos on a coin found in the Minoan palace of Phaistos portrays him as a youthful, winged, and unclothed figure. His body was entirely crafted from bronze, except for a single vein running from his neck to his ankles, which served as the source of his life. Instead of blood, molten metal flowed through this vein, and a bronze nail on his ankle acted as a plug to retain this life-sustaining fluid. Talos had a significant role in safeguarding Crete from external threats by preventing ships from approaching the island and hurling massive rocks at potential invaders. When confronted with a trespasser, his body would radiate heat and glow, and he would embrace and fatally eliminate the intruder. Not only did Talos protect Crete from outside adversaries, but he also ensured justice for its citizens. Utilizing his wings, he would tour Cretan villages thrice a year, carrying bronze plates inscribed with divinely inspired laws to enforce their observance throughout the province. The faithful dedication of Talos to justice highlights the paramount importance ancient Cretans placed on upholding principles of fairness and righteousness (Mayor, 2018).

Chinese mythology is also present on the history of AI (Buchanan, 2007; Mayor, 2018). Zhuge Liang, the famous chancellor in Chinese history, married a young Chinese girl (Miss. Huang) after been impressed by her cleverness. She was making excellent "intelligent machines." When the chancellor went to Huang's house for the first time, he was greeted by two big dogs. The dogs rushed toward him aggressively and were stopped by force by servants of the house. When the chancellor went closer found out that the dogs were actually "intelligent machines" made of wood. He was impressed by the wisdom of Huang and decided to marry her. The two "intelligent machine" dogs present another form of AI in ancient mythical stories. It suggests that humans should have the ability to start or end the operation of "artificial intelligent machines." When the two machine dogs received the stop sign by the servants, they stopped immediately. Humans today still believe that control completely the AI.

3. A Historical Roadmap of AI

Despite all the recent buzz, AI is not a brand-new area of research. Excluding the line of pure philosophical thought that runs from Hobbes, Leibniz, and Pascal to the Ancient Greek philosophers (such as Aristotle, Plato, Socrates, and others), we can say that AI as we know it today. Everyone agrees that the Dartmouth Summer Research Project on AI, which took place in the summer of 1956, is what gave rise to the area of AI as a science. The most prominent and prestigious experts of the era gathered in Dartmouth to discuss intelligence theories and simulation.

However, to better comprehend and understand AI, it is necessary to investigate theories that predate the 1956 Dartmouth summer workshop. In the late 1940s, there were various names for the field of "thinking machines": (1) cybernetics, (2) automata theory, and (3) complex information processing. The variety of names suggests the diversity of conceptual orientations that are paramount in comprehending the issues, challenges, opportunities, risks, and threats of AI. A brief explanation of each will be useful in studying AI.

(1) *Cybernetics:*

The field of cybernetics has a long history of growth and development, with multiple definitions provided by different experts (Johnson, 1998; Turing, 1950). Cybernetics involves exploring and understanding various systems and their interactions, particularly with regard to circular causality and feedback processes. In such processes, the results of one part of a system serve as input for another part. The term "cybernetics" comes from the Greek word "steersman" and was used in ancient texts to signify the governance of people (Johnson, 1998). The French word "cybernétique" was also used in 1834 to denote the sciences of government in human knowledge classification (La cybernétique est l'art de l'efficacité de l'action originally a French definition formulated in, 1953). The famous Nobert Wiener in 1948 wrote the book "Cybernetics, or Control and Communication in the Animal and Machine". In this book, the English term "cybernetics" was used for the first time (Wiener, 1948). Robert Wiener is considered the father of "cybernetics."

Cybernetics has been used to several fields: engineering, medicine, psychology, international affairs, economics, and architecture. It is often used to comprehend the operation of a process and develop algorithms or models that optimize inputs and minimize delays or overshoots to ensure stability (von Foerster, 1951). This understanding of processes is fundamental to optimizing and refining them, making cybernetics a valuable tool in different fields. Margaret Mead emphasized the importance of cybernetics as a cross-disciplinary language, facilitating communication among diverse fields. Understanding and decoding different processes, cybernetics can help refine and optimize them, making it a valuable tool across various fields (Glushkov, 1966). Margaret Mead clarified in scientific ways the role of cybernetics as a form of cross-disciplinary concept. It facilitated easy communication between members of different disciplines, allowing them to speak a common language (von Foerster et al., 1968).

(2) *Automata theory:*

The theory of abstract automata, which includes finite automata and other types of automata such as pushdown automata and Turing machines, emerged in the mid-20th century (Booth, 1967). Automata theory used abstract algebra to describe information systems and their theories unlike previous work on systems theory, which used differential calculus to describe physical systems (Ashby et al., 1956). The finite-state transducer, which is a type of finite automaton that maps one finite-state machine to another, was developed independently by different research communities under various names (Arbib, 1969). Meanwhile, the concept of Turing machines, which are theoretical models of general-purpose computers, was also included in the discipline of automata theory. Overall, automata theory has had a great influence on computer science and other fields, as it provides a way to formally model and reason about the behavior of computational systems.

(3) *Complex information processing:*

The complex information processing theory is a simplified scientific expression, which compares the human brain to a computer (Newell & Simon, 1956). According to this theory, information processing in the brain occurs in a sequence of stages, like how a computer operates. The sequence has three stages. The first stage involves the receipt of input, which is received by the brain through the senses. The information is then processed in the short-term or working memory, where it can be used to address immediate surroundings or solve problems. In the second stage if the information is deemed important or relevant, it is encoded and stored in the long-term memory for future use. This information can be retrieved and brought back to the working memory when needed using the central control unit. This action can be thought of as the conscious mind. Finally, the output of the system is delivered through an action, like how a computer would deliver an output. While this theory has its limitations and has been criticized by some researchers, it has contributed to our understanding of how information is processed in the brain and has been influential in the development of cognitive psychology and related fields (Atkinson & Shiffrin, 1968; Baddeley & Hitch, 1974).

4. The Summer and Winter of AI

4.1. Basics

This study has employed a cross-sectional study design in order to examine the in-service postgraduate science teachers' belief, concern, and practice toward solid waste management and recycle (SWMR). Salkind (2010) and Sedgwick (2014) are of the view that the cross-sectional studies often use questionnaire surveys as comparatively inexpensive and quick to conduct at one point in time. AI has gone through several peaks and down cycles called "AI Summers" and "AI Winters," respectively. AI from the beginning is running after the dream of building an intelligent machine that can think like, behave like, and act like a human. Each "AI Summer" cycle begins with optimistic claims that a fully, generally intelligent machine is just a decade or so away. Funding pours in and progress seems swift. Then, a decade or so later, AI progress stalls and funding dry up. The dream of building such an intelligent machine is postponed for future decades. An "AI Winter" follows and research and funding are reduced (Gonsalves, 2018). An "AI Winter" ensues, and research and funding are reduced (Gonsalves, 2018). Figure 1 shows the "AI Summers" and "AI Winters" evolution over the years since the AI conception has been officially accepted by the scientific communities in the summer of 1956 (Francesconi, 2022).

4.2. AI Winters and AI Summers

An "AI Summer" is a time when there is a surge in investment and interest in AI and there are high hopes for scientific advancements. An "AI Summer" has seen the majority, if not all, of the notable developments in AI. The creation and use of AI technology are receiving more financial support. Due to anticipated scientific advancements, there are high expectations during these times, and promises about the future of AI are made, which encourage market investments (Agar, 2020; Lighthill, 1973). The period from 1955 to 1974 is often referred to as the first "AI Summer," during which progress appeared to come swiftly as researchers developed computer systems capable of playing chess, deducing mathematical theorems, and even engaging in simple discussions with humans. Government funding flowed generously, and a significant amount of hype was spurred during the mid-50s by a collection of the following AI projects.

(1) An AI machine program to translate word-to-word Russian to English languages.
(2) An AI machine program that could play chess.
(3) Crude replications of the human brain's neurons by Artificial Neural Networks (ANNs) been consisted of numerous perceptrons.
(4) The first humanoid robot, (WABOT), developed by Ichiro Kato of Waseda University, Japan.

During the first "AI Summer," the U.S. Defense Advanced Research Projects Agency (DARPA) funded AI research with few requirements for developing functional projects. This "AI Summer" lasted almost 20 years and saw significant interest and fundamental scientific contributions during what some have called AI's Golden Era. Optimism was so high that in 1970, Minsky famously proclaimed, "In three to eight years we will have a machine with the general intelligence of a human being." However, Minsky's optimism remained wishful thinking never been met.

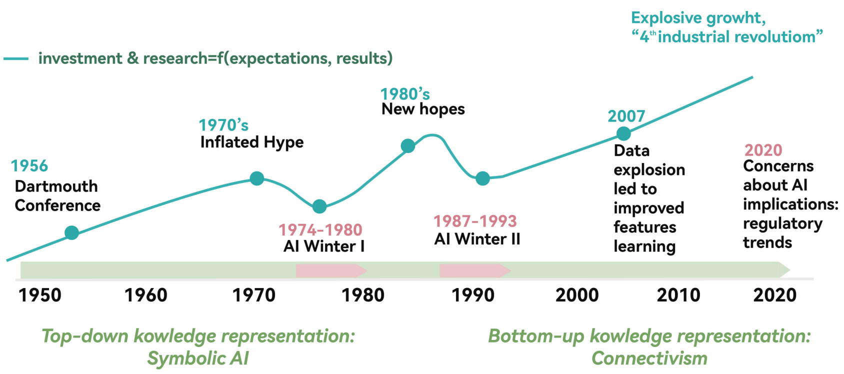
Around the mid-1970s, the advancement of AI encountered a significant slowdown. Numerous innovations from the preceding decade turned out to have limited practicality, resembling more like novelties or playthings rather than substantial strides toward achieving a comprehensive form of AI. The "Lighthill report," an evaluation of academic research in the field of AI, was published in 1973 (Agar, 2020; Lighthill, 1973). It was highly critical stating that "AI research had essentially failed to live up to the grandiose objectives it laid out" (Agar, 2020). The funding for AI research became so scarce that researchers eventually refrained from using the term "AI" in their proposals seeking financial support. The lack of resources led to a reluctance in associating their work directly with the field of AI to improve their chances of securing funding from alternative sources. A book titled "Perceptrons: An Introduction to Computational Geometry" by Marvin Minsky and Seymour Papert pointed out the flaws and limitations of neural networks (NNs). The Lighthill report and this book influenced DARPA and the UK government to cease funding for AI projects. The first "AI Winter" had arrived and took place between 1974 and 1980 (see Figure 1).

"AI Winters"

AI Winters are periods of time when interest and funding for AI decrease (Floridi, 2020). Several factors are the reason for the arrival of an AI Winter, and typically, it is a culmination of factors rather than one sole cause. These factors include hype, overestimation of AI tool capabilities, economic factors, institutional constraints, and a lack of new innovative and creative minds.

Most of the developmental funding during the first "AI Summer" came from the DARPA and the UK government. Early in the 1970s the US congress forced the stopping of DARPA for AI. Also, in 1973, the Parliament of the United Kingdom asked James Lighthill to review the state of AI in the UK. The Lighthill report (Lighthill, 1973) criticized the achievements of AI and proclaimed that all of the worked been performed in the study of AI could be achieved in computer science and in electrical engineering. Additionally, Lighthill reported that the discoveries have not lived up to the hype surrounding them (Agar, 2020). However, without funding from DARPA and the release of the

Figure 1
The AI evolution over time (Francesconi, 2022)



Lighthill report, the hype surrounding AI could not sustain development, and the world fell into an "AI Winter." This led to the first notable "AI Winter" in the early 1970s.

It would be years before expert systems, which employed if-then, rule-based reasoning, would rekindle interest in AI. A program called an expert system is made to solve issues at a level comparable to that of a human expert in each field (Cooper, 1989; Weng et al., 1992).

The second "AI Summer" arrived in the early 1980s, and everything seemed to be heading in the right direction. Funding was increasing, and many scientists were eager to get involved in AI research. New theoretical results were being achieved, and AI was finding its way into many applications across various scientific fields. However, this period lasted less than the first "AI Summer" and eventually ended with another "AI Winter," which lasted from 1987 to 1993. However, in the mid-1990s, AI research began to flourish again. Thus, AI was back on a rising curve, and the summers and winters experienced in the history of AI can be succinctly expressed in the words of Menzies (2003). Since the beginning of the 21st century, most people believe that we have entered a new "AI Summer," some even call it the "Third AI Summer." The exact starting point of this "AI Summer" is irrelevant, as we can see from Figure 1 that it began around 2007. We are currently in one of the longest periods of sustained interest in AI in history, with many contributions due to the explosive growth of IT and Industry 4.0, the fourth industrial revolution, and the digitization revolution (Bai et al., 2020; Philbeck & Davis, 2018).

Most recent impressive breakthroughs in AI since roughly 2012, when GPUs and large data sets were first applied, have been based on a specific type of AI algorithm known as DL. However, even with the fastest hardware configurations and largest data sets available, ML still faces significant challenges, including sensitivity to adversarial examples and the risk of overfitting or getting stuck in a local minimum. Furthermore, the scientist Geoff Hinton, often called the "father of deep learning," has raised doubts about the broad applicability of DL and one specific technique used in convolutional neural networks (CNN) called "back propagation," stating that he does not believe it is how the brain works (Ashby et al., 1956; Hinton, 2002; Hinton, 2009).

While several AI methods and applications will be reviewed in the next section, it remains an open question how far AI technology can go, given these obstacles. Although AI is currently at the "peak of inflated expectations," an "AI Winter" is likely to follow in the coming years. It is impossible to predict exactly when this winter will occur.

5. Basic of AI

The term of AI has never had clear boundaries (Warwick, 2011). Despite that AI has changed over time, the central idea remains the same. One of the main objectives of AI has always been to build intelligence machines suitable of thinking and acting like humans. AI was introduced at the summer of 1956 in a workshop at Dartmouth College. From that time, it was mainly understood to mean developing an intelligent machine behaving intelligently like a human being. Human beings have demonstrated a unique ability to interpret the physical world around us and use the information we perceive and apprehend to influence changes (Buchanan, 2007). Therefore, if we want to develop "intelligent machines" that can help humans to perform their everyday actions in a better and more efficient way, it is very smart to use humans as a model or prototype.

The growth of AI has been impressive. Attempts to advance AI technologies over the past 50–65 years have emerged in several incredible innovations and developments (Arbib, 2002; Baldi, 2021; Cybenko, 1989; Deng et al., 2013; Dignum, 2019; Frey et al., 1995; Fukushima, 1980; Groumpos, 2016; Hawkins, 2019; Heykin, 2009; Hubel & Wiesel, 1959; Ivakhnenko, 1971; Levshun & Kotenko, 2023; Mendez et al., 2022; O'Reilly et al., 2021; Schmidhuber, 2015; McCulloch & Pitts, 1943; Roberts et al., 2022; Schmidhuber & Prelinger, 1993; Russel & Norvig, 2020; Shrager & Johnson, 1995). To comprehend better the several challenging issues of AI, we need to understand well the four basic AI concepts: (1) ML, (2) NNs, (3) DL, and (4) EI as follows.

5.1. Machine learning

ML is one of the early and most exciting subfields of AI (Murphy, 2012). ML as subfield of AI entails developing and constructing systems that can learn based on input and output data of the system. Essentially, a ML system learns through observations and experience; actually, according on specific training, the ML system can generalize based on exposure to several cases and then perform actions in response to new unsought or unforeseen events. AI and ML have been exciting topics for the last 50 years (Luger, 2005; Nilsson, 2005; Warwick, 2011). Although both are often used interchangeably (Luger, 2005; Warwick, 2011), they are not identical concepts. On one hand, AI is a broader concept that can carry out tasks in a way that can be considered intelligent. On the other hand, ML machine is permitted to have free access to data and using them to be able to learn on their own. ML uses a variety of specific algorithms, frequently organized in taxonomies (Murphy, 2012; Utgoff & Stracuzzi, 2002).

5.2. Neural networks

The development of NNs is key to making intelligent machines comprehend the world as humans do. They do this exceptionally well, accurately, fast, and objectively. Historically, NNs were motivated by the functionality of the human brain. The first NN was devised by McCulloch and Pitts (1943) to model a biological neuron. Thus, NNs are a set of algorithms modeled loosely after the human brain activities. They interpret sensory data through a kind of machine perception, clustering raw input. A NN can be constructed by linking multiple neurons together in the sense that the output. A simple model for such a network is the multilayer perceptron (Heykin, 2009). NNs are constructed to recognize patterns on given data. Over the last few decades, industrial and academic communities have invested a lot of money on NN developments for a wide set of applications obtaining some noticeable results (Hinton, 2002, 2009). These promising results have been implemented in several fields, such as face recognition, space exploration, optimization, image processing, modeling of nonlinear systems, and also automatic control. More information on NNs can be found in Arbib (2002) and Heykin (2009).

5.3. Deep learning

(A) Basics of DL

To state that DL has revolutionized the world would not be an exaggeration. Within the AI community, there is a strong belief that AI and its methodologies have ushered in a revolutionary and transformative era, offering solutions to a wide array of global problems. Interestingly, DL, which represents a modern form of NNs, is an ancient branch of AI that has experienced a resurgence, thanks to several factors, including novel and advanced algorithms, increased computing power, and the prevalence of big data. Despite its roots, DL serves as a crucial and illuminating subfield of AI for gaining a better understanding of the broader field. By exploring DL, individuals can delve deeper into the intricacies of AI and its potential to shape the world in diverse and meaningful ways.

DL is undeniably one of the most sought-after and highly valued abilities in the realm of AI technology. Its capability to process vast amounts of data, recognize complex patterns, and make accurate predictions has made it a critical and indispensable tool in various industries and applications. As the demand for AI continues to grow, proficiency in DL has become a key skillset for researchers, developers, and data scientists seeking to harness the full potential of AI (DL) (Baldi, 2021; Dignum, 2019; Hinton, 2002, 2009; Roberts et al., 2022; Russel & Norvig, 2020). The fundamental tenet of DL is straightforward: rather than a human manually creating the system, a machine learns the characteristics and is typically quite good at classification. Thanks to advances in mathematical methods, intelligent theories, and rising computer power, computer scientists can now simulate many more layers of virtual neurons than ever before (Hawkins, 2019; O'Reilly et al., 2021).

While AI and ML may appear interchangeable, AI is commonly regarded the universal term, with ML and the other three topics being subsets of AI. Recently, DL has been considered as a totally new scientific field, which slightly complicates the theoretical foundation of AI concepts (Baldi, 2021; Marcus, 2012; Roberts et al., 2022). DL is revisiting AI, ML, and ANNs with the main goal of reformulating all of them due to specific recent scientific and technological developments. DL has been promoted as a buzzword or a rebranding of AI, ML, and NNs (Bengio, 2009). Recently, Schmidhuber provides a thorough and extensive overview of DL showing clearly that is a subset of the original AI definition (Schmidhuber, 2015).

(B) Architectures and methods

Today, DL is popular namely for three important reasons: (1) the significantly increased size of data used for training, (2) the drastically increased chip processing abilities (e.g., general-purpose graphical processing units), and (3) recent developments in ML and signal/information processing research. These three advances have enabled DL methods to effectively exploit complex, compositional nonlinear functions and make effective use of both structured and unstructured data (Cybenko, 1989).

There are several DL methods and architectures with the most known:

(1) ANNs
(2) deep neural networks (DNNs)
(3) convolutional deep neural networks (CDNNs)
(4) Deep belief network (DBNs)
(5) Recurrent neural networks (RNNs) and
(6) long short-term memory (LSTM)

More details and full analysis of the six and other DL methods can be found in Philbeck & Davis (2018); Hinton (2009); Deng & Yu (2014); Hochreiter & Schmidhuber (1997); Murphy (2012); Utgoff & Stracuzzi (2002); Weng et al. (1997); Weng et al. (1992); Bengio (2009); Bierly et al. (2000); Marwala (2015); Levshun & Kotenko (2023); Arbib (2002); Heykin (2009); Roberts et al. (2022); Baldi (2021); Russel & Norvig (2020); Dignum (2019); O'Reilly et al. (2021); and Ball et al. (2017). However, studying them carefully, all are revised old methods of AI including ML and NN!

(C) A brief historical overview of DL

This historical overview perspective of DL has been chosen to be given now since it will demonstrate the deep roots and strong relationships of DL to AI, ML, NNs, ANNs, and computer vision. The first general, working learning algorithm for supervised deep feedforward multilayer perceptron was published by Ivakhnenko in 1971. Other DL working architectures, specifically those built from ANNs, were introduced by Kunihiko Fukushima in 1980. Warren McCulloch and Walter Pitts created the first computational model for ANNs based on mathematics and algorithms called threshold logic in 1943 (McCulloch & Pitts, 1943). This was further inspired by the 1959 biological model proposed by Nobel laureates David H. Hubel and Torsten Wiesel (Hubel & Wiesel, 1959). Many ANNs can be considered as cascading models of cell types inspired by certain biological observations (Schmidhuber & Prelinger, 1993).

In 1993, Schmidhuber introduced a neural history compressor in the form of an unsupervised stack of RNNs, which could solve a "very deep learning" task requiring more than 1,000 subsequent layers in an RNN unfolded in time (Shrager & Johnson, 1995). In 1995, Brendan Frey demonstrated that a network containing six fully connected layers and several hundred hidden units could be trained using the wake-sleep algorithm, which was co-developed with Frey et al. (1995). However, the training process still took 2 days.

The real impact of DL in industry apparently began in the early 2000s when CNNs were estimated to have processed 10%–20% of all checks written in the USA in 1 year. But the industrial application of large-scale speech recognition started around 2010. In late 2009, Li Deng and Geoffrey Hinton got together and worked at Microsoft Research Lab. Along with other researchers of the Microsoft Lab applied DL to speech recognition obtaining some very interesting results. Going one step further, in the same year, they co-organized the 2009 NIPS Workshop on DL for large-scale speech recognition. Two types of systems were found to produce recognition errors with different characteristics, providing scientific understanding on how to integrate DL into the existing highly efficient run-time speech decoding system deployed in the speech recognition industry (Deng et al., 2013). Recent books and articles have described and analyzed the history of this significant development in DL, including Deng and Yu's (2014) article. A comprehensive survey of DL is provided in Ball et al. (2017). All these historical remarks demonstrate that DL is not totally a new scientific field; rather, it is part of AI trying to avoid a new "AI Winter." Unfortunately, AI will continue to face challenges unless it acknowledges that cybernetics cannot be left out.

(D) Discussions and some criticism on DL

Many scientists strongly believe that DL has been marked as a buzzword or a rebranding of NN and AI. Considering the wide-ranging implications of AI, the realization that DL is emerging as one of the most powerful techniques. Thus, DL understandably attracts various discussions, criticisms, and comments. This comes not only from outside the field of computer science but also with insiders from the computer science itself.

A primary criticism of DL regards the mathematical foundations of the algorithms been used. Most methods and algorithms of DL lack of a fundamental theory. Most DL designs use gradient descent to implement learning. Unlike contrastive divergence, whose theory is less obvious (i.e., does it converge?), gradient descent has been understood for a while. Then how quickly? (What does it roughly represent?). Since most confirmations of DL approaches are empirical rather than theoretical, they are frequently viewed as a "black box."

Some researchers contend that DL should not be viewed as a revolutionary new approach, but rather as a step toward the development of a powerful AI. A study psychologist named Gary Marcus said, "Realistically, DL is only part of the larger challenge of building intelligent machines" (Marcus, 2012). The most powerful AI systems, like Watson, "use techniques such as DL as just one element of deductive reasoning" (Deng et al., 2013). It must be noted that all DL algorithms require a large amount of data. However, DL is a useful tool in creating new knowledge (Groumpos, 2016).

5.4. Edge intelligence

The term "edge intelligence," (EI) also known as edge AI (EAI) and sometimes referred to as "intelligence on the edge," is a recent term used in the past few years to describe the merging of ML or AI with edge computing (Mendez et al., 2022). EI is a challenging field that is currently in its infancy, but its vast potential has generated considerable enthusiasm among researchers and companies eager to explore and exploit its possibilities. The concept of the "edge" has evolved to become "intelligent" through the application of analytics, which were previously confined to cloud computing or in-house data centers. In this paradigm, smart remote sensor nodes have the capability to make real-time decisions locally or transmit data to a gateway for further screening before sending it to the cloud or another centralized storage system. This distributed and intelligent approach allows for more efficient data processing and analysis at the edge, opening up new avenues for diverse applications and advancements in the field of EI.

A challenging question is posed here: what are we seeking? EI, EAI, or simply intelligence on the edge? At first glance, this question may cause us to wonder and raise more important questions. Do the three terms refer to the same issues, different issues, or identical ones? How are all these questions and issues related in our pursuit of true scientific knowledge to solve society's problems? Are there any risks associated with scientific knowledge and/or its associated technologies when searching for solutions? And what is their role in the broader scientific area of AI?

We are witnessing an exponential growth of devices, thanks to the advancements in Internet of Things (IoT) technologies, software tools, and hardware architectures. This is having a significant impact on conventional household devices such as smartwatches, smartphones, and smart dishwashers, as well as industrial settings like surveillance cameras, robotic arms, smart warehouses, production conveyor belts, and more. We are now entering an era where devices can independently think, act, and respond in smarter ways, making everything smarter everywhere on the planet.

Before the advent of edge computing, streams of data were sent directly from the IoT to a central data storage system. EI or EAI is a new and young subfield of AI and has long way before proves that is useful. Mendez et al. (2022) conduct a comprehensive survey of recent research efforts on EI or EAI, providing 122 informative references. Zhou et al. (2019) also discuss EI or EAI and provide 202 references. Thus, these two reference papers indicate that although EI or EAI is in its early stages, it has attracted the interest of many scientists.

6. Correlation and Causation in AI

The word "correlation" is commonly used in everyday life to indicate some form of association between variables (Leetaru, 2019; Marwala, 2015). However, it is astonishing how many people confuse correlation with causation. It is frequently emphasized to journalists that "correlation doesn't imply causation." However, these two phrases continue to be among the most typical mistakes in the reporting of scientific and medical investigations. Theoretically, it should be simple to discern between the two: an event or action can either cause another (e.g., smoking causes lung cancer) or it can correlate with another (e.g., smoking is associated with heavy drinking). They are undoubtedly related if one causes the other. Even if it would seem logical, simply because two things happen at the same time does not necessarily entail that one of them caused the other. Although correlation does not imply causation, the reverse is always true: causality always implies correlation.

Correlation means association – more precisely it is a measure of the extent to which two variables are related. There are three possible results of a correlational study:

1. Positive correlation

If with increase in random variable A, random variable B increases too, or vice versa.

2. Negative correlation

If increase in random variable A leads to a decrease in B, or vice versa.

3. Zero or no correlation

When both the variables are completely unrelated and change in one lead to no change in other.

Correlation is a statistical measure that shows the relationship between two variables. Pearson coefficient (linear) and Spearman coefficient (nonlinear) are two types of correlation coefficients that capture different degrees of probabilistic dependence but not necessarily causation. The correlation coefficients range from -1 (perfect inverse correlation) to 1 (perfect direct correlation), with zero indicating no correlation. You may have observed that the less you sleep, the more tired you are, or that the more you rehearse a skill like dancing, the better you become at it. These simple observations in life form the foundation of correlational research.

Having enough data points and being aware of how the variables interact will determine whether correlations can be used to make predictions. Correlation is the statistical term used to describe the relationship between two quantitative variables. We presume that the relationship is linear and that there is a fixed amount of change in one variable for every unit change in the other. Another method that is frequently employed in these situations is regression, which entails determining the optimal straight line to summarize the association to swiftly and effectively rework and rewrite your material (Marwala, 2015).

The connection between random variables A and B can be deemed causal when there is a direct cause-and-effect relationship between them, indicating that the presence or occurrence of one variable results in or influences the other variable. This concept is known as causation or causality. It is crucial for AI to distinguish between correlation and causation because AI methods rely heavily on correlation and large amounts of data. Many AI studies focus on testing correlation but cannot determine a causal relationship. Without considering causation, researchers may arrive at incorrect conclusions regarding the cause of a problem.

Correlation and causation can coexist, as is often the case in our daily lives. However, it is more important to ask what causes the existence of two variables than to establish their correlation. In 2019, Leetaru published an article titled "A Reminder That Machine Learning Is About Correlations Not Causation" (Leetaru, 2019), emphasizing the importance of causal AI. To avoid another "AI Winter" that could be catastrophic for humanity, AI needs to integrate cybernetics into its future research studies.

A fundamental question that arises is: How can we establish causality in AI studies? This is one of the most challenging tasks for the academic and scientific communities, and it is crucial for society as a whole, particularly for the manufacturing sector and companies. It requires careful study and analysis by all concerned parties. Some answers can be found in cognitive science, specifically in the emerging scientific field of fuzzy logic and FCMs (Kosko, 1986; Glykas, 2010).

7. Challenges and Opportunities of AI

AI represents a paradigm shift for science, which basically relies on theories and models formalized with scientific theories. The field of AI offers numerous exciting opportunities and challenges, depending on the technology used. ML, data mining, and DL are all branches of AI that rely on a lot of data. However, a critical question arises: can we trust the reliability of the data? This challenge demands radically a different approach in studying and designing CDS. It must focus on the development of new algorithms that can build models from the big data-driven world (BDDW) area. In the past, humans developed mathematical models, methods, and algorithms. However, in recent years, machines have performed the same tasks and developed models and algorithms independently of humans, raising concerns about the trustworthiness and control over these models. Moreover, there have been several AI failures that have not received proper attention, leading to serious consequences. The first AI Winter occurred after overestimating the capabilities and benefits of AI, given the significant funding received by the academic and research communities. Some notable examples of AI failures include Face ID being cracked by a mask, Google AI confusing rifles with helicopters, fooling facial recognition, street-sign setbacks, an AI-related loss leading to a lawsuit, AI despising humans, and AI believing that members of Congress resemble criminals. One of the most severe AI failures was the fatal collision in Arizona caused by the system's basic functions failing, resulting in the death of a woman. In April 2021, a Tesla Model S car crashed in Houston, killing two people, due to an autopilot failure. Preliminary investigations suggest that the driver's seat was empty during the crash, indicating that Tesla's Autopilot or Full Self-Driving system was engaged at the time. Therefore, one of the significant challenges for AI is to address all failures in using AI technologies seriously. It is imperative to consider all limitations of AI and develop safeguards to guarantee the reliability, trustworthiness, and control over AI models and algorithms.

AI abilities and accomplishments are advancing at an extraordinary, fantastic, and remarkable rate. Other related technologies such as ML, NNs, DL, EI, and big data-driven algorithms are following suit. These technologies have numerous widely beneficial applications (Arbib, 2002; Baldi, 2021; Ball et al., 2017; Bengio, 2009; Bierly et al., 2000; Cybenko, 1989; Deng et al., 2013; Dignum, 2019; Frey et al., 1995; Fukushima, 1980; Groumpos, 2016; Hawkins, 2019; Heykin, 2009; Hochreiter & Schmidhuber, 1997; Hubel & Wiesel, 1959; Ivakhnenko, 1971; Levshun & Kotenko, 2023; Marcus, 2012; Marwala, 2015; McCulloch & Pitts, 1943; Mendez et al., 2022; Murphy, 2012; O'Reilly et al., 2021; Roberts et al., 2022; Russel & Norvig, 2020; Schmidhuber & Prelinger, 1993; Schmidhuber, 2015; Shrager & Johnson, 1995; Utgoff & Stracuzzi, 2002; Weng et al., 1992; Weng et al., 1997). Historically, less attention has been paid to the malicious uses of AI, which poses a challenge to the AI community. It is necessary to perform studies to identify potential security risks from malicious use of AI technologies and to suggest solutions for better foreseeing, preventing, and eradicating these risks. The investigations ought to cover the long-term balance of attackers and defenders as well.

Opportunities for AI are spreading across all sectors of society, especially in industries and enterprises (Ball et al., 2017; Deng et al., 2013; European Commission, 2022; Soni et al., 2019; Wirtz et al., 2019). This is especially true now, as data collection and analysis have significantly increased recently because of reliable IoT connectivity and quick computer processing (European Commission, 2022). While some sectors have already benefited from these opportunities, others are just beginning to realize their potential. These sectors include manufacturing, healthcare, energy, environment, transportation, education, media, customer service, space, e-commerce, navigation, lifestyle, sociology, robotics, agriculture, gaming, marketing, social media, chatbots, finance, and economics. A recent review article gives examples of research on AI for dairy farms and highlights some emerging opportunities (De Vries et al., 2023). It must be stated that AI has not been used as properly as needed in agriculture applications. Recent studies also provide necessary material for AI opportunities in pharmacology (Kumar et al., 2023) and in societal problems using GPT (Haluza & Jungwirth, 2023).

8. Threats of AI

In recent years, AI has witnessed a surge in popularity, capturing the attention of both the scientific community and the public. AI is often credited with numerous positive contributions across various social sectors, including medicine, energy, and the economy. However, there is also a growing apprehension regarding its potential adverse effects on society and individuals. As AI continues to advance and integrate further into our lives, it becomes essential to carefully consider its implications and take proactive measures to address any potential challenges and concerns.

Frequently, public opinion polls delve into the fear that people have concerning autonomous robots and AI. This phenomenon has also become a subject of scholarly investigation and research. The rising interest in understanding public perceptions and concerns about AI and robotics reflects the growing impact of these technologies on society and underscores the importance of addressing any apprehensions to ensure responsible and ethical development and implementation.

AI has indeed brought about a revolution in various industries, including healthcare, finance, manufacturing, and transportation. Its capacity to automate and streamline processes, coupled with its exceptional predictive and decision-making capabilities, has led to significant advancements and improvements in efficiency and accuracy within these sectors. The transformative impact of AI continues to reshape how these industries operate, creating new opportunities and driving innovation in numerous ways.

Indeed, despite the remarkable advancements AI has achieved, there remains a legitimate concern about the potential consequences if this powerful technology falls into the wrong hands. The prospect of misuse or malicious intent with AI raises apprehension and unease. It emphasizes the importance of responsible AI development, robust security measures, and ethical considerations to ensure that AI is harnessed for the benefit of humanity and does not pose unnecessary risks or harm. As AI continues to evolve, addressing these concerns and implementing safeguards will be crucial to fostering a positive and secure AI-driven future (Autor, 2019; Bécue et al., 2021; Brundage, 2018; Creese, 2020; Zaman et al., 2021). One of the significant concerns surrounding AI is the potential displacement of human jobs. As AI systems continue to advance in sophistication, they can increasingly perform tasks that were traditionally associated with human intelligence, like data analysis, prediction-making, and even autonomous driving.

This trend could lead to job displacement and unemployment, particularly for workers in low-skilled jobs, as these tasks become automated, and AI systems prove more efficient and cost-effective in certain areas (Autor, 2019). It becomes crucial for society to address these challenges and develop strategies to reskill and upskill the workforce, ensuring that people are equipped to embrace new roles that complement AI technology. Additionally, fostering innovation and finding ways to harness AI's potential to create new job opportunities becomes vital to mitigate the negative impact on employment and to foster a smooth transition toward a future where AI and humans can collaborate effectively.

Another potential threat of AI is its ability to be used for malicious purposes. For example, AI algorithms can be used to create fake news or deepfake videos, which can be used to spread misinformation and propaganda. AI can also be used to create autonomous weapons, which can operate without human intervention and make decisions about who to target and when to attack.

In addition, there are concerns about the ethics of AI. As AI systems become more complex, they can become difficult to understand and control, which raises questions about who is responsible for their actions. There is also the issue of bias in AI algorithms, which can perpetuate existing inequalities and discrimination.

To address these potential threats, it is important to develop ethical guidelines and regulations for AI. This includes ensuring that AI is developed and used in a way that is transparent, accountable, and respects human rights. It is also important to invest in education and training programs to help workers transition to new industries and roles, as well as to promote digital literacy and critical thinking skills to combat the spread of misinformation. In May 2014, the famed Stephen Hawking, a prominent physicist of the 20th century, gave the world a substantial wakeup shot.

The same year several well-known scientists from all over the planet warned that the intelligent machines been developed for pure commercial use, could be "potentially our worst mistake in history." In January 2015, Stephen Hawking, Elon Musk, and several experts of AI signed an open letter calling for research on the impacts of AI in the society (Sparkes, 2015). The letter indicated: "AI has the potential to eradicate disease and poverty, but researchers must not create something that cannot be controlled" (Sparkes, 2015). "Although we are facing potentially the best or worst thing ever to happen to humanity," and continued: "little serious research is devoted to these issues outside small nonprofit institutes." The report had the following important remark: "The potential benefits (of AI) are huge since everything that civilization has to offer is a product of human intelligence; we cannot predict what we might achieve when this intelligence is magnified by the tools AI may provide, but the eradication of disease and poverty is not unfathomable. Because of the great potential of AI, it is important to research how to reap its benefits while avoiding potential pitfalls." That was 7 years ago! So where are we now? Unfortunately, not much better. The AI threats have not been eliminated but, on the contrary, have increased in numbers and have become more concrete and dangerous (Kieslich et al., 2021; Thomas, 2021). This topic is extremely difficult and very sensitive to analyze. There are people who are dead against AI and spread various theories about the AI threats. On the other hand, there are many people who support AI fanatically. Thus, in this paper, only scientists' concrete ideas regarding AI threats are stated. Thomas (2021) reports remarks of Elon Musk, founder of Space X, made in a conference, in which he said: "Mark my words, AI is far more dangerous than nukes". In the same report (Thomas, 2021), several threats of AI are mentioned:

(1) Automatic job losses
(2) Violation of private life
(3) Algorithmic bias caused by bad data
(4) Inequality of social groups
(5) Market volatility
(6) Development of dangerous weapons
(7) Potential AI arms race
(8) Stock market instability caused by algorithmic high frequency trading
(9) Certain AI methodologies may be fatal to humans

Finally, Stephen Hawking was free and honest in expressing his true feelings and opinions when he told an audience in Portugal "that AI's impact could be cataclysmic unless its rapid development is strictly and ethically controlled." Without analyzing further, the threats of AI, I would encourage the reader of this paper to seek his own conclusions on all aspects of AI threats and risks. You can start with Araujo et al. (2020), Bourne (2019), Hinks (2020), Kieslich et al. (2021), Liang and Lee (2017), McClure (2018), So et al. (2016), Sparkes (2015), Thomas (2021), and Wirtz et al. (2019). See for example Hinks (2020); Liang & Lee (2017); and McClure (2018) and investigate yourself, the recent robot developments, and search for future threats of humanized robots to the society. See also Autor (2019); Ball et al. (2017), Bécue et al. (2021), Brundage (2018), Creese (2020), Dostonbek and Jamshid (2023), European Commission (2022), Federspiel et al. (2023), Soni et al. (2019), and Zaman et al. (2021).

Overall, while there are potential threats associated with AI, it is important to recognize its potential benefits and to work toward developing responsible and ethical AI systems.

9. Why AI and Not Cybernetics?

In Section 3, three names were given for the field of "thinking machines": (1) cybernetics, (2) automata theory, and (3) complex information processing. All three were scientifically developed, analyzed, and defined long before AI as we know it today was officially started in 1956 at Dartmouth College. Of the three names, the one that had been well-known and investigated, at that time, is cybernetics. One of today's most significant and misunderstood sciences is AI. A large part of this misconception stems from a failure to acknowledge cybernetics, which was its direct forerunner. The same basic idea underlies both AI and cybernetics, both of which are based on binary logic. Although the reasoning is universal, the intent varies depending on the culture.

The 1956 Dartmouth Workshop was organized by Marvin Minsky, John McCarthy, and two senior scientists: Claude Shannon and Nathan Rochester of IBM. The proposal for the conference included this assertion: "every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it." The conference was attended by 47 scientists, and at the conference, different names for the scientific area were proposed, among them cybernetics and logic theorist. McCarthy persuaded the attendees to accept "AI" as the name of the new field. The 1956 Dartmouth conference is largely regarded as the event that gave AI its name, purpose, initial triumph, and key participants. McCarthy adopted the phrase "artificial intelligence" to avoid connotations with cybernetics and ties to the eminent cyberneticist Norbert Wiener (1948). McCarthy has said: "one of the reasons for inventing the term 'artificial intelligence' was to escape association with 'cybernetics'." Its concentration on analog feedback seemed misguided, and I wished to avoid having either to accept Norbert (not Robert) Wiener as a guru or having to argue with him. "Norbert Wiener (November 26, 1894–March 18, 1964) was an American mathematician and philosopher. At the Massachusetts Institute of Technology (MIT), he taught mathematics. An early researcher in stochastic and mathematical noise processes, Wiener was a child genius who made contributions to the fields of electronic engineering, electronic communication, and control systems. That Wiener was not invited to the 1956 Dartmouth conference is astounding.

They purposefully adopted the term AI, despite the fact that many scientists were aware of the significant scientific contributions of cybernetics. Despite the fact that AI was greatly impacted by cybernetics, cybernetics has frequently been overshadowed by AI in recent years. Cybernetics is once again being employed in many sectors, and it has just re-entered the public consciousness. It must be pointed out that cybernetics is an interdisciplinary discipline that focuses on how a system handles information, responds to it and changes, generates control actions, or restructures the entire system for better performance. It is a broad theory of decision-making, feedback regulation, and information processing. The definition of "cybernetics" as it is used today – first coined by Norbert Wiener in 1948 – as "the scientific study of control and communication in the animal and the machine" – is more applicable to our lives than ever before.

Cybernetics, for a long time, has been the science of human–machine interaction that studies and uses the principles of systems control, feedback, identification, and communication. Cybernetics has undergone some recent redefinition. It now focuses more on the investigation of control mechanisms that are mechanical, electrical, biological, physical, or cognitive in character. It primarily investigates the ideas of communication and control in biological things, machines, and organizations, including self-organization. The question is: Does AI accept the same principles of cybernetics, and how does it proceed to solve the challenging problems of society? I am afraid to say that although AI is close to cybernetics, it still fails to provide realistic and viable solutions to the world's problems. Recently, scientists and mathematicians have begun to think in innovative ways to make machines smarter and approach human intelligence. AI and cybernetics are perfect examples of this human–machine merger. Binary logic is the main principle in both fields. Both terms are often used interchangeably, but this can cause confusion when studying them. They are slightly different; AI is based on the view that machines can act and behave like humans, while cybernetics is based on a cognitive view of the world. Further studies on this scientific aspect between AI and cybernetics will clarify several scientific differences between them.

CAI would be a more appropriate term to describe the modeling and control of CDS. A comparably relevant and healthy fusion of human intellect (cybernetics) and "machines" (AI) would be achieved through such a new scientific field. It will take a significant effort and creative thinking to start this issue.

10. Can FCMs be Useful to AI?

The most interesting and challenging question of this research study is: why are FCMs useful in creating new knowledge from the BDDW and cyber-physical systems? FCMs possess valuable characteristics that can create new data and knowledge by addressing the cause-and-effect principle, which is the driving force behind most complex dynamic systems. This raises a further question: can FCMs be useful for AI? FCMs are a combination of fuzzy logic and NNs and were first introduced by Kosko (1986) just 35 years ago. It is a very recent scientific technique for simulating CDS, and it exhibits every characteristic of a CDS. A more thorough explanation of FCM was described in Glykas (2010). FCM is a computational method that can be used to look at situations where human brain processes produce foggy, fuzzy, imprecise, or ambiguous descriptions. An FCM, which provides a graphical representation of the cause-and-effect linkages between nodes, can be used to describe the behavior of a CDS simply and graphically. FCMs, which embody the collective knowledge and expertise of specialists who comprehend how the dynamic system operates in various situations, ensure the system's functionality. Language-based variables are used to extract this knowledge, which are subsequently defuzzified into numerical values. In other words, FCMs suggest a modeling approach that consists of a collection of variables (nodes) Ci, as well as the connections (weights) W that connect them. Weights belong in the range [-1, 1], while concepts take values in the range [0, 1]. Figure 2 shows a representative diagram of an FCM.

FCMs may evaluate scenarios in which human thought processes entail fuzzy or uncertain settings using a reasoning process that can manage uncertainty and ambiguity descriptions. FCMs are useful in dealing with complicated dynamic systems.

The full method for the development of an FCM has four steps and is provided in Glykas (2010), Groumpos (2018), and Groumpos and Stylios (2000).

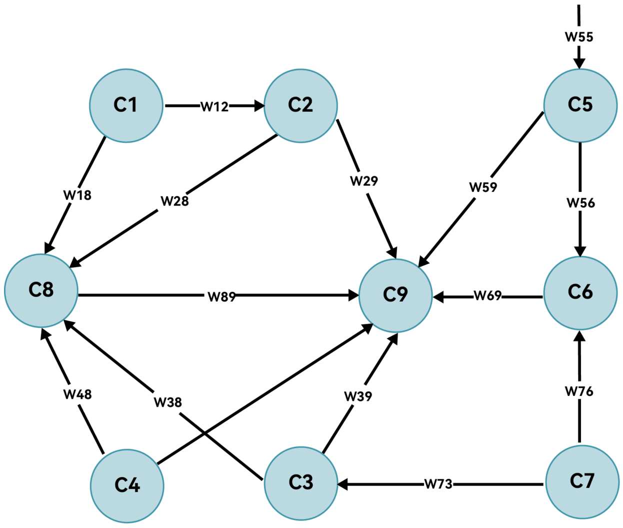
The sign of each weight W_{ij} represents the type of influence (causality and not correlation) between concepts. There are three types of interconnections between two concepts C_i and C_j and are fully explained in Glykas (2010).

The absolute value of W_{ij} indicates the degree of influence between two concepts, C_i and C_j. The mathematical formulation calculates the value of each concept using the following equation (1):

$$A_i(k+1) = f\left(k_2 A_i(k) + k_1 \sum_{j=1, j\neq i}^{N} A_j(k) W_{ji}\right) \tag{1}$$

where N is the number of concepts, $A_i(k+1)$ is the value of the concept C_i at the iteration step $k+1$, $A_j(k)$ is the value of the concept C_j at the iteration step k, W_{ji} is the weight of interconnection from concept C_j to concept C_i, and f is the sigmoid function. "k_1" expresses the influence of the interconnected concepts on the configuration of the new value of the concept A_i and "k_2" represents the proportion of the contribution of the previous value of the concept in computing the new value. The sigmoid function f is defined with equation (2):

Figure 2
A simple fuzzy cognitive map (FCM)



$$f = \frac{1}{1 + e^{-\lambda x}} \quad (2)$$

where $\lambda > 0$ determines the steepness of function f. The FCM's concepts are given some initial values which are then changed depending on the weights; the way the concepts affect each other. The calculations stop when a steady state is achieved; the concepts' values become stable. A more comprehensive mathematical presentation of FCMs with application to real problems with very useful results is provided in Kosko (1986), Glykas (2010), Groumpos (2018), Groumpos and Stylios (2000), Papageorgiou et al. (2003), Giabbanelli et al. (2012), Groumpos (2015), Neocleous and Schizas (2012), Groumpos (2019), Li and Jiang (2022), and Groumpos (2021).

The above methodology and using learning algorithms have been used to create new knowledge (Cole & Persichitte, 2000; Mpelogianni & Groumpos, 2018). This is the only mathematical model that can describe the dynamic behavior of any system, using recursive equations (equation (1)) and the experience of experts with deep knowledge of the system. The experts use methods of cognitive science and fuzzy logic. This approach has been used to address difficult problems with very useful results: in energy (Kyriakarakos et al., 2012; Mahboub et al., 2019; Pereira et al., 2020), in health (Amirkhani et al., 2017; Apostolopoulos & Groumpos, 2020; Bevilacqua et al., 2012; Bhatia & Kumar, 2015; Bhatia et al., 2014; de Moraes Lopes et al., 2013; Janmenjoy et al., 2015; Oye & Thomas, 2019; Papageorgiou, 2012; Savage, 2019), in business and economics (Lopez & Ishizaka, 2019; Paes de Faria et al., 2020; Groumpos, 2015; Neocleous & Schizas, 2012), in social and international affairs (Groumpos, 2018, 2019; Cole & Persichitte, 2000; Mago et al., 2013; Wang et al., 2022), on COVID-19 (Akinnuwesi et al., 2021; Goswami et al., 2021; Groumpos, 2020, 2021), in agriculture (Christen et al., 2015; Correa et al., 2012; Groumpos et al., 2016), and in renewable energy sources (Çoban & Onar, 2017; Jetter & Schweinfort, 2011; Karlis et al., 2007). Reviews of FCMs for several applications are provided in Papageorgiou and Salmeron (2013) and Janmenjoy et al. (2015). New knowledge is generated not based on statistical analysis and correlation, but on causality and the past knowledge of the system acquired by experts. Neuroscience studies are part of causality and AI methods (Groumpos, 2018). Results obtained in several applications using FCM theories and methods with real data, and comparing them with other AI, DL, and ML methods, were 20–25% better. Therefore, FCM theories can be used in combination with AI to merge methods and algorithms to address all societal problems, and thus find viable and realistic solutions. It is important to stress that FCM and AI can create for the first time knew knowledge in a synergistic way (Mpelogianni & Groumpos, 2018).

11. The Future of AI

AI has been considered as a world-changing revolution, much like the industrial revolutions that emerged since the early 18th century (McCarthy, 1988). We are currently in the 4th IR, or INDUSTRY 4.0, and moving toward INDUSTRY 5.0 or according to some to INDUSTRY 6.0! While all preceding technological revolutions have drastically changed the world, AI is completely different. AI is shaping the future of humanity across nearly every aspect of it, serving as the main driving force for emerging technologies like big data, robotics, nanotechnology, neuroscience, and IoT (Dahlin, 2021). AI has gone through "summers" and "winters," and currently, we are in the third "AI Summer." However, no one can be sure for how long. Some believe we will stay forever in this magnificent "AI Summer," while others fear that a new "AI Winter" is coming, which could be catastrophic for the world.

The question that arises now is what would be the impact of AI on the future of "Humanity"? Tech giants like Google, Apple, Microsoft, and Amazon are investing annually billions on AI to create several products and services to meet the needs of the society. The state and private sources are pouring generously research funding to many scientists and research institutes. Nevertheless, it is not unclear what the future of AI holds for the planet. Several researchers promise that AI will make the life of the individual better than todays' over the next few decades. However, many have serious concerns about how advances in AI will affect what it means to be human, productive, and exercise free will (Gill, 2022; Groumpos, 2022).

Academicians all over the planet are including AI on their curricula. Researchers are intensifying their efforts in AI and all related subfields of AI, and some developments are already on their way to being fully realized. Still, others are merely theoretical and may remain so. All are disruptive, for better and potentially worse, and there is no downturn in sight. Globalization is at full speed, but it remains to be seen how advances in AI will shape the future of humanity. The digital world is augmenting human capacities and disrupting centuries-old human practices and behaviors. Software-driven systems have spread to more than half of the world's inhabitants in ambient information and connectivity, offering previously unimagined opportunities but at the same time unprecedented threats.

In the summer of 2018, just 5 years ago, almost 1000 technology experts from all sectors of society were asked this question, with the year 2030 as the target time. Overall, 63% of respondents said they hope that most individuals will be mostly better off in 2030, while 37% said are afraid that people will not be better off. The experts predicted that advanced AI would amplify human effectiveness but also threaten human freedom, autonomy, agency, and capabilities.

Yes, AI may match or even exceed human intelligence and capabilities in all activities that humans perform today. Indeed, AI "smart" systems everywhere as well as in many everyday processes will save time, money, and lives. Furthermore, all "smart systems" will provide opportunities to every individual to enjoy and appreciate a more customized future. But at what expense? No one knows or wants to address these questions from the standpoint of human values and ethics. Today's economic models fail to consider these questions. Most people believe that fundamental inherent values in humans include love, peace, truth, honesty, loyalty, respect for life, discipline, friendship, and other ethics. These values bring out the fundamental goodness of human beings and society at large (Groumpos, 2018; Marwala, 2015).

"Let's face the truth about AI: it can be both constructive and destructive, depending on who is wielding it." We also need to be honest with ourselves. Most AI tools are, and will continue to be, in the hands of companies always aiming for profit or governments seeking to hold political power. Digital systems (also considered smart!) when asked to make decisions for humans and or the environment do not take into consideration fundamental ethics and values. As a matter of fact, they have not part of their functionality these ethical issues. Only if the people that own the digital system provide them these values and with instructions how to use them. These "smart systems" are globally connected and difficult to be controlled or regulated. We need wise leaders who value the human values mentioned above. Questions about privacy, freedom of speech, the right to assemble, and the technological construction of personal life will all re-emerge in this new "AI world," especially now that the COVID-19 pandemic is over according to recent statement by the WHO. Who benefits and who is disadvantaged in this new "AI world" depends on how broadly we analyze these questions today for the future. How can engineers create AI systems that benefit society and are robust? Humans must remain in control of AI; our AI systems must "do what we want them to do." The required research is interdisciplinary, drawing from almost all scientific and social areas. This is the reason that in this paper I stress the need to combine the AI and cybernetics to a new scientific field: the CAI.

Here are some actions that our society should follow:

1. We should take the open letter from scientists in 2015 seriously (Sparkes, 2015).
2. Digital cooperation should be prioritized to serve better the needs of the humanity.
3. We need to define the type of society we want to live in.
4. We should strive to develop a new IR, the "wise anthropocentric revolution" (Groumpos, 2022).
5. We should develop "smart systems" to avoid divisions between digital "haves" and "have-nots."
6. New economic and political systems are needed to ensure that technology aligns with our values and that AI is in the "right hands."
7. A new scientific field, "cybernetic artificial intelligence" (CAI), should be developed rapidly and vigorously.
8. EI or EAI should be developed for each isolated field, such as healthcare, and even for specific topics, such as orthopedics.
9. The new "AI world" should be governed with people respecting the fundamental huma values and ethics.

Many more could be developed and pursued by specific groups.

It is up to all of us to work together to develop viable, realistic, reasonable, practical, and wise solutions. We owe it to our children and future generations to do so. To achieve this, we need to accept and follow a solid code of ethics, which sets professionally accepted values, and guiding principles that have been established by superior civilizations for centuries. As the ancient Greek philosopher Plato said: "Every science separated from justice and other virtues is cunning, it does not seem to be wisdom." In simpler terms, knowledge without justice and other virtues is better described as cunning than wisdom. This statement expresses the importance of implementing knowledge with justice to turn it into true wisdom.

Progressing in AI without making a similar progress in humanitarian values is like walking with one leg or seeing with just one eye. What an irony! Despite the world's thirst for peace and sustainable development, people fail to achieve them. But we could if we realize that the solutions to today's problems can be easily found. We only need as free citizens, policy makers, or members of the scientific community practice philosophy genuinely and satisfactorily addressing and then solve our problems, according to Plato's statement. Professional organizations usually establish codes of professional ethics to guide their members in performing their job functions according to sound and consistent ethical principles. The underlying philosophy of having professional ethics is to ensure that individuals in such jobs follow sound, uniform ethical conduct. These include integrity, honesty, transparency, respectfulness towards the job, fair competition, confidentiality, objectivity, among others. For example, the Hippocratic Oath taken by medical students is an example of professional ethics that is adhered to even today.

In my humble opinion, there is a "smiling" future for AI if it embraces cybernetics and the wise anthropocentric ethics and social ethics. In this way, I hope we can make AI more human and less artificial.

12. Conclusion and Future Research Directions

In this historical overview paper on AI, a range of issues and concepts have been examined for the first time. Looking back at ancient times, it becomes clear that humanity has always dreamed of creating machines that could mimic living animals and humans. The historical overview provides extensive coverage of all AI developments since the 1956 Dartmouth College conference, which marked the official beginning of AI as we know it today. Although the field of AI could be given many names, many consider "AI" to be the least accurate of them all. The term "cybernetics" has been largely ignored. All of today's methods and algorithms for AI have been briefly presented and devoting more scientific material for DL.

AI is a relatively young science that follows the traditional historical evolution of any science. Science is built upon theories and models that are formalized with mathematical methods, formulas, and complex equations, formulated by academicians, theoretical scientists, and applied engineers. These theories are then tested and proven useful in society. AI has seen tremendous success in almost all scientific fields but also faces many challenges, some of which are outlined in this paper. One important challenge is addressing potential failures and striving to prevent them.

In addition, this paper highlights the many open opportunities that lie ahead for AI. AI has experienced its "AI Summers and Winters." Today, AI is experiencing an "AI Summer." The paper analyzes the two "Winters" and three "AI Summers" and draws lessons from each case. The paper also raises the question of why AI did not take the name cybernetics and provides a detailed explanation of why the term cybernetics should be part of AI. The paper proposes a new scientific area combining AI and cybernetics, called "CAI," for the first time.

For the first time, the importance of the young scientific field of FCMs was presented and briefly formulated. Since FCMs deal with the causal factors that are always present in the dynamic and complex world, it is recommended that AI research should pay serious attention to FCMs. Finally, the future of AI was considered and briefly analyzed. Despite the optimism and enthusiasm of many people, the future of AI might turn out to be a "catastrophic winter" for the whole world. It all depends on whose hands AI will be held. The only hope for the survival of the planet is the quick development of "CAI" and the "wise anthropocentric revolution." Some specific solutions for achieving these two goals were given.

If we are to discuss future research directions, I propose starting with what Hawking said in 2015 (Cybenko, 1989): "Comparing the impact of AI on humanity to the arrival of 'a superior alien species,' Hawking and his co-authors found humanity's current state of preparedness deeply wanting. 'Although we are facing potentially the best or worst thing ever to happen to humanity,' they wrote, 'little serious research is devoted to these issues outside small nonprofit institutes.'" Furthermore, the future research directions for the AI field are wide open. The proposed 9 actions in Section 11 are only the beginning. Mathematical and scientific approaches must be used to realize these fundamental actions. Additionally, for each action, software tools need to be developed and used on real applications.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

References

Agar, J. (2020). What is science for? The Lighthill report on artificial intelligence reinterpreted. *The British Journal for the History of Science*, *53*(3), 289–310. https://doi.org/10.1017/S0007087420000230

Akinnuwesi, B. A., Fashoto, S. G., Mbunge, E., Odumabo, A., Metfula, A. S., Mashwama, P., . . . , & Amusa, O. O. (2021). Application of intelligence-based computational techniques for classification and early differential diagnosis of COVID-19 disease. *Data Science and Management*, *4*, 10–18. https://doi.org/10.1016/j.dsm.2021.12.001

Amirkhani, A., Papageorgiou, E. I., Mohseni, A., & Mosavi, M. R. (2017). A review of fuzzy cognitive maps in medicine: Taxonomy, methods, and applications. *Computer Methods and Programs in Biomedicine*, *142*, 129–145. https://doi.org/10.1016/j.cmpb.2017.02.021

Apostolopoulos, I. D., & Groumpos, P. P. (2020). Non-invasive modelling methodology for the diagnosis of coronary artery disease using fuzzy cognitive maps. *International Journal of Computer Methods in Biomechanics and Biomedical Engineering*, *23*(12), 879–887. https://doi.org/10.1080/10255842.2020.1768534

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI & Society, 35*, 611–623.

Arbib, M. A. (1969). *Theories of abstract automata*. USA: Prentice-Hall.

Arbib, M. A. (2002). *The handbook of brain theory and neural networks*. USA: MIT Press.

Aristotle (1963). *Clarendon aristotle series: Categories and de interpretatione*. In Ackrill, J. L. (Eds.). UK: Oxford University.

Ashby, W. R. (1956). *An introduction to cybernetics*. UK: Chapman & Hall.

Ashby, W. R., Shannon, C. E., & McCarthy, J. (1956). *Automata studies*. USA: Princeton University Press.

Asimov, I. (1951). *I, Robot*. USA: Gnome Press.

Atkinson, R. C., & Shiffrin, R. M. (1968). *Human memory: A proposed System and its control processes. Psychology of Learning and Motivation*, *2*, 89–195. https://doi.org/10.1016/S0079-7421(08)60422-3

Autor, D. (2019). *Artificial intelligence and employment: Will robots take your job?* USA: National Bureau of Economic Research.

Baddeley, A. D., & Hitch, G. (1974). Working memory. *Psychology of Learning and Motivation, 8*, 47–89. http://dx.doi.org/10.1016/S0079-7421(08)60452-1

Bai, C., Dallasega, P., Orzes, G., & Sarkis, J. (2020). Industry 4.0 technologies assessment: A sustainability perspective. *International Journal of Production Economics*, *229*, 107776. https://doi.org/10.1016/j.ijpe.2020.107776

Baldi, P. (2021). *Deep learning in science*. UK: Cambridge University Press.

Ball, J. E., Anderson, D. T., & Chan, C. S. (2017). Comprehensive survey of deep learning in remote sensing: Theories, tools, and challenges for the community. *Journal of Applied Remote Sensing*, *11*(4), 042609–042609. https://doi.org/10.1117/1.JRS.11.042609

Bécue, A., Praça, I., & Gama, J. (2021). Artificial intelligence, cyber-threats and industry 4.0: Challenges and opportunities. *Artificial Intelligence Review*, *54*, 3849–3886. https://doi.org/10.1007/s10462-020-09942-2

Bengio, Y. (2009). Learning deep architectures for AI. *Foundations and trends in Machine Learning*, *2*(1), 1–127. http://dx.doi.org/10.1561/2200000006

Bevilacqua, M., Ciarapica, F. E., & Mazzuto, G. (2012). Analysis of injury events with fuzzy cognitive maps. *Journal of Loss Prevention in the Process Industries*, *25*(4), 677–685. https://doi.org/10.1016/j.jlp.2012.02.004

Bhatia, A., Mago, V., & Singh, R. (2014). Use of soft computing techniques in medical decision making: A survey. In *IEEE 2014 International Conference on Advances in Computing, Communications and Informatics*, 1131–1137. http://doi.org/10.1109/ICACCI.2014.6968460

Bhatia, N., & Kumar, S. (2015). Prediction of severity of diabetes mellitus using fuzzy cognitive maps. *Advances in Life Science and Technology*, *29*, 71–78.

Bierly III, P. E., Kessler, E. H., & Christensen, E. W. (2000). Organizational learning, knowledge and wisdom. *Journal of Organizational Change Management*, *13*(6), 595–618. https://doi.org/10.1108/09534810010378605

Booth, T. L. (1967). *Sequential machines and automata theory*. USA: John Wiley & Sons.

Bourne, C. (2019). AI cheerleaders: Public relations, neoliberalism and AI. *Public Relations Inquiry*, *8*(2), 109–125. https://doi.org/10.1177/2046147X19835250

Brundage, M., Avin, S., Clark, J., Toner, H., Eckersley, P., Garfinkel, B., . . . , & Amodei, D. (2018). The malicious use of artificial intelligence: Forecasting, prevention, and mitigation. *arXiv Preprint: 1802.07228*.

Buchanan, B. G. (2007). A (very) brief history of artificial intelligence. *AI Magazine*, *26*(4), 53–60. https://doi.org/10.1609/aimag.v26i4.1848

Christen, B., Kjeldsen, C., Dalgaard, T., & Ortega, J. M. (2015). Can fuzzy cognitive mapping help in agricultural policy design and communication? *Land Use Policy*, *45*, 64–75. https://doi.org/10.1016/j.landusepol.2015.01.001

Çoban, V., & Onar, S. Ç. (2017). Modelling solar energy usage with fuzzy cognitive maps. *Intelligence Systems in Environmental Management: Theory and Applications*, 159–187. https://doi.org/10.1007/978-3-319-42993-9_8

Cole, J. R., & Persichitte, K. A. (2000). Fuzzy cognitive mapping: Applications in education. *International Journal of Intelligent Systems*, *15*(1), 1–25. https://doi.org/10.1002/(SICI)1098-111X

Cooper, G. F. (1989). Current research directions in the development of expert systems based on belief networks. *Applied Stochastic Models and Data Analysis*, *5*(1), 39–52. https://doi.org/10.1002/asm.3150050106

Correa, C., Valero, C., Barreiro, P., Diago, M. P., & Tardáguila, J. (2012). Feature extraction on vineyard by Gustafson Kessel FCM and K-means. In *2012 16th IEEE Mediterranean Electrotechnical Conference*, 481–484. http://doi/org/10.1109/MELCON.2012.6196477

Creese, S. (2020). *The threat from AI*. In Baker, D. J. & Robinson, P. H. (Eds.), *Artificial Intelligence and the Law* (pp. 21). Routledge.

Cybenko, G. (1989). Dynamic load balancing for distributed, memory multiprocessors. *Journal of Parallel and Distributed Computing*, *7*(2), 279–301. https://doi.org/10.1016/0743-7315(89)90021-X

Dahlin, E. (2021). Mind the gap! On the future of AI research. *Humanities and Social Sciences Communications*, *8*(1), 1–4. https://doi.org/10.1057/s41599-021-00750-9

De Moraes Lopes, M. H. B., Ortega, N. R. S., Silveira, P. S. P., Massad, E., Higa, R., & de Fátima Marin, H. (2013). Fuzzy cognitive map in differential diagnosis of alterations in urinary elimination: A nursing approach. *International Journal of Medical Informatics*, *82*(3), 201–208. https://doi.org/10.1016/j.ijmedinf.2012.05.012

De Faria, A. C. P., Ferreira, F. A., Dias, P. J., & Cipi, A. (2020). A constructivist model of bank branch front-office employee evaluation: An FCM-SD-based approach. *Technological and Economic Development of Economy*, *26*(1), 213–239. https://doi.org/10.3846/tede.2020.11883

De Vries, A., Bliznyuk, N., & Pinedo, P. (2023). Invited review: Examples and opportunities for artificial intelligence (AI) in dairy farms. *Applied Animal Science*, *39*(1), 14–22. https://doi.org/10.15232/aas.2022-02345

Deng, L., Hinton, G. E., & Kingsbury, B. (2013). New types of deep neural network learning for speech recognition and related applications: An overview. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing*, 8599–8603. http://doi/org/10.1109/ICASSP.2013.6639344

Deng, L., & Yu, D. (2014) *Deep learning: Methods and applications. foundations and trends® in signal processing*, *7*, 197–387. http://dx.doi.org/10.1561/2000000039

Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way*. Switzerland: Springer Nature.

Dostonbek, T., & Jamshid, M. (2023). Use of artificial intelligence opportunities for early detection of threats to information systems. *Central Asian Journal of Theoretical and Applied Science*, *4*(4), 93–98.

European Commission (2022). *Opportunities and challenges of artificial intelligence technologies for the cultural and creative sectors*. Retrieved from: https://op.europa.eu/en/publication-detail/-/publication/359880c1-a4dc-11ec-83e1-01aa75ed71a1/language-en

Federspiel, F., Mitchell, R., Asokan, A., Umana, C., & McCoy, D. (2023). Threats by artificial intelligence to human health and human existence. *BMJ Global Health*, *8*(5), e010435. http://dx.doi.org/10.1136/bmjgh-2022-010435.

Floridi, L. (2020). AI and its new winter: From myths to realities. *Philosophy and Technology*, *33*, 1–3.

Francesconi, E. (2022). The winter, the summer and the summer dream of artificial intelligence in law. *Artificial Intelligence and Law*, *30*(2), 147–161.

Frey, B. J., Hinton, G. E., & Dayan, P. (1995). Does the wake-sleep algorithm produce good density estimators? *International Journal in Advances in Neural Information Processing Systems*, *8*, 661–667.

Fukushima, K. (1980). Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. *Biological Cybernetics*, *36*(4), 193–202. https://doi.org/10.1007/BF00344251

Giabbanelli, P. J., Torsney-Weir, T., & Mago, V. K. (2012). A fuzzy cognitive map of the psychosocial determinants of obesity. *Applied Soft Computing*, *12*(12), 3711–3724. https://doi.org/10.1016/j.asoc.2012.02.006

Gill, K. S. (2022). *The application and misapplication of artificial intelligence today*. Retrived from: https://www.chathamhouse.org/events/all/members-event/application-and-misapplication-artificial-intelligence-today

Glushkov, V. (1966). *Introduction to cybernetics*. USA: Academic Press.

Gonsalves, T. (2018). The summers and winters of artificial intelligence. *Advanced Methodologies and Technologies in Artificial Intelligence, Computer Simulation, and Human-Computer Interaction,* 168.

Goswami, R., Roy, K., Dutta, S., Ray, K., Sarkar, S., Brahmachari, K., . . . , & Majumdar, K. (2021). Multi-faceted impact and outcome of COVID-19 on smallholder agricultural systems: Integrating qualitative research and fuzzy cognitive mapping to explore resilient strategies. *Agricultural Systems*, *189*, 103051.

Groumpos, P. P. (2010). Fuzzy cognitive maps: Basic theories and their application to complex systems. In M. Glykas (Ed.), *Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications* (pp. 1–22). Germany: Springer.

Groumpos, P. P. (2016). Deep learning vs wise learning: A critical and challenging overview. *IFAC-PapersOnLine*, *49*(29), 180–189. https://doi.org/10.1016/j.ifacol.2016.11.099

Groumpos, P. P. (2018). Intelligence and fuzzy cognitive maps: Scientific issues, challenges and opportunities. *Studies in Informatics and Control*, *27*(3), 247–264.

Groumpos, P. P. (2018). Making the world a better place to live through wisdom and philosophy:«Πάντων χρημάτων μέτρον άνθρωπος» "Men is the measure of all things" *Protagoras. IFAC-PapersOnLine*, *51*(30), 744–749. https://doi.org/10.1016/j.ifacol.2018.11.203

Groumpos, P. P. (2020). A new mathematical model for COVID-19: A fuzzy cognitive map approach for coronavirus diseases. In *IEEE 11th International Conference on Information, Intelligence, Systems and Applications*, 1–6.

Groumpos, P. P. (2021). Modelling COVID-19 using fuzzy cognitive maps (FCM). *EAI Endorsed Transactions on Bioengineering and Bioinformatics*, *1*(2). http://dx.doi.org/10.4108/eai.24-2-2021.168728

Groumpos, P. P., & Stylios, C. D. (2000). Modeling supervisory control systems using fuzzy cognitive maps. *Chaos, Solitons*

& Fractals, *11*(1-3), 329–336. https://doi.org/10.1016/S0960-0779(98)00303-8

Groumpos, P. P. (2015). Modelling business and management systems using fuzzy cognitive maps: A critical overview. *IFAC-PapersOnLine*, *48*(24), 207–212. https://doi.org/10.1016/j.ifacol.2015.12.084

Groumpos, P. P. (2019). Using fuzzy cognitive maps in analyzing and studying international economic and political stability. *IFAC Online Proceedings*, *52*(25), 23–28. https://doi.org/10.1016/j.ifacol.2019.12.440

Groumpos, P. P. (2022). Ethical AI and global cultural coherence: Issues and challenges plenary paper. *IFAC PapersOnLine*, *55*(39), 358–363. https://doi.org/10.1016/j.ifacol.2022.12.052

Groumpos, V. P., Biniari, K., & Groumpos, P. P. (2016). A new mathematical modelling approach for viticulture and winemaking using fuzzy cognitive maps. In *IEEE 2016 ELEKTRO International Conference*, 57–61.

Haluza, D., & Jungwirth, D. (2023). Artificial intelligence and ten societal megatrends: An exploratory study using GPT-3. *Systems*, *11*(3), 120. https://doi.org/10.3390/systems11030120

Hawkins, J. (2019). *A thousand brains: A new theory of intelligence*. USA: Basic Books.

Heykin, S. (2009). *Neural networks and learning machines*. India: Pearson Education.

Hinks, T. (2020). Fear of robots and life satisfaction. *International Journal of Social Robotics*, *98*, 792. https://doi.org/10.1007/s12369-020-00640-1

Hinton, G. E. (2002). Training products of experts by minimizing contrastive divergence. *Neural Computation*, *14*(8), 1771–1800.

Hinton, G. E. (2009). Deep belief networks. *Scholarpedia*, *4*(5), 5947.

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.

Hubel, D. H., & Wiesel, T. N. (1959). Receptive fields of single neurones in the cat's striate cortex. *The Journal of Physiology*, *148*(3), 574–591.

Ivakhnenko, A. (1971). Polynomial theory of complex systems. *IEEE Transactions on Systems, Man, and Cybernetics*, *4*, 364–378.

Janmenjoy, N., Naik, B., & Behera, Sr., H. (2015). Fuzzy C-means (FCM) clustering algorithm: A decade review from 2000 to 2014. In *Computational Intelligence in Data Mining-Volume 2: Proceedings of the International Conference on CIDM*, 133–149.

Jetter, A., & Schweinfort, W. (2011). Building scenarios with fuzzy cognitive maps: An exploratory study of solar energy. *Futures*, *43*(1), 52–66. https://doi.org/10.1016/j.futures.2010.05.002

Johnson, B. D. (1998). *The cybernetics of society. The governance of self and civilization*. Retrieved from: https://jurlandia.org/cybsoc/

Karlis, A. D., Kottas, T. L., & Boutalis, Y. S. (2007). A novel maximum power point tracking method for PV systems using fuzzy cognitive networks (FCN). *Electric Power Systems Research*, *77*(3–4), 315–327. https://doi.org/10.1016/j.epsr.2006.03.008

Kieslich, K., Lünich, M., & Marcinkowski, F. (2021). The threats of artificial intelligence scale (TAI) development, measurement and test over three application domains. *International Journal of Social Robotics*, *13*, 1563–1577. https://doi.org/10.1007/s12369-020-00734-w

Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, *24*(1), 65–75. https://doi.org/10.1016/S0020-7373(86)80040-2

Kumar, M., Nguyen, T. N., Kaur, J., Singh, T. G., Soni, D., Singh, R., & Kumar, P. (2023). Opportunities and challenges in application of artificial intelligence in pharmacology. *Pharmacological Reports*, *75*(1), 3–18. https://doi.org/10.1007/s43440-022-00445-1

Kyriakarakos, G., Dounis, A. I., Arvanitis, K. G., & Papadakis, G. (2012). A fuzzy cognitive map–petri nets energy management system for autonomous polygeneration microgrids. *Applied Soft Computing*, *12*(12), 3785–3797. https://doi.org/10.1016/j.asoc.2012.01.024

Leetaru, K. (2019). *A reminder that machine learning is about correlations not causation*. Retrieved from: https://www.forbes.com/sites/kalevleetaru/2019/01/15/a-reminder-that-machine-learning-is-about-correlations-not-causation/

Levshun, D., & Kotenko, I. (2023). A survey on artificial intelligence techniques for security event correlation: Models, challenges, and opportunities. *Artificial Intelligence Review*, 1–44. https://doi.org/10.1007/s10462-022-10381-4

Li, Z., & Jiang, W. (2022). Research on the Teaching Reform of Inorganic Chemistry Based on SPOC and FCM during COVID-19. *Sustainability*, *14*(9), 5707. https://doi.org/10.3390/su14095707

Liang, Y., & Lee, S. A. (2017). Fear of autonomous robots and artificial intelligence: Evidence from national representative data with probability sampling. *International Journal of Social Robotics*, *9*, 379–384. https://doi.org/10.1007/s12369-017-0401-3

Lighthill, J. (1973). Artificial intelligence: A general survey. In *Artificial intelligence: A paper symposium* (pp. 1–21). UK: Science Research Council.

Lopez, C., & Ishizaka, A. (2019). A hybrid FCM-AHP approach to predict impacts of offshore outsourcing location decisions on supply chain resilience. *Journal of Business Research*, *103*, 495–507. https://doi.org/10.1016/j.jbusres.2017.09.050

Luger, F. G. (2005). *Artificial intelligence: Structures and strategies for complex problem solving*. USA: Pearson.

Mago, V. K., Morden, H. K., Fritz, C., Wu, T., Namazi, S., Geranmayeh, P., . . . , & Dabbaghian, V. (2013). Analyzing the impact of social factors on homelessness: A fuzzy cognitive map approach. *BMC Medical Informatics and Decision Making*, *13*(1), 1–19. https://doi.org/10.1186/1472-6947-13-94

Mahboub, A., Mounir, A., Hamid, B., Younes El Assari, Y., & El Oualkadi, A. (2019). An energy-efficient clustering protocol using fuzzy logic and network segmentation for heterogeneous WSN. *International Journal of Electrical and Computer Engineering*, *9*(5), 4192.

Marcus, G. (2012) Is "Deep Learning" a revolution in artificial intelligence? Retrieved from: https://www.newyorker.com/news/news-desk/is-deep-learning-a-revolution-in-artificial-intelligence

Marwala, T. (2015). *Causality, correlation and artificial intelligence for rational decision making*. Singapore: World Scientific Publishing Co.

Mayor, A. (2018). *Gods and robots: Myths, machines, and ancient dreams of technology*. USA: Princeton University Press.

McCarthy, J. (1988). Review of the question of artificial intelligence. *Annals of the History of Computing*, *10*(3), 224–229.

McClure, P. K. (2018). "You're fired," says the robot: The rise of automation in the workplace, technophobes, and fears of unemployment. *Social Science Computer Review*, *36*, 139–156.

McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The Bulletin of*

Mathematical Biophysics, *5*, 115–133. https://doi.org/10.1007/BF02478259
Mead, M. (1968). The cybernetics of cybernetics. In von Foerster, H., J. D. White, L. J. Peterson, & J. K. Russell (Eds.), *Purposive systems* (pp. 1–11). USA: Spartan Books.
Mendez, J., Bierzynski, K., Cuéllar, M. P., & Morales, D. P. (2022). Edge intelligence: Concepts, architectures, applications, and future directions. *ACM Transactions on Embedded Computing Systems*, *21*(5), 1–41. https://doi.org/10.1145/3486674
Menzies, T. (2003). Menzies, T. (2003). 21st-century AI: proud, not smug. *IEEE Intelligent Systems*, *18*(3), 18–24.
Merlet, J. P. (2000). A historical perspective of robotics. In *International symposium on history of machines and mechanisms proceedings HMM 2000*, 379–386. Netherlands: Springer.
Moss, S. (2018). The potential of robots for humankind. *MRS Bulletin*, *43*(5), 391–392. https://doi.org/10.1557/mrs.2018.117
Mpelogianni, G. V., & Groumpos, P. P. (2018). Re-approaching fuzzy cognitive maps to increase the knowledge of a system. *International Journal AI & Society*, *33*, 175–188. https://doi.org/10.1007/s00146-018-0813-0
Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. USA: MIT Press.
Neocleous, C., & Schizas, C. N. (2012). Modeling socio-politico-economic systems with time-dependent fuzzy cognitive maps. In *IEEE 2012 International Conference on Fuzzy Systems*, 1–7.
Newell, A., & Simon, H. (1956). The logic theory machine–A complex information processing system. *IRE Transactions on Information Theory*, *2*(3), 61–79.
Nilsson, N. (2005). *Principles of artificial intelligence*. USA: Tioga Press.
Organization for Economic Cooperation and Development. (2007). *Innovation and growth rationale for an innovative strategy*. Retrieved from: https://www.oecd.org/sti/39374789.pdf
O'Reilly, R. C., Russin, J. L., Zolfaghar, M., & Rohrlich, J. (2021). Deep predictive learning in neocortex and pulvinar. *Journal of Cognitive Neuroscience, 33*(6), 1158–1196. https://doi.org/10.1162/jocn_a_01708
Oye, N. D., & Thomas, L. L. (2019). Fuzzy model for diagnosis of bacterial meningitis. *International Journal of Computer Applications Technology and Research*, *8*(02), 33–51.
Papageorgiou, E. I., Stylios, C. D., & Groumpos, P. P. (2003). Fuzzy cognitive map learning based on non-linear Hebbian rule in advances in artificial intelligence. In *Proceedings AI 2003: Advances in Artificial Intelligence: 16th Australian Conference on AI*, *16*, 256–268.
Papageorgiou, E. I., & Salmeron, J. L. (2013). A review of fuzzy cognitive maps research during the last decade. *IEEE Transactions on Fuzzy Systems*, *21*(1), 66–79. http://doi.org/10.1109/TFUZZ.2012.2201727
Papageorgiou, E. I. (2012). Fuzzy cognitive map software tool for treatment management of uncomplicated urinary tract infection. *Computer Methods and Programs in Biomedicine, 105*(3), 233–245. https://doi.org/10.1016/j.cmpb.2011.09.006
Pereira, I. P., Ferreira, F. A., Pereira, L. F., Govindan, K., Meidutė-Kavaliauskienė, I., & Correia, R. J. (2020). A fuzzy cognitive mapping-system dynamics approach to energy-change impacts on the sustainability of small and medium-sized enterprises. *Journal of Cleaner Production*, *256*, 120154.
Philbeck, T., & Davis, N. (2018). The fourth industrial revolution. *Journal of International Affairs*, *72*(1), 17–22.
Pickering, A. (2011). *The cybernetic brain: Sketches of another future*. USA: University of Chicago Press.
Prigogine, I. (1980). *From being to becoming*. USA: WH Freeman.
Roberts, D., Yaida, S., & Hanin, B. (2022). *The principles of deep learning theory: An effective theory approach to understanding neural networks*. UK: Cambridge University Press.
Robin, S. (2017). *Aristotle's logic*. Retrieved from: https://plato.stanford.edu/cgi-bin/encyclopedia/archinfo.cgi?entry=aristotle-logic
Russel, S., & Norvig, P. (2020). *Artificial intelligence: A modern approach*. USA: Prentice Hall.
Sajadi, M. R., & Esfahani, H. N. (2017). Mechanical design, construction and control of a lower extremity exoskeleton robot prototype with a new structure in the form of three-wheeled Mobile robot. In *2017 IEEE 5th RSI International Conference on Robotics and Mechatronics*, 520–526.
Salkind, N. J. (2010). *Encyclopedia of research design*. UK: Sage.
Sedgwick, P. (2014). Cross sectional studies: Advantages and disadvantages. *BMJ, 348*, 2276. https://doi.org/10.1136/bmj.g2276.
Savage, N. (2019). How AI and neuroscience drive each other forwards. *Nature*, *571*, S15–S17.
Schilling, R. J. (1990). *Fundamentals of robotics: Analysis and control*. USA: Prentice Hall.
Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. https://doi.org/10.1016/j.neunet.2014.09.003
Schmidhuber, J., & Prelinger, D. (1993). Discovering predictable classifications. *Neural Computation*, *5*(4), 625–635. https://doi.org/10.1016/j.neunet.2014.09.003
Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*, 379–423. http://doi.org./10.1002/j.1538-7305.1948.tb01338.x
Shrager, J., & Johnson, M. (1995). Timing in the development of cortical function: A computational approach. In B. Julesz & I. Kovacs (Eds.), *Maturational windows and adult cortical plasticity*. Addison-Wesley.
Smuts, J. C. (1926). *Holism and evolution*. UK: McMillan.
So, J., Kuang, K., & Cho, H. (2016). Reexamining fear appeal models from cognitive appraisal theory and functional emotion theory perspectives. *Communication Monographs*, *83*(1), 120–144. https://doi.org/10.1080/03637751.2015.1044257
Soni, N., Sharma, E. K., Singh, N., & Kapoor, A. (2019). Impact of artificial intelligence on businesses: From research, innovation, market deployment to future shifts in business models. *arXiv preprint:1905.02092*.
Sparkes, M. (2015). *Top scientists call for caution over artificial intelligence*. Retrieved from: https://www.telegraph.co.uk/technology/news/11342200/Top-scientists-call-for-caution-over-artificial-intelligence.html
Spong, M. W., Hutchinson, S., & Vidyasagar, M. (2006). Robot modeling and control. *IEEE Control Systems, 26*(6), 113–115. https://doi.org/10.1109/MCS.2006.252815
Stafford, B. (1976). *Cybernetics and management*. UK: English Universities Press.
Thomas, M. (2021). 7 Dangerous risks of artificial intelligence. *AI Journal*.
Thrun, S., Burgard, W., & Fox, D. (2005). *Probabilistic robotics*. USA: MIT Press.

Turing, M. A. (1950). Computing machinery and intelligence. *Mind*, *59*(236), 433–460.

Upchurch, M. (2018). Robots and AI at work: The prospects for singularity. *New Technology, Work and Employment*, *33*(3), 205–218. https://doi.org/10.1111/ntwe.12124

Utgoff, P. E., & Stracuzzi, D. J. (2002). Many-layered learning. *Neural Computation, 14*(10), 2497–2529. https://doi.org/10.1162/08997660260293319

Von Foerster, H. (1951). *Cybernetics: Circular Causal and Feedback Mechanisms in Biological and Social Systems*.

Wang, T., Zhu, Y., Ye, P., Gong, W., Lu, H., Mo, H., & Wang, F. Y. (2022). A new perspective for computational social systems: Fuzzy modeling and reasoning for social computing in CPSS. *IEEE Transactions on Computational Social Systems*, 1–16.

Warwick, K. (2011). *Artificial intelligence, the basics*. UK: Routledge.

Weng, J., Ahuja, N., & Huang, T. S. (1992). Cresceptron: A self-organizing neural network which grows adaptively. In *IEEE International Joint Conference on Neural Networks*, *1*, 576–581.

Weng, J. J., Ahuja, N., & Huang, T. S. (1997). Learning recognition and segmentation using the cresceptron. *International Journal of Computer Vision*, *25*(2), 109–143.

Wiener, N. (1948). *Cybernetics: Or control and communication in the animal and the machine*. USA: MIT Press.

Wirtz, B. W., Weyerer, J. C., & Geyer, C. (2019). Artificial intelligence and the public sector–applications and challenges. *International Journal of Public Administration*, *42*(7), 596–61. https://doi.org/10.1080/01900692.2018.1498103

World Economic Forum. (2019). *The global risks report 2019*. Retrieved from: https://www.weforum.org/reports/the-global-risks-report-2019/

Zaman, S., Alhazmi, K., Aseeri, M. A., Ahmed, M. R., Khan, R. T., Kaiser, M. S., & Mahmud, M. (2021). Security threats and artificial intelligence-based countermeasures for internet of things networks: A comprehensive survey. *IEEE Access*, *9*, 94668–94690. http://doi.org/10.1109/ACCESS.2021.30896681

Zhou, Z., Chen, X., Li, E., Zeng, L., Luo, K., & Zhang, J. (2019). Edge intelligence: Paving the last mile of artificial intelligence with edge computing. In *Proceedings of the IEEE*, *107*(8), 1738–1762.

How to Cite: Groumpos, P. P. (2023). A Critical Historic Overview of Artificial Intelligence: Issues, Challenges, Opportunities, and Threats. *Artificial Intelligence and Applications*, *1*(4), 181–197, https://doi.org/10.47852/bonviewAIA3202689