# AI’s next frontier: The rise of ChatGPT and its implications on society, industry, and scientific research



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# La próxima frontera de la IA: El surgimiento de ChatGPT y sus implicaciones en la sociedad, la industria y la investigación científica

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**Abstract**

*Artificial intelligence (AI) refers to the capability of computer systems to carry out tasks requiring human-like intelligence, such as decision-making, natural language processing, problem-solving, and learning. The development of AI has been a rapidly growing field in recent years. With the recent release of AI text-generation software in late 2022, a transformative breakthrough in the field seems to have been achieved. Within a matter of months, the ChatGPT software garnered over two million subscribers and has since been widely adopted as a promising tool in both academic and industrial settings. This paper presents a compilation of the basic concepts of AI, including its definition, history, challenges, and opportunities. It also discusses the potential impacts of AI on society and the crucial ethical and social considerations that need to be addressed. The innovative nature of this work is that the ChatGPT text-generation AI was involved in its conception through guided sessions of inputs and answers. Then, the text and references were edited. This demonstrates the power of AI to construct knowledge, particularly to deploy research text in journal articles, reviews, and perspectives. It also raises awareness of the specific new tasks of scientific journals' editors and reviewers, since text-generation AI seems to write novel text constructed from the knowledge of the AI algorithm. This work also highlights the dramatic changes that AI will possibly bring to our everyday life among other considerations.*

**Key words**: ChatGPT, text-generation, artificial intelligence, artificial neural networks, generative adversarial networks, natural language processing.

**Resumen**

*La inteligencia artificial (IA) hace referencia a la capacidad de los sistemas computacionales para llevar a cabo tareas que requieren una inteligencia similar a la humana, como la toma de decisiones, el procesamiento de lenguaje natural, la resolución de problemas y el aprendizaje. El desarrollo de la IA ha sido un campo en constante crecimiento en los últimos años. El desarrollo de software de generación de texto ChatGPT a finales de 2022, fue un avance transformador en este campo. En cuestión de meses, el software ChatGPT obtuvo más de dos millones de suscriptores y desde entonces ha sido ampliamente adoptado como una herramienta prometedora tanto en entornos académicos como industriales. Este trabajo presenta una recopilación de los conceptos fundamentales de la IA, incluyendo su definición, historia, desafíos y oportunidades. También se discuten los posibles impactos de la IA en la sociedad y las consideraciones éticas y sociales claves que deben abordarse. La naturaleza innovadora de este trabajo se encuentra en que ChatGPT fue utilizado en su concepción a través de sesiones guiadas de preguntas y respuestas. Luego, el texto y las referencias fueron editados para dar una correcta estructura y formato al artículo, para cumplir con las normativas y estándares científicos. Esto demuestra el poder de la IA para construir conocimiento, especialmente para redactar el texto de artículos de investigación, revisión y editoriales. También se destaca el nuevo rol de editores y revisores de revistas científicas, ya que el generador de texto de IA demuestra escribir texto novedoso y coherente construido a partir del conocimiento del algoritmo, similar al humano. Este trabajo también resalta los cambios drásticos que la IA posiblemente traerá a nuestra vida cotidiana, entre otras consideraciones.*

**Palabras clave**: ChatGPT, generación de texto, inteligencia artificial, redes neuronales artificiales, redes generativas adversarias, procesamiento de lenguaje natural.

## 1 Introduction

Artificial intelligence (AI) has evolved rapidly in recent years, and the development of Generative Pre-trained Transformer technology (GPT) has been one of the fundamental driving forces behind this progress (Floridi y Chiriatti, 2020). One of the innovative applications of GPT technology is text-generation. This allows AI models to produce coherent, understandable, and consistent human-like text.

The origin of text-generation dates back to the 1960s when scientists attempted to automate the process of generating language for the first time (Weizenbaum, 1966; Newell y Simon, 1995). Early efforts in text-generation focused mainly on rule-based systems, where text was generated based on pre-established rules (Weizenbaum, 1966). However, the limitations of these systems were evident in their inability to generate coherent and contextually appropriate texts. The emergence of deep learning in the 2010s brought about a significant change in the field. It enabled the development of more robust and sophisticated language models capable of producing high-quality text with a level of consistency and accuracy that was previously unattainable (Lecun, Bengio, y Hinton, 2015; G. Hinton, Vinyals, y Dean, 2015; G. E. Hinton, Osindero, y Teh, 2006).

Some pioneering work, such as that of *Hinton et al.* (G. Hinton y cols., 2015), *Sutskever et al.* (Sutskever, Vinyals, y Le, 2014), and *Vaswani et al.* (Vaswani y cols., 2017), laid the foundations for creating the text-generation models of the future. These works have inspired the development of larger and more sophisticated language models, such as the GPT model that OpenAI introduced in 2018 (Radford y cols., 2019).

While the development of GPT technology has been primarily focused on text-generation, it has also had an impact on other areas of AI, including image generation. The relationship between text-generation and image generation is rooted in the idea of adversarial training. In this paradigm, two AI models, the generator and the discriminator are trained together. The former model generates images from text intending to fool the discriminator, and the latter tries to identify the fake (generated) images from the real ones correctly (Wang y cols., 2023). This allows for obtaining robust models with better overall performance. Thanks to this, we now have models capable of generating high-quality images based on textual descriptions that are indistinguishable between real and fake (Borji, 2022).

In this work, we use the ChatGPT text generation AI to provide an overview of AI's history, fundamentals, and current state. We focus mainly on GPT technology and its various applications. We also explore examples of text generation and analyze the existing challenges and opportunities in this field. Thus showing the power of text generation AI to write plausible research ideas and literature reviews faster, correct text, and add suggestions. There are just a few publications so far that have used input and response prompts from an AI text-generation model to produce a compilation of the basic concepts in the field. We aim to demonstrate the technology potential in this type of task and explore its implications across various domains such as academia and industry.

The structure of this paper is organized as follows. Section 2 presents the methodology used to prepare this work. Section 3 describes the basic concepts of artificial intelligence. Section 4 presents a brief history of the development of AI from early research in the 1960s to recent advances. In Section 5, an overview of the different approaches, capabilities, limitations, and examples of AI is outlined. Section 6 discusses challenges in AI development, the role of human supervision, and ethical considerations. Section 7 presents potential areas for growth and innovation in AI research and development. Section 8 presents perspectives, challenges, and opportunities, focusing on text-generation models. Finally, section 9 addresses the conclusions of the work.

## 2 Methodology

A comprehensive publications search and classification was conducted on AI-generated text. For this, we searched the online databases Dimensions and Scopus using the query: *"text" AND "generation" AND "AI"*. The query was performed in the abstract, keywords and title of the articles. Then, the full articles were checked for correspondence with the subject.

Subsequently, text generation and data collection was performed with the ChatGPT V.2 Dec 15 model to create written content. Input prompts were given to the AI system, and written responses were generated to aid in writing Sections 3 to 8 of the present work.

The generated text was organized into categories, and the quality and coherence of the generated text was evaluated. Also, the generated text was compared with the scientific literature, and appropriate citations were inserted. Finally, the manuscript was reviewed by the authors to ensure that the results and data analysis are accurately explained and that the work followed academic writing standards. Figure 1 shows the flowchart used to complete this work.

We performed data analytics with the metadata of the available articles. Figure 2 shows the distribution of articles from 2010 to 2023. It is evident that before 2015 the number of publications in the field of text-generation AI was low. Beginning from this year, and with works such as those of (Lecun y cols., 2015), (G. Hinton y cols., 2015), and (Nielsen, 2015), there is a significant exponential growth from 2018 onwards.

In Figure 3, a conceptual map is presented. We used the VOSviewer software, which is a tool developed by researchers at Leiden University in the Netherlands for data analysis. It provides tools that facilitate text mining and data visualization tasks. It shows the leading countries in terms of

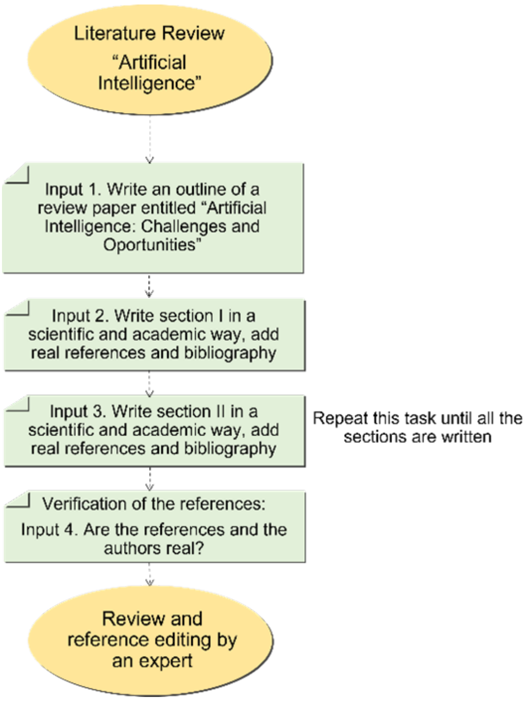


**Fig. 1:** Flowchart used to write this work by using the ChatGPT text-generation AI.

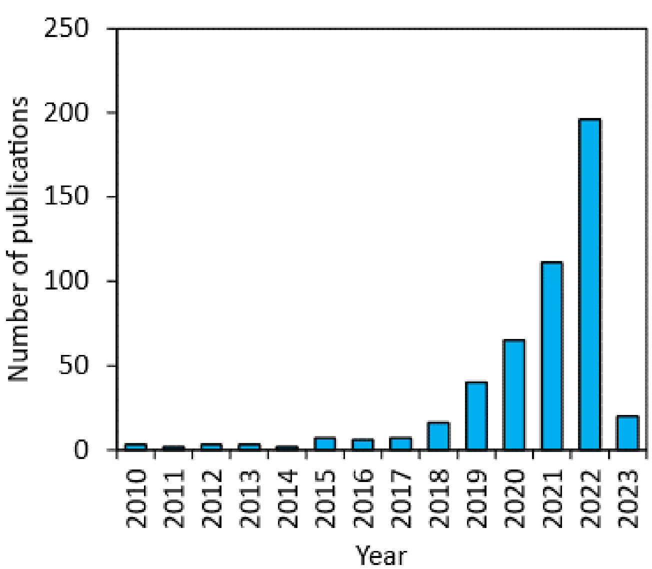


**Fig. 2:** Number of publications by year on the text-generation AI model subject.

text-generation publications. The visual representation shows the number of publications and collaborations, with circle and line, respectively, the weight indicating their frequency. Likewise, the countries represented by the same color form a cluster.

It is evident that the United States has the highest number of publications related to text-generation, followed by China and India. This could be related to the number of inhabitants of each country and the number of scientific research centers they have. Interestingly, European countries are dispersed and form different clusters. Specifically, three clusters of European countries can be identified. The first cluster comprises the United Kingdom and Spain. The second cluster comprises Switzerland, France, and Italy. The third cluster is integrated by Germany, Poland, and the Netherlands. This behavior could be attributed to the geographical proximity between these countries; however, it may also reflect the challenges that European nations must overcome in collaborative work. A broad collaborative network may be why China and the United States have taken the lead.

## 3 Artificial intelligence basics

### *3.1 Machine learning*

Machine learning (ML) is a sub-field of AI that focuses on developing algorithms and models that can learn and improve from data to solve a problem without being explicitly programmed. ML involves using statistical techniques to enable computers to identify patterns and relationships in data to make predictions and decisions based on these (Cortes, Vapnik, y Saitta, 1995; Oztemel y Gursev, 2020; Domingos, 2015). ML can be categorized into supervised, unsupervised, semi-supervised, and reinforcement learning.

#### *3.1.1 Supervised learning*

It is a type of machine learning in which a model is trained on a labeled data set. This means that the correct output or target is known. The model can then make predictions about new and unseen data based on patterns and relationships learned from the training data. Several types of supervised learning algorithms exist, including linear regression, logistic regression, and support vector machines (Cortes y cols., 1995).

#### *3.1.2 Unsupervised learning*

In this type of machine learning, a model is trained on an unlabeled data set and must learn to identify patterns and relationships that lead to the correct output on its own. These algorithms can be used for different tasks, including clustering, anomaly detection, and dimensionality reduction. Some of the most famous algorithms are hierarchical clustering and k-means for clustering and principal component analysis (PCA) for dimensionality reduction (MacQueen, 1967).

#### *3.1.3 Semi-supervised learning*

Semi-supervised learning is a blend of both supervised and unsupervised learning methods. The data utilized in this method is a mixture of labeled and unlabeled information

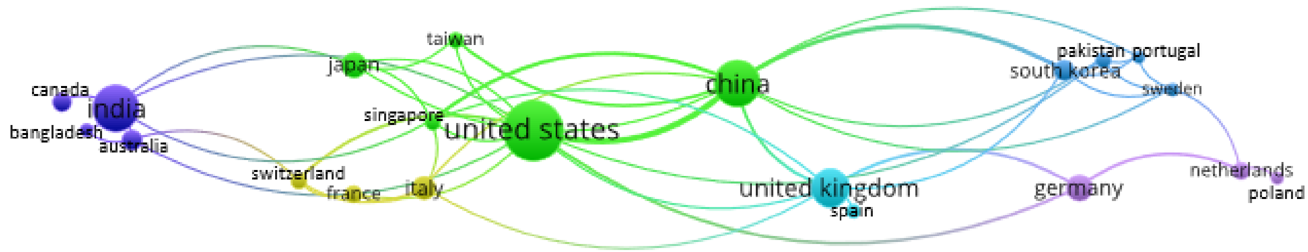


**Fig. 3:** Top countries in terms of text-generation AI publications. The number of publications and collaborations are shown with a circle and line, respectively, the weight indicating their frequency.

(Maleki y cols., 2020). These models primarily learn from the unlabeled data and then apply that knowledge to complete supervised tasks (Choi, Coyner, Kalpathy-Cramer, Chiang, y Campbell, 2020).

#### *3.1.4 Reinforcement learning*

In reinforcement learning, an agent learns to interact with its environment to learn through experience. The agent receives positive or negative feedback based on its actions and learns to optimize its behavior over time to maximize a reward. These algorithms can be used for tasks such as robotic control, games, and recommendation systems. Several reinforcement learning algorithms exist, including Q-learning (Watkins y Dayan, 1992) and Monte Carlo methods (Robert, Casella, y Casella, 1999).

### *3.2 Artificial intelligence classification*

Although there are several approaches to classifying AI, it can be broadly divided into two main categories: narrow or weak AI and general or strong AI. The details of these are described below.

#### *3.2.1 Narrow artificial intelligence*

Narrow AI, also known as domain-specific AI, is designed to perform a specific task within a limited domain. These systems are trained on a large amount of data and specialize in recognizing patterns and making predictions or decisions. Some of the applications include playing chess and recognizing objects in an image.

#### *3.2.2 General artificial intelligence*

General artificial intelligence is designed to perform any intellectual task a human can perform. For example, understanding natural language, solving abstract problems, or learning knowledge through experience. These kinds of systems are not limited to a specific domain and can adapt to new tasks and dynamic environments. While fully robust AI has not yet been achieved, efforts are focused on these types of systems, and it is a long-term goal of AI research and development (Russell, 2010).

AI systems can also be classified according to their level of autonomy, that is, the degree to which they can operate without human intervention. Here we find autonomous AI systems that can make decisions and perform actions independently and non-autonomous AI systems that require human supervision and intervention.

## 4 Artificial intelligence history

The concept of artificial intelligence has been around for centuries. Its roots go back to ancient Greek mythology and the creation of the mythical robot Talos (Figure 4). However, the modern field of AI was founded in the 1950s, with the development of the first artificial neural network by Warren McCulloch and Walter Pitts (McCulloch y Pitts, 1943). Also, the establishment of the Dartmouth Summer Research Project on Artificial Intelligence laid the foundation for AI research. During this time, AI researchers focused on developing connectionist approaches, which involved using artificial neural networks to simulate how the human brain processes information. The development of the perceptron (or McCulloch-Pitts neuron) (Rosenblatt, 1958), a type of artificial neural network, exemplified this approach.

### *4.1 The early days of artificial intelligence*

The artificial neural network, also known as a perceptron (Figure 5), was first implemented by Frank Rosenblatt in the 1950s (Rosenblatt, 1958). This is a simple model of how the human brain processes information. As McCulloch said, “the nervous system is a device that, given a set of stimuli, produces a set of responses. The computation we get from the network corresponds to how the nervous system processes data (McCulloch y Pitts, 1943).” The perceptron is capable of recognizing patterns and making simple decisions. However, it is limited in its capabilities and cannot learn complex patterns from data.

In 1956, the Dartmouth Conference was held, which brought together leading researchers in the field of AI and

**Fig. 4:** Representation of Talos generated by AI.

**Fig. 5:** Representation of the concept of artificial neural network generated by AI.

laid the foundations for the field of AI research. During the conference, the term "artificial intelligence"was coined, and the goal of creating "machines that think and act like human beings"was established. As John McCarthy, one of the organizers of the conference, said at the time, "The study is to proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it."

In 1956, the Dartmouth Summer Research Project on Artificial Intelligence was held. It brought together leading researchers in the field of AI and laid the foundation for the field of AI research. During the conference, the term "artificial intelligence" was coined, and the goal of creating machines that think and act like humans was established. As John McCarthy, one of the conference organizers, said, "the study must proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can, in principle, be so accurately described that a machine can be made to simulate it."

In the 1950s and 1960s, AI researchers focused on developing symbolic approaches. These involved the use of rules and logical representations to solve problems. This approach was exemplified by the development of early expert systems, such as ELIZA, a natural language processing program developed by Joseph Weizenbaum (Weizenbaum, 1966). Weizenbaum said of ELIZA, "the program was not intended to be a realistic simulation of a psychotherapist; it was intended to be a computer program to engage people in conversation."

Other approach is the General Problem Solver (GPS), a problem-solving program developed by Herbert Simon and Allen Newell in 1957 (Newell y Simon, 1995). GPS was designed to solve any problem that could be represented in a particular formal language and could solve a wide range of problems, including puzzles and mathematical problems. As Simon and Newell said about GPS, "we claim that GPS, when it is finally implemented, will be able to solve any solvable problem that can be described in a precise and formal manner."

During this time, the Turing test (Figure 6), developed by Alan Turing in 1950, became a well-known measure of a machine's ability to exhibit intelligent behavior equivalent to or indistinguishable from that of a human being (Turing, 2009). The test involves a human evaluator who engages in natural language conversations with another human and a machine and must determine which is the machine. If the evaluator cannot distinguish the machine from the human, the machine is said to have passed the Turing test; otherwise, it has not. While the Turing test has been influential in AI, it has also been criticized for focusing on human-like behavior rather than more broadly defined intelligence.

In the 1970s and 1980s, AI experienced its first wave of hype, known as the "AI winter." This was followed by a period of stagnation due to the limited capabilities of early AI systems and a lack of funding and computational resources. AI researcher Marvin Minsky (Minsky, 1961) said, "AI is a very difficult problem; it's like trying to figure out how to make a person, but there is no scientific theory of how to make it."

### 4.2 *The modern days of artificial intelligence*

In the 1980s and 1990s, AI experienced a resurgence known as the AI spring."The development of expert systems and the rise of machine learning especially fueled this era.

**Fig. 6:** Representation of Alan Turing generated by AI.

ML, above all, was put into practice thanks to the development of the backpropagation algorithm, which is a technique that allows the neural network to learn from the training data and improve its predictions over time. Key figures involved in developing the backpropagation algorithm include Paul Werbos (Werbos, 1974), David Rumelhart, Geoffrey Hinton, and Ronald Williams (Rumelhart, Hinton, y Williams, 1986). Another important figure in the field of machine learning was Tom Mitchell (Mitchell y Mitchell, 1997). He defined the concept of machine learning as "the ability to learn from experience."Mitchell states that a computer system learns from experience concerning some class of tasks if its performance on that task can be measured and it improves with experience.

In the 21st century, AI experienced another wave of development and hype, with significant advances in natural language processing, robotics and deep learning (Goodfellow, Bengio, y Courville, 2016; Goodfellow y cols., 2020).

Natural language processing involves the development of algorithms and systems that can understand and generate human-like language. This has led to the development of virtual assistants, such as Apple's Siri and Amazon's Alexa (Kepuska y Bohouta, 2018), as well as improved systems for machine translation and text analysis. Robotics, for its part, is a field that involves the design and development of robots, which are intelligent agents that can feel, perceive, and act in the physical world. In collaboration with AI, robotics has played an essential role in the development of autonomous robots, which are capable of making decisions and performing tasks on their own, as well as in the development of robotic applications in fields such as manufacturing, healthcare, and transport (Piazza, Grioli, Catalano, y Bicchi, 2019; Makhataeva y Varol, 2020). Key figures in the field of robotics include Rodney Brooks and Hans Moravec.

Deep learning is a machine learning type that involves using multi-layered artificial neural networks, known as deep neural networks (DNNs), to learn patterns and relationships in data. This approach has led to significant advances in tasks such as image and speech recognition and has been applied to a wide range of fields, including healthcare, finance, and transportation. Yann LeCun played a key role in the development of deep learning. He is one of the prominent figures in this world thanks to his work focused on convolutional neural networks (Lecun y cols., 2015), a type of neural network specialized for working with images. Other important figures are Geoffrey Hinton and Andrew Ng. Subsequently, the emergence of generative adversarial networks (GANs) was another milestone breakthrough in deep learning and has been a trending topic in recent years (G. E. Hinton y cols., 2006; Goodfellow y cols., 2020; Rasp, Pritchard, y Gentine, 2018; Won, Gopinath, y Hodgins, 2021).

These powerful ML techniques have led to numerous advances and innovations in a wide range of fields, including language generation and image generation. An example of a language generation model that has been developed using DNN and adversarial training is the ChatGPT model developed by OpenAI. This model is based on the GPT language model and is designed specifically for chat-bot applications. It can generate human-like text that is consistent and appropriate for a specific context. The ChatGPT model has been widely recognized as a state-of-the-art model in the field of natural language processing and has been used to develop a variety of chat-bots and virtual assistants (Floridi y Chiriatti, 2020; Radford y cols., 2019).

In the field of image generation, DNNs and GANs have also made significant advances. An example of an AI-based image generator developed using these techniques is the Deep Dream generator. This tool uses a DNN to generate unique, dream-like images based on an input text or a sample image provided by the user. The resulting images are highly detailed and often show surreal abstract shapes and patterns.

## 5 Approaches, capabilities, limitations, and examples of artificial intelligence.

### *5.1 Approaches to artificial intelligence development*

In the field of AI, there are several different approaches to creating intelligent machines, each with its own set of strengths and limitations. This section describes some of them.

#### *5.1.1 Symbolic approaches to artificial intelligence*

This approach involves using rules and logical representations to solve problems and represent knowledge. It is based on the idea that intelligence can be reduced to a set of rules and symbols that can be manipulated to solve problems. Key researchers in this field include Herbert Simon and Allen Newell (Newell y Simon, 1995), who developed the General

Problem Solver in 1957, and John McCarthy, who coined the term *artificial intelligence* and organized the Dartmouth Summer Research Project on Artificial Intelligence in 1956.

The development of expert systems was one of the key discoveries in the field of symbolic AI. These are computer programs that use a set of predefined rules and heuristics to solve problems in a specific domain. One of the earliest and best-known expert systems was ELIZA, a natural language processing program developed by Joseph Weizenbaum (Weizenbaum, 1966) in 1966. ELIZA could engage in natural language conversations with users using predefined rules and responses, marking a breakthrough in the field.

### *5.1.2 Connectionist approaches to artificial intelligence*

This approach involves using artificial neural networks to simulate how the human brain processes information. This approach is based on the idea that intelligence arises from the interaction of simple processing units, known as neurons, that are connected in a network. Key researchers in this field include Warren McCulloch and Walter Pitts, who developed the first artificial neural network in 1943, and Frank Rosenblatt, who first implemented the perceptron in 1958.

One of the key discoveries in this field was the development of the backpropagation algorithm in the 1980s. This is used to train artificial neural networks and revolutionized the field of machine learning. The backpropagation algorithm was developed by Paul Werbos and David Rumelhart (Werbos, 1974), and has played a key role in developing advanced deep learning and a wide range of applications.

### *5.1.3 Evolutionary approaches to artificial intelligence*

These approaches involve using evolutionary algorithms (EAs) to optimize the performance of a system over time. This approach is based on the idea that intelligence arises through natural selection, in which the fittest individuals survive and reproduce. Key researchers in this field include Ingo Rechenberg, who developed the concept of evolutionary computation in the 1960s, and John Holland, who developed the concept of genetic algorithms (GAs) in the 1970s.

Evolutionary algorithms are a family of optimization algorithms inspired by the process of biological evolution. Evolutionary algorithms aim to find the best solution to a given problem by iteratively generating a population of candidate solutions and applying various operations to transform and improve the solutions over multiple generations.

Genetic algorithms (Figure 7) are a subset of evolutionary algorithms. In this type of algorithms, candidate solutions to a problem are represented as strings of bits or numbers, called chromosomes. The chromosomes recombine and mutate over several generations to generate new and potentially improved solutions. The best solutions are selected based on their fitness, which measures how well they solve the problem. Genetic algorithms are often used to solve optimization problems, such as finding the shortest path between two points or the optimal combination of parameters for a machine learning model.

**Fig. 7:** Representation of genetic algorithms generated by AI.

Each of these AI approaches has its own strengths and limitations and has been applied to a wide range of tasks and problems. Symbolic approaches' key advantages include their ability to reason and solve problems using logical rules and accurately and explicitly represent knowledge. However, symbolic approaches can be limited in handling complex and uncertain environments and can be sensitive to errors in the knowledge base. On the other hand, connectionist approaches can handle complex and dynamic environments and learn from data but may have difficulties with tasks that require explicit reasoning and symbolic representation. Finally, evolutionary approaches are suitable for solving optimization problems but may be less effective in tasks requiring more complex intelligence forms (Holland, 1992).

## *5.2 Current capabilities and limitations of artificial intelligence*

AI has significantly improved many tasks and applications in recent years. Among the most prominent applications are image and speech recognition, natural language processing, and decision-making. However, AI also has some limitations and challenges that must be addressed to realize its full potential. Here, a detailed description of the current capabilities and limitations of AI is presented.

### *5.2.1 Capabilities of artificial intelligence*

One of the key capabilities of AI is its ability to process and analyze large amounts of data quickly and accurately. This has led to significant advances in machine learning and deep learning, which involve the use of algorithms to learn patterns and relationships in data automatically. Another key capability of AI is to perform tasks that require precise and repetitive actions, such as manufacturing and assembly line work. This has led to the development of robotic systems that can perform a wide range of tasks in manufacturing and other industries.

#### 5.2.2 *Limitations of artificial intelligence*

One of the key limitations of AI is its inability to understand and reason about complex and abstract concepts in the same way humans do. This can make it difficult for AI systems to handle complex and changing environments and to understand the context and implications of their actions. Another limitation of AI is its reliance on data and the need for large amounts of data to train machine learning algorithms. Also, the quality of the data is critical since if the data is not representative of the real world or accurately labeled, AI systems can be biased and error-prone.

### 5.3 *Examples of applications of artificial intelligence in various fields*

There is a wide range of applications for AI in various fields. Here we present some examples of application in the fields of healthcare, finance and transportation.

#### 5.3.1 *Healthcare*

AI can improve the accuracy and efficiency of medical care by analyzing large amounts of data and detecting patterns that may not be obvious to human doctors. Also, AI can analyze and process information without the physical limitations of a human, as it does not need to rest or eat. An example of an application of AI in healthcare is the development of systems capable of diagnosing and suggesting treatments based on data from electronic health records. Below, we list some relevant real-life examples where AI is being applied.

- In 2017, the Mayo Clinic and IBM Watson Health announced a partnership to develop an AI-powered tool that could help doctors diagnose and treat cancer by analyzing data from electronic health records and clinical trials.
- In 2017, the University of California, San Francisco, announced that it was using machine learning algorithms to analyze data from electronic health records and predict the risk of hospital readmission for patients with chronic conditions.
- In 2018, DeepMind, a subsidiary of Alphabet, announced that it was using machine learning algorithms to analyze data from electronic health records and predict the risk of kidney injury in patients.
- In 2019, the Cleveland Clinic announced that it was using machine learning algorithms to analyze data from electronic health records and predict which patients were at risk for certain conditions, such as diabetes and heart disease.

Figure 8 shows a graphical representation of AI applications in healthcare.

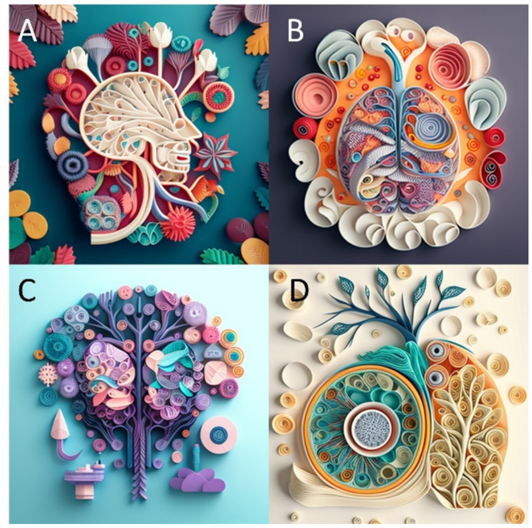


**Fig. 8:** Representation of the potential applications of AI in healthcare: A) Alzheimer's diseases, B) Brain diseases, C) Flu viruses, D) Cardiovascular and oncology diseases.

#### 5.3.2 *Finance*

AI has the potential to improve the efficiency and accuracy of financial decision-making by analyzing large amounts of data and detecting patterns that may not be obvious to human analysts. Machine learning algorithms can be used, for example, to predict stock prices and detect fraudulent activity. Some examples of applications in this field are listed below.

- In 2017, the Royal Bank of Scotland announced that it was using machine learning algorithms to detect fraudulent activity on credit cards.
- In 2017, Bank of America announced that it was using machine learning algorithms to analyze data from customer interactions and improve customer service efficiency.
- In 2018, JPMorgan Chase announced that it was using machine learning algorithms to analyze data from credit card transactions and detect fraudulent activity.
- In 2019, Goldman Sachs announced that it was using machine learning algorithms to analyze data from financial markets and make trading recommendations to clients.

#### 5.3.3 *Transportation*

AI has the potential to improve transportation safety and efficiency by enabling the development of autonomous vehicles that can sense and navigate their environment. These use sensors, cameras, and machine learning algorithms to navigate roads and avoid obstacles. Some relevant examples of applications in this field are listed below.

- In 2017, Waymo, a subsidiary of Google's parent company, Alphabet, announced that it was using machine learning algorithms to improve its self-driving cars' accuracy and reduce accidents.
- In 2018, Tesla announced that it was using machine learning algorithms to improve its Autopilot feature's accuracy, allowing drivers to hand over control of their car to the self-driving system under certain conditions.
- In 2019, Uber announced that it was using machine learning algorithms to optimize its UberPool service's routes, allowing riders to share trips with others in the same direction.

## 6 Current trends and challenges in artificial intelligence research and development: the role of human oversight and ethical considerations

### *6.1 Current trends and challenges*

AI research and development is an active and rapidly evolving field. There are many trends and challenges that are continually being explored and addressed. Here is a discussion of some current trends and challenges in AI research and development.

#### *6.1.1 Deep learning and neural networks*

Deep learning, which involves using artificial neural networks with multiple layers of interconnected neurons (Nielsen, 2015), has become a key trend in AI research and development in recent years. Deep learning algorithms have made significant advances in a wide range of tasks. One of the key advantages of deep learning is its ability to learn and generalize from data without the need for explicit programming or feature engineering. Deep learning algorithms can automatically learn different patterns, making them more accurate and efficient than traditional machine learning algorithms that require manual feature engineering.

However, there are also challenges associated with deep learning. One of the main challenges is the need for large amounts of labeled data to learn and generalize effectively. This presents a limitation in domains where the amount of available data is limited. Another challenge is the potential for bias in the data. This happens when the data is not representative of the real world and can lead to biased or unfair decisions. In addition, there are also computational challenges associated with deep learning as the algorithms require significant amounts of computing power and time to train. This can present a challenge for researchers and developers who do not have access to high-performance computing resources.

#### *6.1.2 Explainable artificial intelligence*

Explainable AI, also known as interpretable AI or transparent AI, is a research and development field focusing on developing algorithms and methods to explain the reasoning behind their decisions (Hoffman, Mueller, Klein, y Litman, 2018). There is a growing demand for explainable AI to increase transparency and accountability and enable better understanding and trust in AI systems. One of the critical challenges of explainable AI is the trade-off between accuracy and interpretability. In some cases, it can be challenging to explain the reasoning behind a decision made by an AI system without sacrificing some of the accuracy of the decision. This can be a challenge for researchers and developers who need to balance the need for accuracy with interpretability.

Another challenge of explainable AI is to explain complex and abstract concepts. Some AI systems can make decisions based on complex and abstract concepts that are difficult to explain in simple terms. This can be a challenge for researchers and developers who need to find ways to explain these concepts in a way understandable to human users. In addition, there are social and ethical challenges associated with explainable AI, such as the need to ensure that explanations provided by AI systems are fair and unbiased and to limit the possibility of AI systems being used to deceive or manipulate users.

### *6.2 The role of human oversight in the development and deployment of artificial intelligence*

The role of human oversight in AI development and deployment is an important and hotly debated topic. Numerous efforts exist to establish ethical guidelines and principles for AI development and deployment. The European Union has developed "Ethics Guidelines for Trustworthy AI,"which provide recommendations to ensure that AI is developed and used ethically and responsibly (Smuha, 2019; Floridi, 2019). The guidelines cover areas such as transparency, accountability, equity, and non-discrimination. However, there are also controversies and debates surrounding the development of ethical guidelines for AI. There are disagreements about the extent to which AI should be held accountable for its actions and whether specific regulations or laws should govern its use.

Below are some examples of human intervention and collaboration with AI systems.

- **Human-in-the-loop systems.** Human-in-the-loop systems, which involve the integration of human decision-making and oversight into the AI process, have been used in several different contexts. Some AI-powered medical systems have been designed to provide recommendations to doctors, but a human doctor makes the final treatment decision. Similarly, some AI-powered financial systems have been designed to provide recommendations to investors, but a human investor makes the final decision on investments (Zanzotto, 2019).

Some critics have argued that using these systems could lead to a *delegation of responsibility* in which humans rely too much on AI and are not accountable for their decisions.

- **Human-machine collaboration.** Human-machine collaboration, where humans and AI systems work together to achieve a common goal, has the potential to leverage the strengths of both humans and AI. In some cases, humans and AI systems have achieved better results by working together than they could have achieved individually.

One concern is the possibility of AI displacing human workers, as these systems can perform specific tasks more efficiently and accurately than humans. There is also a risk that humans will become too dependent on AI systems, leading to a loss of skills and expertise. In addition, social and ethical concerns surround the integration of humans and AI, such as the possibility of AI being used for harmful acts.

### 6.3 *Ethical considerations related to artificial intelligence*

Ethical considerations related to AI are an important and hotly debated topic, as the development and implementation of AI has the potential to have a significant impact on society. In this section, some of the key ethical considerations related to AI are discussed, along with examples of laws and regulations that address these issues.

#### 6.3.1 *Automation and job displacement*

One of the main ethical and social concerns surrounding AI is the potential for technology to automate jobs and displace human workers. As AI systems become more capable, there is a risk that they could replace human workers in a wide range of tasks and industries, leading to job loss and unemployment. This is a particularly sensitive issue in the context of the current economic climate, where many workers are already facing job insecurity and income inequality.

#### 6.3.2 *Privacy and security*

Another critical ethical and social concern surrounding AI is the impact of the technology on privacy and security. As AI systems collect and analyze large amounts of data, there is a risk that this data could be misused or that systems could be hacked or tampered with. This is a critical issue in the context of sensitive areas such as healthcare and finance, where the potential consequences of a data breach or malicious attack could have severe results (Oseni y cols., 2021).

#### 6.3.3 *Bias*

Another primary ethical consideration related to AI is the potential for the technology to perpetuate and amplify biases and inequalities already existing in society. For example, if an AI system is trained on biased data, it could make biased decisions that disproportionately affect certain groups of people. To address this problem, it is essential to ensure that the data used to train AI systems is representative and unbiased and that appropriate measures are implemented to mitigate the potential impacts of bias.

For example, in the United States, the Equal Employment Opportunity Commission (EEOC) has issued guidance on using AI in the workplace. This recommends that employers take steps to ensure that their AI systems are not biased against certain groups of people. Similarly, in the European Union, the General Data Protection Regulation (GDPR) requires organizations to take steps to ensure that their AI systems do not discriminate against individuals based on protected characteristics such as race, gender, and age (Panch, Mattie, y Atun, 2019; Ntoutsi y cols., 2020).

#### 6.3.4 *Transparency*

Another critical ethical consideration related to AI is the need for transparency in the development and use of the technology. Users of AI systems need to understand how they work and what data they rely on to ensure that the systems are used ethically and responsibly. In the United States, the Algorithmic Accountability Act, introduced in 2019, calls for companies to conduct audits of their AI systems to identify and address any potential bias or negative impact. Similarly, in the European Union, the AI Regulation, which is currently being proposed, aims to have organizations explain the decisions made by their AI systems to increase transparency and accountability (Felzmann, Fosch-Villaronga, Lutz, y Tamò-Larrieux, 2020; Larsson y Heintz, 2020).

#### 6.3.5 *Accountability*

Another key ethical consideration related to AI is the need for accountability in developing and using the technology. It is important to ensure that mechanisms are in place to hold organizations and individuals accountable for their AI systems' impacts to mitigate the technology's risks and negative impacts. In the United States, the Algorithmic Accountability Act would require companies to report on their AI systems' potential biases and negative impacts and take steps to mitigate identified risks. In the European Union, the AI Regulation would establish a system of "co-regulation,"where AI developers and users would be required to follow specific guidelines and principles to ensure that the technology is used ethically and responsibly.

There is a trend towards integrating AI with other technologies, such as the Internet of Things (IoT), robotics, and blockchain, towards creating new and more powerful systems. For example, integrating AI with IoT technologies can enable the development of smart cities, where sensors and devices are connected to the Internet and can collect and analyze data to improve the efficiency and quality of urban life. Integrating AI with robotics can enable the development of advanced manufacturing systems and autonomous vehicles. Integrating AI with blockchain can enable the development of decentralized and secure systems for transactions and data storage. However, integrating AI with these types of technologies is also associated with challenges.

One of the main challenges is ensuring interoperability and compatibility between different technologies. In order to create effective and seamless systems, it is essential to ensure that technologies can work together and exchange data and information without any problems. Another challenge is the potential for security and privacy risks. As AI systems become more integrated with other technologies, there is a risk that systems could be hacked or sensitive data compromised. It is crucial to ensure that systems are secure and that appropriate measures are in place to protect the data and information they collect and analyze.

## 7 Potential areas for growth and innovation in artificial intelligence research and development: the role of governments in its regulation.

There are many potential areas for growth and innovation in AI research and development. Here are some examples of areas where AI could significantly impact the future, along with arguments and research that support these areas as potential areas for growth and innovation.

### *7.1 Healthcare*

One potential area for growth and innovation in AI is healthcare. AI has the potential to revolutionize the way healthcare is delivered by enabling the analysis of large amounts of data to improve diagnosis and treatment recommendations. Machine learning algorithms could be used to analyze electronic health records, imaging data, and other types of data to identify patterns and trends that could be used to improve the effectiveness of the medicine.

There is already a significant amount of research and development underway in this area. In some work, machine learning algorithms are used to analyze electronic health records and imaging data to predict the likelihood of patients developing Alzheimer's or oncological diseases (Ngiam y Khor, 2019; Huang, Pareek, Seyyedi, Banerjee, y Lungren, 2020). In other work, machine learning algorithms are used to analyze electronic health records to predict the likelihood of patients developing cardiovascular disease (Weng, Reps, Kai, Garibaldi, y Qureshi, 2017).

### *7.2 Transportation*

Another potential area for growth and innovation in AI is transportation. AI has the potential to revolutionize the way we travel by enabling the development of autonomous vehicles and other types of transportation systems and services.

For example, machine learning algorithms could be used to analyze sensors and other data types to enable vehicles to navigate more safely and efficiently (Figure 9). There is already a significant amount of research and development underway in this area. In some areas, machine learning algorithms are used to train an autonomous car to navigate in a complex urban environment (Fayjie, Hossain, Oualid, y Lee, 2018). In others, machine learning algorithms are used to develop autonomous flying drones that can navigate cluttered environments and avoid obstacles (Gandhi, Pinto, y Gupta, 2017).

**Fig. 9:** Representation of the potential applications of AI in self-driving and energy-saving transportation

### *7.3 Climate change*

Another potential area for growth and innovation in AI is the use of technology to address climate change (Figure 10). AI has the potential to enable the analysis of large amounts of data to identify patterns and trends that could be used to mitigate the impacts of climate change.

Machine learning algorithms can be used to analyze satellite data, weather data, and other types of data to improve our understanding of the planet's climate and develop strategies to reduce greenhouse gas emissions. There is already a significant amount of research and development underway in this area. For example, in (Huntingford y cols., 2019), researchers described how they used machine learning algorithms to analyze satellite data to improve our understanding of the Earth's climate. Similarly, in (Rasp y cols., 2018), researchers used machine learning algorithms to analyze weather data and develop more accurate climate models.

### *7.4 The role of government and industry in shaping the future of artificial intelligence*

The role of government and industry in AI is a topic of intense debate and speculation. Here are some points that

**Fig. 10:** Representation of the potential applications of AI in climate change and global warming.

could be included in a more detailed discussion of the topic, along with actual examples from government and industry.

#### *7.4.1 Government regulation*

Governments play an essential role in shaping the development and implementation of AI through the development and enforcement of standards and policies. For example, governments can establish guidelines and standards for the development and use of AI and regulate the use of data and other resources necessary to train and implement AI systems. Several government regulations and policies related to AI already exist.

For example, the European Union has developed the General Data Protection Regulation, which establishes guidelines for using personal data in developing and deploying AI systems. The United States has also issued guidance on using AI in the workplace through the Equal Employment Opportunity Commission. In addition, several additional regulations and policies are under consideration, such as the Algorithmic Accountability Act in the United States and the AI Regulation in the European Union.

#### *7.4.2 Industry standards*

The industry also plays an essential role in shaping the future of AI through the development of standards and best practices for developing and implementing the technology. For example, industry groups and organizations can establish guidelines and standards for AI's ethical and responsible use and develop tools and resources to support AI development and implementation. Some industry standards and best practices related to AI already exist.

For example, the IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems has developed a set of ethical guidelines for the development and use of AI. The Partnership on AI, a collaboration between several leading technology companies and research organizations, has also developed a set of best practices for the responsible development and use of AI.

## 8 Perspectives, challenges and opportunities in the development of artificial intelligence.

The future of AI and its potential impact on society is a topic of intense debate and speculation. Here are some important points to consider on this topic.

### *8.1 Increased automation and job displacement*

One of AI's most widely predicted impacts is the potential for increased automation of tasks and jobs. Some experts have argued that AI has the potential to automate a wide range of tasks and industries, leading to significant job displacement and unemployment. Some argue that AI will eventually be able to perform any task that a human can perform and will be able to do so more cheaply and accurately. This could have significant implications for the future of work, as many jobs that humans currently perform could be automated. However, other experts have argued that the impact of AI on employment is more complex and nuanced. AI could augment jobs rather than automate them entirely, meaning that AI could enhance the skills of human workers rather than replace them.

### *8.2 Improved decision-making*

Another potential impact of AI is the ability to improve decision-making in a wide range of contexts. AI systems can analyze and process large amounts of data quickly and accurately, which can help decision-makers make more informed and accurate decisions. AI could be used to improve diagnosis and treatment recommendations in healthcare or to optimize supply chain management in manufacturing. However, there are also concerns about the potential risks of AI and its adverse impacts on decision-making. In (Mitchell y Mitchell, 1997), the researchers argue that AI systems may perpetuate and amplify biases and inequalities that already exist in society and that AI systems should be transparent and accountable. They also argued that decisions made by AI systems should be subject to human oversight and control.

### *8.3 Enhanced personalization and customization*

AI also has the potential to enable better personalization and customization of products and services. AI-powered personal assistants, such as Siri and Alexa, can provide personalized recommendations and assistance to users. Likewise, AI-powered marketing systems can provide personalized ads and recommendations based on user interests and preferences. However, there are also concerns about personalization and its potential risks and negative impacts. Arguments include that personalization can be used to manipulate and mislead people and that there is a need to ensure that it is used ethically and responsibly.

In summary, the future of AI and its potential impact on society is a complex and hotly debated topic. Many factors influence its development and deployment. For this reason, it is important for researchers, policymakers, and society to carefully consider the potential risks and benefits of AI and ensure that the technology is developed and used correctly.

### 8.4 *Use of artificial intelligence-based text-generation in education, scientific research, medicine, law, and programming*

The field of artificial intelligence-based text-generation is rapidly evolving and has the potential to significantly impact several industries, including education, industry, and programming.

In education, text-generation models have the potential to revolutionize the way we approach this field. They can be used to automate grading, create educational content, facilitate language translation, add suggestions (Biswas, 2023; Dowling y Lucey, 2023), and provide personalized learning experiences. However, there are discussions about whether such models can replace human teachers and serve as fully autonomous teaching tools.

While text-generation models can be used as a teaching tool, they cannot serve as a complete teacher. These models can enhance the learning experience by making it more accessible and efficient for both students and teachers (Márquez y cols., 2016). However, they cannot provide human interaction and emotional support, which are crucial components of effective teaching. In addition, text-generation models may not always provide accurate or unbiased information, and they cannot adjust their teaching approach to accommodate individual learning styles or address student misconceptions. Therefore, it is essential to view text-generation models as a complement to human teachers rather than a replacement. They can help automate specific tasks and provide additional support to students, but they cannot completely replace the human element of teaching.

In the medical field, text generation models make it possible to automate certain tasks and generate written content. For example, they can be used to generate patient summaries, medical reports, and discharge summaries, saving time and effort for healthcare professionals. In addition, text-generation models can be used to generate personalized treatment plans and recommendations based on patient data, helping improve patient care's accuracy and efficiency.

There are concerns about the use of these models in medicine. One of these is privacy and security, as text generation models would require access to confidential patient data to generate recommendations. This raises questions about the secure storage and use of this information. Also, highly accurate models with a risk of bias close to zero would be required since an incorrect diagnosis or treatment recommendation could risk the patient's health.

In the field of law, text generation models also help automate specific tasks and processes that are usually performed manually. For example, they can generate legal documents, such as contracts and pleadings. They can also be used to analyze and summarize large amounts of legal text, such as case law, making it easier for lawyers to find relevant information and make informed decisions.

Also, some of the concerns with using these models in this field are bias and inaccuracy. This could result in incorrect legal decisions or advice, putting clients at risk. Also, inaccurate systems could perpetuate existing biases and discrimination in the legal system. For example, if models are trained with data that reflect racial or gender biases, they may generate content that reinforces these.

Text-generation models have the potential to play a role in the programming field by automating specific coding tasks and generating code snippets. It can also automate testing and support software development, improving software quality and reliability. This can save programmers time and effort, making development processes faster and more efficient. For example, text generation models can generate code for repetitive tasks. They can also be used to generate code snippets based on natural language inputs, making it easier for non-technical stakeholders to contribute to the development process.

However, there are some concerns about using text generation models in programming. One concern is that the generated code may contain bugs or be of poor quality, leading to security vulnerabilities or decreased performance. Also, the generated code is likely to be poorly documented, making it difficult for other programmers to understand and maintain it in the future. Therefore, it would be necessary for human programmers to continuously monitor and evaluate the quality and accuracy of the generated code to ensure that it meets the desired standards.

In industry, text generation models have the potential to automate several tasks and processes, including report writing, the creation of novel materials, and the generation of customer support responses. They can generate product descriptions, advertisements, and email campaigns in marketing and advertising. This can improve efficiency and increase the quality of employees' work, allowing them to focus on more strategic and creative tasks.

There are some common concerns across all industry fields regarding using text-generation models. Like any ML model, there is the potential for any content generated to be biased or inaccurate, especially if the models are trained on biased or incomplete data. There is also a risk that the use of AI could lead to the job displacement of human workers, raising ethical questions about job displacement and the possibility of AI being used for harmful purposes. It is essential that companies carefully consider these potential implications and address any concerns before fully incorporating text generation models into their operations. In doing so, text generation models can potentially impact any field positively.

## 9 Conclusions

This paper presents a comprehensive compilation of the basic concepts of AI, including its definition, history, challenges, and opportunities. To this end, the ChatGPT text-generation model was used as a tool to support the conception of this work through guided prompts and response sessions. This was performed to demonstrate the applicability of this technology in this type of task and use it as inspiration to discuss what implications such systems would have in different domains, such as academia, industry, and others.

Artificial intelligence has seen significant advances in recent decades. However, the development and implementation of AI raises several fundamental challenges and considerations, including bias, transparency, accountability, and ethics. Addressing these challenges and ensuring AI's responsible use requires collaboration between stakeholders, researchers, policymakers, and industry representatives. This involves the development of guidelines and standards for the ethical and responsible use of AI and establishment of oversight and accountability mechanisms. The future of AI remains uncertain, and many factors could affect its development and implementation. Therefore, it is of utmost importance that society carefully considers AI's potential risks and benefits to ensure that the technology is developed and used ethically and responsibly. This will require ongoing dialogue and collaboration between stakeholders, as well as continued research and development of the technology.

The advancement of AI could allow the deployment of new tools for education and learning in schools, universities, and industrial environments. Text-generation AI is one such development that has the potential to transform the way educational institutions and individuals apply the teaching and learning process, although with challenges related to its application, including initial bans in some schools. On the other hand, several opinions lean toward using AI tools, specifically the ChatGPT text generation model, to teach.

Consequently, using AI as a virtual instructor that can answer questions and identify correct questions and answers in an educational environment is a concept that can have promising applications in an educational framework. Text-generation AI could provide students with a more personalized learning experience, including generating ideas, brainstorming sessions, and procedures to apply product-based learning strategies. An AI-powered virtual instructor can interact with students and provide them with tailored responses based on their individual needs and abilities. This can lead to more effective learning, as students receive feedback and support designed to address their individual needs.

Although this is a breakthrough in the field of research, scientific journal publishing faces challenges in writing and reviewing research articles. Recent publications have indicated that ChatGPT text generation can help write plausible research ideas and literature reviews faster, correct text, and add suggestions. While there are advantages, there are also challenges related to the originality of the papers. As an example, we show in the present research that ChatGPT AI could write and construct an article, which can pass plagiarism tests with the help of editing and adding citations by a knowledgeable person. In the present work, less than 5 % plagiarism was found.

In addition, there are new text-generation analysis tools, such as GPTZero, albeit with mixed results. One of the consequences in the field of scientific journal publishing may be longer reviewer times. However, another solution could be the development of AI text generation checkers for editors, which would be used similarly to plagiarism checkers when a paper is submitted and reaches the handling editor.

The next few months will be crucial because text generation technology is evolving rapidly, and the arrival of GPT-4 evidences this. GPT-4 is a new language model created by OpenAI that brings multimodal functionality to the GPT model, allowing it to handle text input and images. GPT-4 is now integrated with Microsoft Bing, customized for search. It combines data from the GPT-4 model and Bing to generate answers based on real-time information quickly. GPT-4 can process up to 25,000 words of text from the user and even receive web links and interact with the text on that page.

Likewise, Microsoft has also integrated GPT-4 with Office 365 in a new component called Microsoft 365 Copilot. Copilot uses natural language to interact with users and is integrated into Microsoft 365 applications such as Word, Excel, PowerPoint, Outlook, and Teams. This allows, among other things, to analyze data automatically, create tables, summarize, write texts, and make customized slides.

The advancement of AI, specifically in the field of text-generation, presents both opportunities and challenges in various domains such as education and scientific publishing. It is crucial that we continue to carefully consider and address the ethical and responsible use of AI, including issues related to bias, transparency, accountability, and ethics. As the technology continues to evolve rapidly, it is important to engage in ongoing dialogue and collaboration between stakeholders to ensure that AI is developed and used in ways that benefit society. With responsible use, AI has the potential to transform and improve various aspects of our lives, from education to scientific research and beyond.

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