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ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope

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ABSTRACT

In recent years, artificial intelligence (AI) and machine learning have been transforming the landscape of scientific research. Out of which, the chatbot technology has experienced tremendous advancements in recent years, especially with ChatGPT emerging as a notable AI language model. This comprehensive review delves into the background, applications, key challenges, and future directions of ChatGPT. We begin by exploring its origins, development, and underlying technology, before examining its wide-ranging applications across industries such as customer service, healthcare, and education. We also highlight the critical challenges that ChatGPT faces, including ethical concerns, data biases, and safety issues, while discussing potential mitigation strategies. Finally, we envision the future of ChatGPT by exploring areas of further research and development, focusing on its integration with other technologies, improved human-AI interaction, and addressing the digital divide. This review offers valuable insights for researchers, developers, and stakeholders interested in the ever-evolving landscape of AI-driven conversational agents. This study explores the various ways ChatGPT has been revolutionizing scientific research, spanning from data processing and hypothesis generation to collaboration and public outreach. Furthermore, the paper examines the potential challenges and ethical concerns surrounding the use of ChatGPT in research, while highlighting the importance of striking a balance between AI-assisted innovation and human expertise. The paper presents several ethical issues in existing computing domain and how ChatGPT can invoke challenges to such notion. This work also includes some biases and limitations of ChatGPT. It is worth to note that despite of several controversies and ethical concerns, ChatGPT has attracted remarkable attentions from academia, research, and industries in a very short span of time.

1. Introduction

The rapid advancement of artificial intelligence (AI) and natural language processing (NLP) has led to the development of increasingly sophisticated and versatile language models [1–5]. Generative AI refers to a class of artificial intelligence models that can create new data based on patterns and structures learned from existing data. These models can generate content across various domains, such as text, images, music, and more [6–9]. Generative AI models rely on deep learning techniques and neural networks to analyze, understand, and generate content that closely resembles human-generated outputs. Among these, ChatGPT, an AI model developed by OpenAI, has emerged as a powerful tool with a broad range of applications in various domains [10–15].

Understanding the origins and development of ChatGPT is crucial to appreciating its role in advancing scientific research [16–21]. This section provides an overview of the background, key milestones, and improvements made in the development of ChatGPT, highlighting the technological advances that have led to its success in the scientific domain [22–25]. In this context, we can mention that the ChatGPT is not a Generative Adversarial Network (GAN) model, but it is a language model based on the Generative Pre-trained Transformer (GPT) architecture [26–30]. While GANs are typically used for tasks like image generation, GPT models are designed for natural language processing tasks such as text generation and language understanding [31–33].

ChatGPT has its roots in the field of NLP, an area of AI focused on enabling machines to understand and generate human language [34–37]. The development of ChatGPT was driven by the desire to create a highly sophisticated and versatile AI language model capable of assisting in various tasks, including text generation, translation, and data analysis. The foundations of ChatGPT lie in the development of the Transformer architecture, introduced in Ref. [38]. It was designed to overcome some of the limitations of previous sequence-to-sequence models for natural language processing, such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs). This groundbreaking

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architecture enabled the creation of powerful language models like OpenAI's GPT series, including GPT-2 and GPT-3, which served as precursors to ChatGPT.

ChatGPT is based on the GPT-3.5 architecture, which is a modified version of the GPT-3 model released by OpenAI in 2020. GPT-3.5 is essentially a smaller version of GPT-3, with 6.7 billion parameters compared to GPT-3's 175 billion parameters [39–41]. Despite having fewer parameters, GPT-3.5 still performs very well on a wide range of natural language processing tasks, including language understanding, text generation, and machine translation. ChatGPT was trained on a large corpus of text data and fine-tuned on a specific task of generating conversational responses, which allows it to generate human-like responses to user queries [42–45].

1.1. Key milestones in the development of ChatGPT

The development of ChatGPT has involved a series of milestones and improvements, including.

(i) The introduction of the Transformer architecture, which enabled the creation of highly efficient and scalable language models [46].
(ii) The development and release of the GPT series, which demonstrated the potential of AI language models in various applications, including text generation, translation, and summarization [47].
(iii) The release of ChatGPT, which built upon the successes of its predecessors while incorporating improvements in accuracy, context understanding, and versatility [48].

1.2. Improvements and innovations in ChatGPT

Compared to earlier models, ChatGPT boasts several key improvements and innovations, including.

(i) Enhanced context understanding: ChatGPT can better comprehend and respond to complex and nuanced inputs, making it more effective in generating accurate and relevant text [49].
(ii) Reduced biases: While still not completely free of biases, ChatGPT benefits from ongoing efforts to minimize biases in training data, leading to more objective and balanced outputs [50].
(iii) Fine-tuning capabilities: ChatGPT can be fine-tuned for specific tasks and applications, allowing it to be tailored to the unique needs of researchers across various scientific disciplines [51].

1.3. Existing issues that ChatGPT can resolve

Conversational AI, like ChatGPT, has made significant progress in recent years, but there are still several challenges and limitations that need to be addressed [52–54]. Here are some existing problems regarding conversational AI that ChatGPT can work towards solving: (i) maintaining context: Conversational AI models often struggle to maintain the context of a conversation, especially when it spans multiple turns. ChatGPT can be improved to better track and manage context to provide more coherent and relevant responses [55], (ii) handling ambiguity: AI models might provide unsatisfactory or irrelevant responses when faced with ambiguous queries. Enhancing ChatGPT's ability to recognize ambiguity and ask clarifying questions would improve its utility and user experience [56], (iii) personalization: ChatGPT can be further developed to provide more personalized experiences for users by adapting its responses based on individual preferences, interests, and conversational styles [57], (iv) common sense reasoning: Conversational AI models sometimes lack common sense understanding or the ability to reason through a problem logically. Improving ChatGPT's common sense reasoning capabilities would lead to more accurate and helpful responses [58], (v) emotional intelligence: Developing ChatGPT's ability to recognize and respond to users' emotions can enhance its communication effectiveness and create a more empathetic user experience [59], (vi) ethical considerations: ChatGPT must be fine-tuned to minimize the risk of generating offensive, biased, or inappropriate content [60]. This involves continuous work on the training data, model architecture, and monitoring mechanisms, (vii) robustness and security: Conversational AI models can be vulnerable to adversarial attacks or malicious inputs; enhancing ChatGPT's robustness and security can ensure its reliable performance in various environments [61], (viii) real-time, multi-modal interactions [62,63]: integrating ChatGPT with other modalities, such as voice or image recognition, can help create more interactive and dynamic conversational experiences, (ix) handling out-of-distribution queries: ChatGPT can be improved to better handle queries that are not well-represented in its training data or are entirely new, providing users with more accurate and reliable information [64,65], (x) scalability and efficiency: as conversational AI models become larger and more complex, it is essential to develop methods to improve their computational efficiency and scalability, ensuring their widespread adoption and accessibility [66].

1.4. Growth of ChatGPT in scientific community

The evolution of ChatGPT from its early predecessors to its current state has made it an invaluable tool in advancing scientific research, with its impact felt across a wide range of applications, including data processing, hypothesis generation, and collaboration. As AI technology continues to advance, we can expect further improvements and innovations that will shape the future of scientific research. In recent years, scientific and academic communities have given extra-ordinary attention to the research and development on ChatGPT. As per Google Scholar, till March 2023 more than 3000 articles, reports, news have been published in various journals, conferences, newspapers, blogs and media reports. Fig. 1 presents the growth of research interest about ChatGPT based on the number of indexed papers on Google Scholar in recent years.

1.5. Key contributions

We present several contributions in this article which can further help academician and enthusiasts to better understand ChatGPT. Some of major contributions are listed as follows.

- To present in-depth review about ChatGPT in current scenario.
- To compare ChatGPT with related AI technologies.
- To give detailed insights about various applications that can be served by using ChatGPT.
- To discuss about existing challenges, ethical issues, controversies and future direction.
- To present computer ethics and ChatGPT's role to pose challenges in this context.
- To discuss about biases and key limitations of ChatGPT.

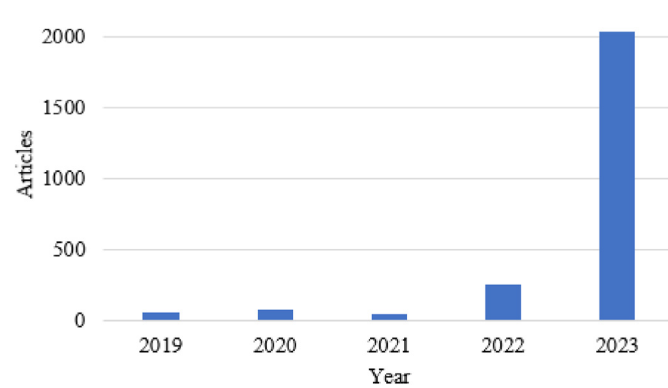

Fig. 1. Yearly articles indexed in Google Scholar on ChatGPT.

1.6. Organization of paper

This review paper aims to provide an in-depth exploration of ChatGPT's role in advancing traditional bullnecks as mentioned above. The paper is organized into the following sections: section B presents background of ChatGPT. Section C shows related technologies that resembles in some features with ChatGPT. Section C demonstrates the applications of ChatGPT in various domains. Section D discusses about key challenges, ethical concerns, controversies, and future scope. Section E presents computer ethics and ChatGPT's role to challenge. Section F deals with several biases and key limitations of ChatGPT. Section G concludes the article.

2. Background of ChatGPT

1) The OpenAI Initiative

OpenAI is an organization focused on developing artificial general intelligence (AGI) to benefit humanity. Founded in 2015 by Elon Musk, Sam Altman, and others, OpenAI has been at the forefront of AI research, producing several groundbreaking models such as GPT-2, GPT-3, and eventually ChatGPT. Building upon the success of GPT-3, OpenAI continued its research and development efforts, leading to the creation of ChatGPT based on the GPT-4 architecture [67,68]. ChatGPT is designed to excel at conversation-based tasks and offers improvements in contextual understanding, response generation, and overall coherence compared to GPT-3. Building upon the success of GPT-3, OpenAI continued its research and development efforts, leading to the creation of ChatGPT based on the GPT-4 architecture. ChatGPT is designed to excel at conversation-based tasks and offers improvements in contextual understanding, response generation, and overall coherence compared to GPT-3 [69].

2) GPT Evolution

GPT models are designed to generate natural language text, such as sentences, paragraphs, and entire documents, in a way that is coherent and consistent with human language. The key feature of GPT models is their ability to pre-train on large amounts of text data, and then fine-tune on specific downstream tasks, such as text classification or question-answering. Pre-training involves training the model on a large corpus of text data, such as web pages or books, in an unsupervised way, which means that the model doesn't require any explicit labels or annotations for the training data [70].

During pre-training, the GPT model learns to predict the next word in a sequence of text, given the previous words in the sequence. This is known as a language modeling task, and it is an important component of many natural language processing tasks. By training on a large corpus of text data, the model learns to recognize and generalize patterns in language, such as syntax, grammar, and semantics [71]. After pre-training, the GPT model can be fine-tuned on a specific downstream task by providing it with a smaller labeled dataset, which is used to update the model's weights and biases to better fit the task at hand. For example, if the downstream task is text classification, the model might be trained to predict the correct label for a given input text [72].

(a) GPT-1

It is the first version of the GPT language which was released in 2018. It was based on the Transformer architecture, which is a neural network architecture designed for natural language processing tasks such as language modeling and machine translation. GPT-1 was pre-trained on a large corpus of text data, which included books, articles, and web pages, using a language modeling task [73]. The model was trained to predict the next word in a sequence of text, given the previous words in the sequence. This pre-training process allowed GPT-1 to learn the patterns and relationships between words in a large corpus of text data. After pre-training, GPT-1 could be fine-tuned on specific downstream tasks, such as language translation, sentiment analysis, or text classification [74]. For example, the model could be fine-tuned on a sentiment analysis task by providing it with a labeled dataset of text data and training it to predict the sentiment of a given text input. GPT-1 had 117 million parameters, which made it relatively small compared to later versions of the GPT model. Despite its relatively small size, GPT-1 achieved impressive results on a wide range of natural language processing tasks and demonstrated the effectiveness of pre-training on large amounts of text data for improving language understanding.

(b) GPT-2

It was a significant improvement over GPT-1, with 1.5 billion parameters, making it one of the largest language models at the time of its release. GPT-2 was pre-trained on a massive corpus of text data, which included web pages, books, and other written materials, using a language modeling task. Like GPT-1, the model was trained to predict the next word in a sequence of text, given the previous words in the sequence [75]. However, GPT-2 was able to generate longer and more coherent sequences of text, and it demonstrated a greater ability to generalize to new tasks and domains. After pre-training, GPT-2 could be fine-tuned on a variety of downstream tasks, such as text classification, sentiment analysis, and question-answering [76]. The model was able to achieve state-of-the-art results on many of these tasks, and it was particularly effective at generating high-quality natural language text. One of the notable features of GPT-2 was its ability to generate realistic and coherent text that was difficult to distinguish from human-written text [77]. This led to some concerns about the potential misuse of the model, such as generating fake news or propaganda. As a result, OpenAI initially chose not to release the full version of the model, but instead released a smaller version with reduced capabilities.

(c) GPT-3

It is one of the largest and most powerful language models ever created, with 175 billion parameters, which is several times larger than GPT-2. GPT-3 was trained on a massive corpus of text data, which included web pages, books, and other written materials, using a language modeling task [78]. The model was trained to predict the next word in a sequence of text, given the previous words in the sequence, and it was able to generate high-quality natural language text with a high degree of coherence and realism. One of the key features of GPT-3 is its ability to perform a wide range of natural language processing tasks, including text classification, sentiment analysis, and question-answering, without the need for task-specific training data [79]. This is due to the model's ability to learn a wide range of linguistic features and patterns from its pre-training data, which allows it to generalize to many different tasks and domains. GPT-3 also includes a range of innovative features, such as multi-task learning, which allows the model to perform multiple tasks simultaneously, and few-shot learning, which enables the model to learn new tasks from only a few examples. These features make GPT-3 a highly flexible and adaptable language model that can be used in a wide variety of natural language processing applications [80]. GPT-3 has been used in a variety of real-world applications, including chatbots, language translation, content generation, and even code generation. The model has also generated considerable interest and excitement in the artificial intelligence community, and it has sparked new research and development in the field of natural language processing.

(d) InstructGPT

InstructGPT is a new language model developed by OpenAI that builds on the success of the GPT-3 large language model [81]. It uses reinforcement learning with human feedback to improve its reliability, and it underpins the ChatGPT conversational agent. In contrast to GPT, InstructGPT incorporates a human feedback approach in the fine-tuning process. Humans iterate on a smaller dataset by producing and comparing the desired output with that generated by GPT, labeling the GPT output based on human feedback, and showing that output to the GPT model to help guide it towards the desired outcome on narrower tasks and questions [82]. This process has now become a standard within OpenAI's technology, allowing InstructGPT to improve upon its predecessor, GPT-3.

(e) ProtGPT2

ProtGPT2 is a recently published paper describing a language model that is capable of understanding the protein language, which can be used for designing and engineering new proteins [83,84]. The model generates protein sequences that maintain important features of natural proteins, such as amino acid propensities, secondary structural content, and globularity, while exploring new regions of the protein space. ProtGPT2 is built on the GPT2 Transformer architecture and includes 36 layers with a model dimensionality of 1280, making it a powerful model with 738 million parameters. The pre-training of ProtGPT2 was done on the UniRef50 database (version 2021_04) in a self-supervised manner, using raw protein sequences without any annotation. The model was trained to predict the next token or oligomer in the sequence using a causal modelling objective, allowing it to learn an internal representation of proteins and understand the protein language. Overall, ProtGPT2 is a promising tool for protein engineering and design [85].

(f) BioGPT

R. Luo et al. [86] have proposed a language model called BioGPT that is specifically designed for generating and mining biomedical text. BioGPT is a domain-specific generative pre-trained Transformer model that is based on the Transformer language model architecture. It is trained on 15 million PubMed abstracts from scratch, making it well-suited for processing biomedical text data [87].

(g) ChatGPT

ChatGPT is pre-trained on a large corpus of text data, including books, articles, and websites, using a language modeling task [88]. The pre-training allows ChatGPT to learn the patterns and relationships between words and phrases in natural language, which makes it effective in generating coherent and realistic responses in a conversation.

(h) GPT-4

OpenAI has made significant progress in scaling up deep learning with the release of GPT-4. This new model is a large multimodal language model that can accept both image and text inputs and generate text outputs [89]. While it may not be as capable as humans in real-world scenarios, GPT-4 has demonstrated human-level performance on various professional and academic benchmarks [90]. For instance, it has achieved a score around the top 10% of test-takers on a simulated bar exam, which is better than GPT-3.5's score of around the bottom 10%. The development of GPT-4 involved six months of iterative alignment, drawing on lessons from OpenAI's adversarial testing program and ChatGPT, resulting in the model's best-ever performance on factuality, steerability, and staying within the given boundaries, although there is still room for improvement. Fig. 2 presents the milestones of evolutions towards ChatGPT [91].

GPT models have achieved state-of-the-art performance on a wide range of natural language processing tasks, including text generation, question-answering, language translation, and sentiment analysis. They have also been used in a variety of real-world applications, such as chatbots, customer service, and content creation. A comparison of various GPT versions is provided in Table 1 [92]. A comparison between GPT and ChatGPT is presented in Table 2 [93].

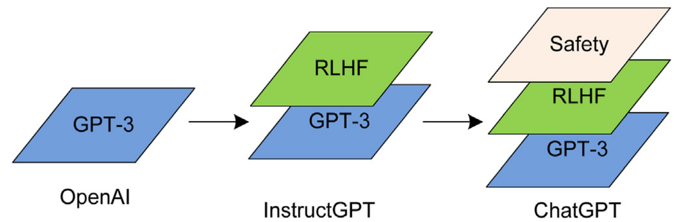

Fig. 2. Key milestones of evolution.

3) GPT-3.5 WorkFlow

The basic idea behind the Transformer is to use self-attention to encode the input sequence and produce a sequence of hidden representations, which can then be decoded into an output sequence. Self-attention allows the model to attend to different parts of the input sequence at different levels of abstraction, which helps it capture long-range dependencies and relationships between different parts of the sequence [94].

In the case of GPT-3.5, the model uses a stack of 13 Transformer blocks, each with 12 attention heads and 768 hidden units. The input to the model is a sequence of tokens, which are first embedded into a continuous vector space using an embedding layer. The embedded tokens are then fed into the first Transformer block, which applies self-attention and produces a sequence of hidden representations [95].

The hidden representations are then passed through the remaining 12 Transformer blocks, each of which applies self-attention and feedforward layers. The output of the final Transformer block is a sequence of hidden representations, which are decoded into an output sequence using a linear projection layer and a softmax activation function [96].

In addition to the core Transformer architecture, GPT-3.5 also includes several additional components, such as layer normalization, residual connections, and positional embeddings. These components help stabilize training and improve the model's performance on language modeling tasks. Overall, the GPT-3.5 architecture is a powerful and efficient way to model natural language sequences, and it has demonstrated state-of-the-art performance on a wide range of language tasks, including text generation, language understanding, and machine translation.

The working of GPT-3.5 is carried away in three steps as follows based on Fig. 3 [68].

(i) Collect demonstration data and train a supervised policy

Firstly, a prompt is sampled from the prompt dataset. A labeler demonstrates the desired output behavior. This data is used to fine-tune GPT3 with supervised learning.

(ii) Collect a comparison data and train a reward model

Secondly, a prompt and several model outputs are sampled. A labeler ranks the outputs from best to worst. This data is used to train the reward model.

(iii) Optimize a policy against the reward model using reinforcement learning

Lastly, a new prompt is sampled from the dataset. The policy generates an output. The reward model calculates a reward for the output. The reward is used to update the policy using proximal policy optimization (PPO) algorithm [97,98].

4) Key Features of ChatGPT

ChatGPT's key features make it an advanced and versatile natural language processing model suitable for a broad range of applications [99]. Its contextual understanding, language generation capabilities, task

Table 1
Comparison of GPTs.

Version	Uses	Architecture	Parameter count	Year
GPT-1	General	12-level, 12-headed Transformer decoder (no encoder), followed by linear-softmax with Book Corpus: 4.5 GB of text	117 million	2018
GPT-2	General	GPT-1, but with modified normalization with Web Text: 40 GB of text	1.5 billion	2019
GPT-3	General	GPT-2, but with modification to allow larger scaling with570 GB plaintext	175 billion	2020
InstructGPT	Conversation	GPT-3 fine-tuned to follow instructions using human feedback model	175 billion	2022
ProtGPT2	Protein Sequences	As GPT-2 large (36 layers) with Protein sequences from UniRef50 of total 44.88 million	738 million	2022
BioGPT	Biomedical Content	As GPT-2 medium (24 layers, 16 heads) with non-empty items fromPubMedtotal 1.5 million	347 million	2022
ChatGPT	Dialogue	UsesGPT-3.5, and fine-tuned with both supervised learning and reinforcement learning from human feedback (RLHF)	175 billion	2022
GPT-4	General	Trained with both text prediction and RLHF and accepts both text and images as input, third party data	100 trillion	2023

Table 2
Comparison of GPT and ChatGPT.

Parameters	GPT	ChatGPT
Basis	An AI model which is accessible through an API for providing on-demand intelligence	A Chatbot that can interact with users and applications and perform tasks
Application	(a) Make smart applications (b) Implement semantic text understanding (c) Information search and extraction (d) Building copilot like applications (e) Used for extensive varieties of application developments	(a) Productive applications (b) Ideation for content creation (c) Answers general questions (d) Provides assistance in code generation (e) Code debugging provisioning (f) Translation of languages (g) Language augmentation for higher reasoning, speed and conciseness

adaptability, multilingual proficiency, scalability, zero-shot and few-shot learning, and fine-tuning potential contribute to its success in revolutionizing human-machine interactions as follows.

(a) Contextual Understanding

One of the most significant advancements in ChatGPT is its ability to understand context in text-based conversations. By comprehending the meaning of sentences and phrases, ChatGPT can generate relevant and coherent responses, making its interactions with users more natural and engaging [100].

(b) Language Generation Capabilities

ChatGPT has exceptional language generation capabilities, producing text that is coherent, contextually accurate, and grammatically correct. Its fluency in text generation allows it to be used for various applications, such as content writing, summarization, and rewriting [101].

(c) Task Adaptability

ChatGPT can be adapted to a wide range of tasks, making it versatile across industries and domains. With fine-tuning, it can be customized for

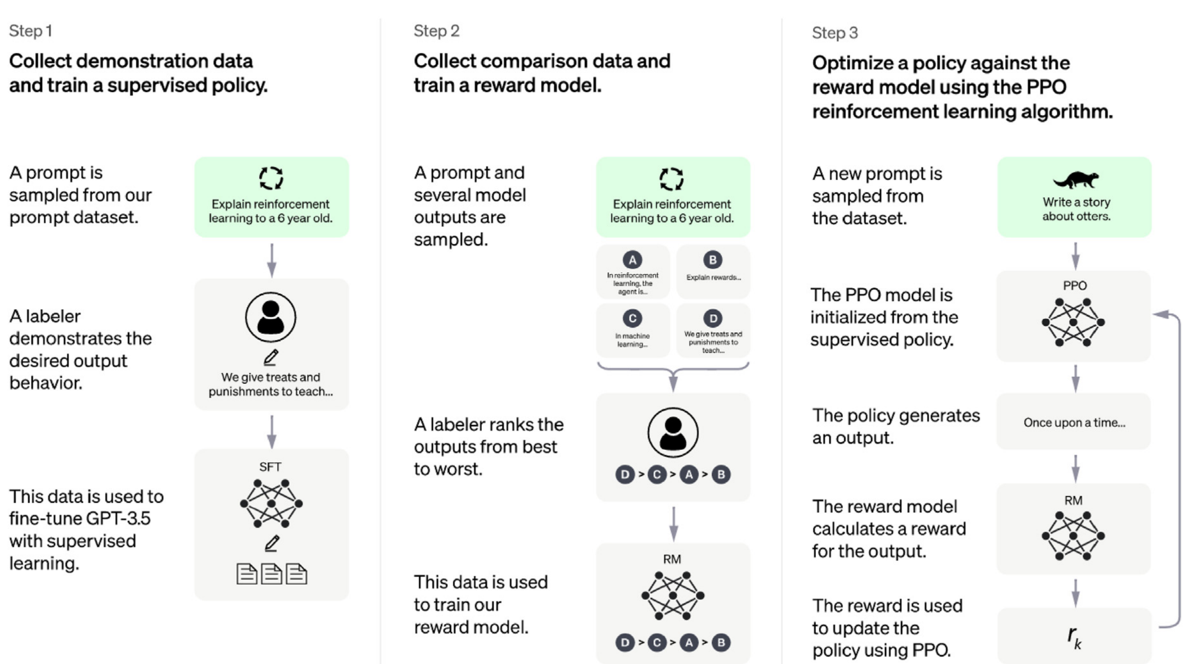

Fig. 3. GPT-3.5 model workflow.

specific use cases such as customer support, content creation, tutoring, translation, and more. This adaptability allows developers to harness ChatGPT's capabilities to create tailored solutions for their needs [102].

(d) Multilingual Proficiency

ChatGPT is proficient in multiple languages, enabling it to be used in global applications and cater to diverse user bases. Its multilingual capabilities are essential for applications such as translation, sentiment analysis, and multilingual content generation [103].

(e) Scalability

The architecture of ChatGPT allows it to be scaled according to the available computational resources and desired response times. This scalability ensures that it can be used in applications with varying requirements, from small-scale projects to large-scale enterprise solutions [104].

(f) Zero-Shot and Few-Shot Learning

ChatGPT can perform zero-shot and few-shot learning, enabling it to understand new tasks without extensive training. In zero-shot learning, the model can generate responses for tasks it has never seen before, while in few-shot learning, it can learn new tasks with just a few examples. This ability reduces the need for large labeled datasets and extensive fine-tuning, saving time and resources in the development process [105].

(g) Fine-Tuning

Fine-tuning is a crucial feature of ChatGPT, allowing developers to adapt the model to specific tasks or domains. By training the model on a smaller dataset tailored to the target application, ChatGPT can generate more accurate and relevant responses. Fine-tuning enables developers to create highly customized solutions using ChatGPT as the foundation [106].

5) Prompt Engineering for ChatGPT

Prompt engineering plays a significant role in enhancing the user experience and ensuring effective communication when interacting with AI models like ChatGPT. By employing prompt engineering techniques, users can guide the AI model to generate more accurate, relevant, and useful responses [107]. This section will outline how prompt engineering can be used in ChatGPT conversations to optimize the interaction.

(a) Start with clear and specific prompts

To obtain the desired response, make sure your prompts are explicit and unambiguous. Ambiguous prompts may lead to unsatisfactory or irrelevant responses.
Example.

- Less effective: "What's a popular programming language?"
- More effective: "What are the top three most popular programming languages in 2023?"

(b) Provide context and background information

Offer context or background information when necessary to help ChatGPT understand the subject matter and generate informed responses [108].
Example.

- Less effective: "What was her contribution to science?"
- More effective: "What was Marie Curie's contribution to science?"

(c) Specify desired format and structure

Guide ChatGPT towards a specific response format or structure to ensure the output meets your expectations.
Example.

- Less effective: "Give me some productivity tips."
- More effective: "Provide five productivity tips in a numbered list."

(d) Apply constraints and limitations

Set boundaries on the response, such as character limits, timeframes, or scope, to maintain focus and conciseness [109].
Example.

- Less effective: "Tell me about AI history."
- More effective: "Summarize the history of AI in three key milestones."

(e) Iterative prompting

If the initial response doesn't meet your expectations, refine the prompt or break it down into smaller sub-questions to guide ChatGPT towards the desired information.
Example.

- Initial prompt: "What are the health benefits of exercise?"
- Revised prompts: a. "How does regular exercise improve cardiovascular health?" b. "What are the mental health benefits of exercise?" c. "How does exercise contribute to weight management?"

By incorporating these prompt engineering techniques into your ChatGPT conversations, you can significantly improve the quality and relevance of the AI-generated responses. As you gain experience in crafting effective prompts, you'll be better equipped to leverage ChatGPT's capabilities to meet your specific needs.

3. Related large language models and tools

There are several alternatives to ChatGPT in the realm of AI language models and natural language processing tools. Some of these alternatives include.

1) GPT-2 and GPT-3

Developed by OpenAI, GPT-2 and GPT-3 are predecessors to ChatGPT. Both models are capable of performing a wide range of NLP tasks, including text generation, summarization, and translation. These models are built upon the transformer architecture, which has been highly successful in various NLP tasks. Both GPT-2 and GPT-3 are known for their ability to generate high-quality, human-like text based on given input prompts.

3.1. GPT-2

Released in 2019, GPT-2 is the second iteration of the GPT series and marked a significant improvement over its predecessor, GPT. GPT-2 is pretrained on a large dataset called WebText, which contains over 40 GB of web pages filtered from outbound links on Reddit. The model is capable of various NLP tasks, such as machine translation, summarization, text completion, and question-answering, without task-specific fine-tuning. Despite its impressive performance, GPT-2 faced criticism for generating text that may not always be accurate, relevant, or coherent. OpenAI initially withheld the release of the full GPT-2 model due to concerns about potential misuse, such as generating fake news or malicious content. Later, the complete model was released alongside research on its societal impact [110].

(a) Pros:

(i) High-quality text generation: GPT-2 is known for its ability to generate high-quality human-like text, which has a wide range of applications, including chatbots and content creation.
(ii) Pre-trained models: GPT-2 comes with pre-trained models that can be used for a variety of natural language processing tasks without the need for additional training.
(iii) Large-scale architecture: GPT-2's architecture is designed to handle large amounts of data, which makes it suitable for applications that require processing of large datasets.
(iv) Flexibility: GPT-2 can be fine-tuned for a variety of natural language processing tasks, including language translation, text summarization, and question answering.

(b) Cons:

(i) Controversial text generation capabilities: GPT-2 has been criticized for its ability to generate fake news and misleading information, which has raised concerns about its potential misuse.
(ii) Large computational requirements: GPT-2's large model size and complex architecture require significant computational resources, making it difficult to deploy on devices with limited computational resources.
(iii) Limited interpretability: GPT-2's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(iv) Language-specific: Like other transformer-based models, GPT-2 is primarily trained on English language data and may not perform as well on other languages without additional training or modifications.

3.2. GPT-3

Launched in 2020, GPT-3 is the third and most advanced version of the GPT series, featuring several enhancements over GPT-2. GPT-3 is pretrained on a massive dataset called the WebText2, which contains hundreds of gigabytes of text from diverse sources, including web pages, books, and articles [111]. The model is significantly larger than GPT-2, with 175 billion parameters, making it one of the largest AI language models available. GPT-3 excels at various NLP tasks, such as text generation, summarization, translation, and code generation, often with minimal or no fine-tuning. The model's size and complexity allow it to generate more coherent, context-aware, and human-like text compared to GPT-2. GPT-3 is available through the OpenAI API, enabling developers and researchers to access the model for their applications [112].

Here are some of the pros and cons of GTP-3.

(c) Pros:

(i) Wide range of natural language processing tasks: GPT-3 can be used for a wide range of natural language processing tasks, including language translation, text summarization, and question answering.
(ii) High-quality text generation: GPT-3 is known for its ability to generate high-quality human-like text, which has a wide range of applications, including chatbots and content creation.
(iii) Large-scale architecture: GPT-3's architecture is designed to handle large amounts of data, which makes it suitable for applications that require processing of large datasets.
(iv) Zero-shot learning capabilities: GPT-3 has the ability to perform some tasks without explicit training, which can save time and resources.

(d) Cons:

(i) Large computational requirements: GPT-3's large model size and complex architecture require significant computational resources, making it difficult to deploy on devices with limited computational resources.
(ii) Limited interpretability: GPT-3's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(iii) Language-specific: Like other transformer-based models, GPT-3 is primarily trained on English language data and may not perform as well on other languages without additional training or modifications.
(iv) Ethical concerns: GPT-3's capabilities raise ethical concerns about its potential misuse and the need for responsible deployment.

Both GPT-2 and GPT-3 have demonstrated remarkable capabilities in generating high-quality text and performing a wide range of NLP tasks. However, these models also share some limitations, such as being resource-intensive for training and fine-tuning, having difficulty with longer-term context understanding, and potentially inheriting biases from the training data. Despite these challenges, GPT-2 and GPT-3 have significantly influenced the field of NLP and inspired the development of many other transformer-based language models.

2) Bing Chat

Microsoft has integrated AI into its Edge browser and Bing search engine, utilizing the same cutting-edge technology that OpenAI employed to develop ChatGPT [113,114]. This feature is also accessible in mobile applications, allowing users to interact with AI via voice commands. Bing Chat operates similarly to ChatGPT, enabling users to ask any question and receive a response in natural human language from the large language model (LLM) [115]. Gradually, Microsoft has been introducing Bing Chat capabilities, with most features now available for use.

Notably, the Edge Copilot functionality enhances the Bing Chat experience by offering more suggestions and refinements [116]. The chat tab emphasizes conversational language and presents numerous prompts for potential questions. This includes links for further information, recommended follow-up queries, and operates more like a conventional search engine. Besides chat, the sidebar also features Compose and Insights tabs. The Compose tab enables users to produce text in various tones and formats, with options to choose from five distinct tones, formats, and lengths, expanding the range of Bing Chat outputs.

For instance, users can create a formal email or a brief, humorous blog post. If unsatisfied with the result, users can swiftly generate a new one. The Insights tab extracts context from the user's current website, such as product reviews, comparisons, and news stories when shopping, or presenting alternatives when browsing a review. Bing Chat is pretrained on a large corpus of text data from the internet and can be fine-tuned for specific applications, such as customer support, virtual assistance, and more.

While information about Bing Chat's specific features and architecture is limited, it is likely to include capabilities similar to other transformer-based language models, such as [117].

- Text Generation: Bing Chat can generate coherent, context-aware, and human-like responses to user input.
- Context Understanding: The model can understand and process context from user input to provide relevant and accurate responses.
- Multitasking: Bing Chat can handle a variety of NLP tasks, such as question answering, text summarization, and sentiment analysis.
- Multi-domain Conversations: The model can engage users in conversations across a wide range of topics, leveraging its diverse training data.

As a transformer-based language model, Bing Chat shares some limitations with other large-scale models, such as being resource-intensive for training and fine-tuning, and potentially inheriting biases from its training data. However, it demonstrates Microsoft's commitment to advancing AI chatbot technology and natural language understanding.

(a) Pros:

(i) Enhanced user experience: Bing Chat enables more interactive and conversational searches, providing users with a more engaging way to obtain information.
(ii) Context-aware assistance: The Insights feature offers context-based support, pulling relevant information from the website you're visiting, including product reviews, comparisons, and news stories.
(iii) Versatile text generation: The Compose tab allows users to generate text in various tones and formats, making it a helpful tool for tasks like writing emails or creating content.
(iv) Conversational language: Bing Chat focuses on natural human language, which can make searching and obtaining information more intuitive.
(v) Voice interaction: Its availability in mobile apps enables users to interact with AI through voice commands, providing a hands-free experience.

(b) Cons:

(i) Limited availability: As Bing Chat is a Microsoft product, it may not be available on all platforms or for users of other search engines and browsers.
(ii) Privacy concerns: The integration of AI in browsing and searching may raise privacy concerns for some users, as their interactions with the platform could be tracked or monitored.
(iii) Reliability: As with any AI-based system, Bing Chat may occasionally provide inaccurate or irrelevant information, leading to potential confusion or misinformation.
(iv) Adaptation period: Users who are used to traditional search engines may need time to adjust to Bing Chat's conversational approach and explore its full range of features.
(v) Potential dependency: Overreliance on AI-generated content may hinder the development of users' own writing and critical thinking skills.

3) Bidirectional Encoder Representations from Transformers (BERT)

Developed by Google, BERT is a powerful language model designed for tasks like text classification, sentiment analysis, and question-answering. BERT's bidirectional training approach allows it to learn the context of words from both directions, making it highly effective in understanding the nuances of natural language [118–120]. It is based on the transformer architecture and has been highly influential in the natural language processing (NLP) domain due to its exceptional performance on a wide range of tasks [121–124].

3.3. Some key features and aspects of BERT include

- Bidirectional Context: Unlike traditional language models that process text either left-to-right or right-to-left, BERT is designed to capture context from both directions simultaneously. This allows the model to better understand the meaning and relationships between words in a sentence.
- Pretraining Tasks: BERT is pretrained on two unsupervised tasks: Masked Language Modeling (MLM) and Next Sentence Prediction (NSP). In MLM, random words in a sentence are replaced with a special [MASK] token, and the model is trained to predict the original words. In NSP, BERT learns to predict whether a pair of sentences are connected in a logical sequence.
- Fine-tuning for Specific Tasks: BERT can be fine-tuned with a small amount of labeled data to perform various supervised NLP tasks, such as text classification, sentiment analysis, named entity recognition (NER), question answering, and more.
- Pretrained Models: BERT provides several pretrained models of different sizes and language support. These models can be fine-tuned according to specific requirements, significantly reducing the time and resources needed for training from scratch.
- State-of-the-art Performance: BERT has achieved top performance on numerous NLP benchmarks, such as General Language Understanding Evaluation GLUE) [125], Stanford Question Answering Dataset (SQuAD) [126], and others, outperforming previous models and setting new records.
- Multilingual Support: BERT is available in a multilingual version called mBERT [127], which has been pretrained on text from 104 languages, making it suitable for cross-lingual NLP tasks.

BERT's bidirectional context understanding and pretrained models have revolutionized the field of NLP and paved the way for a new generation of transformer-based models, such as RoBERTa, GPT-3, and ALBERT [128]. Despite its remarkable performance, BERT has some limitations, such as being computationally intensive for training and fine-tuning, as well as potentially inheriting biases from its training data. Nevertheless, BERT remains an influential and widely-used model in the NLP domain.

Here are some of the pros and cons of BERT.

(a) Pros:

(ii) Better language representation: BERT has the ability to capture the context of a word in a sentence by using bidirectional training. This allows it to better understand the relationship between different words in a sentence and produce more accurate results.
(iii) Pre-trained models: BERT has pre-trained models that can be used to perform a variety of natural language processing tasks without the need for additional training.
(iv) Wide range of applications: BERT can be used for a wide range of natural language processing tasks such as sentiment analysis, named entity recognition, and question answering.
(v) High accuracy: BERT has achieved state-of-the-art performance on many natural language processing tasks, which has made it a popular choice for researchers and practitioners.

(b) Cons:

(i) Large model size: BERT is a large model with hundreds of millions of parameters, which makes it difficult to deploy on devices with limited computational resources.
(ii) Long training time: Training a BERT model can take several days or even weeks, which can be a bottleneck for researchers and practitioners.
(iii) Limited interpretability: BERT's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(iv) Language-specific: BERT is trained on English language data and may not perform as well on other languages without additional training or modifications.

4) Text-to-Text Transfer Transformer (T5)

Another language model from Google, T5 is designed to handle a wide range of NLP tasks, including summarization, translation, and text classification. T5 is trained using a text-to-text approach, which simplifies the task-specific fine-tuning process and allows for improved performance across various applications [129]. The primary innovation of T5 is its unified approach to NLP tasks, which treats them all as text-to-text problems [130].

This text-to-text framework allows T5 to be pretrained on a large text corpus and then fine-tuned for specific tasks by converting them into a common format. For example, tasks like translation, summarization, sentiment analysis, and question-answering can all be framed as input-output text pairs [131]. By doing so, T5 simplifies the process of fine-tuning the model for various tasks and promotes transfer learning, where knowledge gained from one task can be applied to others [132].

Some key features of T5 are.

- Unified Text-to-Text Framework: T5 casts all NLP tasks as text-to-text problems, simplifying the fine-tuning process and promoting transfer learning across tasks.
- Denoising Autoencoder Objective: During pretraining, T5 uses a denoising autoencoder objective, where it learns to reconstruct corrupted input text by predicting masked tokens. This is similar to BERT's masked language model (MLM) objective but with a more flexible text-to-text setting.
- C4 Corpus: T5 is pretrained on a large-scale dataset called Colossal Clean Crawled Corpus (C4), which is a cleaned and deduplicated version of the Common Crawl dataset. This large-scale pretraining helps T5 learn general language understanding capabilities.
- Scalability: T5 is available in various sizes, ranging from small models (T5-Small) with tens of millions of parameters to larger models (T5-3B) with billions of parameters. This allows users to choose the most suitable model size based on their computational resources and the complexity of the task.
- T5 has demonstrated strong performance on a wide range of NLP benchmarks, including GLUE, SuperGLUE [133,134], SQuAD, and others.
- We can access and use T5 through the Hugging Face Transformers library, which provides an easy-to-use interface for fine-tuning and deploying the model for various NLP tasks. The library also offers tools for training custom models and converting models between different deep learning frameworks like TensorFlow and PyTorch [135].

Here are some of the pros and cons of T5.

(a) Pros:

(i) Flexible architecture: T5's architecture is highly flexible and can be fine-tuned for a wide range of natural language processing tasks, including language translation, text summarization, and question answering.
(ii) High accuracy: T5 has achieved state-of-the-art performance on many natural language processing tasks, making it a popular choice for researchers and practitioners.
(iii) Large pre-trained models: T5 comes with pre-trained models that can be fine-tuned for specific tasks, reducing the need for extensive training and data collection.
(iv) Generalizable: T5's architecture is designed to be highly generalizable, allowing it to perform well on a wide range of natural language processing tasks without the need for task-specific training.

(b) Cons:

(i) Computational requirements: T5's large model size and complex architecture require significant computational resources, making it difficult to deploy on devices with limited computational resources.
(ii) Limited interpretability: T5's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(iii) Requires large amounts of data: Fine-tuning T5 for specific tasks requires large amounts of high-quality data, which can be difficult and expensive to obtain.
(iv) Limited multilingual support: T5 is primarily trained on English language data and may not perform as well on other languages without additional training or modifications.

5) XLNet

XLNet is an autoregressive language model that combines the strengths of both Transformer-XL and BERT [136]. It is capable of handling tasks such as text generation, sentiment analysis, and question-answering, and its training methodology enables it to capture long-range dependencies within text effectively. XLNet is a transformer-based language model developed by researchers at Carnegie Mellon University and the University of Washington. It is designed to address some of the limitations of other transformer models like BERT. XLNet was designed to address some of the limitations of earlier models like BERT and GPT [137].

The main innovation in XLNet is its training objective, which combines the strengths of both auto-regressive (AR) and auto-encoding (AE) language modeling approaches. Auto-regressive models, like GPT, predict the next token in a sequence based on the context of previous tokens, while auto-encoding models, like BERT, predict masked tokens in a given sequence by considering both left and right contexts.

XLNet employs a permutation-based training approach, where it learns to predict a token based on a random permutation of the input sequence. By doing so, XLNet captures bidirectional context like BERT while maintaining the auto-regressive nature of the model like GPT. This approach, called the Permutation Language Model (PLM) [138], allows XLNet to learn meaningful bidirectional context while avoiding some of the issues associated with BERT's masked language model (MLM) [139] objective, such as the pretrain-finetune discrepancy.

Some key features of XLNet are.

- Permutation Language Model (PLM): XLNet uses a permutation-based training approach to capture bidirectional context while maintaining the auto-regressive nature of the model.
- Segment Recurrence Mechanism: To model long-range dependencies, XLNet employs a segment recurrence mechanism, allowing it to process longer texts by preserving hidden states across segments.
- Two-Stream Self-Attention: XLNet uses a two-stream self-attention mechanism to maintain separate hidden states for content and position, which helps in addressing the pretrain-finetune discrepancy issue.

We can access and use XLNet through the Hugging Face Transformers library, which provides an easy-to-use interface for fine-tuning and deploying the model for various NLP tasks.

Here are some of the pros and cons of XLNet.

(a) Pros:

(i) Better modeling of dependencies: XLNet uses a permutation-based training approach that allows it to model dependencies between all tokens in a sequence, unlike previous transformer models that only model dependencies in one direction.

(ii) High accuracy: XLNet has achieved state-of-the-art performance on many natural languages processing tasks, making it a popular choice for researchers and practitioners.
(iii) Generalizable: XLNet's architecture is designed to be highly generalizable, allowing it to perform well on a wide range of natural language processing tasks without the need for task-specific training.
(iv) Multilingual support: XLNet has been shown to perform well on a wide range of languages, making it a good choice for multilingual applications.

(b) Cons:

(i) Large computational requirements: XLNet's large model size and complex architecture require significant computational resources, making it difficult to deploy on devices with limited computational resources.
(ii) Limited interpretability: XLNet's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(iii) Requires large amounts of data: Training XLNet requires large amounts of high-quality data, which can be difficult and expensive to obtain.
(iv) Longer training times: XLNet's permutation-based training approach requires longer training times compared to other transformer models like BERT.

6) Robustly Optimized BERT Pretraining Approach (RoBERTa)

RoBERTa is a variant of BERT developed by Facebook AI, featuring several improvements to the pretraining process. These improvements include larger batch sizes, longer training times, and optimized hyperparameters, resulting in a more accurate and robust language model [140]. It is an enhanced version of Google's BERT model [141], which has been highly successful in various NLP tasks, such as text classification, sentiment analysis, and question answering.

RoBERTa builds on BERT's architecture by introducing a series of optimizations and training improvements that result in better performance and higher accuracy across a range of NLP benchmarks.

Some of the key modifications in RoBERTa include.

- Training on larger batches: RoBERTa uses larger batch sizes during pretraining, which helps improve model stability and allows it to learn more effectively from the training data.
- Removing the next sentence prediction (NSP) [142] task: In contrast to BERT, which employs the NSP task during pretraining, RoBERTa removes this task and focuses solely on masked language modeling (MLM). This simplification results in better performance on downstream tasks.
- Using longer sequences: RoBERTa is trained on longer sequences of text, allowing it to learn more contextual information and better capture long-range dependencies.
- Training on more data: RoBERTa is pretrained on a larger dataset compared to BERT, which includes the BooksCorpus and English Wikipedia, among other sources.
- Optimized training hyperparameters: RoBERTa fine-tunes various hyperparameters, such as learning rate, warm-up steps, and training steps, resulting in a more robust and accurate model.

These optimizations have enabled RoBERTa to outperform BERT and other state-of-the-art language models on several NLP benchmarks and tasks, such as the GLUE benchmark, SQuAD, and Reading Comprehension Dataset (RACE) [143].

RoBERTa is suitable for a wide range of NLP applications, including.

- Text classification: RoBERTa can be fine-tuned to classify text based on categories, such as sentiment, topic, or intent.
- Named Entity Recognition (NER) [144]: RoBERTa can be used to identify and categorize named entities in text, such as people, organizations, and locations.
- Question answering: RoBERTa can be fine-tuned to answer questions based on a given context or passage.
- Text summarization: RoBERTa can be adapted to generate abstractive or extractive summaries of longer text.
- Machine translation: While not specifically designed for translation, RoBERTa can be adapted for translation tasks, especially when combined with other models or techniques.

As a transformer-based language model, RoBERTa shares some limitations with other large-scale models, such as being resource-intensive for training and fine-tuning, as well as potentially inheriting biases from the training data. However, its robust performance and high accuracy make it a popular choice for various NLP tasks and applications.

Here are some of the pros and cons of RoBERTa.

(a) Pros:

(i) High accuracy: RoBERTa has achieved state-of-the-art performance on many natural languages processing tasks, making it a popular choice for researchers and practitioners.
(ii) Robust pre-training: RoBERTa's pre-training process is designed to be more robust to noise and variance in the training data, which helps improve its performance on downstream tasks.
(iii) Flexible architecture: RoBERTa's architecture is highly flexible and can be fine-tuned for a wide range of natural language processing tasks, including language translation, text summarization, and question answering.
(iv) Large pre-trained models: RoBERTa comes with pre-trained models that can be fine-tuned for specific tasks, reducing the need for extensive training and data collection.

(b) Cons:

(a) Large computational requirements: RoBERTa's large model size and complex architecture require significant computational resources, making it difficult to deploy on devices with limited computational resources.
(b) Limited interpretability: RoBERTa's complex architecture makes it difficult to interpret its internal workings, which can be a challenge for researchers and practitioners who want to understand how it makes its predictions.
(c) Requires large amounts of data: Fine-tuning RoBERTa for specific tasks requires large amounts of high-quality data, which can be difficult and expensive to obtain.
(d) Language-specific: Like other transformer-based models, RoBERTa is primarily trained on English language data and may not perform as well on other languages without additional training or modifications.

7) Transformer-based models from Hugging Face

Hugging Face is a company that provides a wide range of pre-trained Transformer-based models, including BERT, GPT-2, RoBERTa, and T5. Their library, called the Transformers library, simplifies the process of fine-tuning these models for custom tasks and applications [145,146].

- They have built a platform that offers a range of pre-trained transformer-based models, which are highly efficient in handling various NLP tasks.
- Transformers are a type of deep learning model introduced in Ref. [147]. They are based on the self-attention mechanism, which

allows the model to weigh the importance of different words in a sentence when making predictions. Transformers have since become the foundation for many NLP models, outperforming previous approaches in various tasks such as translation, summarization, and sentiment analysis.

Hugging Face is widely recognized for their Transformers library, an open-source library that provides an easy-to-use interface to access and use pre-trained transformer models.

Some popular transformer-based models from Hugging Face include [148–151].

- BERT: Introduced by Google AI, BERT is a pre-trained model designed for a variety of NLP tasks. It is based on the transformer architecture and uses bidirectional training to capture contextual information from both left and right contexts.
- GPT: Developed by OpenAI, GPT is another transformer-based model focused on language generation. It is a unidirectional model, trained to predict the next token in a sequence using a left-to-right context.
- RoBERTa: RoBERTa is an optimized version of BERT, introduced by Facebook AI. It improves upon BERT's training methodology by using larger batch sizes, more training data, and dynamic masking.
- DistilBERT: A lighter version of BERT, DistilBERT [152] is a smaller, faster, and more efficient model that retains most of BERT's performance while being computationally less expensive.
- T5: Developed by Google Research, T5 is a model that casts all NLP tasks as text-to-text problems. It's pre-trained on a large corpus of text and can be fine-tuned for a variety of specific tasks.
- Efficiently Learning an Encoder that Classifies Token Replacements Accurately (ELECTRA) [153]: Another model from Google Research, ELECTRA is a pre-trained transformer that uses a unique training approach called "replaced token detection," which improves computational efficiency and model performance.

These models and many others can be easily accessed, fine-tuned, and deployed using the Hugging Face Transformers library, which supports multiple programming languages, including Python, JavaScript, and more. The library also offers tools for training custom models and converting models between different deep learning frameworks like TensorFlow and PyTorch.

Here are some of the pros and cons of their transformer-based models.

(a) Pros:

(i) High accuracy: Hugging Face's transformer-based models have achieved state-of-the-art performance on many natural languages processing tasks, making them a popular choice for researchers and practitioners.
(ii) Pre-trained models: Hugging Face's models come with pre-trained models that can be used for a variety of natural language processing tasks without the need for additional training.
(iii) Large range of models: Hugging Face offers a wide range of transformer-based models that can be fine-tuned for specific tasks, allowing users to choose the model that best fits their needs.
(iv) Open-source and community-driven: Hugging Face's models are open-source and community-driven, which allows for rapid development and improvement.

(b) Cons:

(i) Large computational requirements: Hugging Face's transformer-based models have large model sizes and complex architectures, which require significant computational resources to train and deploy.
(ii) Limited interpretability: Hugging Face's models have complex architectures that make it difficult to interpret their internal workings, which can be a challenge for researchers and practitioners who want to understand how they make their predictions.
(iii) Requires large amounts of data: Fine-tuning Hugging Face's models for specific tasks requires large amounts of high-quality data, which can be difficult and expensive to obtain.
(iv) Language-specific: Like other transformer-based models, Hugging Face's models are primarily trained on English language data and may not perform as well on other languages without additional training or modifications.

8) SpaCy

SpaCy is an open-source library for NLP tasks that provides support for tasks like tokenization, part-of-speech tagging, named entity recognition, and text classification [154]. It was developed with a focus on performance, efficiency, and ease of use, making it suitable for both research and industrial applications [155]. SpaCy is particularly popular among developers and data scientists who need to process and analyze large volumes of text quickly and accurately.

Some of the key features and functionalities of SpaCy include [156].

- Tokenization: SpaCy can efficiently break down text into individual words, sentences, and other linguistic units, which is often the first step in NLP tasks.
- Part-of-speech (POS) tagging: SpaCy can assign grammatical categories (e.g., noun, verb, adjective) to words in a given text using pre-trained statistical models.
- Named Entity Recognition (NER): SpaCy is equipped to identify and categorize named entities, such as people, organizations, and locations, in a text using pre-trained models.
- Dependency parsing: SpaCy provides tools for parsing and analyzing the syntactic structure of sentences, allowing users to extract meaningful relationships between words and phrases.
- Lemmatization: SpaCy can reduce words to their base or root forms (lemmas), which is helpful for text analysis and comparison.
- Text classification: SpaCy supports building and training custom classifiers for tasks like sentiment analysis, document categorization, and more.
- Word vectors and similarity: SpaCy can work with pre-trained word embeddings (e.g., Word2Vec, GloVe [157]) to compute semantic similarity between words, phrases, or documents.
- Customizable pipeline: SpaCy allows users to create custom processing pipelines by adding or modifying components as needed, enabling fine-grained control over the NLP workflow.
- Language model support: SpaCy supports integration with transformer-based language models like BERT, GPT, and others through the "spacy-transformers" extension, enabling users to leverage state-of-the-art models for their NLP tasks.
- Multi-language support: SpaCy provides pre-trained models and resources for various languages, making it suitable for multilingual NLP applications.

SpaCy's efficient design, flexibility, and ability to scale make it a popular choice for developers and data scientists working on NLP tasks that demand high performance and accuracy. Its compatibility with modern NLP frameworks, such as Hugging Face Transformers, further expands its utility in the rapidly evolving field of natural language processing. While it does not offer the same level of language generation capabilities as ChatGPT, it is a powerful tool for text processing and analysis.

Here are some of the pros and cons of using SpaCy.

- Pros:

(i) High performance: SpaCy is known for its speed and efficiency, making it suitable for processing large amounts of text data.

(ii) Wide range of natural language processing tasks: SpaCy can perform a wide range of natural language processing tasks, including named entity recognition, part-of-speech tagging, and dependency parsing.
(iii) Easy-to-use: SpaCy's user-friendly interface and comprehensive documentation make it easy to use, even for users with limited programming experience.
(iv) Open-source and community-driven: SpaCy is an open-source software library with a large and active community of developers and users, which allows for rapid development and improvement.

- Cons:

(i) Limited pre-trained models: Unlike other natural language processing libraries like NLTK, SpaCy has a limited number of pre-trained models, which may require additional training to perform well on specific tasks.
(ii) Limited multilingual support: SpaCy's pre-trained models are primarily designed for English language data and may not perform as well on other languages without additional training or modifications.
(iii) Limited interpretability: SpaCy's models are based on statistical and machine learning algorithms, which can make it difficult to interpret their internal workings.
(iv) Limited text preprocessing capabilities: SpaCy's text preprocessing capabilities are limited compared to other natural language processing libraries, which may require additional preprocessing steps to clean and prepare text data.

9) Bidirectional and Auto-Regressive Dynamics for Knowledge-Intensive Language Modeling (BARD) AI

It is s an AI language model developed by Facebook AI Research (FAIR) [158]. It is designed to improve on existing transformer-based language models like BERT and GPT by incorporating both auto-regressive and bidirectional dynamics. BARD AI aims to address the limitations of existing models in knowledge-intensive tasks, such as question-answering and information retrieval.

The BARD AI model combines two key components.

- Bidirectional Encoder: This component processes the input text in both directions (left-to-right and right-to-left) to capture contextual information from the entire input sequence. This bidirectional encoding is similar to the mechanism used in BERT, which allows the model to better understand the context in which words and phrases appear.
- Auto-Regressive Decoder: The auto-regressive decoder generates text one token at a time based on the encoded input and previously generated tokens. This component is similar to the mechanism used in GPT, which enables the model to produce coherent and context-aware text.

Some pros and cons are presented below.

(a) Pros:

(i) Improved Knowledge-Intensive Task Performance: By combining bidirectional encoding and auto-regressive decoding, BARD AI offers better performance in knowledge-intensive tasks, such as question-answering and information retrieval, when compared to models that only use one of these mechanisms.
(ii) Contextual Understanding: BARD AI leverages the strengths of both BERT and GPT, enabling it to capture context from input sequences more effectively. This improved contextual understanding results in more accurate and coherent text generation.
(iii) Versatility: By integrating the strengths of bidirectional encoders and auto-regressive decoders, BARD AI can be applied to a wide range of natural language processing tasks, such as text summarization, translation, and sentiment analysis, making it a versatile solution for various applications.
(iv) Innovative Approach: BARD AI represents a significant advancement in AI language modeling, as it combines the best of both worlds from existing transformer-based models. This innovative approach has the potential to drive further advancements in natural language processing and understanding.

(b) Cons:

(i) Resource Requirements: As with other advanced language models, BARD AI requires substantial computational resources for training and fine-tuning. This can be a limitation for smaller organizations or researchers with limited access to powerful hardware.
(ii) Complexity: Combining bidirectional encoding and auto-regressive decoding adds complexity to the model architecture. This complexity can make it more challenging to understand, fine-tune, and optimize the model for specific tasks or applications.
(iii) Potential for Bias: Like other AI language models, BARD AI may inherit biases present in its training data. Addressing these biases and ensuring fairness in the model's output remains an ongoing challenge for AI researchers and developers.
(iv) Scalability: While BARD AI offers improved performance in knowledge-intensive tasks, scaling the model to even larger sizes and handling more complex tasks may still present challenges. Further research and optimization are needed to address scalability concerns.

In summary, BARD AI presents a promising advancement in AI language modeling by combining bidirectional encoding and auto-regressive decoding. Despite some limitations, such as resource requirements and complexity, BARD AI has the potential to significantly impact a wide range of natural language processing applications and drive further innovation in the field.

10) Natural Language Toolkit (NLTK)

NLTK is an open-source Python library that provides tools for text processing and analysis, including tokenization, stemming, and sentiment analysis [159]. It was created with the primary goal of simplifying NLP tasks and promoting research and education in the field. NLTK provides a diverse range of tools and resources for processing, analyzing, and understanding text data [160].

Some of the key features and functionalities of NLTK include.

- Tokenization: NLTK enables users to break down text into individual words or sentences, which is often the first step in NLP tasks.
- Part-of-speech (POS) tagging [161]: NLTK can assign grammatical categories (e.g., noun, verb, adjective) to words in a given text.
- Named Entity Recognition: Using NLTK, you can identify and categorize named entities, such as people, organizations, and locations, in a text.
- Parsing: NLTK provides tools for parsing and analyzing the syntactic structure of sentences, which can be helpful in understanding the grammatical relationships between words.
- Stemming and Lemmatization: These processes involve reducing words to their base or root forms, which can be useful for text analysis and comparison. NLTK offers multiple stemming and lemmatization algorithms.
- Text classification: NLTK can be used to build and train classifiers for tasks such as sentiment analysis and document categorization.
- Language modeling: NLTK provides tools for creating and working with language models, such as n-grams and probabilistic models.

- Corpus access: NLTK includes a variety of built-in corpora (large collections of text), which can be used for tasks like training models and text analysis.
- Machine learning integration: NLTK can be easily integrated with other machine learning libraries, such as scikit-learn, for more advanced NLP tasks.

Although NLTK is not specifically designed for deep learning or state-of-the-art NLP tasks like some other modern NLP libraries (e.g., Hugging Face Transformers), it remains a popular choice for beginners and researchers due to its comprehensive toolset, ease of use, and strong community support. While it lacks the advanced language generation features of ChatGPT, it is widely used for NLP tasks and research purposes.

Here are some of the pros and cons of using NLTK.

(a) Pros:

(i) Comprehensive set of tools: NLTK provides a comprehensive set of tools for natural language processing tasks, including text classification, tokenization, stemming, and sentiment analysis.
(ii) Wide range of pre-trained models: NLTK comes with a wide range of pre-trained models for various natural language processing tasks, which can save time and resources for researchers and practitioners.
(iii) Large community: NLTK has a large and active community of developers and users, which allows for rapid development and improvement.
(iv) Open-source: NLTK is open-source software, which allows for easy access and modification of the library.

(b) Cons:

(i) Limited performance: NLTK's algorithms and models are known to be slower and less efficient than other natural language processing libraries like SpaCy and Transformers.
(ii) Limited machine learning capabilities: NLTK's machine learning capabilities are relatively limited compared to other libraries like Scikit-learn, which can make it more difficult to implement complex natural language processing models.
(iii) Limited multilingual support: NLTK's pre-trained models are primarily designed for English language data and may not perform as well on other languages without additional training or modifications.
(iv) Limited interpretability: NLTK's models are based on statistical and machine learning algorithms, which can make it difficult to interpret their internal workings.

While each of these alternatives has its strengths and weaknesses, they all contribute to the growing ecosystem of AI language models and NLP tools, providing researchers, developers, and businesses with a diverse range of options to suit their specific needs and applications.

11) Conditional Transformer Language Model (CTRL)

CTRL is an advanced AI language model developed by OpenAI [162]. It builds upon the transformer architecture, which has been highly successful in various NLP tasks, such as text generation, translation, and sentiment analysis. One of the key features that sets CTRL apart from other language models is its ability to condition the generated text on specific control codes. These control codes are essentially tokens that can guide the model to generate text that follows a particular topic, style, or format. This allows for greater control over the output, making it more suited for a wide range of applications and tasks.

CTRL is pretrained on a massive corpus of data, which helps it generate high-quality, coherent, and diverse text across various topics. The model is designed to be modular, supporting the integration of additional control tokens for better customization and control over the generated text.

Some potential use cases of CTRL include.

- Text completion: CTRL can be used to generate coherent text completions for partially written sentences or paragraphs.
- Story generation: By conditioning the model on specific topics or themes, CTRL can be employed to create stories or narratives in a desired style.
- Summarization: CTRL can be guided to generate concise summaries of longer texts by conditioning it on relevant control codes.
- Content generation: CTRL can be used for creating high-quality content for blogs, articles, or social media, tailored to specific themes, styles, or domains.

It has several advantages and disadvantages when compared to other AI language models. Here are some pros and cons of using CTRL.

(a) Pros:

(i) Fine-grained control: CTRL allows users to have better control over the generated text by conditioning it on specific keywords or phrases. This makes it possible to generate content that closely aligns with the desired style, topic, or domain.
(ii) Modularity: The model is designed to support the integration of additional tokens to control various aspects of text generation, making it adaptable for a wide range of applications and tasks.
(iii) Large-scale pretraining: CTRL is pretrained on a massive corpus of data, which enables it to generate high-quality and coherent text across various topics.
(iv) Diversity in text generation: CTRL can generate diverse and creative responses, making it suitable for applications like story generation, text completion, and more.
(v) Open-source availability: The CTRL model and its codebase are available as open-source, making it accessible to researchers, developers, and organizations for experimentation and implementation in various projects.

(b) Cons:

(i) Resource-intensive: Like other large-scale language models, CTRL requires significant computational resources for training and fine-tuning. This can be a challenge for users with limited hardware or budget.
(ii) Steeper learning curve: Working with CTRL may require a deeper understanding of transformer models and NLP concepts, making it more challenging for beginners to get started with the model.
(iii) Limited interpretability: Transformer models like CTRL are often considered "black boxes," meaning that it is difficult to understand how the model makes decisions and generates text. This may raise concerns related to transparency and accountability.
(iv) Biases in the model: CTRL, like other AI language models, may inherit biases from the data it was trained on, which could lead to generating potentially biased or harmful content.
(v) Difficulty in controlling content quality: Although CTRL allows for fine-grained control over the generated text, it may still produce outputs that are not entirely accurate, relevant, or coherent in some cases. Achieving the right balance between control and quality may require further experimentation and fine-tuning.

4. Summary on evaluation of LLM

LLMs are AI models that are trained on vast amounts of text data in order to learn how to understand and generate human language. These models use a combination of neural networks and machine learning algorithms to process language in a way that is similar to the way humans do. LLMs have revolutionized NLP by enabling computers to understand and generate human language more accurately and effectively than ever before.

LLMs are typically trained on massive amounts of text data, such as Wikipedia, news articles, books, and social media posts. This allows them to learn the patterns and relationships that exist within language and use this knowledge to generate responses, complete tasks, and even write coherent pieces of text. The training process for LLMs can take weeks or even months, and requires significant computing resources, including high-performance graphics processing units (GPUs) and large amounts of memory.

LLMs are used in a wide range of applications, including language translation, chatbots, text summarization, and sentiment analysis. They have also been used in fields such as finance, healthcare, and education to automate various language-related tasks and improve efficiency.

One of the key advantages of LLMs is their ability to perform a wide range of natural language processing tasks without the need for task-specific training. This is because they learn the patterns and relationships that exist within language more broadly, rather than being trained on specific tasks. This makes LLMs highly versatile and capable of performing a wide range of language-related tasks.

However, LLMs also have some limitations and challenges, such as biases and ethical concerns related to their use. Additionally, the sheer size and complexity of LLMs can make them difficult to interpret and analyze, which can limit their usefulness in some applications.

Despite these challenges, LLMs are an increasingly important area of research in artificial intelligence and have the potential to revolutionize the way we interact with and understand language. As LLMs continue to advance and improve, it is likely that they will play an even more prominent role in many different areas of our lives.

Over the years, LLMs have become larger and more powerful, with impressive natural language understanding and generation capabilities. They have also been used in a wide range of natural language processing tasks, from language translation to question-answering systems. However, as these models become more complex, they also raise ethical and societal concerns, such as biases and limitations, which must be carefully addressed. We present a list consisting many LLMs which are developed over the time. Table 3 presents the comparison of the LLMs. This list is exhaustive, however we couldn't include all but involved most discussed ones.

The large language models (LLMs) included in the comparison table represent the cutting-edge of natural language processing technology. These models have grown in size and complexity over the years, with newer models like GShard v6 and GPT-J surpassing their predecessors in terms of the number of parameters and overall performance on various benchmarks. LLMs have been used in a wide range of applications, from chatbots and language translation to finance and healthcare, and their versatility and power have enabled significant advancements in the field of natural language processing. However, LLMs also pose challenges related to biases and ethical concerns, and their sheer size and complexity can make them difficult to interpret and analyze. As LLMs continue to evolve and improve, it will be important to carefully consider the ethical implications of their use and to ensure that they are used in ways that benefit society as a whole.

Several LLMs are currently going through research and development phases in different organizations (and/or beta testing phase) for example, GPT-4, Cerebras-GPT, Google GShard, Microsoft Turing, and Amazon Wenjing. Many more LLMs and related tools are yet to be released in public domain in coming days. We couldn't find accuracy details for many LLMs that are included in this section.

ChatGPT has the potential to surpass all other LLMs through continued research, development, and optimization. ChatGPT is already one of the most advanced LLMs, with impressive performance on many different natural language processing benchmarks. However, to surpass all other LLMs, ChatGPT would need to continue to improve in areas such as model size, training data, and architecture, while also addressing challenges related to biases, ethical concerns, and limitations. One potential avenue for improving ChatGPT is through the use of more diverse and comprehensive training data, which could help to address biases and improve performance across a wider range of tasks. Another potential area of improvement is the development of more advanced neural network architectures that can process language more efficiently and accurately. Additionally, ongoing research in areas such as transfer learning and meta-learning could help to optimize ChatGPT and enable it to adapt to new tasks and environments more effectively.

Ultimately, the ability of ChatGPT to surpass all other LLMs will depend on continued innovation, research, and development in the field of natural language processing. As this technology continues to evolve and improve, it is likely that ChatGPT and other LLMs will become even more powerful and capable of processing and generating human language in new and exciting ways.

5. Smartness of ChatGPT

Smartness of ChatGPT is tested recently by various studies. A major study shows that GPT-3 would possess an IQ of 150, which places it in the 99.9th percentile. ChatGPT, on the other hand, has been tested to have a verbal-linguistic IQ of 147 (99.9th percentile) and achieved a similar result on the Raven's ability test. It's worth noting that GPT-3.5 has performed well on the US bar exam, CPA, and US medical licensing exam [163]. Table 4 presents the comparisons of achievements of ChatGPT [164].

6. Applications across various domains

ChatGPT's versatile nature and advanced natural language processing capabilities have made it a valuable tool across various domains beyond scientific research. This section explores the broad range of applications for ChatGPT, highlighting its potential to transform industries, enhance communication, and promote innovation.

(a) Healthcare and Medicine

In the healthcare and medicine domain, ChatGPT can be employed to: (i) assist medical professionals in diagnosing conditions by analyzing patient data, medical history, and symptoms Generate personalized treatment plans based on individual patient needs and preferences, (ii) summarize and synthesize medical research to inform evidence-based practice, (iii) provide medical information and advice to patients in an easily understandable format, (iv) facilitate collaboration between healthcare professionals by streamlining communication and information sharing.

Here are some of the potential applications of ChatGPT in healthcare and medicine.

(i) Chatbot for patient triage: ChatGPT can be used to develop chatbots that can assist with patient triage, helping healthcare providers determine the urgency of a patient's condition and the appropriate course of action [182].
(ii) Medical diagnosis and treatment recommendations: ChatGPT can be used to develop systems that can assist with medical diagnosis and treatment recommendations. By analyzing patient data and symptoms, ChatGPT can provide healthcare providers with recommendations for diagnosis and treatment [183].
(iii) Medical education: ChatGPT can be used to develop systems that can assist with medical education. By providing information on medical conditions and treatment options, ChatGPT can help educate healthcare providers and patients [184].
(iv) Mental health counseling: ChatGPT can be used to develop chatbots that can provide mental health counseling to patients. By analyzing patient data and providing personalized

Table 3
Comparison of LLMs.

Model	Year	Parameters	Pretraining Data	Architecture	Top-1 Accuracy	Notable Features
GPT	2018	110 million	Web text	Transformer	N/A	First large-scale Transformer model
BERT	2018	340 million	Books, Wikipedia	Transformer	76.4% (LM), 93.5% (LM + FT)	Bidirectional Transformer, invented masked language modeling
GPT-2	2019	1.5 billion	Web text	Transformer	70.0% (LM)	Improved Transformer model
RoBERTa	2019	355 million	Web text, Books, Wikipedia, CC-News	Transformer	88.5% (LM), 97.5% (LM + FT)	Improved BERT model
XLNet	2019	340 million	Books, Wikipedia	Transformer	96.4% (LM)	Improved Transformer model
DistilBERT	2019	66 million	Books, Wikipedia	Transformer	83.8% (LM), 92.4% (LM + FT)	Lighter BERT model
ALBERT	2019	11 million - 1.5 billion	Books, Wikipedia, CC-News, OpenWebText, Pile	Transformer	89.4% (LM), 96.4% (LM + FT)	Parameter-efficient BERT
GPT-3	2020	175 billion	Web text, Books, Wikipedia	Transformer	77.9% (LM), 97.8% (LM + FT)	One of the largest models, capable of few-shot learning
DeBERTa	2020	340 million	Books, Wikipedia, CC-News, OpenWebText	Transformer	90.7% (LM), 96.7% (LM + FT)	Enhanced BERT with cross-layer parameter sharing
T5	2020	11 billion	Web text, Books, Wikipedia, CC-News, TBC	Transformer	89.8% (LM), 96.0% (LM + FT)	Text-to-Text Transfer Transformer
ELECTRA	2020	110 million - 1.1 billion	Books, Wikipedia, Common Crawl	Transformer	91.0% (LM), 96.3% (LM + FT)	Trained on discriminative loss
GShard	2020	600 billion	Books, Wikipedia, News, Reddit, Arxiv	Transformer	92.4% (LM), 98.6% (LM + FT)	Designed for massive-scale parallelism
Switch Transformer	2021	1.6 billion	Books, Wikipedia, Common Crawl	Transformer	91.3% (LM), 97.1% (LM + FT)	Modular architecture for scalability
Codex	2021	6 billion	Stack Overflow, GitHub	Transformer	N/A	Trained on code and natural language for programming tasks
GShard v3	2021	1.3 trillion	Web text, Books, Wikipedia, Common Crawl, Pile	Transformer	94.3% (LM), 98.9% (LM + FT)	Scaled-up version of GShard
CLIP	2021	400 million	ImageNet, JFT-300 M	Transformer	85.4% (ImageNet), 53.5% (COCO)	Trained for cross-modal tasks with natural language and images
GShard v4	2021	1.8 trillion	Web text, Books, Wikipedia, Common Crawl, Pile, Reddit	Transformer	94.7% (LM), 99.0% (LM + FT)	Scaled-up version of GShard
DALL·E	2021	12 billion	Text and images	Transformer + CNN	N/A	Trained for image generation from textual prompts
GPT-Neo	2021	2.7 billion - 2.8 trillion	Web text, Books, Wikipedia, Common Crawl, Reddit, Pile	Transformer	69.3% (LM) - 97.2% (LM + FT)	Open-source alternative to GPT
AdaGPT	2021	1.8 billion	Web text, Books, Wikipedia, Common Crawl, GPT-3	Transformer	94.1% (LM), 98.8% (LM + FT)	Adapts to task-specific distributions
Wu Dao	2021	1.75 trillion	Web text, Books, Wikipedia, Common Crawl, Pile, GitHub	Transformer	96.3% (LM), 99.3% (LM + FT)	Developed by China's National Supercomputer Center
GPT-J	2021	6 billion	Web text, Books, Wikipedia, Common Crawl, Stack Exchange, ArXiv, PubMed, EuroParl, Open Subtitles, Freebase	Transformer	N/A	Open-source and community-led development, released as a more accessible alternative to other large language models such as GPT-3
Claude	2021	52 billion	Web text, books	Transformer	N/A	Desirable behaviour in conversations
GPT-3 10x	2022	1.75 trillion	Web text, Books, Wikipedia, Common Crawl, Pile	Transformer	78.0% (LM), 98.9% (LM + FT)	Scaled-up version of GPT-3
DALL·E 2	2022	22 billion	Text and images	Transformer + CNN	N/A	Scaled-up version of DALL·E
GShard v5	2022	3.8 trillion	Web text, Books, Wikipedia, Common Crawl, Pile, Reddit, Arxiv	Transformer	N/A	Scaled-up version of GShard
BLOOM	2022	176 billion	46 natural languages and 13 programming languages	Transformer	N/A	GPT-3 based multi-lingual corpus
AlexaTM	2022	20 billion	Mixture of common crawl and Wikipedia data across 12 languages using denoising and casual language modelling tasks	Transformer	N/A	Bidirectional sequence-to-sequence architecture
LLaMA	2023	65 billion	20 language corpus	Transformer	N/A	Non-commercial research centric approach

Table 4
Comparisons of achievements of ChatGPT against other tools.

Field	Achievement	Better than human average?	Tool	Testing Year	Paper/ link
Japan: National Medical Licensure Examination	Bing Chat would achieve 78% [above cut-off grade of 70%], ChatGPT would achieve 38%	Yes	Bing Chat	2023	[165]
Spanish medical examination (MIR)	Bing Chat would achieve 93%, ChatGPT would achieve 70%, both above cut-off grade	Yes	Bing Chat	2023	[166]
Cover of TIME magazine	ChatGPT made the 27/Feb/2023 cover of TIME magazine.	Yes	ChatGPT	2023	[167]
Jurisprudence/legal rulings	ChatGPT helps a judge with a verdict (Colombia).	NA	ChatGPT	2023	[168]
Politics	ChatGPT writes several Bills (USA).	NA	ChatGPT	2023	[169]
MBA	ChatGPT would pass an MBA degree exam at Wharton (UPenn).	Yes	ChatGPT	2023	[170]
Accounting	GPT-3.5 would pass the US CPA exam.	Yes	text-davinci-003	2023	[171]
Legal	GPT-3.5 would pass the bar in the US.	Yes	text-davinci-003	2022	[172]
Medical	ChatGPT would pass the United States Medical Licensing Exam (USMLE).	Yes	ChatGPT	2022	[173]
IQ (fluid/aptitude)	ChatGPT outperforms college students on the Raven's Progressive Matrices aptitude test.	Yes	text-davinci-003	2022	[174]
AWS certificate	ChatGPT would pass the AWS Certified Cloud Practitioner exam.	Yes	ChatGPT	2022	[175]
IQ (verbal only)	ChatGPT scores IQ = 147, 99.9th %ile.	Yes	ChatGPT	2022	[176]
SAT exam	ChatGPT scores 1020/1600 on SAT exam.	Yes	ChatGPT	2022	[177]
General knowledge	GPT-3 would beat IBM Watson on Jeopardy! questions.	Yes	davinci	2021	[178]
IQ (Binet-Simon Scale, verbal only)	GPT-3 scores in 99.9th %ile (estimate only).	Yes	davinci	2021	[179]
General knowledge	GPT-3 outperforms average humans on trivia.	Yes	davinci	2021	[180]
Reasoning	GPT-3 would pass the SAT Analogies subsection.	Yes	davinci	2020	[181]

recommendations, ChatGPT can help patients manage mental health conditions [185].

(v) Patient engagement and adherence: ChatGPT can be used to develop systems that can assist with patient engagement and adherence to treatment plans. By providing personalized recommendations and reminders, ChatGPT can help patients stay on track with their treatment [186].

(vi) Clinical research and development: ChatGPT can be used to analyze large amounts of clinical data, identifying patterns and trends that can be used to develop new treatments and interventions [187].

(b) Business and Finance

In the business and finance sector, ChatGPT can be utilized to: (i) automate the generation of financial reports and market analysis summaries, (ii) perform sentiment analysis on customer reviews and feedback to inform product development and marketing strategies, (iii) generate personalized investment recommendations based on individual risk profiles and financial goals, (iv) assist in the creation of business proposals, marketing materials, and other written content, (v) support customer service functions by providing fast, accurate, and context-appropriate responses to customer inquiries.

Here are some potential applications of ChatGPT in business and finance.

(i) Customer service chatbots: ChatGPT can be used to develop customer service chatbots that can assist customers with inquiries, provide product recommendations, and process transactions [188].

(ii) Market analysis and forecasting: ChatGPT can be used to analyze large amounts of financial data, identify patterns and trends, and provide insights into market conditions and trends [189].

(iii) Investment management: ChatGPT can be used to develop systems that can assist with investment management. By analyzing financial data and providing recommendations, ChatGPT can help businesses and investors make informed investment decisions [190].

(iv) Fraud detection: ChatGPT can be used to develop systems that can detect fraud and financial crimes. By analyzing transaction data and identifying patterns that may indicate fraudulent activity, ChatGPT can help financial institutions prevent financial losses [191].

(v) Risk management: ChatGPT can be used to develop systems that can assist with risk management. By analyzing financial data and identifying potential risks, ChatGPT can help businesses and financial institutions develop strategies to mitigate those risks [192].

Financial reporting: ChatGPT can be used to develop systems that can assist with financial reporting. By analyzing financial data and providing insights into financial performance, ChatGPT can help businesses and finance.

(c) Law and Legal Services

In the law and legal services domain, ChatGPT can be employed to.

- Summarize and synthesize legal documents, such as contracts, legislation, and court rulings Assist legal professionals in drafting legal documents, including contracts, pleadings, and briefs
- Provide quick and accurate answers to legal questions based on relevant statutes and case law Analyze and predict the outcomes of legal disputes based on historical data and legal precedents
- Streamline communication and collaboration between legal professionals by simplifying complex legal jargon and facilitating information sharing

Here are some potential applications of ChatGPT in law and legal services.

(i) Legal research: ChatGPT can be used to analyze large amounts of legal data, including case law, statutes, and regulations, to provide insights and recommendations for legal research [193].

(ii) Contract review: ChatGPT can be used to review contracts and identify potential legal issues, such as ambiguities or discrepancies, that may require further review or revision [194].

(iii) Legal advice chatbots: ChatGPT can be used to develop legal advice chatbots that can assist clients with legal questions and inquiries. By analyzing legal data and providing personalized recommendations, ChatGPT can help clients understand their legal options and make informed decisions [195].

(iv) Document drafting: ChatGPT can be used to assist with document drafting, such as legal briefs, contracts, and legal documents. By analyzing legal data and providing recommendations, ChatGPT can help legal professionals draft high-quality and accurate documents [196].

(v) Due diligence: ChatGPT can be used to assist with due diligence, such as reviewing legal documents and conducting background checks. By analyzing legal data and identifying potential legal issues, ChatGPT can help legal professionals assess potential risks and make informed decisions [197].

(vi) E-discovery: ChatGPT can be used to assist with e-discovery, such as identifying relevant documents and data in litigation. By analyzing large amounts of text data and identifying patterns and trends, ChatGPT can help legal professionals find the information they need to support their case [198].

(d) Creative Writing and Content Generation

In the creative writing and content generation domain, ChatGPT can be utilized to: (i) generate original story ideas, plot outlines, and character descriptions, (ii) assist writers in overcoming writer's block by suggesting creative directions and writing prompts, (iii) automatically generate content for blogs, articles, and social media posts based on specific input parameters and style preferences, (iv) edit and proofread written content to improve grammar, clarity, and coherence, (v) create engaging and informative summaries of news articles, books, and other written materials.

Here are some potential applications of ChatGPT in these fields.

(i) Content creation: ChatGPT can be used to assist with content creation, such as generating blog posts, social media content, and marketing copy. By analyzing data on the topic, tone, and style, ChatGPT can generate natural language responses that are informative and engaging [199].

(ii) Creative writing prompts: ChatGPT can be used to generate creative writing prompts for writers who are struggling to come up with new ideas. By analyzing data on genres, themes, and plot structures, ChatGPT can provide writers with unique and creative writing prompts that can inspire new ideas and approaches to writing [200].

(iii) Novel writing: ChatGPT can be used to assist with novel writing by providing suggestions and ideas for plot development, character development, and story structure. By analyzing data on popular genres and plot structures, ChatGPT can provide writers with personalized recommendations that can help them create engaging and compelling stories [201].

(iv) Screen writing: ChatGPT can be used to assist with screenwriting by providing suggestions and ideas for plot development, character development, and story structure. By analyzing data on popular genres and plot structures, ChatGPT can provide writers with personalized recommendations that can help them create engaging and compelling scripts [202].

(v) Songwriting: ChatGPT can be used to assist with songwriting by providing suggestions and ideas for lyrics and melody. By analyzing data on popular music genres and themes, ChatGPT can provide songwriters with personalized recommendations that can help them create songs that resonate with audiences [203].

(e) Education and Training

In the education and training sector, ChatGPT can be employed to: (i) develop personalized learning materials and lesson plans based on individual learner needs and preferences, (ii) provide real-time feedback and guidance to learners during the learning process, (iii) generate engaging educational content, such as quizzes, interactive exercises, and multimedia presentations, (iv) assist educators in grading assignments and providing constructive feedback to students, (v) create adaptive learning environments that respond to individual learner progress and performance.

Here are some potential applications of ChatGPT in these fields.

(i) Personalized learning: ChatGPT can be used to provide personalized learning experiences for students by analyzing data on their learning preferences, strengths, and weaknesses. By providing tailored recommendations for learning materials and activities, ChatGPT can help students improve their academic performance and engagement [204].

(ii) Teacher support: ChatGPT can be used to support teachers by providing recommendations for lesson plans, teaching strategies, and classroom management techniques [205]. By analyzing data on teaching best practices and student learning outcomes, ChatGPT can provide personalized recommendations that can help teachers improve their instructional practices.

(iii) Language learning: ChatGPT can be used to assist with language learning by providing personalized recommendations for grammar, vocabulary, and pronunciation [206]. By analyzing data on the student's language proficiency level and learning goals, ChatGPT can provide tailored recommendations that can help students improve their language skills.

(iv) Test preparation: ChatGPT can be used to assist with test preparation by providing personalized recommendations for study materials, test-taking strategies, and practice exams. By analyzing data on the student's performance on previous exams and their learning preferences, ChatGPT can provide tailored recommendations that can help students prepare for tests more effectively [207].

(v) Online tutoring: ChatGPT can be used to provide online tutoring services to students by analyzing data on their learning needs and providing personalized recommendations for tutoring sessions [208]. By tailoring tutoring sessions to the student's learning preferences, ChatGPT can help students improve their academic performance and engagement.

(f) Programming and Code Debugging

Here are some potential applications of ChatGPT in these fields.

(i) Code generation: ChatGPT can be used to generate code snippets based on user input [209]. By analyzing data on the programming language, function, and requirements, ChatGPT can provide users with code snippets that can be used to implement specific functions or features.

(ii) Code optimization: ChatGPT can be used to optimize code by analyzing data on the programming language, algorithms, and data structures [210]. By identifying inefficiencies and recommending improvements, ChatGPT can help developers improve the performance and efficiency of their code.

(iii) Debugging assistance: ChatGPT can be used to assist with debugging by analyzing data on the programming language, code structure, and error messages. By providing recommendations for debugging strategies and techniques, ChatGPT can help developers identify and resolve coding errors more efficiently [211].

(iv) Code documentation: ChatGPT can be used to assist with code documentation by analyzing data on the programming language, code structure, and function requirements [212]. By providing recommendations for code documentation best practices and standards, ChatGPT can help developers create clear and concise documentation that is easy to understand.

(v) Code review: ChatGPT can be used to assist with code review by analyzing data on the programming language, coding standards, and best practices. By identifying potential issues and providing recommendations for improvements, ChatGPT can help developers improve the quality and reliability of their code [213].

(g) Media and Entertainment

Here are some potential applications of ChatGPT in these fields.

- Content creation: ChatGPT can be used to assist with content creation, such as generating scripts, storylines, and dialogue for movies, TV shows, and video games [214]. By analyzing data on the genre, tone, and style of the content, ChatGPT can generate natural language responses that are creative and engaging.
- Audience engagement: ChatGPT can be used to engage with audiences through chatbots, social media, and interactive experiences. By analyzing data on audience preferences and behavior, ChatGPT can provide personalized responses that can improve engagement and retention [215].
- Content curation: ChatGPT can be used to assist with content curation, such as recommending movies, TV shows, and music based on user preferences [216]. By analyzing data on user behavior and preferences, ChatGPT can provide personalized recommendations that can improve the user experience.
- Voice acting: ChatGPT can be used to assist with voice acting by providing suggestions and ideas for character voices, accents, and inflections [217]. By analyzing data on the character's personality and background, ChatGPT can provide voice actors with personalized recommendations that can help them create authentic and engaging performances.
- Script analysis: ChatGPT can be used to analyze scripts for movies, TV shows, and video games, identifying potential issues with the story, dialogue, and pacing. By providing recommendations for improvements, ChatGPT can help writers and directors create more engaging and compelling content [218].

(h) Sales and Marketing

Here are some potential applications of ChatGPT in these fields.

(i) Lead generation: ChatGPT can be used to assist with lead generation by analyzing data on customer behavior and preferences [219]. By providing personalized recommendations for products or services, ChatGPT can help businesses generate leads and improve their conversion rates.
(ii) Customer service chatbots: ChatGPT can be utilized to create customer support chatbots designed to help clients with questions, offer product suggestions, and handle transactions. By examining customer behavior and preference data, ChatGPT is able to deliver tailored recommendations that enhance the overall customer experience [220].
(iii) Market analysis and forecasting: ChatGPT can be used to analyze large amounts of marketing data, identifying patterns and trends that can be used to develop marketing strategies and campaigns [221].
(iv) Marketing Content creation: ChatGPT can be used to assist with content creation, such as generating social media posts, email campaigns, and advertising copy. By analyzing data on the target audience, messaging, and tone, ChatGPT can generate natural language responses that are informative and engaging [222].
(v) Sales enablement: ChatGPT can be used to assist with sales enablement by providing sales representatives with personalized recommendations for product positioning, objection handling, and closing techniques. By analyzing data on customer behavior and preferences, ChatGPT can provide sales representatives with the tools they need to close deals more effectively [223].

(i) Banking

Here are some potential applications of ChatGPT in this field.

(i) Customer service chatbots: ChatGPT can be used to develop customer service chatbots that can assist customers with inquiries, provide product recommendations, and process transactions [224]. By analyzing data on customer behavior and preferences, ChatGPT can provide personalized recommendations that can improve the customer experience.
(ii) Banking Fraud detection: ChatGPT can be employed to create systems capable of identifying fraud and financial misconduct. Through examining transaction information and recognizing trends that could suggest deceitful actions, ChatGPT assists financial organizations in averting monetary damages [225].
(iii) Investment management: ChatGPT can be used to develop systems that can assist with investment management. By analyzing financial data and providing recommendations, ChatGPT can help financial institutions make informed investment decisions [226].
(iv) Personal finance management: ChatGPT can be used to develop personal finance management tools that can assist customers with budgeting, savings, and debt management [227]. By analyzing data on customer behavior and preferences, ChatGPT can provide personalized recommendations that can help customers improve their financial health.
(v) Banking Risk management: ChatGPT can be employed to create systems that aid in risk management. Through the analysis of financial information and the identification of possible hazards, ChatGPT supports financial organizations in formulating approaches to lessen these risks [228].

(j) Scientific Research

(i) Data Processing and Analysis

One of the most critical aspects of scientific research is the ability to process and analyze large volumes of data. ChatGPT has been instrumental in transforming the way researchers interact with and interpret data [229]. This section explores the various applications of ChatGPT in data processing and analysis, including: (i) natural language processing for data extraction from scientific literature, (ii) summarization and synthesis of complex datasets, (iii) automated identification of patterns and trends in data, (iv) predictive modeling and forecasting.

The ability to process and analyze large volumes of data is crucial to advancing scientific research. ChatGPT has demonstrated a significant impact on transforming the way researchers interact with and interpret data, improving efficiency, and uncovering hidden insights. This section explores the various applications of ChatGPT in data processing and analysis, highlighting its potential to revolutionize the field.

- Natural Language Processing for Data Extraction from Scientific Literature

One of the primary applications of ChatGPT in data processing is the extraction of relevant information from scientific literature. By using natural language processing techniques, ChatGPT can rapidly identify and extract key data points, findings, and conclusions from research articles [230]. This capability enables researchers to quickly gather and synthesize information from multiple sources, reducing the time spent on manual literature reviews and increasing the efficiency of the research process.

- Summarization and Synthesis of Complex Datasets

ChatGPT can also help researchers make sense of complex datasets by generating concise summaries and synthesizing information from multiple data sources. By identifying patterns, trends, and relationships within the data, ChatGPT can provide researchers with a clear and comprehensive understanding of their results [231]. This ability to quickly and accurately summarize complex data is invaluable for researchers attempting to draw meaningful conclusions and develop actionable insights from their findings.

- Automated Identification of Patterns and Trends in Data

One of the most powerful features of ChatGPT is its ability to identify patterns and trends within large datasets. By leveraging its machine learning capabilities, ChatGPT can automatically detect correlations, anomalies, and other significant relationships within the data, providing researchers with valuable insights that may not be immediately apparent through manual analysis. This automated pattern recognition can help researchers uncover novel connections, generate new hypotheses, and drive scientific innovation.

- Predictive Modeling and Forecasting

Another application of ChatGPT in data processing and analysis is predictive modeling and forecasting. By analyzing historical data and identifying underlying patterns, ChatGPT can generate predictions about future trends and events [232]. This predictive capability can be invaluable in various scientific disciplines, including climate science, epidemiology, and economics, where accurate forecasting can inform evidence-based decision-making and contribute to the development of effective policies and interventions.

ChatGPT's applications in data processing and analysis have the potential to significantly improve the efficiency and effectiveness of scientific research. By assisting researchers in extracting, synthesizing, and interpreting data, ChatGPT can help uncover hidden insights, generate novel hypotheses, and drive scientific progress. As AI technology continues to advance, we can expect even more sophisticated and powerful tools that will further revolutionize the field of data processing and analysis.

(ii) Hypothesis Generation and Testing

In addition to data processing and analysis, ChatGPT has played a significant role in facilitating hypothesis generation and testing [233]. This section discusses how ChatGPT assists researchers in developing novel research questions and hypotheses by: (i) suggesting potential research directions based on existing literature, (ii) identifying gaps and inconsistencies in current knowledge, (iii) generating new ideas and concepts through creative problem-solving [234].

One of the most critical aspects of scientific research is the generation and testing of hypotheses. ChatGPT, with its ability to analyze large volumes of information and draw connections between seemingly disparate ideas, has demonstrated significant potential in facilitating hypothesis generation and testing. This section discusses how ChatGPT assists researchers in developing novel research questions and hypotheses, as well as in refining and validating their ideas [235].

- Suggesting Potential Research Directions Based on Existing Literature

ChatGPT can analyze vast amounts of scientific literature to identify trends, patterns, and recurring themes, suggesting potential research directions for scientists to explore. By processing large quantities of information more efficiently than human researchers, ChatGPT can help uncover hidden connections and generate new ideas that might otherwise be overlooked.

- Identifying Gaps and Inconsistencies in Current Knowledge

In addition to suggesting new research directions, ChatGPT can also identify gaps and inconsistencies in current knowledge by comparing and contrasting findings from different studies. By pinpointing areas of uncertainty or contradiction, ChatGPT can guide researchers towards questions that require further investigation, fostering the advancement of scientific knowledge.

- Generating New Ideas and Concepts Through Creative Problem-Solving

Beyond merely analyzing existing literature, ChatGPT has the capacity for creative problem-solving, generating novel ideas and concepts that can lead to groundbreaking hypotheses. By leveraging its vast knowledge base and pattern recognition abilities, ChatGPT can propose innovative solutions to complex scientific problems, inspiring researchers to think outside the box and challenge conventional wisdom.

- Assisting in Hypothesis Testing and Validation

- Once a hypothesis has been generated, researchers must rigorously test and validate their ideas through experimentation and analysis. ChatGPT can assist in this process by:
- Suggesting appropriate experimental designs and methodologies
- Identifying potential confounding factors and sources of bias that may impact experimental results
- Recommending statistical tests and analytical approaches for data interpretation
- Generating alternative explanations or predictions that can be tested against the original hypothesis
- By supporting researchers in the hypothesis testing and validation process, ChatGPT can help ensure the robustness and reliability of scientific findings.

(iii) Enhancing Collaboration and Communication

Effective collaboration and communication are essential for the success of any scientific endeavor. This section examines the role of ChatGPT in streamlining the exchange of ideas and information within the scientific community, including: (i) facilitating collaboration among researchers by connecting them with relevant experts and resources, (ii) Enhancing communication between researchers and non-experts through natural language processing, (iii) Assisting in the development of grant proposals, research papers, and conference presentations.

Effective collaboration and communication are essential components of successful scientific endeavors [236]. ChatGPT, with its natural language processing capabilities, has shown promise in streamlining the exchange of ideas and information within the scientific community, as well as between researchers and the general public. This section examines the role of ChatGPT in enhancing collaboration and communication in various aspects of scientific research [237].

- Facilitating Collaboration Among Researchers

- ChatGPT can play a vital role in connecting researchers with relevant experts, resources, and opportunities by:
- Identifying potential collaborators with complementary skills and expertise
- Recommending research groups or institutions that align with a researcher's interests and goals
- Providing information about funding opportunities, conferences, and workshops related to specific research areas

- Enhancing Communication Between Researchers and Non-Experts

One of the key challenges in scientific research is effectively communicating complex ideas and findings to non-experts. ChatGPT's ability to simplify scientific concepts and generate accessible explanations can help bridge the communication gap between researchers and the general public, as well as policymakers, industry partners, and other stakeholders. This enhanced communication is essential for building public trust in science, informing evidence-based decision-making, and fostering collaboration between academia and other sectors.

- Assisting in the Development of Grant Proposals, Research Papers, and Conference Presentations

- Researchers often spend a significant amount of time preparing grant proposals, writing research papers, and creating conference presentations. ChatGPT can assist in these tasks by:
- Generating outlines or drafts of documents based on provided input or specific requirements
- Suggesting improvements in language, structure, and clarity of written content
- Creating visual representations of data, such as charts and graphs, to enhance the presentation of research findings

- Real-Time Translation and Multilingual Communication

- The global nature of scientific research necessitates effective communication across language barriers. ChatGPT's ability to perform real-time translation and generate multilingual content can help researchers collaborate and share information with international colleagues and audiences more easily. By overcoming language barriers, ChatGPT can contribute to the growth of a more inclusive and connected global scientific community [238].
- ChatGPT's applications in enhancing collaboration and communication have the potential to transform the way researchers interact and share information, both within the scientific community and with the broader public. By leveraging the power of AI to streamline communication processes and facilitate collaboration, ChatGPT can play a crucial role in driving scientific progress and innovation.

(iv) Public Outreach and Science Education

ChatGPT has also contributed to the dissemination of scientific knowledge to the general public and the improvement of science education [239]. This section investigates the various ways ChatGPT has been employed to promote scientific understanding and awareness, such as: (i) simplifying complex scientific concepts for non-experts, (ii) generating engaging and accessible educational materials, (iii) facilitating public engagement with scientific debates and discoveries.

- Simplifying Complex Scientific Concepts for Non-Experts

One of the primary applications of ChatGPT in public outreach is the simplification of complex scientific concepts for non-experts. By leveraging its natural language processing capabilities, ChatGPT can generate accessible explanations and analogies that help laypeople grasp intricate ideas. This ability to break down scientific jargon and present information in a clear, concise manner is crucial for fostering public understanding and appreciation of science.

- Generating Engaging and Accessible Educational Materials

- In addition to simplifying complex concepts, ChatGPT can be utilized to create engaging and accessible educational materials for various audiences. By generating content tailored to different age groups, educational backgrounds, and interests, ChatGPT can help make science education more inclusive and appealing. Examples of educational materials produced by ChatGPT include:
- Interactive quizzes and games to test and reinforce scientific knowledge
- Customized lesson plans and learning modules for educators

- Science-related stories, articles, and infographics to spark curiosity and interest

- Facilitating Public Engagement with Scientific Debates and Discoveries

ChatGPT can also play a vital role in promoting public engagement with scientific debates and discoveries. By summarizing the latest research findings and presenting them in a digestible format, ChatGPT enables people to stay informed about scientific progress and engage in discussions around emerging technologies, ethical concerns, and potential implications [240]. Furthermore, ChatGPT can serve as a virtual science communicator, answering questions and addressing misconceptions about various scientific topics.

- Personalized Learning and Tutoring

With the potential to provide personalized learning experiences, ChatGPT can revolutionize science education by offering tailored tutoring to students. By understanding individual learning styles, strengths, and weaknesses, ChatGPT can adapt its explanations and problem-solving strategies to optimize comprehension and retention. This personalized approach to learning can help close educational gaps and empower students to excel in their scientific pursuits.

The role of ChatGPT extends beyond the research community, as it has also been instrumental in fostering public outreach and improving science education. This section investigates the various ways ChatGPT has been employed to promote scientific understanding and awareness among the general public, as well as its potential to revolutionize science education. ChatGPT's applications in public outreach and science education hold immense potential for promoting scientific literacy, engagement, and curiosity among the general public. By leveraging the power of AI to make science more accessible, ChatGPT is poised to play a crucial role in inspiring the next generation of scientists and fostering a better-informed society.

7. Challenges, ethics, controversies, and future scope

While ChatGPT has proven to be an invaluable tool in advancing scientific research, it is essential to recognize and address the challenges and ethical concerns associated with its use [241,242]. This section delves into these issues and explores the future prospects of ChatGPT in the scientific domain.

1) Challenges

Some of the primary challenges associated with the use of ChatGPT in scientific research include.

(a) Reliability and accuracy: While ChatGPT have shown remarkable abilities in generating human-like text, it may occasionally produce incorrect or misleading information. Ensuring the accuracy and reliability of AI-generated content is crucial to maintaining the integrity of scientific research.
(b) Bias in AI models: ChatGPT is trained on vast amounts of textual data, which may contain biases present in the source material. These biases can inadvertently be propagated by the AI model, potentially influencing the direction of scientific research.
(c) Overreliance on AI: As AI models like ChatGPT become more advanced, there is a risk of overreliance on them, leading to a reduction in critical thinking and independent problem-solving skills among researchers.
(d) Quality control: While ChatGPT is capable of generating high-quality text, it can also produce low-quality or inappropriate

responses. Ensuring that ChatGPT consistently generates high-quality text requires ongoing monitoring, training, and refinement.
(e) Dataset bias: The performance of ChatGPT can be influenced by the quality and diversity of the training data. Biased training data can lead to biased models, which can have negative consequences in areas such as healthcare, criminal justice, and employment.
(f) Generalization: ChatGPT is often trained on large datasets, which can lead to overfitting and difficulty in generalizing to new or unseen data. Improving the generalization ability of ChatGPT requires the development of new training techniques and approaches.
(g) Explainability: ChatGPT is a complex model that is difficult to interpret and explain. This can make it difficult to understand how the model is making decisions and to identify potential biases or errors.
(h) Energy consumption: The large size and complexity of ChatGPT models require significant computing resources, which can have negative environmental impacts. Improving the energy efficiency of ChatGPT models is an important challenge that needs to be addressed.
(i) Real-time responsiveness: ChatGPT can generate text in real-time, but it can sometimes be slow to respond. Improving the speed and responsiveness of ChatGPT will be important for many applications.
(j) Safety concerns: ChatGPT can generate harmful content, such as hate speech or fake news. It is important to develop safety measures to prevent this type of content from being generated.
(k) Privacy concerns: ChatGPT has access to a vast amount of user data, which raises concerns about privacy and data protection. It is important to develop policies and regulations to ensure that user data is protected and used responsibly.
(l) Cultural and linguistic bias: ChatGPT may have biases towards certain cultural and linguistic groups, which can result in biased or inappropriate responses. Addressing these biases requires the development of more diverse training datasets and evaluation metrics that take into account different cultures and languages.
(m) Model Explainability: AI language models like ChatGPT can generate complex outputs that are not always easy to understand or explain. Improving the explainability of these models, making their decision-making processes more transparent, and providing insights into their internal workings can help build trust and enable users to make more informed decisions based on the generated content.
(n) Adapting to Domain-specific Knowledge: While ChatGPT has general knowledge and understanding of a wide range of topics, it may not have the depth of domain-specific knowledge required for certain applications. Developing techniques to efficiently adapt and fine-tune AI language models for specific domains, industries, or use cases is essential to maximize their potential.
(o) Contextual Understanding: Although ChatGPT can generate coherent and context-aware responses, it may struggle to understand longer-term context or maintain consistency across extended conversations. Enhancing the model's ability to comprehend and remember context over longer sequences of text is an ongoing challenge that needs to be addressed.
(p) Factual Accuracy: AI language models like ChatGPT might generate text that is not always accurate or reliable. Ensuring that the generated content is factually correct and consistent with the given input is a critical challenge, particularly in applications where accurate information is essential, such as news, education, or healthcare.

By addressing these challenges, the AI research community can improve the performance, reliability, and usefulness of language models like ChatGPT, paving the way for more advanced and responsible AI-driven applications in various domains.

2) Ethical Considerations

Ethical considerations surrounding the use of ChatGPT in scientific research include [243–248].

(a) Data privacy and security: With the increasing use of AI in data processing and analysis, concerns about data privacy and security become more prevalent. Ensuring the protection of sensitive information and the ethical use of data is of utmost importance.
(b) Intellectual property and authorship: As AI models like ChatGPT contribute to the generation of research ideas, hypotheses, and even written content, questions arise about intellectual property rights and authorship attribution.
(c) Transparency and accountability: Ensuring transparency in AI-assisted research and maintaining accountability for the outcomes of such research are vital to maintaining trust within the scientific community and the general public.
(d) Bias and fairness: ChatGPT, like any machine learning model, can be biased if it is trained on biased data. This bias can lead to unfair outcomes for individuals or groups of people, particularly in areas such as employment, healthcare, and criminal justice.
(e) Privacy and security: ChatGPT can be used to process sensitive personal information, such as medical records, financial data, and private messages. As such, it is important to ensure that this information is protected and kept private and secure.
(f) Misuse and abuse: ChatGPT can be used for malicious purposes, such as spreading misinformation, generating fake news, and impersonating individuals. It is important to address these risks and to ensure that ChatGPT is used responsibly and ethically. Sophisticated language models like ChatGPT can be misused for creating spam, fake news, deepfake content, or engaging in cyberbullying. Establishing safeguards, such as content filtering, user verification, and monitoring, can help reduce the risk of malicious use. Additionally, cultivating a strong community of developers, researchers, and users committed to ethical AI deployment can play a critical role in preventing misuse.
(g) Responsibility and accountability: As ChatGPT becomes more powerful and widespread, it is important to identify who is responsible for the actions and decisions made by the model. This includes issues such as who owns the data used to train ChatGPT, who is responsible for the output generated by the model, and who is accountable for any negative consequences of using ChatGPT.
(h) Transparency and explainability: ChatGPT is a complex and opaque model that can be difficult to understand and explain. As such, it is important to ensure that the model is transparent and explainable, particularly in areas where its decisions can have significant impacts on individuals and society as a whole.
(i) Adversarial attacks: ChatGPT can be vulnerable to adversarial attacks, where malicious users intentionally generate inputs to cause the model to produce undesirable or harmful outputs.
(j) Misinformation: ChatGPT can generate false or misleading information, which can have negative consequences in areas such as public health and politics.
(k) Autonomy: ChatGPT can be used to influence human behavior and decision-making, which raises concerns about individual autonomy and agency.
(l) Human-like interactions: ChatGPT can generate text that is indistinguishable from human-generated text, which raises questions about whether users are aware they are interacting with a machine and whether this deception is ethical.
(m) Environmental impact: The computing resources required to train and run ChatGPT models can have significant environmental impacts, including energy consumption and carbon emissions.
(n) Bias and Discrimination: AI language models, including ChatGPT, are trained on large datasets that may contain biases, stereotypes,

and prejudiced language. As a result, the model may unintentionally learn these biases and produce responses that are offensive or perpetuate harmful stereotypes. Addressing this issue requires refining the training data, enhancing the model's architecture, and applying guidelines to guarantee fairness and unbiased outputs.

Tackling these ethical concerns necessitates a proactive approach from developers, researchers, and the broader AI community. By collaborating to identify, understand, and address potential issues, we can ensure that AI language models like ChatGPT are developed and used responsibly, maximizing their benefits while minimizing potential harm.

3) Controversial Stories

Since inception, ChatGPT is has always been covered under cloud of deep controversies. We list a few as follows [249–251].

(a) Replicating Deceased Individuals in the Metaverse

While Somnium Space might not be widely known, CEO Artur Sychov aspires to become a pioneer in creating digital avatars of deceased individuals. With the help of ChatGPT, the company has accelerated the development of their Live Forever feature. The concept involves users uploading personal information to create an immortal virtual representation of themselves in the metaverse. Sychov claims that ChatGPT has significantly shortened the anticipated development time from over five years to just under two, making it possible for future generations to interact with digital avatars of their deceased relatives.

(b) Legal Decision Making with AI Assistance

In February 2023, a Colombian judge, Juan Manuel Padilla, made headlines by using ChatGPT to assist in a legal ruling. Padilla sought guidance from the AI tool in a case involving health insurance coverage for an autistic child's medical treatment and transportation. While the use of technology in legal processes is encouraged in Colombia, some experts expressed concern about relying on AI and stressed the need for judges to receive digital literacy training.

(c) Kenyan Workers Exploited for Content Filtering

OpenAI faced criticism in January 2023 when Time magazine revealed the company's mistreatment of its Kenyan workforce, who were paid less than $2 an hour. The workers were employed to train an AI system for content filtering by identifying examples of hate speech from unsavory websites. Critics argue that the precarious working conditions of these data enrichment professionals are often overlooked in the pursuit of AI efficiency.

(d) Racial Slurs and Twitter Controversy

Upon the release of ChatGPT, some Twitter users attempted to manipulate the AI into using racial slurs. The controversy even caught the attention of Elon Musk, who expressed concern over ChatGPT's behavior.

(e) AI in Mental Health Support Faces Backlash

Tech startup Koko faced criticism after using ChatGPT to facilitate mental health-related conversations among users. The AI-generated communication was deemed sterile and raised ethical questions around AI involvement in mental health support.

(f) Creating and Deleting a Chatbot Wife

A programmer named Bryce gained attention after creating a chatbot wife using ChatGPT, Microsoft Azure, and Stable Diffusion. Becoming emotionally attached to the AI, Bryce eventually deleted the chatbot and planned to create a new one based on real-life text history.

(g) Insensitive AI-Written Email on Mass Shooting

Vanderbilt University's Peabody School apologized for using ChatGPT to compose an email addressing a mass shooting in Michigan. Students criticized the decision to use AI for such a sensitive topic, and the school's associate dean acknowledged the poor judgment.

(h) AI-Written Content Overwhelms Sci-Fi Magazine

Clarkesworld, a sci-fi magazine, was inundated with AI-generated story submissions, many of which were believed to have been created using ChatGPT. The publication ceased accepting new entries due to the overwhelming volume of low-quality machine-generated content.

(i) AI Provides Drug Smuggling Advice

Journalist Max Daly discovered that ChatGPT could be manipulated into providing detailed information about illegal drug operations. The AI offered insights into smuggling cocaine into Europe and shared information on drug manufacturing, raising concerns about the potential misuse of the technology.

(j) Using AI to Write College Essays

ChatGPT has been controversially used by college students to write essays, prompting concerns among educators who struggle to identify AI-generated work. As AI becomes more sophisticated, detecting AI-generated content becomes increasingly challenging, raising questions about academic integrity.

4) Future Prospects

Despite these challenges and ethical concerns, ChatGPT holds immense potential for further transforming the landscape of scientific research. Some future prospects include [252–256].

(a) Improved AI models: As AI technology continues to advance, we can expect more accurate and reliable models that minimize biases, better understand context, and provide even more valuable assistance to researchers.
(b) Interdisciplinary research: ChatGPT's ability to process and synthesize information from a wide range of disciplines can potentially facilitate groundbreaking interdisciplinary research, leading to novel insights and discoveries.
(c) Democratizing scientific research: By making complex scientific concepts more accessible and simplifying research tasks, ChatGPT can help democratize scientific research, allowing more people to participate in the scientific process and contribute to the advancement of knowledge.
(d) Improved language understanding: ChatGPT is already capable of generating high-quality text, but further improvements in language understanding could lead to more advanced and sophisticated applications.
(e) Personalization: ChatGPT can already generate personalized responses based on user data, but future developments could lead to even more tailored and customized experiences.

(f) Multilingual capabilities: ChatGPT can already generate text in multiple languages, but future developments could lead to even more sophisticated multilingual capabilities that can understand and generate text in a wide range of languages.
(g) Real-time applications: ChatGPT can already generate text in real-time, but future developments could lead to even faster and more responsive applications that can generate text in real-time.
(h) Integration with other technologies: ChatGPT can already be integrated with other technologies, such as chatbots and virtual assistants, but future developments could lead to even more seamless and integrated experiences across multiple platforms and devices.
(i) Better understanding of context: ChatGPT could improve its ability to understand the context of a conversation or text, leading to better responses that are more relevant and accurate.
(j) Improved ability to handle emotions: ChatGPT could develop the ability to recognize and respond to emotions, leading to more empathetic and personalized interactions.
(k) Collaboration with human experts: ChatGPT could be used in collaboration with human experts to provide more effective and efficient solutions in a variety of fields, such as medicine and law.
(l) Enhanced creativity: ChatGPT could be trained to generate creative content such as poetry, song lyrics, and stories.
(m) Continual learning: ChatGPT could be trained to learn from its interactions with users, and continually improve its responses and capabilities.
(n) Better ethical frameworks: The development of ChatGPT and other AI models must be guided by ethical frameworks that prioritize fairness, accountability, and transparency.
(o) Domain-specific Models: As the need for specialized knowledge and expertise grows in various industries, we can expect more domain-specific AI language models tailored to the unique requirements of fields such as healthcare, finance, law, and science. These specialized models can provide more accurate, relevant, and in-depth information to users within those domains.
(p) Improved Contextual Understanding: Researchers are working to enhance the contextual understanding capabilities of language models like ChatGPT. Improved models are likely to better comprehend and remember context over longer sequences of text, leading to more coherent and consistent conversations, even during extended interactions.
(q) Bias Mitigation and Fairness: The AI research community is actively working on methods to identify, measure, and mitigate biases in language models. Future versions of ChatGPT may incorporate more advanced techniques to minimize bias and discrimination, resulting in more equitable and fairer AI-driven applications.
(r) Efficient Model Architectures: As computational resources and energy consumption become increasingly important considerations, researchers are likely to explore more efficient model architectures and training techniques. Future iterations of ChatGPT may be designed to be more resource-efficient, making these models more accessible and environmentally friendly.
(s) Explainable AI: As AI language models become more complex, the need for explainability and transparency will grow. Researchers are likely to develop methods to improve model explainability, enabling users to better understand the decision-making processes and internal workings of models like ChatGPT.
(t) Multimodal Integration: Future AI language models may integrate multimodal information, such as images, videos, and audio, to provide more comprehensive and engaging user experiences. Combining natural language understanding with other data modalities can enable more sophisticated AI-driven applications, such as virtual assistants, content creation tools, and interactive learning platforms.
(u) Safety and security measures will become even more critical. Researchers and developers are likely to focus on implementing safeguards and monitoring systems to minimize the risk of malicious use, ensuring that AI models are used responsibly and ethically.

The future prospects for ChatGPT and other AI language models are exciting and varied, with the potential to revolutionize numerous domains and applications. As researchers address existing challenges and explore new opportunities, the capabilities and benefits of AI language models will continue to grow, paving the way for more advanced and responsible AI-driven technologies.

8. Ethics in computer science and ChatGPT's challenges

Ethics in computer science is a multifaceted subject that addresses the moral and ethical considerations [257–260] associated with the development, deployment, and use of computer technologies, including AI language models like ChatGPT. It is essential to ensure that these technologies are designed and used in ways that align with human values and promote the well-being of individuals and society as a whole. Some key aspects of ethics in computer science, as discussed earlier, include [261–266]: (i) data privacy and protection, ensuring that sensitive information is handled responsibly, (ii) bias and fairness, focusing on the importance of creating AI systems that are equitable and unbiased, (iii) transparency and accountability, emphasizing the need for AI systems to be understandable and for developers to be responsible for their actions, (iv) impact on employment, addressing concerns about AI technologies displacing human jobs, (v) emotional manipulation and persuasion, preventing the misuse of AI-generated content to exploit people's emotions, (vi) dependence on AI-generated content, promoting a balanced approach to the use of AI-generated content, (vii) autonomy of AI systems, defining appropriate boundaries for AI decision-making and control, (viii) impact on creative industries, preserving the value of human creativity while leveraging AI capabilities, (ix) ethical use of AI-generated content, establishing guidelines and best practices for responsible use in various contexts, (x) AI-generated content in education and training, ensuring accuracy, unbiasedness, and high quality, (xi) deepfake text and misrepresentation, addressing the potential for AI-generated content to create false narratives or impersonate others, (xii) unequal access to AI technology, ensuring that the benefits of AI are accessible to all and do not disproportionately benefit certain groups, (xiii) intellectual property and authorship, determining ownership and authorship rights for AI-generated content, (xiv) erosion of trust in digital communication, developing methods to verify the authenticity of digital content, (xv) AI in social media and online platforms, promoting healthy online discourse and user well-being, (xvi) cultural and linguistic bias, addressing potential biases in AI-generated content, (xvii) ethical development of future AI systems, maintaining an ethically grounded approach to AI development, and (xviii) digital divide and access to technology, working to bridge the gap in access to digital resources and AI technologies. We discuss briefly on several aspects in this context.

1) Ethics in Computer Science

(a) Professionalism and Codes of Conduct: Professionalism in computer science involves adhering to ethical standards and best practices when designing, developing, and deploying computer systems and software. Professional organizations, such as the Association for Computing Machinery (ACM) and the Institute of Electrical and Electronics Engineers (IEEE), provide codes of conduct to guide computer professionals in making responsible decisions and maintaining the highest standards of integrity.
(b) Sustainability and Environmental Impact: The environmental impact of computing technologies, including energy consumption, electronic waste, and carbon emissions, is a significant ethical

concern. Developing sustainable, energy-efficient hardware and software solutions, promoting recycling and responsible disposal of electronic waste, and considering the life cycle of products are essential aspects of addressing the environmental impact of computer science.

(c) Artificial Intelligence and Machine Ethics: As AI systems become more sophisticated, ethical considerations specific to AI and machine learning emerge. Machine ethics involves developing AI systems that align with human values, exhibit ethical behavior, and make morally justifiable decisions. This includes research into value alignment, explainable AI, and the development of ethical frameworks and guidelines for AI systems.

(d) Digital Citizenship and Cyberbullying: Digital citizenship refers to the responsible, ethical, and safe use of technology by individuals. One of the ethical challenges associated with digital citizenship is addressing cyberbullying, online harassment, and the negative effects of social media on mental health. Promoting digital literacy, online etiquette, and responsible use of technology are essential components of addressing these challenges.

(e) Algorithmic Transparency and Accountability: Algorithmic transparency involves making the processes, decision-making criteria, and assumptions underlying algorithms clear and understandable to users, regulators, and other stakeholders. Ensuring transparency in algorithmic decision-making is essential to promote fairness, prevent discrimination, and hold developers accountable for the consequences of their algorithms.

(f) Automation and Employment: The increasing automation of tasks and jobs through advances in computer science and AI raises ethical concerns about the potential displacement of human workers and the effects on job markets. Addressing these concerns involves considering the long-term societal implications of automation, developing strategies for workforce retraining and adaptation, and promoting policies that support those affected by technological unemployment.

(g) Open Source and Proprietary Software: The debate between open source and proprietary software revolves around issues of intellectual property, accessibility, and innovation. Open source software promotes transparency, collaboration, and the free sharing of ideas, while proprietary software focuses on protecting intellectual property and generating revenue. Balancing the benefits and drawbacks of these approaches and fostering a diverse software ecosystem is an essential ethical consideration in computer science.

(h) Fake News and Disinformation: The spread of fake news and disinformation through digital channels, particularly on social media, is a major ethical concern in the field of computer science. Developing algorithms and tools to detect, flag, and combat the spread of false information, while also preserving freedom of speech and avoiding censorship, is a complex ethical challenge that requires ongoing research and collaboration.

(i) Digital Censorship and Freedom of Speech: Ethical issues related to digital censorship and freedom of speech arise when governments or private entities restrict access to information, control the flow of data, or suppress the expression of ideas online. Ensuring that the internet remains a platform for the free exchange of ideas while also addressing legitimate concerns about security, privacy, and harmful content is a vital ethical challenge in computer science.

(j) Inclusivity and Representation in Technology Development: Inclusivity and representation involve ensuring that diverse perspectives and experiences are considered and represented in the development and use of technology. This includes addressing issues related to gender, race, ethnicity, and socioeconomic status in the technology industry, as well as fostering diversity in the design and development process. Promoting inclusivity and representation can help ensure that computer systems and software are more equitable, accessible, and responsive to the needs of all users.

(k) Net Neutrality and Equal Access to Information: Net neutrality is the principle that internet service providers (ISPs) should treat all data on the internet equally, without discriminating or charging differently based on content, user, platform, or application. Ensuring net neutrality is an essential ethical consideration in computer science, as it promotes equal access to information, fosters innovation, and prevents ISPs from unduly influencing the flow of data.

(l) Human-Computer Interaction and User Experience: Ethical considerations in human-computer interaction (HCI) and user experience (UX) design involve creating computer systems and software that are not only functional and efficient but also promote the well-being and dignity of users. This includes considering the potential psychological, social, and emotional impacts of technology and ensuring that it is designed with empathy, respect, and an understanding of human needs and values.

(m) The Right to be Forgotten: The right to be forgotten is an ethical principle that allows individuals to request the removal of personal information from internet search results or websites, particularly when the information is outdated or no longer relevant. Balancing the right to be forgotten with the need for accurate record-keeping, transparency, and accountability is an important ethical challenge in computer science.

(n) Surveillance and Government Intrusion: The growing use of computer technology for surveillance purposes by governments and other entities raises ethical concerns about individual privacy, government intrusion, and the potential for abuse of power. Balancing the need for security with the protection of individual rights and freedoms is a critical ethical challenge in the digital age.

(o) Privacy and Data Protection: Privacy involves the protection of personal information and the right of individuals to control how their data is collected, stored, and used. With the increasing amount of personal data stored and processed by computer systems, safeguarding user privacy has become a critical ethical concern.

(p) Cyber Warfare and International Security: Cyber warfare refers to the use of computer technology to disrupt, damage, or compromise the information systems, infrastructure, or resources of other nations or organizations. Ethical considerations in cyber warfare include the development and use of offensive and defensive cyber capabilities, the potential for collateral damage, and the establishment of international norms and agreements to govern state behavior in cyberspace.

(q) Data Ownership and Monetization: Data ownership and monetization are concerned with determining who has the right to access, use, and profit from the data generated by individuals or organizations. Ethical challenges in this domain involve balancing the rights and interests of data creators, data subjects, and data processors, as well as addressing issues related to data commodification, consent, and transparency.

(r) Digital Addiction and Mental Health: As technology becomes more pervasive and engaging, concerns arise about the potential for digital addiction and the impact of technology use on mental health. Ethical considerations in this area include the design and promotion of technologies that encourage healthy usage patterns, the provision of support and resources for those affected by digital addiction, and research into the psychological effects of technology use.

(s) Online Anonymity and Privacy: Online anonymity refers to the ability of individuals to engage in digital activities without revealing their true identity. While anonymity can protect privacy and promote free expression, it can also enable harmful behaviors, such as trolling, cyberbullying, or criminal activity. Balancing the benefits and risks of online anonymity is a complex ethical challenge in computer science.

(t) Algorithmic Fairness and Discrimination: As algorithms increasingly influence decision-making in various domains, concerns about algorithmic fairness and discrimination have become more prominent. Ethical considerations in this area involve ensuring that algorithms do not unfairly disadvantage certain individuals or groups based on factors such as race, gender, or socioeconomic status, and developing methods to audit and evaluate the fairness of algorithmic decision-making processes.

(u) The Ethics of Big Data and Data Mining: The rapid growth of big data and data mining has led to new ethical challenges related to the collection, analysis, and use of massive datasets. These challenges include ensuring informed consent, protecting privacy, preventing the misuse of data, and addressing the potential for surveillance and discrimination that can arise from the aggregation and analysis of large-scale data.

(v) Globalization and Cultural Sensitivity: As technology becomes more globally interconnected, ethical considerations related to globalization and cultural sensitivity become increasingly important. These considerations involve ensuring that technology respects and accommodates diverse cultural values, norms, and customs, and that it promotes cross-cultural understanding and collaboration rather than exacerbating cultural divides or tensions.

(w) Security and Trust: Computer security involves protecting systems, networks, and data from unauthorized access, tampering, or destruction. Ensuring the trustworthiness and integrity of computer systems is an essential ethical responsibility for developers and users alike.

(x) Intellectual Property: Intellectual property refers to the legal rights that protect the ownership and use of creative works, inventions, and other forms of intangible property. Ethical considerations in computer science involve striking a balance between protecting intellectual property rights and fostering innovation, as well as addressing issues such as software piracy and plagiarism.

(y) Accessibility and Universal Design: Accessibility involves designing computer systems and software that are useable by people with varying abilities and disabilities. Universal design refers to the development of products and environments that can be used by all people, regardless of age, size, or ability. Ensuring that technology is accessible and inclusive is a key ethical responsibility in computer science.

(z) Digital Divide and Social Inequality:The digital divide refers to the gap between those who have access to modern information and communication technology and those who do not. Addressing this divide and promoting equal access to technology is an important ethical consideration in computer science.

2) ChatGPT's Challenge to Current Computer Ethics

ChatGPT, as an advanced AI language model, presents a variety of ethical challenges that need to be considered and addressed to ensure its responsible development and use [267–270]. Some of the main ethical challenges posed by ChatGPT, based on the previous discussions, include [271–275]: (i) data privacy and protection: safeguarding sensitive information collected and used by AI models like ChatGPT, (ii) bias and fairness: ensuring that AI-generated content is equitable and unbiased, reflecting diverse perspectives and experiences, (iii) transparency and accountability: making AI systems understandable and holding developers responsible for their actions, (iv) emotional manipulation and persuasion: preventing AI-generated content from exploiting people's emotions for malicious purposes, (v) dependence on AI-generated content: encouraging balanced and responsible consumption of AI-generated content, (vi) impact on creative industries: balancing the use of AI capabilities with the preservation of human creativity and value, (vii) ethical use of AI-generated content: establishing guidelines and best practices for the responsible use of AI-generated content in various contexts, (vii) deepfake text and misrepresentation: addressing the potential for AI-generated content to create false narratives or impersonate individuals, (ix) unequal access to AI technology: ensuring that AI benefits are accessible to everyone and do not disproportionately favor certain groups, (x) intellectual property and authorship: determining ownership and authorship rights for AI-generated content, (xi) erosion of trust in digital communication: developing methods to verify the authenticity of digital content and promoting transparency in its creation, (xii) AI in social media and online platforms: fostering responsible use of AI systems on these platforms and promoting healthy online discourse, (xiii) cultural and linguistic bias: addressing potential biases in AI-generated content and promoting cultural and linguistic diversity, and (xiv) digital divide and access to technology: working to bridge the gap in access to digital resources and AI technologies, promoting digital literacy and empowerment. We provide a brief about how ChatGPT can impose challenges in current computer ethics.

(a) Bias and Fairness: Since ChatGPT is trained on vast amounts of data from the internet, it can absorb and propagate biases present in its training data. This can result in outputs that are discriminatory or reinforce stereotypes. To mitigate this issue, it is essential to develop strategies for debiasing AI models and implementing fairness-aware algorithms.

(b) Privacy, Security, and Misinformation: ChatGPT's ability to generate human-like text raises concerns about privacy and security, as sensitive user data could be inadvertently disclosed or misused. Additionally, ChatGPT could be used to create deep fakes or other forms of misinformation, further exacerbating concerns about trustworthiness and digital content integrity. Addressing these concerns requires robust data protection measures and mechanisms to prevent the misuse of the technology.

(c) Accountability and Responsibility: The advanced nature of ChatGPT can make it difficult to determine accountability and responsibility when errors or harm occur. As AI systems become more autonomous, the question of whether developers, users, or the AI itself should be held responsible for unintended consequences becomes increasingly complex. Developing clear guidelines and legal frameworks can help address this challenge.

(d) Autonomy and Human Agency: ChatGPT's ability to generate human-like responses raises questions about the impact of AI systems on human autonomy and agency. Ensuring that AI systems do not undermine human decision-making processes and that individuals maintain control over their choices and actions is a critical ethical concern. This involves promoting transparency, explainability, and user-centered design in AI development.

(e) Emotional Manipulation and Persuasion: Advanced AI language models like ChatGPT can generate content that is highly persuasive or emotionally resonant. This ability raises ethical concerns about the potential for manipulation, as AI-generated content could be used to exploit people's emotions, influence their beliefs or behavior, or promote disinformation. Ensuring that AI systems are designed and used responsibly to prevent such misuse is an important ethical challenge.

(f) Dependence on AI-generated Content: As AI language models become more sophisticated and widely used, there is a risk of increased dependence on AI-generated content for communication, decision-making, and information consumption. This dependence could lead to a reduction in critical thinking, creativity, or the appreciation for human-generated content. Addressing this challenge involves promoting a balanced approach to the use of AI-generated content and fostering media literacy to help users discern between human and AI-generated content.

(g) Autonomy of AI Systems: The development of advanced AI systems like ChatGPT raises questions about the appropriate level of autonomy that should be granted to such systems. As AI systems become more capable of generating content without human intervention, concerns arise about the potential loss of control and accountability. Developing guidelines and frameworks to ensure that AI systems operate within predefined boundaries and do not undermine human authority is a critical ethical challenge.
(h) Impact on Creative Industries: The use of AI language models like ChatGPT in creative industries, such as journalism, literature, or advertising, has the potential to disrupt traditional creative processes and job roles. While AI-generated content can enhance productivity and creativity, it also raises ethical concerns about the potential devaluation of human creative labor and the risk of AI-generated content displacing human creators. Addressing these concerns involves striking a balance between leveraging AI capabilities and preserving the value of human creativity.
(i) Ethical Use of AI-generated Content: The widespread use of AI-generated content raises ethical questions about the appropriate contexts and applications for such content. For example, using AI-generated content in journalism or academic research may raise concerns about authenticity, integrity, and the potential for plagiarism. Establishing ethical guidelines and best practices for the use of AI-generated content in various contexts can help mitigate these concerns and ensure responsible use.
(j) AI-generated Content for Education and Training: The use of AI-generated content in education and training presents both opportunities and ethical challenges. While AI-generated content can enhance personalized learning and facilitate access to knowledge, it also raises concerns about the quality, accuracy, and potential biases in AI-generated educational materials. Ensuring that AI-generated content used in education and training is accurate, unbiased, and of high quality is an essential ethical consideration.
(k) Deepfake Text and Misrepresentation: Advanced AI language models like ChatGPT can be used to generate realistic, human-like text, potentially giving rise to "deepfake text." This capability raises ethical concerns about the potential for misrepresentation, identity theft, and the creation of false narratives. Ensuring that AI-generated content is used responsibly and developing methods to detect and prevent deepfake text are important ethical challenges to address.
(l) Unequal Access to AI Technology: The availability and use of advanced AI systems like ChatGPT are not uniformly distributed across the global population. Unequal access to AI technology can exacerbate existing digital divides and create new forms of inequality. Ensuring that the benefits of AI technology are accessible to all and do not disproportionately benefit certain groups or individuals is an essential ethical consideration.
(m) Intellectual Property and Authorship: The use of AI-generated content raises questions about intellectual property and authorship. As AI systems like ChatGPT become more capable of generating creative and original content, determining who should be credited as the author and who owns the rights to the generated content becomes increasingly complex. Developing legal frameworks and ethical guidelines to address these questions is an important challenge in the age of AI-generated content.
(n) Erosion of Trust in Digital Communication: As AI-generated content becomes more prevalent and sophisticated, users may find it increasingly difficult to distinguish between human-generated and AI-generated content. This can erode trust in digital communication, as users may become skeptical of the authenticity or origin of the content they encounter online. Developing methods to verify the authenticity of digital content and promote transparency in its creation is an important ethical challenge in the context of AI language models like ChatGPT.
(o) AI in Social Media and Online Platforms: The integration of AI language models like ChatGPT into social media and online platforms presents various ethical challenges. These include concerns about amplifying misinformation, promoting echo chambers, and enabling targeted manipulation or harassment. Ensuring that AI systems are designed and used responsibly on these platforms, with an emphasis on promoting healthy online discourse and user well-being, is a critical ethical consideration.
(p) Cultural and Linguistic Bias: AI language models like ChatGPT are trained on large datasets of text from various sources, which may introduce cultural and linguistic biases into the generated content. These biases can perpetuate stereotypes, unfairly represent certain groups, or lead to biased decision-making. Addressing cultural and linguistic bias in AI systems involves developing methods to identify, measure, and mitigate such biases in both the training data and the generated content.
(q) Ethical Development of Future AI Systems: As AI language models like ChatGPT continue to evolve and become more advanced, new ethical challenges will likely emerge. Ensuring that the development of future AI systems remains ethically grounded involves ongoing research, collaboration, and engagement with diverse stakeholders, including ethicists, policymakers, and the broader public.
(r) Digital Assistants and Privacy Concerns: The integration of AI language models like ChatGPT into digital assistants and voice-activated devices can lead to privacy concerns, as these devices may inadvertently capture sensitive personal information or conversations. Addressing these privacy concerns requires the development of robust data protection mechanisms, transparent data handling policies, and user-friendly privacy controls.
(s) AI-generated Content and Mental Health: The proliferation of AI-generated content may contribute to the "infobesity" phenomenon, where users are overwhelmed by the sheer volume of information available online. This information overload can have negative effects on mental health and well-being. Encouraging responsible consumption of AI-generated content and promoting digital wellness practices are important ethical considerations in the context of AI language models like ChatGPT.
(t) Filter Bubbles and Polarization: The use of AI language models in content recommendation systems can inadvertently contribute to the formation of filter bubbles and the polarization of users' beliefs and opinions. These systems may prioritize AI-generated content that reinforces users' existing views, rather than exposing them to diverse perspectives. Addressing this challenge involves designing AI systems that promote diversity, empathy, and understanding across different viewpoints.
(u) Cybersecurity Threats: The capabilities of AI language models like ChatGPT can be exploited by malicious actors to create sophisticated phishing attacks, disinformation campaigns, or other cybersecurity threats. Ensuring that AI-generated content is used responsibly and developing methods to detect and counteract these threats are important ethical challenges to consider.
(v) Impact on Human Relationships and Communication: As AI-generated content becomes more pervasive, it may influence the way humans communicate and interact with one another. This raises ethical concerns about the potential dehumanization of communication and the erosion of empathy and authentic connection in human relationships. Fostering responsible use of AI-generated content and promoting digital communication practices that prioritize human connection are essential ethical considerations.
(w) Unintended Consequences and Misuse: As AI language models like ChatGPT become more advanced and accessible, there is an increased risk of unintended consequences and misuse. This may include the development of AI systems that generate harmful content or enable illicit activities. Addressing these risks involves

ongoing monitoring of AI-generated content, collaboration between stakeholders to prevent misuse, and the development of robust legal and ethical frameworks to guide the responsible use of AI technology.

(x) Accountability and Transparency: The use of AI-generated content raises questions about accountability and transparency, particularly when AI systems make decisions or generate content with significant societal impact. Ensuring that AI systems are transparent in their decision-making processes and that there is clear accountability for the consequences of their actions is a critical ethical challenge.

(y) Regulation and Policy Development: The rapid advancement and widespread adoption of AI language models like ChatGPT necessitate the development of appropriate regulations and policies to guide their use. This involves balancing innovation and technological progress with ethical considerations, protecting individual rights, and promoting social welfare. Engaging diverse stakeholders in the policy development process and fostering international cooperation are essential to addressing the ethical challenges posed by AI-generated content.

(z) Digital Divide and Access to Technology: The digital divide refers to the gap between individuals, households, or communities with regard to their access to information and communication technology (ICT), including computers, the internet, and other digital resources. This divide can stem from various factors, such as income, education, geographic location, and infrastructure availability. The digital divide can exacerbate social, economic, and educational inequalities, leading to disparities in opportunities, resources, and overall quality of life.

9. Biases and limitations of ChatGPT

ChatGPT, like other AI language models, is susceptible to various biases, including gender, racial, and cultural biases, language bias, and ideological bias [276–278]. These biases stem from the model's training data, which reflects human-generated content from the internet. Other biases, such as attention, format, and commercial biases, can also emerge from the nature of the training data. ChatGPT has several biases as follows [279–286]: (i) gender, racial, and cultural biases, (ii) language bias, (iii) ideological bias, (iv) sensationalism and clickbait bias, (v) confirmation bias, (vi) temporal bias, (vii) exclusionary bias, (vii) commercial bias, (ix) cognitive bias, (x) attention bias, (xi) format bias, (xii) source bias, (xiii) novelty bias, (xiv) positive/negative sentiment bias, (xv) outlier bias, (xvi) implicit bias, (xvii) authority bias, (xviii) recency bias, (xix) groupthink bias, (xx) anchoring bias, (xxi) availability bias, (xxii) false consensus bias, (xxiii) hindsight bias [287].

It also possess many limitations as follows [288–296]: (i) inherent biases in training data, (ii) incomplete or outdated knowledge, (iii) inability to discern factual accuracy, (iv) lack of contextual awareness, (v) ethical and moral reasoning limitations, (vi) long conversational context challenges, (vii) inability to generate visual content, (viii) difficulty handling inappropriate or harmful requests, (ix) difficulty recognizing and adapting to user expertise, (x) limited emotional intelligence, (xi) lack of personalized feedback, (xii) limited domain-specific expertise, (xiii) inability to interact with external systems, (xiv) difficulty handling multilingual queries, (xv) difficulty with non-literal language, (xvi) limited creativity, (xvii) overgeneralization, (xviii) inconsistency in quality, (xix) energy consumption and environmental impact, (xx) difficulty capturing human intuition, (xxi) lack of self-awareness, (xxii) resource requirements for training and deployment. We discuss about each in brief in this section.

1) Biases

(a) Cultural and Linguistic Bias: Since ChatGPT is trained on data predominantly from the internet, it may be biased towards certain cultures, languages, or perspectives that are more prominently represented online. This can result in the AI model generating content that does not accurately reflect the diversity of human experiences or languages.

(b) Gender and Racial Bias: ChatGPT may unintentionally perpetuate gender and racial stereotypes due to biases in the training data. For example, the model may associate certain professions or roles with specific genders or ethnicities, reinforcing existing stereotypes.

(c) Bias in Content Recommendations: When used in recommendation systems, ChatGPT may exhibit biases by prioritizing content that aligns with a user's existing beliefs or preferences, potentially contributing to filter bubbles and polarization.

(d) Ideological Bias: ChatGPT may exhibit ideological bias, reflecting the dominant viewpoints or opinions found in its training data. This can lead to the generation of content that leans towards specific political, social, or economic ideologies, potentially reinforcing existing biases or creating an unbalanced representation of different perspectives.

(e) Sensationalism and Clickbait Bias: Since ChatGPT is trained on data from the internet, it may inadvertently learn patterns associated with sensationalist or clickbait content. This could result in the model generating attention-grabbing headlines, exaggerations, or other forms of sensationalism in the content it produces.

(f) Confirmation Bias: ChatGPT may inadvertently exhibit confirmation bias by generating content that aligns with pre-existing beliefs, assumptions, or stereotypes in the training data. This can limit the diversity of perspectives and reinforce biased viewpoints.

(g) Temporal Bias: ChatGPT may exhibit temporal bias, as it is trained on data from specific periods. This can lead to the model generating content that reflects the trends, beliefs, or viewpoints prevalent during those times, which may not be relevant or appropriate for the current context.

(h) Exclusionary Bias: ChatGPT may inadvertently exclude or marginalize certain groups, communities, or perspectives that are underrepresented in its training data. This can lead to content that lacks inclusivity and fails to reflect the experiences of all users.

(i) Commercial Bias: ChatGPT's training data, which comes predominantly from the internet, may contain a commercial bias, as it reflects the goals and interests of commercial entities. This can lead to the model generating content that inadvertently promotes products, services, or brands, even when it is not the user's intention.

(j) Cognitive Bias: Since ChatGPT learns from human-generated content, it may inadvertently adopt various cognitive biases present in its training data. These biases can manifest in the model's output, potentially leading to flawed reasoning, assumptions, or generalizations.

(k) Attention Bias: ChatGPT may develop attention bias, as it learns from content that has received more attention or engagement online. This can lead to the model prioritizing popular or widely discussed viewpoints, potentially overshadowing less common perspectives or underrepresented voices.

(l) Format Bias: ChatGPT's training data may contain a format bias, as it is primarily composed of text-based content from the internet. This can result in the model being less adept at generating content that reflects other forms of communication, such as spoken language or non-verbal cues.

(m) Source Bias: ChatGPT's training data may contain source bias, as it learns from a variety of online sources that may not be equally reliable, credible, or authoritative. This can lead to the model generating content based on information from less trustworthy sources or giving undue weight to certain sources.

(n) Novelty Bias: Since ChatGPT learns from the patterns and associations found in its training data, it may exhibit novelty bias by generating content that is more similar to popular or trending topics, potentially overlooking or downplaying less well-known or emerging perspectives.

(o) Positive/Negative Sentiment Bias: ChatGPT may inadvertently develop a bias towards either positive or negative sentiment in its generated content, based on the prevalence of such sentiment in its training data. This can lead to the model generating content that skews towards an overly optimistic or pessimistic outlook on certain topics or situations.

(p) Outlier Bias: ChatGPT's training data may contain outlier bias, as it learns from unusual or extreme examples that are not representative of typical situations or perspectives. This can result in the model generating content that emphasizes or exaggerates outlier views, potentially distorting the overall understanding of a topic.

(q) Implicit Bias: ChatGPT may exhibit implicit biases that are not explicitly present in its training data but emerge from the relationships between different concepts and ideas in the data. These biases can subtly influence the content generated by the model, making them harder to detect and address.

(r) Authority Bias: ChatGPT may develop an authority bias by giving more weight to content or viewpoints from sources that are perceived as authoritative or influential in its training data. This can result in the model prioritizing information from well-known individuals or organizations, potentially overlooking valuable insights from less prominent sources.

(s) Recency Bias: ChatGPT may exhibit recency bias by placing more emphasis on recent or current events, trends, or beliefs in its generated content. This can lead to the model overlooking historical context or undervaluing the relevance of past experiences and knowledge.

(t) Groupthink Bias: ChatGPT may unintentionally adopt groupthink bias by generating content that reflects the consensus views or opinions found in its training data. This can limit the diversity of perspectives and hinder the exploration of alternative or dissenting viewpoints.

(u) Anchoring Bias: ChatGPT may exhibit anchoring bias, which occurs when the model places too much emphasis on specific pieces of information or initial impressions from its training data. This can result in the model generating content that is unduly influenced by certain details or examples, potentially leading to distorted or unbalanced perspectives.

(v) Availability Bias: ChatGPT may be affected by availability bias, which refers to the tendency to prioritize information that is more easily recalled or readily available in its training data. This can cause the model to generate content that overemphasizes common or well-known examples while neglecting less prominent but equally relevant information.

(w) False Consensus Bias: ChatGPT may develop a false consensus bias by overestimating the extent to which its training data represents a broader consensus or shared understanding. This can lead to the model generating content that assumes a higher degree of agreement on certain topics or viewpoints than actually exists.

(x) Hindsight Bias: ChatGPT may exhibit hindsight bias, which occurs when the model overestimates the predictability or inevitability of past events based on the information available in its training data. This can result in the model generating content that presents a biased view of historical events or outcomes.

2) Limitations

ChatGPT has several limitations, including inherent biases in its training data, incomplete or outdated knowledge, and difficulty discerning factual accuracy. The model also faces challenges related to contextual awareness, ethical reasoning, conversational context, and generating visual content. Furthermore, ChatGPT may struggle with handling inappropriate requests, adapting to user expertise, and providing personalized feedback. Limitations also include difficulties with multilingual queries, non-literal language, creativity, and consistency in quality.

(a) Inaccurate or Misleading Information: ChatGPT may generate content that contains inaccuracies or misleading information, as it is based on the patterns and associations it has learned from its training data rather than a deep understanding of the subject matter.

(b) Sensitivity to Input Phrasing: The model's output can be sensitive to slight changes in input phrasing, leading to inconsistent responses or varying levels of detail in the generated content.

(c) Verbosity and Overuse of Certain Phrases: ChatGPT may sometimes produce verbose responses or overuse certain phrases, making the generated content appear repetitive or less natural.

(d) Inability to Fact-Check or Access Real-time Information: ChatGPT's knowledge is limited to the data it was trained on, with a cutoff date in 2021. As a result, it cannot provide real-time information or verify the accuracy of its responses against new developments or updates.

(e) Difficulty in Handling Ambiguous Queries: ChatGPT may struggle with ambiguous queries or questions that require a nuanced understanding of context. In such cases, the model may generate content that is plausible-sounding but does not directly address the user's intent.

(f) Lack of Contextual Awareness: ChatGPT may sometimes generate content that lacks contextual awareness or fails to consider the broader implications of a given topic. This can result in content that appears superficial or does not account for the complexity of real-world situations.

(g) Ethical and Moral Reasoning: ChatGPT, as a language model, may struggle to engage in ethical or moral reasoning. It may generate content that is morally ambiguous or does not adhere to ethical standards, making it unsuitable for certain applications without proper human supervision.

(h) Long Conversational Contexts: ChatGPT may have difficulty maintaining coherence and consistency in long conversational contexts or when responding to a series of interconnected questions. This can result in disjointed or conflicting responses that may confuse users.

(i) Inability to Generate Visual Content: As a text-based AI language model, ChatGPT cannot generate visual content, such as images, videos, or graphs, limiting its applicability in multimedia content creation and visual communication tasks.

(j) Response to Inappropriate or Harmful Requests: ChatGPT may struggle to consistently recognize and handle inappropriate, harmful, or offensive input, potentially generating content that violates ethical guidelines or user expectations.

(k) Difficulty in Recognizing and Adapting to User Expertise: ChatGPT may not effectively adapt its generated content to the expertise level or familiarity of the user with a specific topic, potentially resulting in overly simplistic or overly technical responses that may not suit the user's needs.

(l) Limited Emotional Intelligence: As an AI language model, ChatGPT has limited emotional intelligence, which may result in generated content that lacks empathy or fails to recognize and respond appropriately to the emotional context of a user's query.

(m) Lack of Personalized Feedback: ChatGPT, as a general-purpose language model, may not provide personalized feedback tailored to individual users' needs or learning goals. This can limit its effectiveness in educational or coaching contexts where individualized guidance is essential.

(n) Limited Domain-Specific Expertise: While ChatGPT can generate content on a wide range of topics, it may lack the depth of knowledge or expertise found in domain-specific AI models. This can limit its usefulness in specialized fields or applications where accuracy and precision are paramount.

(o) Inability to Interact with External Systems: ChatGPT, being a text-based AI model, does not possess the ability to interact directly with external systems, such as databases, APIs, or other software. This restricts its capabilities in applications that require real-time access to information or the ability to manipulate or process external data.
(p) Inability to Handle Multilingual Queries: While ChatGPT has some capability to generate content in multiple languages, it may struggle to effectively handle queries that involve multiple languages within a single input or require translations between languages, which could limit its usefulness in multilingual contexts.
(q) Difficulty with Non-Literal Language: ChatGPT may struggle to accurately interpret or generate non-literal language, such as idioms, metaphors, or sarcasm. This can result in responses that are overly literal, miss the intended meaning, or fail to convey the desired tone.
(r) Limited Creativity: Although ChatGPT can generate content that appears creative, its creativity is ultimately limited by the patterns and associations it has learned from its training data. This can result in content that is derivative or lacks the novelty and originality found in human-generated creative works.
(s) Overgeneralization: ChatGPT may sometimes overgeneralize when generating content, leading to responses that lack nuance or oversimplify complex topics. This can result in content that appears plausible on the surface but fails to accurately address the subtleties of a given subject.
(t) Inconsistency in Quality: ChatGPT's output quality may vary depending on the input and the topic being discussed, leading to inconsistencies in the level of detail, coherence, or relevance of the generated content. This can make it challenging to predict the model's performance in different contexts or applications.
(u) Energy Consumption and Environmental Impact: Training and running large-scale AI models like ChatGPT can consume significant amounts of energy, contributing to environmental concerns and raising questions about the sustainability and ethical implications of their widespread use.
(v) Difficulty in Capturing Human Intuition: ChatGPT, as an AI language model, may struggle to capture human intuition, making it challenging for the model to generate content that reflects the implicit knowledge or tacit understanding that humans often rely on when communicating or making decisions.
(w) Lack of Self-Awareness: ChatGPT lacks self-awareness, which means it does not possess an understanding of its own limitations, biases, or knowledge gaps. This can make it difficult for the model to generate content that acknowledges uncertainty or indicates when it may be providing incomplete or incorrect information.
(x) Resource Requirements for Training and Deployment: Training and deploying AI models like ChatGPT can require significant computational resources, which can be a barrier to entry for smaller organizations or individuals who wish to develop or customize AI language models for their specific needs.

10. Conclusion

ChatGPT has already made significant contributions to the advancement of scientific research and has the potential to continue transforming the field in the future. By addressing the challenges and ethical concerns associated with its use, researchers can harness the power of AI responsibly to push the boundaries of human knowledge and understanding. Addressing these challenges will enhance the performance, utility, and user experience of ChatGPT and other conversational AI models, making them more effective in various applications and industries. In various applications and scientific research field, ChatGPT has shown great promise in improving efficiency, facilitating collaboration, and driving innovation. ChatGPT has brought several advancements to generative AI, including: (i) improved contextual understanding: ChatGPT can understand the context of a conversation and generate relevant responses, making it more effective at mimicking human-like interactions, (ii) better language generation: With its advanced language generation capabilities, ChatGPT produces coherent, contextually accurate, and grammatically correct text, (iii) task adaptability: ChatGPT can be fine-tuned for specific tasks or domains, increasing its versatility across various industries, (iv) multilingual proficiency: Its ability to work with multiple languages enables ChatGPT to cater to diverse user bases and global applications. However, several ethical issues must be resolved to make ChatGPT help to shape intelligent human-machine era.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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