Ethical opportunities and risks of using ChatGPT for open science: evidence from a three-year mixed-methods study

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Abstract

Purpose – The open science movement is gaining traction worldwide but faces persistent human and structural challenges. This study aims to explore whether large language models (LLMs), specifically ChatGPT, can meaningfully interpret and promote open science principles while identifying relevant literature and proposing solutions to current barriers.

Design/methodology/approach – This study combined a bibliometric analysis of open science publications indexed in the Web of Science Core Collection (2015–2024) with a longitudinal comparison of ChatGPT responses across three versions (3.5, 4 and 4.5) tested between 2023 and 2025.

Findings – Designed for researchers, educators and policymakers interested in artificial intelligence (AI) applications in scholarly communication, this work reveals both the potential and limitations of LLMs as tools for advancing open science. The findings show that ChatGPT-4.5 demonstrates improved conceptual clarity and citation reliability compared with earlier versions, although issues such as thematic biases and occasional hallucinations persist.

Originality/value – This study remains exploratory and is limited by a single database and nonsystematic search design. By empirically highlighting ChatGPT's evolving capabilities, this paper contributes to the emerging discourse on the role of generative AI in fostering open science and underscores critical considerations for its responsible use in research and education.

Keywords Artificial intelligence, Large language models, Open data, Open peer review, Replication

Paper type Research paper

1. Introduction: what is open science?

Open science is a concept that represents a transformative approach to scientific research that emphasizes transparency, accessibility and collaborative efforts throughout the research process, ultimately expressed in publishing. Vicente-Saez and Martinez-Fuentes (2018) defined it as "transparent and accessible knowledge that is shared and developed through collaborative networks" (p. 435). This paradigm encompasses the accessibility and reuse of

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scientific data and publications and extends to methodologies, the dissemination of scientific knowledge through collaborative tools and public engagement (Lee and Chung, 2022). Shmagun *et al.* (2023) described open science as involving various practices of scientific communication, aiming to make scientific research more accessible to the broader community, thus facilitating a more inclusive environment for knowledge creation and sharing. The ethos of open science is rooted in the belief that a more collaborative and open approach to science can accelerate innovation by making it easier for researchers and the public to contribute to and benefit from scientific knowledge.

Open science's evolution has been endorsed for a decade by three globalist institutions: the OECD (2015), the European Commission (2015) and UNESCO (2023). These initiatives reflect a growing global consensus on the importance of integrating open science into the mainstream of scientific discourse, with the desire – or promise – to enhance the reliability and efficiency of research by making it more accessible and collaborative. Different countries have adopted unique approaches to open science, reflecting specific cultural, academic and governmental contexts: Estonia (Olesk *et al.*, 2019), Europe broadly (Sveinsdottir *et al.*, 2021; Moradi and Abdi, 2023), Ukraine (Nazarovets, 2022) and South Korea (Shmagun *et al.*, 2024). For instance, Finland transitioned from a state-driven oversight model to a more community-centric approach in monitoring open science, adopting flexible and organization-specific indicators to assess the effectiveness and reach of open science initiatives, ultimately promoting greater involvement and accountability among Finnish research communities (Himanen and Nykyri, 2024). De Filippo and Sastrón-Toledo (2023) noted how government funding and policies support the integration of open science practices into Spanish research institutions, emphasizing that such support is crucial for sustaining the momentum toward open science, in turn influencing national research output and public engagement with science. The values underpinning these shifts include ensuring integrity and transparency in scientific inquiry and the dissemination of results, promoting inclusivity to make science accessible to a greater diversity of populations from varied range of backgrounds and fostering collaboration that extends participation in research beyond traditional academic boundaries (Rafols *et al.*, 2024).

Open science practices are diverse and cover various aspects of the research process, from initial data collection to final publication and beyond. Thibault *et al.* (2023) introduced the concept of "Open Science 2.0" that emphasizes the availability of research results as well as the dynamic interactions among scientific actors. This approach encourages transparency at each and all stages of the research process, including hypothesis generation, data collection, analysis and peer review, aiming to make these elements openly accessible and participative, thereby enhancing the collaborative and democratic nature of scientific inquiry. Open science practices can be adopted effectively by researchers as a practical way to address the credibility, reliability and reproducibility of research findings, enhancing the reliability of results and facilitating wider scrutiny and validation, which are essential for scientific progress, but the effectiveness of implementation depends on suitable training and the willingness and readiness of the scientific community to adopt them (Nosek *et al.*, 2015; McKiernan *et al.*, 2016; Bisol *et al.*, 2014; Banks *et al.*, 2019). These practices are pivotal in fostering an environment where scientific knowledge can be freely accessed, reviewed and built upon, thus accelerating the pace of innovation and discovery in the scientific community.

The conversation surrounding open science includes both enthusiastic support for its potential benefits and cautionary perspectives regarding its possible drawbacks. On the positive side, open science is lauded for its ability to enhance accessibility to papers, data, code and other scholarly outputs and collaboration within the scientific community (McKiernan *et al.*, 2016; Manco, 2024). By democratizing access to research output and processes, open science enables a broader range of scholars to contribute to and benefit from scientific knowledge, which can speed up the pace of discovery and innovation (Woelfle *et al.*, 2011; Guzzo *et al.*, 2022).

However, open science also faces challenges and criticisms. Among the principal obstacles identified are the need to safeguard confidential data and intellectual property, alongside the dominance of commercial priorities in research agendas (Liu and Liu, 2023; Redman, 2023). This requires that researchers strike a delicate balance between the complete openness of their data and the protection of information integrity, requiring critical decisions regarding the extent of data disclosure and the modalities of its dissemination. For instance, researchers with industry funding are twice as likely to refuse requests for research materials than those without such funding (Czarnitzki *et al.*, 2015). Furthermore, Ross-Hellauer *et al.* (2022) suggested that open science practices might inadvertently reinforce or magnify existing disparities within the scientific community by concentrating benefits among those with greater resources and access to technology, and by perpetuating economic barriers through, as one example, the author-pays model, which disadvantages researchers from developing countries. Consequently, while open science is capable of fostering public engagement and democratizing access to scientific data, it also presents formidable challenges that require meticulous planning, proficient communication and robust data management strategies (Grand *et al.*, 2016). In summary, the promise of open science to transform the research landscape through increased collaboration and transparency also demands a nuanced consideration of potential risks and hurdles.

Recent literature further emphasizes the evolving complexity and multifaceted nature of open science. For instance, Abrams *et al.* (2025) explored how existing norms of authorship and evaluation constrain the open sharing of intermediate research resources, highlighting the necessity for novel governance mechanisms within scientific consortia. Scotti *et al.* (2025), in a comprehensive review, revealed how academic libraries in the USA increasingly engage with open science practices, moving beyond traditional roles toward integrated, lifecycle-spanning services. Finally, Huang and Soete (2025) pointed out a critical contemporary challenge – balancing the ideals of open science with emerging demands for technological sovereignty, especially under geopolitical tensions. They argue for a strategic integration of openness with national interests, suggesting that such a balance is crucial for addressing global challenges, including climate change. A recent study also explored how artificial intelligence (AI) tools are reshaping bibliometric and research-evaluation practices, emphasizing both their potential and methodological challenges (Pereira *et al.*, 2025). Recent scholarship has also questioned the universality of dominant open science frameworks, arguing that openness may take different forms across disciplines and research traditions (Adams *et al.*, 2026). Rather than representing a single set of practices, openness can encompass diverse approaches to participation, knowledge sharing, communication and research dissemination. Collectively, these studies underscore that open science should be considered not merely as a set of technical practices, but as a comprehensive framework embedded within broader organizational, political and societal contexts.

In this introduction, we provided a summarized human-based assessment and interpretation of open science and its guiding principles using select literature that, we felt, was informative to us and readers. We were then interested to appreciate how AI software, in the form of the popular large language model (LLM), ChatGPT (Gao *et al.*, 2023; Lund and Wang, 2023), would perform when queried regarding this topic.

To guide our investigation, we posed the following research questions:

RQ1. To what extent is ChatGPT able to provide a coherent and conceptually accurate appreciation of open science?

RQ2. Can ChatGPT reliably identify and cite relevant academic literature on open science?

RQ3. How do the responses of successive ChatGPT versions (3, 4 and 4.5) evolve over time with regard to structure, accuracy and depth of insight?

2. Methodology

For this paper's introduction, as its human authors, we did not apply a systematic review protocol such as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, which provides structured reporting standards for systematic literature reviews. Instead, we used a focused search strategy in Scopus, Web of Science (WoS) and Google Scholar using "open science" as the search term. We selected approximately two dozen references published between 2014 and 2025 that offered, akin to an informal SWOT (strengths, opportunities, weaknesses and threats) analysis:

(1) an appreciation of what open science entails and aims to achieve;

(2) group- or culture-specific interpretations of open science; and

(3) challenges and limitations of its principles.

We limited the introductory review to 1,000 words, including references, to maintain conciseness and relevance.

To supplement that selection, we conducted a bibliometric analysis using the WoS Core Collection database. On May 23, 2025, we searched for publications from 2015 to 2024 containing the term "open science" in the title, abstract or keywords. Duplicate records and false positives were manually screened and removed, resulting in the data set provided in Zenodo: 10.5281/zenodo.15501527. We note that a recently published PRISMA-based scoping review identified 485 documents related to open science until June 2023 (Klebel *et al.*, 2025). In addition, to identify the main conceptual clusters and thematic directions in the literature on open science, a keyword co-occurrence analysis was performed using VOSviewer (version 1.6.20), a software tool used for constructing and visualizing bibliometric networks, such as co-authorship, citation or keyword co-occurrence maps (van Eck and Waltman, 2010). The main bibliometric indicators used in this study, such as citation counts, co-authorship links and keyword co-occurrence frequencies, represent complementary dimensions of research impact and structure. Citation counts reflect scholarly influence, co-authorship links indicate collaboration patterns, and keyword co-occurrence reveals thematic connections within the analyzed literature.

We then set out to appreciate whether ChatGPT would be able to offer a comparable or different assessment and/or interpretation of open science. In addition to gaining a crude appreciation of the human-versus AI-based form of knowledge capture and interpretation, given that ChatGPT (and other LLMs) may be used not only be established researchers, but also by students, novice scientists or early career researchers to develop sections of their research reports, theses, or scientific papers, we also wanted to gain an appreciation of how ChatGPT could serve as a tool to achieve knowledge discovery, specifically related to open science. This work will be of interest to researchers, educators and policymakers, exploring the intersection of open science practices and AI-assisted scholarly workflows.

To achieve the latter goal, we set four objectives for the use of ChatGPT-3.5 (accessed through ChatGPT) on February 28, 2023:

(1) to seek its advice regarding how to make science (more) open;
(2) to test its ability to identify the most highly cited academic literature on this topic;
(3) to appreciate its association with Google Scholar and other databases; and
(4) to request it to suggest novel ways to overcome limitations associated with the uptake or adoption of open science, as a way to overcome human limitations.

We did not impose any word limits, giving ChatGPT-3.5 "freedom" to independently set its search and interpretation parameters, which are based on trained data sets (Roumeliotis and Tselikas, 2023; Briganti, 2024). In addition, we conducted a replication trial approximately one year later (April 29, 2024) to assess whether the 2024 output matched or differed from the 2023 output. Although this 14-month gap was not part of a predefined longitudinal design, it coincided with the release of a major model upgrade (ChatGPT-4), which presented a natural opportunity to observe performance differences over time. This temporal spacing allowed us to capture changes in structure, conceptual framing and citation behavior, thereby serving as an informal replication that reflects the real-world evolution of generative AI tools. Finally, considering that ChatGPT is constantly improving and that its training data set is in constant expansion (Chen *et al.*, 2024), we completed a second replication, approximately two years after our initial trial, on May 23, 2025.

The 14-month interval between testing phases (March 2023–May 2024) was intentional, allowing sufficient time to capture major updates in the ChatGPT ecosystem. Each prompt was tested once under identical conditions to ensure comparability across versions. However, the versions compared in this study differed not only in their underlying language models but also in the functionality available to users. Notably, the May 2025 version had access to public Web-search capabilities, whereas the earlier versions did not. Consequently, the observed differences should be interpreted as reflecting the combined effects of model development and changes in available system functionality rather than model evolution alone.

When assessing the output and interpretation of ChatGPT-3.5, 4 and 4.5, we then offered our own interpretation of its strengths and weaknesses, fortifying the informal SWOT analysis that we conducted in the introduction, expanding our literature base to several dozen more papers.

The study intentionally focused on the WoS Core Collection to ensure data consistency and metadata quality, as this database provides well-curated records and transparent indexing policies suitable for reproducibility. While systematic review protocols such as PRISMA were not applied, the study's aim was exploratory rather than exhaustive, seeking to illustrate methodological possibilities rather than produce a comprehensive review. Future studies may expand to other databases (e.g. Scopus, Dimensions) or AI tools for comparative purposes.

3. Results and discussion

3.1 Bibliometric context of open science research

The initial search in the WoS Core Collection database yielded a total of 6,249 publications related to open science published from 2015 to 2024. After refining to include only primary document types, the data set comprised predominantly original research articles (3,720; 59.5%), followed by review articles (1,265; 20.2%), conference proceeding papers (627; 10.0%), editorial materials (613; 9.8%) and a minor proportion of letters (39; 0.6%). The annual distribution of publications reveals a steady and pronounced increase over the 2015–2024 period, underscoring the growing scholarly attention devoted to open science

(Figure 1). The consistent year-on-year growth suggests that open science is no longer perceived as a peripheral movement but rather as a foundational framework for responsible research and innovation.

The research on open science demonstrates strong interdisciplinary engagement. The most represented research areas include computer science (885 records; 14.2%), psychology (758; 12.1%) and information science and library science (659; 10.5%). These are followed by contributions in medicine, science and technology studies, education and environmental sciences, which confirms that open science principles have diffused into both STEM and social science domains.

In terms of publication outlets, the most active journals include *BMJ Open* (185 publications; 3.0%), *Behavior Research Methods* (51; 0.8%) and *Advances in Methods and Practices in Psychological Science* (30; 0.5%). As for publishers, the leading contributors are Elsevier (736 publications; 11.8%), MDPI (242; 3.9%), Frontiers Media (237; 3.8%), BMJ Publishing Group (230; 3.7%) and PLOS (191; 3.1%), reflecting the role of both commercial and open access publishing models.

Geographically, open science research is led by the USA (2,058 publications; 32.9%), followed by the UK (977; 15.6%), Germany (922; 14.8%), Canada (691; 11.1%), Australia (496; 7.9%), The Netherlands (516; 8.3%) and several other European countries. Regarding institutional output, Harvard University (61 publications; 1.0%), University College London (59; 0.9%), Stanford University (53; 0.8%), Charité – Universitätsmedizin Berlin (43; 0.7%) and the University of Oxford (42; 0.7%) are among the most prolific contributors, underscoring the role of top-tier global universities in advancing the open science agenda.

To explore the thematic structure of research in open science, a keyword co-occurrence analysis was performed using VOSviewer (version 1.6.20). The resulting network visualization (Figure 2) reveals a dense and interconnected conceptual space, with open science, reproducibility, transparency and replication forming the central core, but with two

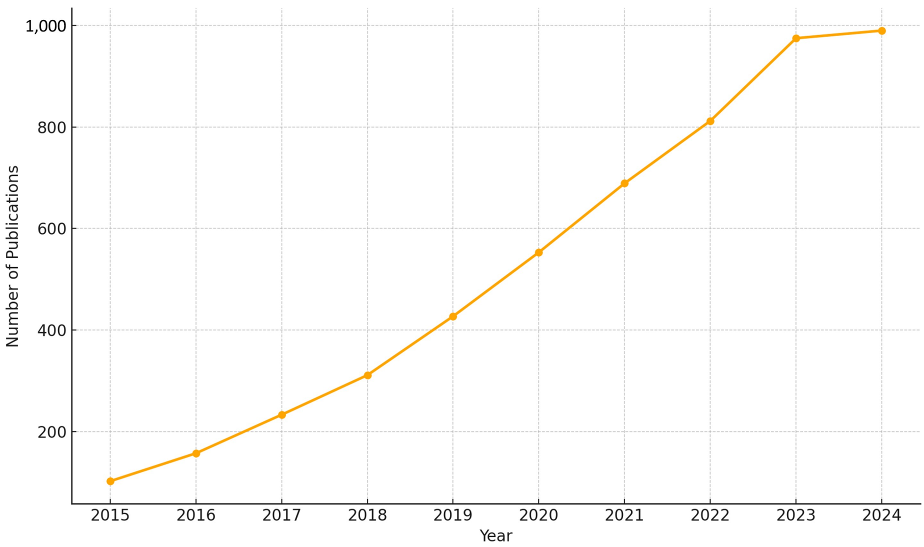

Figure 1. Annual growth of open science publications (2015–2024) according to the Web of Science Core Collection

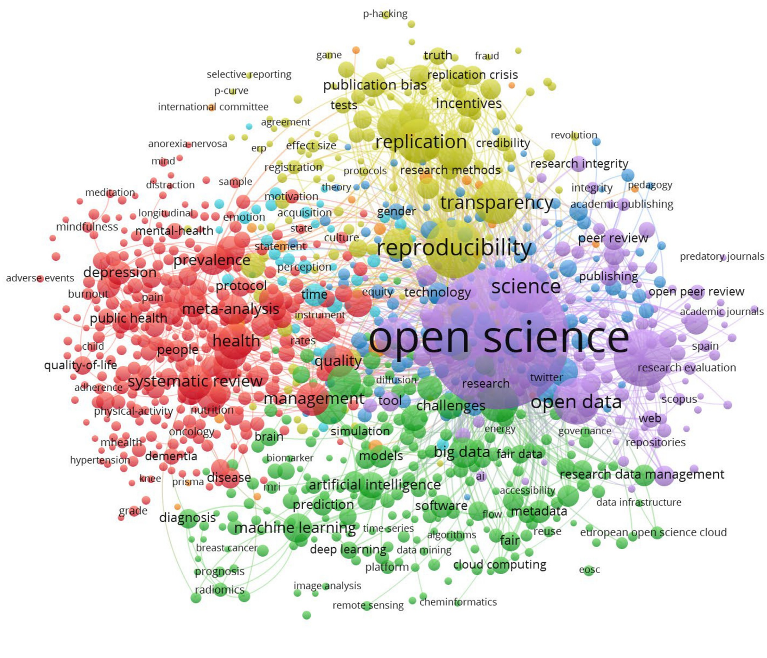

Figure 2. Keyword co-occurrence map generated using VOSviewer, illustrating clusters of terms that frequently appear together in the analyzed publications

Note(s): Larger nodes represent more frequent keywords, and closer distances indicate stronger co-occurrence relationships. The interactive visualization is available at https://tinyurl.com/ysptuf4d

large nodes related to open data and research evaluation. This indicates that the foundational concerns of the field remain strongly tied to scientific credibility and research integrity.

Radiating from this core are several major thematic concentrations. One cluster is oriented toward health-related research, particularly in the context of systematic reviews, prevalence, public health and mental health. Another area of focus involves data-intensive methodologies, with frequent terms like machine learning, metadata and cloud computing. A distinct cluster centers on meta-research and publication culture, with terms such as publication bias, replication crisis and incentives. The analysis also highlights topics related to infrastructure and policy, such as open data, peer review and research evaluation.

The prominence of reproducibility, transparency and research evaluation within the keyword network suggests that open science is increasingly framed not only as a mechanism for access to knowledge but also as a response to concerns about research quality and trustworthiness. The strong presence of policy- and infrastructure-related terms further indicates that the implementation of open science depends not only on individual researcher behavior but also on institutional support, governance frameworks and technological infrastructures.

In summary, the bibliometric analysis reveals that open science is an expanding and increasingly diversified research domain, with steady growth in scholarly output, wide disciplinary reach, strong international participation and a well-defined thematic structure that connects methodological reform, technological tools and policy frameworks.

3.2 ChatGPT-3.5's advice regarding open science (2023)

In its 2023 responses, ChatGPT-3.5 described open science as a set of practices promoting accessibility and transparency in research, highlighting open access journals, repositories, data and code sharing, preprints, open peer review and the use of open-source software (Table 1). It also mentioned "human" dimensions such as responsible research, public engagement and inclusion.

When asked to identify features of journals that embody open science, ChatGPT-3.5 listed open access, data sharing, reproducibility, preregistration, replication studies, article-level metrics, collaborative platforms and transparent peer review. These reflect a broad but uneven understanding of openness, combining technical and cultural aspects without clear hierarchy or prioritization.

Applying the framework by Fecher and Friesike (2014), ChatGPT-3.5's perspective cannot be linked to any single "school of thought." Rather, it blends elements from all of them while omitting several key principles, indicating a selective and partly superficial grasp of the concept of open science.

ChatGPT-3.5 notably omitted several essential aspects that, as human authors, we consider central to open science. These include distributed computing, which democratizes access to large-scale data analysis through shared computational resources (Hand, 2010; Fecher and Friesike, 2014); altmetrics, which complement traditional citation counts by tracking societal impact via online engagement (European Commission, 2018; De Filippo and Sastrón-Toledo, 2023); and citizen science initiatives, engaging non-specialists in data collection and analysis (Roman *et al.*, 2021; Schade *et al.*, 2021). It also failed to mention open licenses such as Creative Commons, which promote reuse and dissemination (Open Science Training Handbook, 2018) and academic social networks, which facilitate collaboration and visibility among researchers (Jamali *et al.*, 2016).

Open access ensures that scientific articles are freely available, promoting the wider dissemination of knowledge and fostering collaboration and innovation (Ni and Waltman, 2024). Data sharing enhances reliability, enables replication and supports collective progress (van Gend and Zuiderwijk, 2023). Reproducibility builds trust in science and is reinforced by publishing replication studies (Wallach *et al.*, 2018; Brodeur *et al.*, 2023). Preregistration of methods reduces bias and improves research credibility (Dirnagl, 2020). Transparent and

Table 1. Ten things that scientists should do to make science open, based on ChatGPT's assessment

Advice by ChatGPT-3.5 (2023)	Advice by ChatGPT-4 (2024)	Advice by ChatGPT-4.5 (2025)
Share research findings openly	Publish in open access journals	Publish in open access journals
Use open source software and data	Data sharing	Share research data
Share raw data	Open methodologies	Use open licenses
Make use of preprint servers	Preprint posting	Practice open peer review
Collaborate with others	Collaborative tools	Utilize open research software
Use open peer-review	Engage in open peer review	Adopt preprints
Share negative results	Use open educational resources	Promote open methods and protocols
Engage with the public	Public engagement	Support open citations
Promote diversity and inclusion	Training and workshops	Engage in open science education and outreach
Practice responsible research	Advocate for open science policies	Collaborate transparently

open peer review mitigates unfair evaluation (Wolfram *et al.*, 2020; Teixeira da Silva and Nazarovets, 2022). Article-level metrics broaden impact assessment beyond citations (Jamali *et al.*, 2016), collaborative platforms facilitate global teamwork (Thibault *et al.*, 2023) and flexible open licenses ensure legal reuse and sharing (Open Science Training Handbook, 2018).

Although these are indeed core features of open-science-oriented journals, ChatGPT-3.5's reference list raised concerns about thematic bias. Roughly half of its cited sources focused on data and reproducibility within psychology, while other areas such as open peer review, altmetrics and negative results were represented by only one source each. This imbalance suggests that ChatGPT-3.5 selected literature unevenly, reflecting discipline-specific bias rather than a comprehensive understanding of open science.

ChatGPT-3.5's reference list also contained several bibliographic inaccuracies. Some entries lacked DOIs, an essential bibliometric element, one had an incorrect publication year and another showed an incomplete page range. One cited paper was entirely fabricated: it did not exist in the indicated journal and searches across databases yielded no results. Such hallucinations in AI-generated bibliographies are well documented (Orduña-Malea and Cabezas-Clavijo, 2023; Sebo, 2024; Walters and Wilder, 2023).

When asked to list the ten most-cited papers on open science, ChatGPT-3.5 produced entries with DOIs, but three of them were fictitious, with an error rate of roughly 30%. The fabricated records reused valid DOIs from real papers, and one falsely described itself as an updated version of the 2017 Manifesto for Reproducible Science. Verification through the journal's archive, Google Scholar and the author's profile confirmed that no such update existed. The remaining seven items were genuine and widely cited works on open access, data sharing and reproducibility, showing that ChatGPT-3.5 could combine accurate and fabricated references within a single output.

To verify that the "top-cited papers" list was not simply scraped from a database, we asked ChatGPT-3.5 whether it had live access to Google Scholar or other scientific databases. It confirmed that it does not have direct access and is instead trained on a large text corpus that includes scientific papers from various fields.

According to a survey, one of the most popular applications of ChatGPT related to science has been to brainstorm research ideas (Owens, 2023). Therefore, finally, we asked ChatGPT-3.5 to suggest innovative ways for open science to succeed as a sustainable academic publishing model. It offered quite logical or rational and expected directions: open peer-review (for some unknown reason, it separated "open peer-review" from "collaborative peer-review platforms"), decentralized publishing, preprint servers, crowdfunding and community support. However, in its answer, ChatGPT-3.5 made many inaccuracies in the examples of online services (error rate of approximately 40%). For example, it mentioned *PLOS ONE* [1] as an example of a collaborative peer-review platform, the Open Science Fund [2] from The Dutch Research Council as a crowdfunding platform and the content management system PubPub [3] and Open Publishing Awards [4] as blockchain publishing platforms. Moreover, ChatGPT-3.5 suggested five sources to support these ideas, indicating bibliographic information about these publications. However, in one case, it was not possible to find a paper with the title in the University of Sussex SPRU Working Paper Series archive [5], and in another case in the archive of the journal *Insights* [6], and it was also not possible to confirm the existence of these publications using available search engines.

These observations are based on a single response generated for each prompt, and should therefore be interpreted as illustrative rather than statistically representative.

3.3 ChatGPT-4's advice regarding open science (2024)

A year later, on April 29, 2024, we repeated the experiment as a replication trial to evaluate how ChatGPT-4's understanding of open science had evolved. Compared with ChatGPT-3.5, the newer version produced more structured and comprehensive answers. Among the ten recommended actions to advance open science, ChatGPT-4 introduced three new elements: open methodologies, emphasizing transparent reporting of research procedures (Abele-Brehm *et al.*, 2019); the use of open educational resources under permissive licenses (Liu and Liu, 2023); and advocacy for open-science policies at institutional and international levels (Manco, 2024).

It also expanded the list of journal characteristics aligned with open-science principles (Table 2), adding registered reports, which facilitate replication (Manago, 2023), and public engagement and innovation, seen as crucial for sustaining research autonomy and public trust (Grand *et al.*, 2016).

Regrettably, ChatGPT-4 did not identify highly cited papers specifically on open science, instead referring to general top-ranking articles from Nature and the Royal Society, suggesting a possible publication bias. As in 2023, it confirmed having no direct access to Google Scholar or other scientific databases. Regarding innovative approaches, ChatGPT-4 added two new themes (Table 3): funding models for open access (Wise and Estelle, 2020) and training and education in open-science practices (Schmidt *et al.*, 2016).

3.4 ChatGPT-4.5's advice regarding open science (2025)

On May 23, 2025, one year after the second replication, we repeated the experiment using ChatGPT-4.5 and posed the same four questions. The results showed notable differences in both structure and content compared with the 2023 and 2024 outputs. ChatGPT-4.5's recommendations on fostering open science remained grounded in familiar principles, like open-access publishing, FAIR data sharing and open licensing, but were expressed with greater clarity, coherence and precision. The model also demonstrated a stronger grasp of

Table 2. The main characteristics of a journal that practices open science, based on ChatGPT's assessment

Advice by ChatGPT-3.5 (2023)	Advice by ChatGPT-4 (2024)	Advice by ChatGPT-4.5 (2025)
Open access	Global and multilingual accessibility	Provides immediate open access to all articles
Data sharing	Accessibility of data and materials	Requires data and code sharing upon publication
Reproducibility	Transparency in methodology	Accepts and encourages registered reports
Preregistration	Preregistration of studies	Uses transparent peer review processes
Peer review transparency	Ethical standards and integrity	Publishes replication studies
Replication studies	Encouragement of replication	Applies open licenses to all content
Open peer review	Open peer review	Offers article-level metrics
Article-level metrics	Registered reports	Supports preprint-friendly policies
Collaborative platforms	Inclusive authorship and collaboration	Encourages community and public engagement
Licensing	Promotion of innovation and public engagement	Promotes innovation in publishing workflows

Table 3. Innovative ways for open science, based on ChatGPT's assessment

Advice by ChatGPT-3.5 (2023)	Advice by ChatGPT-4 (2024)	Advice by ChatGPT-4.5 (2025)
Collaborative peer-review platforms	Development of collaborative platforms	Develop sustainable funding models for open access
Crowdfunding and community support	Policy and advocacy	Implement diamond and subscribe-to-open publishing schemes
Decentralized publishing	Technological innovation and infrastructure support	Integrate open science into academic reward systems
Preprint servers	Incorporation of preprints and post-publication peer review	Expand training and education in open science practices
Open peer review	Open metrics and evaluation systems	Support decentralized and blockchain-based publishing platforms
	Funding models for open access	Promote multilingual publishing to enhance inclusivity
		Encourage institutional and governmental open science mandates
		Facilitate interoperability between open science infrastructures
		Incentivize community-driven peer review initiatives
		Foster global equity in access to publishing resources

infrastructure-level mechanisms and more clearly distinguished between practical practices (e.g. open peer review, preregistration) and cultural drivers (e.g. education, outreach, collaboration).

Its response on journal characteristics was notably improved, providing a structured list of ten features, such as immediate open access, transparent editorial policies, support for replication studies and mandatory data/code sharing, accompanied by brief rationales and references. Although some citations still pointed to general web sources (e.g. Wikipedia, institutional pages), DOI and journal details were considerably more accurate than before.

When asked to identify the most-cited literature, ChatGPT-4.5 performed more reliably than its predecessors. The list showed a recurring bias toward psychology and meta-science but contained no fabricated entries. Compared with the earlier outputs, GPT-4.5 produced more accurate references and fewer observable hallucinations. However, part of this improvement may be attributable to the availability of web-search functionality in 2025, which was not available during the earlier testing rounds.

Furthermore, ChatGPT-4.5 provided more nuanced explanations of its access to external databases. It reiterated that it cannot reach platforms such as Google Scholar or Scopus, but correctly identified OpenAlex and the DOAJ as publicly available tools, accurately describing their functions, something absent or poorly formulated in earlier responses (2023–2024).

When asked to propose innovative solutions for overcoming resistance to open science, the model displayed greater conceptual maturity. It suggested sustainable funding mechanisms, decentralized peer-review infrastructures, blockchain-based systems and institutional mandates, emphasizing community ownership, policy integration and equity, a broader systems perspective missing in 2023.

Overall, ChatGPT-4.5 demonstrated clearer reasoning, stronger bibliographic precision and more coherent structure than previous versions. Despite remaining limitations, such as thematic bias and surface-level generalization, its 2025 responses marked a substantial improvement in factual consistency and alignment with scholarly standards compared to 2023 and 2024. As discussed in Annex 13, LLM outputs exhibit inherent variability; consequently, these comparisons should be interpreted as single-response snapshots rather than stable estimates of model performance.

3.5 ChatGPT: applications to science and education

Beyond its direct outputs on open science, ChatGPT also demonstrates potential value in educational and research contexts that intersect with open science goals, including transparency, inclusivity and accessibility. The application of ChatGPT in educational settings has been marked by enhancements in student engagement and personalized learning. ChatGPT can tailor educational content to individual needs, thus improving learning experiences in science education (Cooper, 2023). Montenegro-Rueda *et al.* (2023) showed that, when integrated thoughtfully, ChatGPT can support teaching innovation and curriculum design. These developments are aligned with open educational resources and the broader open science mission of democratizing knowledge. Lin (2023) emphasizes that embracing generative AI in academic life requires not only technical skill but also ethical engagement, highlighting how tools like ChatGPT can empower researchers and students to navigate scientific knowledge more effectively while advocating for open practices, such as transparent peer review and data sharing.

In research, particularly in data-intensive fields such as healthcare and environmental science, ChatGPT has been used to assist in hypothesis generation, data analysis and public communication (Agathokleous *et al.*, 2023; Lucas *et al.*, 2024; Shorey *et al.*, 2024). Such functions mirror the goals of the open science movement by promoting accessibility, early-stage sharing and cross-disciplinary collaboration. Nonetheless, these applications must be viewed through the lens of responsible open science practices. Shaw *et al.* (2023) warned that LLMs like ChatGPT may foster academic dishonesty or weaken critical thinking. Nam and Bai (2023), as well as Nazarovets and Teixeira da Silva (2025), raised concerns about authorship integrity and the risk of eroding scholarly trust if AI-generated content is not transparently acknowledged.

In summary, while ChatGPT's broader applications extend beyond open science *per se*, its capacity to support openness in education and research justifies brief inclusion. Future work should more directly assess how such tools can advance open science training, open pedagogy and open research workflows in practice.

3.6 Current impact of ChatGPT's limitations and future challenges

ChatGPT has quickly become part of the scholarly ecosystem, with researchers using it to assist in writing (Castellanos-Gomez, 2023), systematic reviews (Qureshi *et al.*, 2023), peer review facilitation (Biswas *et al.*, 2023) and automating editorial tasks (Hosseini *et al.*, 2024). While these applications suggest value for research workflows, our study focused specifically on its usefulness in supporting open science principles.

In our experiment, ChatGPT-3.5 and ChatGPT-4 were able to provide basic overviews of open science practices, but demonstrated recurring issues. ChatGPT-3.5 fabricated references, including realistic but nonexistent articles, and displayed thematic bias toward psychology. ChatGPT-4 showed marked improvements in citation precision, but still failed to synthesize novel or interdisciplinary insights. ChatGPT-4.5, by contrast, produced accurate and structured responses, although it was still unable to generate unexpected connections or offer deeper conceptual innovations.

Such limitations are consistent with widely reported weaknesses of LLMs, including hallucinated citations (Stokel-Walker and Van Noorden, 2023), unreliable quantitative estimates (Tsigaris and Teixeira da Silva, 2024) and failure to meet authorship criteria (Teixeira da Silva, 2023; Thorp, 2023; Yeo-The and Tang, 2024). Kitamura (2023) further highlighted these issues in the medical domain, noting that while ChatGPT can effectively assist with drafting, it frequently fabricates plausible references and lacks originality, reinforcing the necessity of human judgment and editorial oversight in academic writing. In addition, the inability to evaluate source credibility (van Dis *et al.*, 2023) and potential for misuse (Chatterjee and Dethlefs, 2023; Grimaldi and Ehrler, 2023) further limits the unsupervised use of ChatGPT in open science contexts.

These constraints also echo broader societal patterns in how AI is perceived and regulated across countries. Howell (2025) showed that positive attitudes toward AI are significantly lower in Western, Educated, Industrialized, Rich and Democratic societies than in emerging economies. Stronger democratic institutions and higher education levels tend to correlate with greater skepticism and stronger demand for regulation, whereas countries with weaker institutions often show higher levels of trust in AI tools. This indicates that concerns about ChatGPT's reliability and oversight are not only technical but also deeply embedded in institutional and cultural contexts, underscoring the need for governance approaches tailored to specific research environments within open science.

Global survey data confirm this variation. Mohammadi *et al.* (2026) found substantial international, disciplinary and gender-based differences in the academic adoption of generative AI across 20 countries. While awareness of ChatGPT and similar tools is widespread, intensive use for research purposes is concentrated in non-Western regions such as East and South Asia and the Middle East, partly due to translation and accessibility advantages. Female academics report markedly lower rates of regular AI use, and adoption is highest in the social sciences and engineering. Across all respondent groups, the dominant concerns mirror those highlighted in our own analysis: plagiarism, inaccuracy, reduced critical thinking and limited transparency. Together, these findings suggest that the global integration of generative AI into academic practice amplifies existing inequalities in access, trust and digital readiness, challenges that must be addressed if AI is to contribute responsibly to the open science agenda.

For open science specifically, these shortcomings underscore the continuing need for transparency, verifiability and human oversight. While ChatGPT can articulate the visible components of open science practice, it remains unable to generate genuinely novel insights or contextual understanding beyond preexisting textual patterns. As such, it may function as a useful entry point for early-career researchers, but not as a replacement for expert-driven inquiry or systematic literature searches. This aligns with the findings of Clark *et al.* (2025), who report that early-career researchers often regard ChatGPT as a helpful language tool but remain uncertain about its legitimacy and ethical standing, particularly regarding authorship and disclosure.

Large-scale evaluations further confirm these methodological and conceptual limitations. Thelwall *et al.* (2025) found that although ChatGPT's quality assessments of research articles correlate positively with expert-based indicators across most disciplines, the model systematically undervalues clinical and applied studies, especially those reporting negative or socially relevant results. Comparable tendencies appear in technical applications: Blázquez-Ochando *et al.* (2025) showed that the quality of ChatGPT-generated code for bibliographic web-scraping depends almost entirely on the clarity and constraints of the prompt, with the model occasionally displaying "free-will" deviations that lead to suboptimal solutions. Collectively, these observations suggest that ChatGPT's evaluative processes remain shaped by linguistic pattern recognition rather than substantive scientific reasoning, reinforcing the indispensable role of human judgment in AI-assisted research assessment.

Recent large-scale textual analyses further indicate that the diffusion of ChatGPT has begun to reshape the linguistic landscape of academic writing itself. Alsudais (2025) examined more than two million arXiv abstracts and found statistically significant declines in readability scores across all disciplines starting in 2023, coinciding with the public release of ChatGPT. Applying four established readability indices, the study revealed that scientific abstracts have become longer, denser and syntactically more complex, suggesting that AI-assisted writing improves grammar but may reduce textual accessibility.

Parallel analyses of public discourse demonstrate a similar dynamic in societal perception. Wang *et al.* (2025) analyzed more than 31,000 posts across social-media platforms, identifying a four-phase trajectory of public sentiment: from latent curiosity and rapid enthusiasm to critical reassessment and eventual normalization. Over time, attention shifted from innovation and productivity toward issues of privacy, bias and digital inequality. These findings imply that ChatGPT's integration into scholarly and social contexts follows a broader technological life cycle, one in which initial excitement gradually gives way to realism, as structural limitations and ethical challenges persist despite technical progress.

From an ethical perspective, the findings illustrate a fundamental tension between the efficiency gains offered by generative AI and the core values of open science. While ChatGPT can improve access to knowledge and lower barriers to participation, its tendency to generate inaccurate information, fabricate references or obscure the provenance of information raises concerns about transparency, accountability and research integrity. Responsible use of AI in open science therefore requires not only technical improvements but also clear norms for disclosure, verification and human oversight.

4. Conclusions

This study sought to explore whether ChatGPT, as an LLM, can meaningfully interpret, explain and promote the principles of open science. In our three rounds of testing – ChatGPT-3.5, 4 and 4.5 – we observed progressively more accurate, structured and coherent responses across the three testing periods. While the two earlier versions provided general and occasionally flawed advice, ChatGPT-4.5 generally demonstrated greater clarity, reduced hallucinations and more robust bibliographic referencing, although these observations are based on single-response comparisons and should be interpreted in light of the inherent variability of LLM outputs. Nevertheless, limitations persist, especially in thematic bias and the inability to generate truly novel insights beyond what has already been reported in the literature or other sources. When used with critical oversight by researchers and educators, ChatGPT can serve as a supportive tool for early-career researchers and educators engaging with open science, but it should not replace human judgment or expert-driven sources. Our findings underscore the importance of combining human expertise with evolving AI tools to foster responsible and accurate communication of open science principles in education, publishing and research policy.

Future research should continue to evaluate the reliability and transparency of LLMs across disciplinary and linguistic contexts. In particular, comparative studies could examine how AI tools perform in tasks such as literature synthesis, peer-review assistance and reference validation. For responsible adoption of AI in open science, different stakeholder groups have distinct roles to play. Researchers should disclose AI use transparently and verify all outputs, educators can integrate AI literacy into research training, while journal editors and publishers should develop consistent disclosure and verification policies, including structured AI-disclosure frameworks, such as GAIDeT (Suchikova *et al.*, 2026), that improve transparency and accountability. Finally, policymakers should promote standards that ensure accountability and data integrity. By addressing these methodological and ethical challenges jointly, the scholarly community can foster a responsible integration of AI that strengthens, rather than undermines, the principles of open science.

5. Limitations of the study

This study has several important limitations that must be acknowledged. First and foremost, our analysis is exploratory in nature and should not be interpreted as providing comprehensive or definitive conclusions about the capabilities of LLMs in understanding or advancing open science. We analyzed the responses of ChatGPT-3.5, 4 and 4.5 at specific moments in time – specifically 2023, 2024 and 2025, respectively – using a fixed (and thus constant) set of prompts. Furthermore, we acknowledge that LLMs, like ChatGPT, are inherently stochastic in nature, meaning that even if identical prompts are submitted multiple times, it may yield varying outputs. However, as the older versions of ChatGPT (3.5 and 4) are no longer accessible, we were unable to perform repeated queries to assess variability retrospectively, i.e. reproducibility. This limited our ability to evaluate the consistency of outputs across multiple trials for those earlier models. As such, our findings are context-dependent and may not fully capture the breadth of responses possible under different prompts, interfaces, or user interactions.

Second, although improvements were observed in the outputs of ChatGPT-4.5, the model still exhibits limitations related to factual accuracy and consistency. Instances of hallucinations – fabricated references (including citations that combined real author names with fabricated article titles and volumes), incorrect metadata, or overly confident misstatements – were observed in earlier versions and remain a concern for critical academic use. These hallucinations, while less frequent in ChatGPT-4.5, stress the need for human verification and triangulation with authoritative sources when LLMs are used for research or educational purposes.

Third, we did not use dedicated Retrieval-Augmented Generation (RAG) systems or external plug-ins connected to curated academic databases such as Scopus, WoS or Crossref. Such tools may mitigate hallucinations and enhance citation reliability (Li *et al.*, 2024), but they fall outside the scope of this study. Although the 2025 version had access to public Web-search functionality, this differs from purpose-built RAG architectures that retrieve and ground responses in predefined scholarly sources.

Fourth, the reproducibility of our findings is constrained by the single-response sampling strategy employed for each prompt. Although this approach was sufficient for capturing an indicative snapshot of ChatGPT's outputs at specific points in time, it does not account for the inherent variability in the model's responses. To empirically demonstrate this limitation, we conducted an additional test with ChatGPT-4.5 in which the same prompt was submitted on three consecutive days. This experiment confirmed that identical prompts can produce overlapping but nonidentical outputs, highlighting the stochastic nature of LLMs. Future studies should consider repeated sampling and response aggregation to mitigate randomness and improve the robustness of findings.

Fifth, the study relied only on the WoS Core Collection, selected for its metadata quality and stable indexing that support reproducibility. Using multiple databases could have introduced inconsistencies in document classification, while not necessarily improving validity.

Finally, our focus was limited to English-language prompts and literature, excluding non-English or region-specific open science discourses. Moreover, our bibliometric analysis focused on publications indexed in the WoS Core Collection, which may underrepresent outputs from developing countries or non-mainstream journals.

Overall, we encourage readers and practitioners to interpret our findings as a snapshot rather than a final verdict on AI's role in and interpretation of open science. Continued monitoring, critical engagement and the incorporation of more diverse tools and perspectives are essential for a fuller understanding of the potential and pitfalls of LLMs in scholarly communication.

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Data availability

All ChatGPT-related data (responses) that was used for this research may be found in the Supplementary file. In addition, the bibliometric dataset retrieved from the Web of Science Core Collection and used for the analysis of open science literature (2015–2024) is openly accessible via Zenodo: 10.5281/zenodo.15501527.

Authors contributions

Except for the ChatGPT queries, which were made by the first author on February 28, 2023, April 29, 2024, May 23, 2025 and July 20–22, 2025, the authors contributed equally to all other aspects of the paper.

Disclaimer

Other than the use of ChatGPT to pose questions as part of the study, no AI tools were used to write or edit the manuscript. However, during the revision process, the first author consulted ChatGPT-4o to assist with language refinement and editorial clarity. All content decisions and final wording were made by the authors. An earlier version of this article was posted as a preprint at *SocArXiv*: https://osf.io/preprints/socarxiv/awhuf/

Notes

[1.] https://journals.plos.org/plosone/

[2.] www.nwo.nl/en/researchprogrammes/open-science/open-science-fund

[3.] www.pubpub.org/

[4.] https://openpublishingawards.org/

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