# Analysis of the Impact of GPT Technological Transformation on Basic Scientific Research: Postprint

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## Abstract

The burgeoning development of GPT generative large models, exemplified by ChatGPT, has sparked extensive discussions in both academia and industry, bringing immeasurable impact to the development of basic scientific research. This article first reviews the developmental trajectory of the GPT technological revolution and discusses the new transformations this technology brings to scientific research. Then, from three perspectives—application-driven, principle-driven, and innovation actor migration—it examines the impacts of the GPT technological revolution on basic scientific research and offers development recommendations for China. The study argues that while GPT technology can indeed play a positive role in knowledge production, scientific research, and other aspects, even promoting paradigm shifts in research, it may also cause problems such as research misconduct, diminished research credibility, amplification of inherent internet biases, and intellectual property "chokepoints." Therefore, this study concludes by discussing how to develop China's basic scientific research based on GPT technology, clarifying that while investing in and developing nationally autonomous, controllable, and intellectual property-protected data and computing platforms, it is essential to encourage human-machine collaboration alongside research integrity supervision, thereby creating an open and transparent environment for artificial intelligence (AI) to advance basic science. This study aims to provide policymakers and frontline researchers with a perspective for understanding the impact of GPT technology on basic science, promote the rational use of GPT technology, and offer references for the healthy development of future academic ecosystems.

# Full Text

## Preamble

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## Title and Authors

### Impact Analysis of GPT Technology Revolution on Fundamental Scientific Research

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## Abstract

The rapid development of generative large-scale models like ChatGPT has sparked extensive discussion in both academia and industry, bringing immeasurable impact to the advancement of fundamental scientific research. This paper first reviews the evolution of the GPT technological revolution and discusses the new transformations it brings to scientific research. Then, from three perspectives—application traction, principle-driven development, and innovation subject migration—we examine the impacts of the GPT technology revolution on fundamental scientific research and propose development recommendations for China. Our study concludes that while GPT technology can positively contribute to knowledge production and scientific research, even promoting paradigm shifts in research, it may also cause issues such as research misconduct, diminished credibility, amplification of inherent internet biases, and intellectual property "chokepoints." Therefore, we conclude by discussing how China should develop its fundamental scientific research based on GPT technology, emphasizing the need to invest in nationally autonomous, controllable, and IP-protected data and computing platforms while encouraging human-machine collaboration alongside research integrity oversight, thereby fostering an open and transparent environment for AI-driven fundamental science. This study aims to provide policymakers and frontline researchers with a framework for understanding GPT technology's impact on fundamental science, promote its rational use, and offer references for the healthy development of future academic ecosystems.

**Keywords:** ChatGPT, large language model, fundamental science, research integrity, research ecology

## 1. GPT Technology Revolution and Applications in Scientific Research

The emergence of GPT technology, exemplified by ChatGPT, has brought transformative changes to academia, education, and industry. Development in fundamental research is a crucial guarantee of a nation's scientific competitiveness and directly determines the pace of societal progress. Currently, GPT-based research in fundamental science has produced numerous breakthroughs. While large language model technology assists researchers in R&D work and understanding fundamental scientific problems, it is also transforming and even disrupting the fundamental research ecosystem. For China, rationally promoting GPT technology in scientific research not only means improved efficiency but also presents an opportunity for "leapfrog development."

However, some scholars have expressed concerns and anxiety. While GPT technology can greatly enhance research efficiency across multiple fundamental research fields, it must be used properly rather than abused. Some even believe GPT technology could eventually take over entire academic research domains. What is the current application status of GPT technology in fundamental scientific research? What are its impacts? Where are the boundaries and hidden dangers? The academic community has yet to provide a systematic analytical framework and discussion. This study addresses these questions by constructing a systematic analysis framework to discuss GPT technology's potential impacts on fundamental scientific research and possible countermeasures, contributing to the healthy development of the scientific research ecosystem.

To understand why ChatGPT demonstrates such superior performance, we must examine the development path of the GPT family of models [Figure 1: see original paper]. The first-generation GPT model adopted an unsupervised pre-training plus supervised fine-tuning paradigm, focusing on training an unsupervised pre-trained language model and then fine-tuning it for specific tasks. GPT-2.0 followed the same paradigm but achieved better results in supervised tasks by substantially increasing training data volume and model scale. GPT-3.0 [2] introduced a new paradigm combining unsupervised pre-training with prompt engineering, completing supervised tasks with only a few examples during training. GPT-3.0 has three versions with 175 billion, 13 billion, and 7.6 billion parameters respectively. GPT-3.5, an upgraded version of GPT-3.0, comprises a series of improved models based on GPT-3.0 (including code-davinci-002), optimized through evaluating model Q&A performance and reinforcement measures. ChatGPT [3] further introduced Reinforcement Learning from Human Feedback (RLHF) [4] and Proximal Policy Optimization (PPO) for fine-tuning, using preferences as reward signals to generate responses aligned with human preferences [5]. Finally, GPT-4.0 [6] realized the connection from text to multimodality based on GPT-3.5.

In summary, the success of the GPT series marks AI's transition from the "craftsmanship era" of specialized small model training to the "industrial era" of general large model pre-training, with ChatGPT's performance in natural language processing becoming a watershed moment in AI development [7,8].

## 2. Impact of GPT Technology Revolution on Fundamental Scientific Research

The outstanding performance of large language models has created broad application prospects for fundamental scientific research, enabling deployment across numerous scientific scenarios and development of domain-specific large language models. This section analyzes GPT technology's impact on fundamental research from three perspectives: application traction, principle-driven development, and innovation subject migration [Figure 2: see original paper].

### 2.1 Application Traction and Impact

Large language models, including GPT, have triggered a technological revolution that is driving breakthroughs in scientific challenges across fundamental science domains, accelerating research processes and improving efficiency.

**2.1.1 Three Modes of Application Traction** GPT technology applications in fundamental scientific research can be categorized into three modes by capability level, from low to high [Figure 3: see original paper]:

1. **Engineering Applications**: This mode primarily adds external interfaces to GPT models, serving them as general digital research assistants to facilitate daily research workflows and improve academic efficiency. Table 1 presents engineering application cases of GPT-derived models developed by Chinese Academy of Sciences.

2. **Disciplinary Research Innovation Assistance**: This mode fine-tunes domain databases to develop GPT-derived models (such as Protein GPT based on protein structure databases), enhancing model performance and adaptability for specific scientific research tasks. While ChatGPT currently performs like a generalist, there remains a significant gap compared to top experts in specialized fields. Fine-tuning ChatGPT as a general AI foundation on local databases can enhance its domain expertise, making it more suitable for solving domain-specific problems and enabling it to become an explorer of scientific hypothesis spaces. Some exploratory research efforts are shown in Table 2 . Additionally, AI-driven fundamental scientific research requires AI technology to understand disciplinary fundamentals and improve the representation and integration of diverse knowledge. The primary difficulty lies in the low mutual understanding between domain scientists and AI experts, with high barriers to mutual promotion.

3. **Promotion of Research Paradigm Transformation**: In current "human-machine symbiosis" research scenarios, machines can be cat-

egorized by intelligence level into: "experimenters" that assist with experiments, "AI research assistants" that aid high-dimensional spatial computations, and "AI scientists" that autonomously conduct full research processes and break through human cognitive bottlenecks. These three forms have different focuses and develop in parallel. GPT technology primarily functions in the latter two roles. The "research paradigm transformation promotion" mode aims to break through the limitation of "GPT models constructing virtual worlds" by empowering physical research equipment, enabling AI scientists to autonomously propose hypotheses, design experiments, and validate them [Figure 4: see original paper].

Currently, GPT technology connects with physical experimental equipment in two main ways: (1) Breaking the barrier between natural language and machine instructions to automatically generate robot operation instructions. Research has used GPT-4 to automatically generate experimental robot operation instructions (OT-2) from natural language experimental commands, significantly saving time previously spent considering machine operation details [18]. (2) Breaking the barrier between research hypotheses and scientific experiments by autonomously generating experimental protocols. For example, the ChemGPT model developed by University of Science and Technology of China, after "learning" 500,000 chemistry papers, can automatically provide recommended chemical experimental protocols and drive a robotic chemist "Xiaolai" to conduct experiments, efficiently completing R&D of Fenton catalysts and other chemical materials.

#### 2.1.2 Three Negative Impacts of Application Modes

1. **Engineering Application Mode**: Inevitably faces research integrity issues. From a text grammar and formatting perspective, ChatGPT is an excellent "paper manufacturer" [19]. However, all GPT framework products share a common characteristic: creators cannot grasp internal changes—what we call a "black box." Due to massive model parameters, GPT models uncontrollably generate large amounts of fabricated information. Moreover, from a research ethics perspective, originality is fundamental to papers. Using ChatGPT for paper writing is formally no different from plagiarism. More concerningly, as large language models develop, editors and publishers will find it increasingly difficult to identify AI-written articles. If ChatGPT and other AI technologies are misused and abused, they will cause uncontrollable impacts on research integrity.

2. **Research Innovation Mode**: Reduced model transparency weakens research credibility. Currently, based on GPT-4's technical report, OpenAI has not disclosed technical details such as model scale due to competition and security considerations, and cutting-edge research increasingly trends toward not publishing open-source technical details. For researchers, lack of transparency in model technical details not only goes against the trend

of open science but also violates the scientific attitude of seeking evidence. Continuing to use GPT open-source models or official APIs to learn domain data will threaten result reproducibility [20], fundamentally weakening research credibility. Simultaneously, it cannot fundamentally answer the mechanisms of major scientific questions, preventing fundamental breakthroughs.

3. **Research Paradigm Transformation Mode**: GPT technology trained on open-source big data potentially amplifies inherent biases. Since ChatGPT's training data comes from massive internet sources that inevitably record potential discrimination and value conflicts in human society, when ChatGPT outputs obviously biased research content, it not only affects researchers' judgment but may also deepen cognitive biases among researchers through widespread application of large text volumes [21]. Additionally, in the open letter co-signed by Musk and thousands of computer scientists, eight AI danger speculations and failure modes were listed, including human enfeeblement, cognitive erosion, and deception [22].

### 2.2 Principle-Driven Development and Impact

GPT-based scientific research has achieved numerous breakthroughs, with protein language models like ProGen and ESMFold demonstrating outstanding performance in protein structure prediction tasks, becoming milestones in GPT model development history. Analyzing the underlying principles, characteristics, and future development of these achievements provides important insights for researchers to clarify positioning and research boundaries.

The core of GPT-like large models remains the Transformer architecture. Their excellence in fundamental scientific research essentially comes from learning massive domain scientific data and effectively fitting high-dimensional spaces of experimental and computational problems through large model parameters. In other words, the output is only statistical possibility, lacking strong theoretical knowledge support.

1. **Primary Battlefield is High-Dimensional Complex Problems in Data-Computing-Intensive Fields**: Analyzing the above cases reveals that GPT technology's main application battlefield in fundamental scientific research lies in experimental and computational domains—fields with rich data accumulation, high structuralization, and clearly defined problems such as molecular biology. This is primarily because GPT technology's essence in fundamental research is the combination of high-dimensional modeling capabilities with scientific first principles. Scientific computing aims to map real-world phenomena across different scales to computational simulation worlds based on first principles and experimental observations. However, as problem complexity increases, classical computational models face the "curse of dimensionality." AI technology helps solve this dimensionality curse in scientific computing by effectively

connecting physical models across different scales. In this process, model parameters are crucial indicators of model complexity and capability, as well as key factors enabling solutions to high-dimensional data computation in fundamental research. More parameters mean the model can process more data, learn more domain knowledge, better explore intrinsic patterns in high-dimensional data, and thus solve more complex scientific problems. For example, in biology, the ProGen model learned the "grammar" of how amino acids combine into 280 million existing proteins based on 1.2 billion parameters, helping researchers quickly build entirely new proteins from scratch [12].

2. **Model Adaptability is Determined by Data Representation**: Since GPT model training and application use natural language sequence data, in experimental computational science problems, only sequential domain data similar to natural language can be compiled with GPT models to learn embedded high-dimensional complex knowledge. Typical domain sequential data includes: (1) Domain papers and patent data are natural language data. For example, Chem-GPT, based on open-source GPT code, "read" nearly 500,000 chemistry papers and can automatically answer researchers' chemistry questions or even provide experimental protocols for compound synthesis, efficiently completing compound R&D. Additionally, PatentGPT-J-6B [23] has been developed for automatic patent claim generation. (2) Biological macromolecules, especially proteins, can be viewed as statements written in genetic code with more complex associated knowledge. Taking the "biological version of ChatGPT" ProGen model as an example, by learning the "grammar" of how amino acids combine into 280 million existing proteins, it learned the patterns of amino acid sequencing and their relationships with protein structure and function, enabling it to generate artificial novel proteins across multiple families and functions from scratch [12].

#### 2.2.2 Application Boundaries of GPT Models from a Principle-Driven Perspective

1. **Breaking Research Boundaries in Experimental Computing**: When model parameters exceed critical values, GPT models break through research boundaries in experimental computing domains, exhibiting certain "emergent properties." In AI large models, "emergence" 通俗 ly refers to capabilities that don't exist in small-scale models but appear in large-scale models when parameters exceed thresholds [24]. These capabilities weren't specifically designated during training but spontaneously emerged through the collaborative interaction between the model's multi-layer structure and parameters [25]. According to Chung et al. [26], when model parameter scale exceeds 6.2 billion, previously non-existent capabilities can emerge, completing a qualitative leap from quantitative change and showing astonishing explosive growth. However,

emergent capabilities in large models also present unresolved questions: what controls which capabilities emerge? How can we control models to emerge desired capabilities while ensuring undesired ones never emerge? Some research questions the "emergence" phenomenon, suggesting it's merely a result of metric selection—when evaluation metrics are replaced with more continuous, smooth ones, emergent phenomena become less obvious [27]. Nevertheless, most current research supports the existence of emergent properties in large models. Due to the unpredictability and uncertainty of emergent phenomena, we need to cautiously handle emergent results and further verify and analyze their outputs.

2. **Not Yet Reaching Theoretical Derivation Boundaries**: Although GPT-like models perform exceptionally well in experimental computational science problems, even passing the Turing test, they cannot yet autonomously conduct theoretical derivation research tasks. Research on "AI Descartes" models suggests that large language models like ChatGPT have limited logical capabilities and cannot yet derive natural phenomenon models from axiomatic knowledge and experimental data [28]. Two main perspectives analyze this issue: (1) The core capability of theoretical derivation requires understanding causality, while GPT model "intelligence" merely stems from data fitting. AI scientist Judea Pearl argues that understanding comes from causal models, not data fitting. ChatGPT relies solely on massive text data for pre-training and fine-tuning, lacking direct observation and experience of the real world, making it difficult to judge causal relationships. Its "intelligence" only comes from existing content in human corpora—when questions lack human-created answers in the corpora, the ChatGPT system is "clueless." However, for theoretical science, the most important task is deriving new theories that explain the world. Although AI large models can produce correct "scientific" predictions (e.g., predicting ball trajectories with the AI Physicist model [29]), such AI systems are more like students who memorize physics textbooks—they know correct answers only if questions appeared in the book, which isn't true scientific innovation! Research by Judea Pearl suggests introducing causal structural models to create intelligent systems with deep functional-structural integration as a potential new direction. (2) The black-box working mechanism of AI models means GPT models lack theoretical interpretability. Philosopher Karl Popper noted that scientists seek not highly probable theories but explanations—powerful and highly improbable theories. However, GPT models remain black-box neural network models that cannot explain their internal working mechanisms. Their exhibited "intelligence" is not similar to human brain structure and cognitive mechanisms but more like a pattern-matching statistical engine, outputting only statistical possibilities. This differs greatly from human thinking patterns—the human brain operates with minimal information because it seeks explanations rather than direct correlations between data points. In other words, current GPT models remain focused on description

and prediction, with outputs always lacking strong support and unable to conduct cross-domain, cross-modal theoretical reasoning like the human brain.

### 2.3 Innovation Subject Migration and Impact

Analyzing the cases above reveals that industry is gradually becoming one of the core subjects in GPT-assisted fundamental scientific research. The reasons are that GPT model participation in scientific research enables knowledge migration while lowering knowledge acquisition barriers, thereby weakening academia's dominant position. Meanwhile, industry, with its abundant AI technology development resources, has become an innovation highland for GPT technology and is expected to become one of the core innovation subjects in fundamental research.

**2.3.1 As an Open-Source Knowledge Integration Library, GPT Models Facilitate Knowledge Migration and Lower Knowledge Acquisition Barriers** The fundamental reason for innovation subject migration is that neural networks trained on massive data become a new data and knowledge storage model. GPT-like models become "experts" with rich knowledge and experience—an open-source knowledge integration library—thus achieving knowledge migration across languages while lowering knowledge acquisition barriers. On one hand, model training corpora are global multilingual knowledge bases, mostly open-sourced to users in Q&A formats, enabling people of any language to use large models to learn knowledge in different languages and achieve cross-language knowledge migration. On the other hand, as GPT-like models become new data and knowledge storage models, they transform information retrieval from keyword-based to natural language human-computer interaction with complete semantics, changing original knowledge query and acquisition methods through intelligent Q&A, even disrupting research methods. In short, the existence of GPT-like large models will lower scientific research barriers, attracting more students and industries to participate in scientific research.

1. **In the era of large model popularization**, GPT models can serve as teaching and learning tools, supporting personalized, adaptive learning for students at all levels and assisting their participation in fundamental scientific research [30]. For example, research tested GPT-4's performance on the physics education assessment tool "Force Concept Inventory (FCI)," finding that GPT-4 scored 28 out of 30, demonstrating its potential in physics education [31]. However, while GPT can provide great help in general and professional knowledge, it cannot replace the critical thinking, curiosity, imagination, experience, and expertise that innovative research talents must possess—these are precisely the advantages of scholars with professional research training and where they can find their positioning in human-machine collaborative research scenarios.
2. **Lowered scientific research barriers** attract more enterprises and non-

academic institutions to participate in fundamental scientific research. For example, Shenzhen Crystal Technology Co., Ltd. trained the Protein GPT model on proteins, empowering experimental robots for biological R&D and gradually shifting its research focus from "experimental robots" to "experimental scientists" with certain biological domain knowledge.

**2.3.2 Abundant GPT Technology Development Resources Position Industry to Become a Core Innovation Subject in Fundamental Research** As an open-source knowledge integration library, GPT models lower knowledge acquisition and research barriers, weakening academia's dominant and controlling position in fundamental scientific research. Industry, with its abundant AI technology development resources—computing power, data, scenarios, talent, and capital—is becoming an innovation highland for GPT technology and is expected to become one of the core innovation subjects in fundamental research.

From the perspective of industry dominance in talent, computing power, and capital investment for AI technology [32], high-tech enterprises have far surpassed academic research institutions. In 2020, approximately 70% of AI PhDs entered industry; in 2021, industry model computing power was on average 29 times larger than academic models; in 2021, global industry spent over $340 billion on AI, far exceeding public policy investment. This critical resource investment is translating into increasingly prominent AI research achievements, such as the ProGen model developed by startup Profluent [11]. Extending from GPT to the entire AI research field, industry also develops and even controls AI model development tools (e.g., PyTorch and TensorFlow), hardware for efficient deep learning model training (e.g., Tensor Processing Units), and publicly accessible pre-trained models (e.g., Open Pretrained Transformer models). In other words, in data-intensive and computing-intensive fundamental science domains like protein structure generation, compound reaction path generation, experimental protocol auto-generation, and polymer material selection, industry's dominance in AI algorithm research will also grant it the power to shape fundamental research directions.

This status quo will impact research positioning for both industry and academia. On one hand, the existence of commercial motivations drives industry to apply GPT and other AI models more to profit-oriented research fields, such as scientific problems in pharmaceutical and materials experimental computing domains. Breakthroughs in computing-intensive domain problems will gradually be achieved through joint efforts of industry and academia, similar to "Pasteur's Quadrant" problems [33] (where applied research and fundamental research overlap). However, this will potentially guide social development directions and create barriers for academic research in low-income countries. On the other hand, for more fundamental research such as theoretical studies on the origin of life, the Big Bang, and quantum entanglement mechanisms, universities and research institutions remain the most important core innovation subjects.

## 3. Recommendations for Developing China's Fundamental Scientific Research Based on GPT Technology

AI large models have become a new productive force by reconstructing basic methods of human knowledge retrieval and application. However, due to characteristics such as heavy investment, long cycles, rapid iteration, and high risk, competition in GPT large models for fundamental scientific research has become a game for major powers. In this race, China is in a critical period of catching up and urgently needs to find a new path for high-quality development. Based on the above analysis, we propose three recommendations:

1. **Invest in R&D of nationally autonomous, controllable, and IP-protected data and computing platforms to provide infrastructure for GPT technology-driven fundamental science development.** Globally, policy adjustments to promote "AI-driven fundamental scientific research" have emerged successively. From GPT implementation elements, increased resource investment should focus on data and platforms. First, establishing high-quality scientific datasets is imperative. A large model's "IQ" depends on training data volume and knowledge density. GPT-3 training used 45 TB of pre-cleaning corpora and 570 GB post-cleaning, indicating extreme requirements for data cleaning quality. However, China currently has few high-quality, autonomous, and controllable scientific databases. One feasible path is automatically extracting scientific data from published achievements, structurally storing it in databases, and transforming it into important production factors and strategic assets in the AI for Science era. Second, AI data computing platforms should be built as infrastructure in the research process with increased hardware and funding support. We recommend developing general data computing platforms embedded in research processes. "General" means developers can solve more targeted problems on this basis and quickly deploy to any discipline. Additionally, scattered construction of intelligent computing centers across regions fragments the unified national AI computing market and service market into isolated small markets, undermining China's advantage as a large country with a large market. Only by relying on large tech companies or R&D institutions to "train large models" can China gradually close the gap with the US at the model level. Third, intellectual property risks must be noted when industrializing open-source AI algorithms. For example, basic architectures of deep neural network algorithms (like Transformer and Attention) have been patented by Google, and products based on these architectures face IP risks that could hinder China's digital research industrialization. Therefore, building China's own autonomous, controllable, and secure alternative technologies is particularly crucial.

2. **Create a sustainable and healthy ecosystem for AI-driven funda-**

**mental science from three aspects: industry-academia-research collaboration, young talent resources, and cross-domain knowledge flow.** First, vigorously promote industry-academia-research models where participants leverage their strengths to ensure healthy AI technology development direction. Universities and research institutions have responsibilities and advantages in cultivating R&D talent and focus on scientific principles; enterprises possess computing power, capital, and platform construction capabilities, with unique advantages in solving engineering problems and can concentrate manpower and financial resources for breakthroughs. Effectively combining the development advantages of universities and research institutions with enterprises' productization advantages will healthily promote China's fundamental science development. Second, attract and cultivate talent to ensure an inexhaustible supply of human resources. Young talent is the most valuable resource for AI technology and fundamental science development. The ChatGPT team has an average age of only 32, igniting a new global wave of AI technology with their interest and belief in AI. Moreover, Chinese scholars are an important scientific innovation force in this team. Therefore, encouraging top international scholars to come to China and domestic scholars to go abroad, stimulating and cultivating young people's interest and belief in science and technology, is also crucial for promoting domestic frontier technology innovation. Third, promote cross-domain knowledge flow to organically combine AI technology with fundamental science development. To ensure sustainability of AI-empowered fundamental research, China could consider introducing relevant cross-domain knowledge exchange policies and encouraging measures for AI-empowered fundamental research projects. For example, on March 27, 2023, the Ministry of Science and Technology and the National Natural Science Foundation launched the "AI-driven Scientific Research" special deployment, encouraging interdisciplinary integration of computer science, data science, materials, chemistry, biology, and other fields to reconstruct knowledge systems [9].

3. **Encourage human-machine collaboration alongside research integrity oversight to create an open and transparent environment for AI-driven fundamental science.** Currently, scientific research is inevitably entering the era of human-machine collaboration, with Microsoft believing GPT-4 represents sparks of general AI [34]. As GPT technology products are applied in research, whether these tools will weaken researchers' capabilities and status has become a major concern. On one hand, cases like AlphaFold [35] and RoseTTAFold [36], which "advanced a recognized major scientific challenge (protein structure generation) to near-complete solution," demonstrate AI tools' potential to pass the Turing test and even win Nobel Prizes [37]. On the other hand, we must 清醒地 recognize that current AI for Science models, including the latest GPT-4, have problems such as generating incorrect text information and low performance in logical reasoning and causal inference, making them

imperfect research tools. Overall, GPT-like large models will help scholars handle primary research tasks in text processing or assist with research computing tasks in high-dimensional data modeling, but their effectiveness still depends on scholars' cognitive levels [38]. Regarding "ChatGPT automatically writing papers," major domestic and international journals mostly hold opposing positions. *Science* explicitly prohibits listing ChatGPT as a co-author and does not allow using ChatGPT-generated text in papers [39]; *Nature* states that large language model-generated text can be used in papers but cannot list them as co-authors, only acknowledging them in methods or acknowledgments [40]. However, the involvement of general-purpose AI like ChatGPT in scientific research is already established. Beyond "insisting on human verification," "establishing accountability rules," and "investing in truly open GPT models," we should accelerate the construction of open and transparent "AI text detectors" to automatically identify AI-generated text, benefiting the entire research ecosystem.

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*Note: Figure translations are in progress. See original paper for figures.*