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The governance of open science: A comparative analysis of two open science consortia

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ABSTRACT

Recent open science efforts recognize that the efficient, credible, and transparent development of scientific knowledge relies on the capacity to verify and reuse the "intermediate resources" employed throughout the research process, including data, computer code, and other research material. Prior research has shown that the disclosure of such resources is often hindered by the incentives and disincentives perceived by individual scientists. Beyond the level of individual incentives, however, the sharing of intermediate resources is obstructed by the governance norms that inform these incentives in the first place, such as the norms of authorship and evaluation. Thus, our central research question asks how the limitations of the established norms of authorship and evaluation are addressed at the organizational level within open science consortia that are premised on the sharing of intermediate resources. Drawing on qualitative methods, we present an in-depth comparative analysis of two open science consortia–the Canadian Open Neuroscience Platform (CONP) and The Cancer Genome Atlas (TCGA)–that illustrates how the limitations of the established norms of authorship and evaluation are navigated in brain and cancer research, respectively. Our findings show that the governance mechanisms designed and implemented in CONP and TCGA reflect two distinct forms of governance, one distributed and the other layered, which are characterized by different understandings of scientific authorship and evaluation. Our study thus contributes to ongoing debates on open science and the governance of scientific collaboration by shedding light on the relationship between governance forms and variable conceptions of authorship and evaluation.

1. Introduction

In recent years, there has been a concerted effort among scholars and policymakers to promote openness in scientific research (e.g., Aspesi and Brand, 2020; Beck et al., 2022; OECD, 2015). Although many open science efforts are focused on free access to publications, others recognize that the efficient, credible, and transparent development of scientific knowledge depends on disclosing and repurposing the intermediate resources employed throughout the research process, such as data, computer code, and other research material (Dasgupta and David, 1994; Walsh et al., 2007; Shibayama and Baba, 2011; Shibayama and Lawson, 2021). The dissemination of these resources bolsters scientific research by allowing scientists to avoid spending time and money creating data, tools, and other materials that already exist. Access to intermediate resources also facilitates replication and enhances credibility.

Despite the growing awareness of these benefits, resource sharing as a default mechanism remains limited (Nature, 2024a). A recent UNESCO report indicates that significant efforts are still required to realize the full potential of open science (UNESCO, 2023). In numerous scientific disciplines, the nondisclosure of resources is still a widely accepted practice (Gomes et al., 2022; Tenopir et al., 2011; Blumenthal et al., 2006; Munafò et al., 2017; Campbell et al., 2002; Andreoli-Versbach and Mueller-Langer, 2014), and resource sharing that does occur tends to happen through direct, one-to-one transactions (Shibayama and Baba, 2011; Wallis et al., 2013). As prior research has shown, resource sharing is often hindered by the incentives and disincentives perceived by

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individual scientists (Haas and Park, 2010; Haeussler et al., 2014; Walsh et al., 2007). Beyond the level of individual incentives, however, resource sharing is obstructed by the norms that govern scientific collaboration and thus shape these incentives in the first place. In particular, sharing is hindered by entrenched norms of authorship and evaluation, which are rooted historically in a culture of secrecy that discourages the disclosure of intermediate resources. Overcoming the challenges that impede sharing thus requires addressing the limitations of these governance norms; as Splitter et al. (2023) aptly state, the enactment of openness involves revisiting the norms that form "the core of an organization's raison d'etre" (p. 14).

In this paper, we zoom in on the governance of open science by examining how the limitations of established norms of authorship and evaluation are addressed in open science consortia that are premised on the sharing of intermediate resources. By norms, we do not refer to abstract cognitive elements or principles constraining action, but to their socio-technical translation and embeddedness in "investments in forms" (Thévenot, 1984) such as protocols, guidelines, codes of conduct, classification tools, and measurement devices. Our data draw on qualitative methods and an in-depth comparative analysis of two prominent open science consortia: the Canadian Open Neuroscience Platform (CONP) and The Cancer Genome Atlas (TCGA). Our findings reveal how the governance mechanisms designed and implemented within CONP and TCGA reflect two different governance forms, one "distributed" and the other "layered," which are in turn characterized by different understandings of scientific authorship and evaluation.

This study advances the discourse on open science and the governance of scientific collaboration by shedding light on the interplay between varying forms of governance and divergent conceptions of authorship and evaluation. Particularly, we show how CONP's distributed governance is characterized by an "atomized" view of authorship that acknowledges all creators of data and code as essential contributors, whereas TCGA's layered governance reflects a "tiered" authorship model that addresses traditional authorship limitations by balancing collective and individual recognition. Moreover, we discuss how CONP's evaluation framework is primarily "functional," focusing on the technical review of intermediate resources to address the needs of an increasingly digital and computational neuroscience field, while TCGA's "quality-based" approach recognizes that impactful cancer research relies on data that is not only extensive but also rigorously vetted for accuracy and consistency.

We conclude by examining the broader implications of our study, highlighting how the limitations of traditional authorship and evaluation norms extend beyond brain and cancer research, and suggesting how the mechanisms developed in CONP and TCGA may be relevant to other open science initiatives. In general, our findings indicate that policy recommendations intended to enhance openness in scientific research should transcend the level of the individual scientist in order to account for broader organizational dimensions. In particular, we underscore the critical role of the tools and practices scientists adopt to coordinate their activities, suggesting that efforts to foster greater collaboration in science should attend to the suitability of changes in the day-to-day work of teams, labs, and wider scientific communities.

2. Theoretical background

While scientific research relies heavily on the sharing and publication of findings, it also draws on a number of intermediate resources that are generated in conjunction with, or are necessary for, the production of published results (Dasgupta and David, 1994). Intermediate resources may include "tacit" techniques developed over time (Collins, 2019; Polanyi, 1966) or more easily shareable material like datasets, equipment, protocols, and computer code (Shibayama and Lawson, 2021). The importance of sharing these resources has been increasingly recognized. Data sharing, in particular, is valued highly because it enables the verification of results, fosters the replication of studies, and increases the potential for new discoveries based on existing datasets (Campbell, 2009; Nosek et al., 2015; Gold, 2021; Leone et al., 2021; Nelson, 2004). In a similar vein, sharing the code used for research enhances transparency, reproducibility, and efficiency, allowing other researchers to understand, verify, and build upon the methodologies employed (Leonelli, 2023). By making code available, researchers enable a deeper scrutiny of their work, fostering a culture of accountability and continuous improvement. The benefits of sharing intermediate resources are especially relevant when faulty outputs may have detrimental effects beyond academia. In the case of Reinhart and Rogoff's (2010) study on the negative relationship between debt and growth, for example, results were used to develop austerity policies despite coding errors that were later uncovered (Andreoli-Versbach and Mueller-Langer, 2014).

While the adoption of open data and open code practices varies with the epistemic culture of the specific scientific discipline (Knorr-Cetina, 1999), the decision of whether or not to share intermediate resources is often left to the discretion of individual scholars (Nelson, 2016; Shibayama and Lawson, 2021), with withholding remaining a prevalent behavior (Gomes et al., 2022; Munafò et al., 2017; Tenopir et al., 2011; Blumenthal et al., 2006). A key obstacle to sharing resources is that scholarly work is still predominantly credited and assessed through traditional criteria (Allen and Mehler, 2019; Mirowski, 2018). Indeed, the governance of scientific collaboration is based on entrenched norms of authorship and evaluation that present considerable limitations for the sharing of intermediate resources, as we illustrate in the following subsections.

2.1. Limitations of authorship norms for the sharing of intermediate resources

Authorship norms play a central role in the governance of scientific collaboration (Glänzel and Schubert, 2004; Katz and Martin, 1997; Fleming, 2021). The International Committee of Medical Journal Editors provide recommendations, for example, for assigning authorship based on significant contributions to the conception, design, execution, or interpretation of research (ICMJE, 2024). Yet, guidelines like these often fail to recognize the contributions involved in the creation and sharing of intermediate resources, particularly when these resources are self-standing and not directly linked to a specific study. As a result, academic success is typically tied not to the sharing of intermediate resources, but to the publication of final outputs (Jabbehdari and Walsh, 2017; Zuckerman, 1968), which fuels a "cycle of credit" (Latour and Woolgar, 1979), leading to a range of benefits like research funding, academic positions, and further research opportunities.

The traditional conception of authorship is thus defined by a focus on final results which discourages researchers from dedicating effort to making intermediate resources publicly available. Indeed, the resources required for data curation and sharing are non-negligible (Bezuidenhout et al., 2017), requiring a significant investment of time, expertise, and sometimes financial resources (Leonelli, 2016; Borgman, 2012). To ensure that shared data is usable to others, it must be documented meticulously and hosted on platforms that offer broad accessibility. Addressing data privacy concerns, especially in research involving human subjects, also requires considerable effort to guarantee compliance with ethical standards and regulations (Graef and Prüfer, 2021). Likewise, making code available is a complex process that involves comprehensive documentation, thorough testing, and ensuring that the format is accessible and intelligible for others. This requires additional time and resources, which can be a significant burden, especially for smaller research teams or individual researchers (Gomes et al., 2022). The need for ongoing maintenance and updates of shared code further complicates open code practices.

Not only is the task of sharing intermediate resources potentially burdensome, but, in the context of established authorship norms, many researchers tend to view these resources as a competitive advantage necessary for maintaining a lead in their respective fields. This competitive mindset discourages the open sharing of data, methods, and tools, since doing so could benefit rivals (Stephan, 1996, 2010; Walsh and Hong, 2003; Hong and Walsh, 2009; Haas and Park, 2010; Honig et al., 2014; Walsh and Huang, 2014; Haeussler et al., 2014; Nelson, 2016; Schaeffer, 2019). In their survey of 1849 scientists across 100 U.S. universities, Campbell et al. (2002) found that 40 % had experienced at least one refusal when requesting information or materials. The majority of those who admitted to intentionally withholding information did so to preserve their team's publishing prospects. Further insights come from Derrick (2015), whose findings reveal a common sentiment among medical researchers that, despite the inherently collegial nature of research, the rise in competitive pressures often leads to a tendency to withhold information. This is particularly true when the resources in question are scarce and the prospective recipient is considered a competitor (Shibayama and Lawson, 2021). Nelson (2016) describes the approach of partially disclosing information while strategically retaining some knowledge as "strategic withholding." To preserve their competitive advantage, researchers might choose to disclose only certain elements of their data, withholding potentially crucial information that would provide a fuller understanding of their work.

Authorship norms also tend to emphasize individual achievement over collaborative contributions, further complicating the sharing process. When intermediate resources are the result of collaborative efforts, the question of who should receive credit becomes complex (Biagioli, 2003; Birnholtz, 2006; Hoekman and Rake, 2024; Rennie et al., 1997). This can lead to conflicts and reluctance to share, as researchers may fear that their contributions will not be adequately recognized vis-à-vis the contributions of others. Such issues are particularly evident in disciplines such as biomedical science, where the success of translational research depends significantly on access to an assemblage of objects, instruments, and multidisciplinary skills and approaches. Although collaborative efforts are essential in this field for creating extensive repositories of materials (Gottweis and Petersen, 2008; Gold, 2016; Mishra and Bubela, 2014; Schaeffer, 2019), researchers tend to regulate their use through material transfer agreements (Marshall, 1997; Rodriguez, 2005). These agreements can be complex, however, and may involve the need for challenging negotiations before any material can be transferred into or out of a research institution (Bubela et al., 2015; Walsh et al., 2005).

Notably, the limitations of authorship norms persist regardless of the specific approach scientists adopt to share their resources. In their 2021 study based on a survey of 1204 resource suppliers or recipients in the UK, Germany, and Japan, Shibayama and Lawson identified three systems of sharing and exchange: generalized exchange, in which researchers expect to benefit indirectly from sharing their resources; direct exchange, which involves tangible benefits to sharers, such as co-authorship or reciprocity; and reputational rewarding, which provides the sharer with general recognition, often through acknowledgements. Shibayama and Lawson (2021) showed how each approach comes with a specific set of authorship-related challenges. Sharing systems that rely on generalized exchange might decline if they are treated primarily as a commons from which to withdraw information without contributing, otherwise known as the "free-rider" problem (Olson, 1965; Hardin, 1968; Ostrom, 1999). Although direct exchanges may help solve the free-rider problem, they are dependent upon mutual agreements between the provider and recipient regarding the terms of the exchange, and situations where one party possesses considerably more bargaining power than the other can result in imbalanced exchange conditions. In some cases, recipients might acquiesce to unfair terms, such as "courtesy authorships," where individuals in influential positions receive authorship credits without making significant contributions to the research (Bennett and Taylor, 2003; Dance, 2012; Haeussler and Sauermann, 2013). Finally, reputational reward systems also present challenges: when members of scientific communities shoulder the burden of monitoring and sharing reputational information informally, the task of processing this information may overwhelm the community, resulting in a breakdown of the reputation system (Shibayama and Lawson, 2021).

Overall, while the credit and reward mechanisms for the sharing of scientific outputs, such as the acknowledgment of authorship for disclosed findings, is well-established (Biagioli and Galison, 2003; Pointille, 2016), governance mechanisms for the sharing of intermediate resources are less defined and more intricate, as they tend not to align neatly with traditional norms of authorship. Yet, the establishment of such mechanisms is pivotal; as Dasgupta and David (1994) point out, serious inefficiencies arise when the existing system prevents scientists from developing resources that are universally useful for future research.

2.2. *Limitations of evaluation norms for the sharing of intermediate resources*

The sharing of intermediate resources presents significant challenges also in the context of established norms of scientific evaluation, which play a key role in the governance of scientific collaboration by informing the standards of what constitutes "good research" (Gläser, 2007). Indeed, the peer review process, which has traditionally centered around the assessment of the scientific rigor, originality, and contribution of the final research paper, remains a core tool for evaluating scientific work and has long been regarded as the primary vehicle of scholarly communication (Zuckerman and Merton, 1971; Cole, 1998). In this process, reviewers are asked to scrutinize the research questions, methodology, analysis, and conclusions presented in the paper and to ensure that these elements meet high academic standards. This emphasis on the final product, however, reflects a "black box" approach to scientific work, where the processes, tools, and data involved in producing scientific knowledge are often hidden from view (Latour and Woolgar, 1979). Most of the time, the majority of the actual research process, including detailed measures, methods, and analysis strategies, is merely summarized in the paper despite the virtually unlimited space afforded by today's digital formats (Nosek and Bar-Anan, 2012). As a result, the review process rarely encompasses the evaluation of data, code, and other intermediate resources unless they are directly embedded in the narrative of the paper.

The limited scope of the peer-review process makes it poorly suited to evaluating the data analysis stage. As Nosek et al. (2012, 620) aptly state, "peer reviewers review only the summary report of the research, not the research itself," which means that mistakes, questionable practices, or even fraud may go undetected (Smith, 2006). Consequently, the peer-review process may well miss errors that could compromise the study's validity, posing risks to the reliability of the published findings.

Although some journals do require authors to disclose data and code along with their manuscript for the sake of the review process (e.g., Nature, 2024b; Science, 2024), the review of these resources is far from straightforward, demanding additional time and effort from reviewers. Given the already substantial workload associated with reviewing manuscripts, adding the responsibility of evaluating supplementary materials risks overburdening reviewers and slowing down the peer review process. Journals are already facing significant challenges in securing timely reviews due to the high volume of submissions and the limited availability of qualified reviewers (Hochberg et al., 2009), and the added complexity of reviewing data and code exacerbates these issues, potentially leading to longer review cycles and delayed publication times. These delays can have broader implications for the dissemination and impact of scientific research, as timely publication is critical for both the advancement of knowledge and the development of research-based policy.

The challenges reviewers currently face extend beyond the additional time and effort required to review intermediate resources. For example, reviewers might grapple with how to evaluate papers that are based on publicly available and therefore identical datasets or methodological tools, potentially questioning their originality. They may also lack the specialized expertise to assess resources which can vary significantly in format and complexity. Unlike the research paper, which follows a relatively standardized structure, intermediate resources such as datasets, code, and protocols can be highly heterogeneous, complicating the development of consistent criteria for their evaluation and thus leading to inconsistencies in review practices. Moreover, reviewing computer code requires proficiency in programming and software engineering principles that reviewers may not have (Wurzel Gonçalves et al., 2023).

Finally, evaluating intermediate resources often requires contextual knowledge that may not be readily available to reviewers. For instance, concerns about data quality are often paramount given that the disclosure and use of poor quality or incomplete data can lead to misinterpretation or misuse of information (Leonelli, 2018), but assessing the quality of a dataset entails a deep understanding of the data collection methods, cleaning processes, and potential biases. The detailed examination of datasets involves checking for proper documentation, gauging data integrity, and ensuring that the data can be reliably used for replication and further research. Likewise, code review entails scrutinizing the logic, structure, and functionality of the software to ensure it performs as described and is free from errors; this can pose challenges, however, if researchers do not meticulously document and make available all the steps involved in their coding process (Sandve et al., 2013).

Overall, the limitations of current evaluation norms pose significant challenges to the sharing of intermediate resources. The traditional peer review process is not properly equipped to handle the complexities associated with evaluating data, code, and other research materials. This gap in the review process can hinder sharing practices as the evaluation of intermediate resources remains haphazard and opaque.

3. Methods

3.1. Research context

To explore the limitations of established authorship and evaluation norms that obstruct the sharing of intermediate resources as well as the governance mechanisms employed to overcome them, we conducted an in-depth comparative analysis of two prominent open science consortia, the Canadian Open Neuroscience Platform (CONP) and The Cancer Genome Atlas (TCGA). Both research contexts are introduced below, followed by a description of our data collection and analysis process.

3.1.1. The Canadian Open Neuroscience Platform (CONP)

Neurological diseases pose a growing global challenge, exacerbated by aging populations and a limited understanding of brain function and disease modification. As many neuroscientists acknowledge, traditional research approaches have resulted in underpowered studies as well as non-transparent, non-reproducible data analyses that have led to contradictory findings (Saxena and Kline, 2021). The Canadian Open Neuroscience Platform (CONP) initiative, which began in 2018, is an ongoing effort to address these challenges and to propel Canada's neuroscience field into a new era of open science (Harding et al., 2023). As a $10 million government-funded initiative, CONP has enrolled leading neuroscientists from 19 universities and 33 research institutions across Canada who are working to establish commonly shared, digitally integrated, data- and algorithmic-rich neuroscience research. Specifically, CONP was launched with the goal of embedding technical capabilities within ethically sound models of data governance and dissemination. As a national network of research centers, CONP continues to develop infrastructure and resources supporting the free sharing of neuroscience data and tools, cross-disciplinary training, policy frameworks for ethical data governance, open publishing, and international collaborations that promote the broader goals of open science.

3.1.2. The Cancer Genome Atlas (TCGA)

The mapping of the human genome around the turn of the twenty-first century marked a significant turning point in how scientists work to understand, treat, and prevent cancer (Wheeler and Wang, 2013). Since then, researchers have been utilizing new sequencing technologies to identify genomic alterations (changes in DNA) that might be associated with different types of cancer. The Cancer Genome Atlas (TCGA) was an initiative led by the United States National Institutes of Health (NIH) that sought to identify the genomic alterations underlying different types of cancer and to compile the results into a publicly available database for future research. This project involved funding hundreds of researchers across dozens of institutions to transform samples of human tissue into different types of genomic data through a range of analysis and sequencing methods–an iterative process of collecting, analyzing, and cataloging data (Plutynski, 2021). TCGA began in 2006 as a $100 million pilot project funded through a joint partnership between the National Cancer Institute (NCI) and the National Human Genome Research Institute (NHGRI). Funding was extended in 2010, and, by the conclusion of the project in 2016, genomic data related to 33 types of cancer had been made publicly available and continue to be used by researchers worldwide.

3.2. Data collection and analysis

This study employs a multisite, comparative methodology that facilitates a robust identification of shared patterns as well as differences between contexts and contributes to the cumulative synthesis of findings and theoretical insights (Bechky and Okhuysen, 2011). In focusing our attention on CONP and TCGA, we followed a “matched” sampling strategy (Bechky and O'Mahony, 2016) that allowed us to highlight commonalities and differences in two open science consortia as well as to develop a nuanced analysis of open science collaborations more broadly (see also Barley, 1986; Edmondson et al., 2001; Kellogg, 2009).

The empirical material we collected included observations of meetings, interviews with key participants, and an analysis of relevant documents. The meetings we observed encompassed live and recorded sessions of the various committees and boards engaged in the development and management of CONP and TCGA. These sessions included diverse individuals and groups ranging from executive leaders to technical teams who provided comprehensive insights into the decision-making processes, operational strategies, and collaborative dynamics within each consortium. Our initial selection of interviewees was based on purposeful sampling, focusing on individuals with unique insights, strategic significance, and the ability to recommend other key informants (Corley and Gioia, 2004). This approach enabled us to utilize the snowball sampling technique, systematically expanding our pool of interviewees and ensuring a comprehensive and multifaceted understanding of the dynamics and operations within each consortium. The protocols we used for interviews were adapted over time as we continued to develop an understanding of each consortium and gradually validated emerging themes (Pratt, 2000). In our analysis of the extensive array of documents we collected, we paid close attention to the author and intended audience of each text, as well as its context, purpose, and limitations.

Starting in June 2018, we collected observational data on CONP by following the development of the consortium over a period of 2.5 years. One author of this study attended regular Zoom meetings of the committees involved in the operations of the consortium, in-person hackathons, plenary meetings, workshops, and conferences. Discussions at these meetings and events ranged from overall goals of the project to specific datasets to technical challenges and solutions.

Observational data for CONP were triangulated with 43 semi-structured interviews with participants as well as document analyses. Each interview lasted between 45 and 90 min. During each interview, interviewees were asked to provide their recollection of events, reflect on the dynamics of openness and secrecy in neuroscience, and describe their efforts to promote open neuroscience along with the challenges they encountered. We interviewed the Executive Director of CONP on a monthly basis to document his ongoing personal recollections of events. The Executive Director also provided relevant documents associated with the project, including internal documents such as meeting agendas and minutes, presentation slides, working drafts, unpublished reports, plans, grant applications, and personal correspondence. In addition, we analyzed scientific publications authored by CONP members and gathered external documents, including media publications, blog posts, workshop and conference programs, published reports, and relevant scientific papers. Overall, 290 documents related to the development of CONP were reviewed and categorized.

Likewise, we collected a variety of data on the design and development of TCGA. We first gathered and categorized an extensive amount of archival material related to both the pilot (2006–2009) and extension (2010–2016) phases of the project. The documents we collected included meeting minutes and PowerPoint slides from a variety of events as well as public documents related to TCGA, such as updates and news reports gathered through the NCI Library and NIH Archive. Given the high-profile nature of the project, a large amount of documentation was available for analysis. Publications of news reports ranged from the *Bulletin of the NCI* to the *New York Times* and included both praise and criticism of the project. We also analyzed scientific publications authored by "The TCGA Research Network" as well as a selection of publications that made use of TCGA data. Overall, we reviewed and categorized 450 documents related to the development of TCGA.

Archival data for TCGA were triangulated with 19 semi-structured interviews and observations of recorded meetings. Interviewees included multiple directors, lead scientists, postdoctoral fellows, and consultants. Interviews lasted between 30 and 120 min. During each interview, interviewees were asked to reflect on their own participation in TCGA as well as the challenges encountered during the project. Topics included funding structures, data management, and career concerns. At times, we found it helpful to discuss specific TCGA publications and/or data produced for specific tumor types. Observational data included meetings of the NIH National Cancer Advisory Board and the NCI Board of Scientific Advisers in which TCGA was substantively discussed. These meetings took place between September 2004 and March 2013 and included proposals, updates, and discussions of the project. We also watched and analyzed recordings of conferences held for researchers who were interested in applying for TCGA funding and for researchers who were already participating in the project. These meetings were especially helpful in elucidating broad characterizations as well as details of the project and how both changed over time.

During and following the data collection phase, we jointly engaged in the analysis of the data. Indeed, our data analysis stage was adaptive and iterative to ensure that our theorizing remained grounded in empirics and to avoid "forcing" preconceived theories onto our emerging findings (Charmaz, 2006, 67). The analysis phase described below involved the examination and discussion of barriers to sharing (deriving from the limitations of established authorship and evaluation norms) and associated governance mechanisms within each consortium, both on their own and in comparison.

To start, we engaged in multiple readings of transcriptions and field notes while considering potential theoretical interpretations (Gehman et al., 2017; Gioia et al., 2013; Langley, 1999). Using manual (color-coding) and computer-assisted (Atlas.ti) techniques, we identified empirical themes that were unique to each consortium as well as those that were common to both. This approach allowed us to highlight commonalities and differences between the two consortia. During our coding process, we made sure to account for the unique interpretations of our research participants. For example, we did not take terms like "open science" or "data" at face value. Instead, we sought to understand what these concepts signified for each participant, acknowledging that these terms could have varying meanings and implications across contexts.

Our initial round of coding pointed to a variety of collaborative challenges within each consortium. For example, we noticed from our data that an issue faced by scientists within both consortia was the fear of being "scooped," that is, the perception that sharing behaviors would benefit other researchers at the expense of one's own career. At the same time, however, our data also indicated dilemmas that were specific to each consortium. For instance, a persistent theme in CONP was the desire to surface auxiliary material alongside data, such as computer code and protocols (e.g., "*The published article is just the tip of the iceberg. And, then, below the surface, we have everything else: the discussions…the protocols"*). On the other hand, one of the main themes that emerged in TCGA was the readiness of the data to be shared (e.g., "*From what we the data generators know is that I don't want to just put it out there until I've had an opportunity to make sure that it's good, and that requires that I do some analysis on it*"). In conversation with prior literature, we categorized these challenges along limitations of authorship and evaluation norms for the sharing of intermediate resources. We then returned to the data and engaged in a second round of coding.

During the second round of analysis, we organized our data based on their relevance to specific limitations of authorship and evaluation norms. This allowed us to zero in on the responses of both consortia to these limitations. Some responses proved to be similar across both sites. For example, we noticed that in both CONP and TCGA, the traditional format for scientific manuscripts was put under scrutiny and reconsidered in light of alternative publication practices. Nevertheless, our data also indicated responses that differed across the two consortia. For example, while CONP worked towards technical solutions for sidestepping the challenges of data transfer and duplication, TCGA created strict criteria to ensure the quality of shared data. Delving deeper into the common as well as varying responses we identified, we began to induce the specific governance mechanisms employed in each consortium, which are discussed in the findings section.

At this point, it became clear that our final round of analysis would benefit from the scholarly literature on the governance of scientific collaboration. Our objective was then to document comprehensively the specific dynamics of the governance mechanisms we identified, understand the underlying reasons for the commonalities and differences we observed, and examine the theoretical implications. From empirical themes, we systematically derived our analytical findings that relate to the shifting understandings of authorship and evaluation in the governance of scientific collaboration. The alignment between analytical findings and empirical themes was iteratively compared through theoretical memos that were discussed in group meetings. Group meetings also allowed for a deeper exploration of our findings and comparative analysis thereof. Overall, this iterative process of data collection and analysis allowed us to theorize how resource sharing became a possibility in the two open science consortia that we studied, and to what extent the governance mechanisms they implemented reflect different understandings of authorship and evaluation.

4. Findings

During the development of CONP and TCGA, participants encountered challenges related to the existing norms of scientific authorship and evaluation, which were ill-suited to the governance of shared resources within each consortium. Our findings reveal that new mechanisms for authorship and evaluation were established in each consortium in order to govern scientific collaboration centered around the sharing of intermediate resources. These mechanisms are detailed in the following subsections and summarized in Table 1.

4.1. New authorship mechanisms

4.1.1. CONP: providing decentralized access to citable resources

A central goal of CONP is to bring the intermediate resources that are distributed across the neuroscience field into the open, making them

Table 1
Limitations of governance norms and new governance mechanisms in CONP and TCGA.

	Limitations in CONP (example quotations)	Limitations in TCGA (example quotations)	CONP governance mechanisms	TCGA governance mechanisms
Authorship norms	"*But what if we are going to be scooped with our own data?*" [#27]	"*And, you know, I feel that everyone should get some aspect of that credit for pulling this off. Right? Because it was a big feat.*" [#Y]	Providing decentralized access to citable resources	Balancing individual and collective outputs
Evaluation norms	"*We have more than 8 million scientists and we have a lot of data and a lot of code, science has gotten very computationally intensive…but how do you actually make sense of it when it's just like drinking from a firehose?*" [#33]	"*I mean, it would be unethical to spend taxpayers dollars analyzing crap. And it would be further unethical to generate data that was artefactual, irreproducible and put that in the medical scientific literature for other people to waste money on…*" [#P]	Enhancing technical and peer scrutiny	Centralizing and aggregating quality controls

widely accessible. Since the beginning of the project, it was clear that existing authorship norms were inadequate for this purpose. To overcome these limitations, CONP transformed intermediate resources into citable research objects and established a decentralized sharing model.

The limitations of established authorship norms for sharing intermediate resources manifested in CONP's early attempts to promote access to the data distributed across neuroscience labs, a key goal aimed at ensuring "that anybody around the world can download it…that [would be] a really major step forward" [#8].[2] For example, in the midst of the acquisition of the "invaluable" (CONP internal report) dataset Alpha,[3] several researchers involved in its production resisted the release, claiming their exclusive rights to use the data. Some scientists were especially reluctant to share the "interesting data," that is, the portions of the dataset that were more likely to lead to valuable findings and publications. As one researcher explained, "You know, [the logic is that] you share the data that's not so interesting and you keep a subset of the very interesting data, at least from your research perspective" [#22].

To overcome this resistance, CONP members worked to remind Alpha researchers of the benefits of data sharing. One informant recalled these kinds of difficult conversations:

CM[4]: We agreed to do this, we have to go ahead and do it.

AR[5]: But what if we are going to be scooped with our own data?

CM: I don't think that's a problem. I think, in fact, you get a much higher profile internationally…When people out there start using your data and ask many more questions on it and produce much more science from the database that you collected than you could do by yourself. But it takes a while to really internalize that this is good for you… And this is also contributing to the commonwealth of data and ideas that should accelerate our path to ultimately find cures for these disorders with more people working on it.

AR: But my career will suffer if I do that.

CM: Actually, your career won't suffer if you do that. In fact, your career will be advanced if you do that because you get a high profile. So, it's a win-win [#27].

Despite these efforts, only a portion of Alpha was disclosed. As one Alpha researcher explained, "Some data were good…they were kind of special for a specific investigator. The investigator wanted to publish the data first and share it later. Right. So, we have some data that we want [that] we will not share this year" [#9]. A CONP member confirmed this outcome: "They withheld some data…to be the first to analyze and publish on it" [#32].

As discussions around the release of Alpha demonstrate, in their initial attempts to promote access to datasets, CONP members encountered researchers who were reluctant to allow the full duplication and transfer of their resources because they wanted to maintain control over data sharing protocols–dictating what to share, with whom, and under what terms–and to preserve future publication opportunities. CONP members thus opted for a decentralized data sharing model, which became a distinctive feature of its approach. In this model, CONP provides access to datasets that remain under the control of their original creators, who can determine which parts of the datasets are sharable, set sharing conditions, and oversee downloads. This model contains both a data layer, which incorporates several independent data repositories, and a metadata layer, which clarifies the access conditions associated with each dataset. The integration of the two layers was achieved through a software tool called DataLad. Importantly, DataLad datasets do not contain the actual data, which remain housed in independent repositories. Rather, DataLad datasets contain only representations of the data, which are created automatically when CONP-tagged datasets are found in the repositories, and are updated automatically when modifications are detected. By allowing data stewards to permit access on a case-by-case basis, the decentralized model ultimately led to the disclosure of a wide spectrum of datasets, sidestepping key challenges related to authorship that often inhibit data sharing.

To further alleviate these challenges and to encourage neuroscientists to share data and code, CONP elevated intermediate resources to citable research objects. Datasets and code scripts for data cleaning and analysis, often referred to as "pipelines," were associated with a Digital Object Identifier (DOI). In this case, the DOI goes beyond its usefulness as an identifier and effectively contributes to transforming each dataset and pipeline into a citable research object. This citability ensures that datasets and pipelines are not only discoverable but can also be formally acknowledged and referenced in scholarly literature. Moreover, the DOI preserves the integrity of the original data and code, ensuring that they remain unaltered.

In addition to being assigned a DOI, each dataset was associated with a Data Tags Suite (DATS) model file, which serves as an exhaustive metadata dossier. The DATS file provides the dataset's name, type, format, and, critically, its collectors' names and affiliations. It also traces the history of the dataset, mapping out locations, institutions, publications, grants, and relationships with other datasets and sub-datasets. This comprehensive information network ensures that the origin of each part of any shared dataset remains traceable. Together, DOIs and DATS files specify with a great level of precision every contributor involved in the collection of data, the curation and maintenance of datasets and sub-datasets, and the development of pipelines.

Along with providing access to data and pipelines, CONP members developed a new manuscript format–the "notebook"–which allows readers to visualize and download the specific resources that are

[2] Quotations from the CONP case were assigned random numbers; quotations from the TCGA case were assigned random letters.
[3] Alpha is a pseudonym.
[4] CONP member.
[5] Alpha researcher.

employed in each study. Indeed, notebooks contain links to the study's data as well as to the pipelines underlying all figures and calculations (Fig. 1).

The CONP notebook is thus a digital reimagination of the traditional manuscript format that embeds text alongside the data and code used to derive scientific outputs. Notebooks are hosted on CONP's NeuroLibre server, where they can run online so that anyone can see precisely how data, code, and findings are related. For CONP members, the notebook represents a radical paradigm shift in science communication: "[The notebook] goes beyond the PDF. So basically, rather than have static documents…we want to breathe new life into academic publishing by incorporating text, data, code and…figures" [#41].

Overall, CONP addressed the limitations of authorship norms by transforming intermediate resources into citable research objects and establishing a decentralized sharing model. In doing so, CONP fostered the disclosure of data and code by allowing their creators to earn credit for and selectively share portions of what they create. Moreover, the CONP notebook allows anyone to easily visualize, download, and cite the specific resources employed in any given study.

4.1.2. *TCGA: balancing individual and collective outputs*

The overall goal of TCGA was to transform samples of particular tumor types into different forms of genomic data that would be available to cancer researchers worldwide. At the same time, TCGA scientists worked to publish their own findings based on this shared data, which raised authorship-related challenges. TCGA leadership addressed these challenges by orchestrating the flow of scientific contributions stemming from their shared, centralized dataset. A waiting period for non-TCGA researchers, together with a combination of collective and individual types of publications, enabled TCGA to effectively allocate credit among researchers.

As a federally funded "community research project," TCGA was expected to make all of its data publicly available, which meant that non-TCGA scientists could use it in their own (commercial or academic) research without restriction: "[TCGA researchers] had to realize that that was not their data," one participant explained, "it was NCI's data, and they were being contracted to help the NCI get it" [#E]. Nonetheless, a general sense of etiquette seemed to suggest that the scientists who produced shared data should be the first to publish an analysis of it, and non-TCGA scientists were asked not to publish using TCGA data until those who had produced it had the opportunity to do so. The first publication assembled by TCGA scientists who had worked to produce and analyze data for a particular cancer type was referred to as a "marker paper." Thus, each TCGA marker paper served as an important benchmark in the project, signaling that the data for that cancer type was ready for public use while giving credit to those who had worked to create it.

Yet, near the start of TCGA, questions emerged about who would be listed on marker papers as first author, last author, corresponding author, etc., which is an important consideration for the allocation of credit in biomedical research. As one TCGA leader recalled, "There were all these discussions, 'Who's first? Who's second? Who's first? Who's second? Who's first? Who's second?' And at that point, [the director] said, 'Well, maybe what we need to do is to have a single author'" [#N]. Indeed, TCGA leadership effectively put an end to conversations about authorship order by deciding that the author of marker papers would be "The Cancer Genome Atlas Research Network." This "network" authorship (both searchable and citable) would include absolutely everyone who had anything to do with generating data and results for the paper, from technicians involved in sample collection to bioinformaticians and data analysts. Although "The Cancer Genome Atlas Research Network" would be listed as the author, individual names were listed in the "Author Information" section, where they were grouped by institution and order was irrelevant. One TCGA scientist referred to this as "inclusive credit":

> "I know some folks don't always believe in that, but there are so many people that were required to make this run smoothly that, you know, they do deserve that part. The, you know, staff computational person

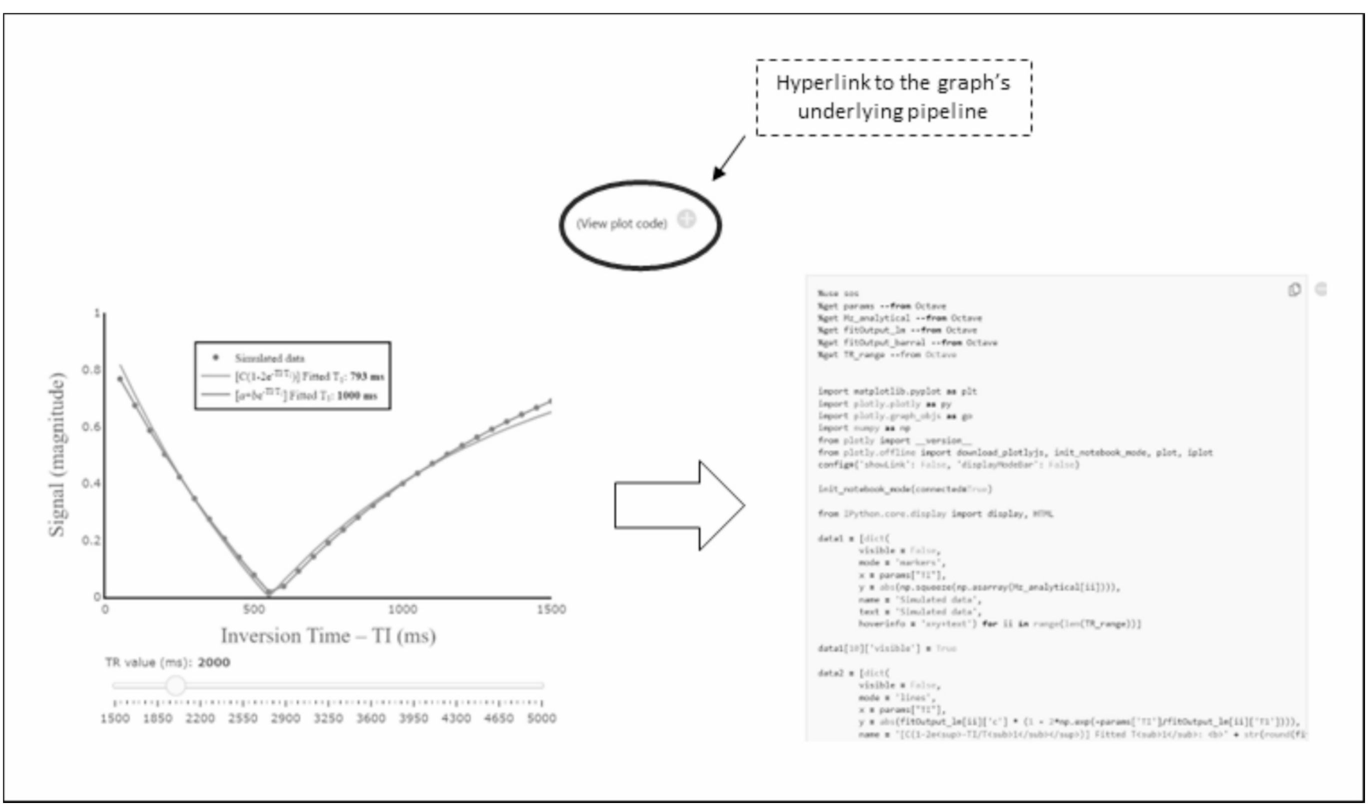

Fig. 1. Example of how CONP notebooks provide access to pipelines.

that was doing the initial [quality control] and doing the upload, that was still a very critical component. The, you know, technician that was pipetting to do the libraries, that also is an important contribution. And, you know, I know some labs think that your authorship should only be intellectual contribution. But this project was to such a scale that it wouldn't have been done without them. And, you know, I feel that everyone should get some aspect of that credit for pulling this off. Because it was a big feat."

[#Y]

For some, the value of being listed as an author on a network-authored marker paper was viewed as an incentive to participate. Indeed, the incentive of authorship was sometimes used to convince biobankers to donate their samples. In recalling these conversations, one TCGA director described biobankers' reactions:

"'You'll include me on the paper, even if I just send you ten samples?' Absolutely. Five samples. I don't care. One sample. I was like, 'If you give me one sample that gets into a paper, you're on the paper. One. Now you might be in the middle of 500 people, but you're on the paper.'"

[#B]

Questions remained, however, about how meaningful it was to be listed among hundreds of names in the Author Information section of a network-authored marker paper. As one participant remarked,

"Personally, I have 200 something publications, so I don't put those on my CV because I… didn't do anything for that paper. You know, they used some of my samples, so therefore I'm listed in the appendix [the Author Information section] as an author and therefore it's indexed in PubMed. But I don't put those on my CV because I'm not a named author... But you could do that if you needed some more publications or something like that."

[#F]

Because the number and quality of papers on which an individual scientist's name is listed as first author remains an important metric for job applications and promotion, some were concerned that marker papers authored by "The Cancer Genome Atlas Research Network" would not be helpful for advancing individual careers. One way to mitigate this issue was to publish an additional analysis of the same cancer type as a "follow-up" to the marker paper. While marker papers were authored by the TCGA network, follow-up papers were authored by individual scientists. As such, they were often referred to as "named-author" or "single-author" publications.

The potential for writing follow-up papers was associated with the content boundaries of each marker paper. For example, when an analysis of DNA methylation was not included in a marker paper because it was not the main focus and there was not enough space, the TCGA experts on DNA methylation had an opportunity to publish a follow-up paper. As one TCGA researcher recalled: DNA methylation abnormalities "didn't make it into" the marker paper for Glioblastoma that was published in *Nature,* "So we investigated in more detail and ended up publishing… We published a paper on DNA methylation-based subtypes of Glioblastoma… And it was named-author as opposed to a consortium since it was a follow-up paper" [#J].

Follow-up papers helped navigate concerns about recognition raised by network authorship, but they also raised new concerns about holding back versus sharing analyses and findings. Although scientists would earn more credit for interesting results that were published in a single-authored follow-up paper, withholding findings would diminish the scientific value of the network-authored marker paper. To prevent this from happening, TCGA relied on adherence to a policy that required all scientists to share the entirety of analyses and results, which could then be considered for inclusion in the marker paper. This policy was policed informally by the community. If scientists withheld ideas that could have been included in the marker paper, others would give them "the cold shoulder" and likely stop collaborating with them [#A].

Later on, a new hybrid solution emerged: the marker paper moved to a "mixed" authorship format, where the "The Cancer Genome Atlas Network" was listed as one of multiple authors and individual scientists who had contributed significantly to the analysis and outputs of the paper were listed by name alongside the network. Named scientists were thus given more credit than others in the network. "But if you didn't really participate or, you know, lead a figure or analysis or whatever, you would still get lumped in with, you know, the network authorship" [#L]. As one of the leaders of TCGA explained, if scientists could not agree on who would be listed by name, the network would become the only author. He recalled saying to scientists who were disputing authorship: "If you don't come to an agreement in the next 15 minutes this is going to be a network paper. And in the next 15 minutes, they came to an agreement" [#R]. In another case, the scientist who would have been listed as first author on a "mixed" paper decided there were too many people who had done important work to list them all, so it should just be published as a network paper.

Overall, TCGA addressed the limitations of authorship by balancing individual and collective forms of credit. Network-authored marker papers helped to award credit to everyone who had been involved in the creation of a particular dataset, ideally before other scientists began publishing with the shared data. At the same time, however, follow-up and mixed-authorship papers helped to allocate credit within the network, recognizing and rewarding those who had contributed most substantially to a particular project.

4.2. New evaluation mechanisms

4.2.1. CONP: enhancing technical and peer scrutiny

The disclosure of intermediate resources such as data and pipelines through CONP notebooks represented a novel approach to scientific publishing that could not be encompassed by the traditional norms of scientific evaluation. To facilitate the integration of notebooks into the traditional publication process, CONP members devised an additional, internal review phase, which is meant to precede the journals' standard scientific assessment. This preliminary "technical review" aims to evaluate the technical validity and functioning of the notebook, including its integration with shared data and pipelines, while the consideration of scientific merit remains with the journals. The technical review is also crucial for ensuring the interactive functionality of the notebook, which itself supports peer review practices.

The introduction of an additional, technical review phase reflects a common viewpoint among CONP members that the established peer review process is no longer suitable for open forms of scientific research. In this view, the current system is not adequately equipped to handle the substantial amounts of data and code that characterize today's scientific environment. In one CONP member's words:

"Academic publishing has evolved through the ages...1731 first peer-reviewed journal…but back in 1731 there were less than 1000 scientists in the world and the visualizations were really beautiful but simple…and the we get to the 21st century and this is where we have more than 8 million scientists and we have a lot of data and a lot of code, science has gotten very computationally intensive…it's just a lot of noise, some of it is good but how do you actually make sense of it when it's just like drinking from a firehose?"

[#33]

The technical review phase in CONP engages four different actors–editors, authors, reviewers, and NeuroLibre technicians–who interact to ensure the technical soundness of notebooks. When authors submit a notebook to the NeuroLibre server, an internal editor assesses its topical relevance and then appoints a technical reviewer, while NeuroLibre technicians supervise the operability of the entire process. The bulk of the responsibility for this review phase rests with the technical reviewers, whose primary role is to assess the clarity and readability of the text, ensuring that figures are well-annotated and contribute to the narrative flow of the notebook, and verifying that the content is segmented appropriately into logical sections. They also check that code cells are concise and intelligible, that the code itself is well-documented and systematically arranged in a coherent directory hierarchy, and that automated tests are in place for verification. Although assessing the scientific rigor of a notebook is officially outside their purview, technical reviewers are expected to raise concerns with the editor through private communication should a submission lack sufficient quality.

If the outcome of the technical review process is positive, the notebook is posted on the NeuroLibre server in an open access format for public consumption. Much like CONP data and pipelines, the notebook, once posted on the server, is associated with a specific DOI. The notebook thus becomes citable. Subsequently, authors may choose to distill a traditional paper from their notebook and submit both to a journal. At that point, the pair is subject to the conventional peer-review process, which evaluates the scientific merit of the work. Rather than fully replacing the traditional publication, the notebook is thus integrated into the publication as a companion that allows researchers to "go beyond the written PDF article, enabling readers and reviewers to dig deep in the data and to not take the paper at face value" (CONP internal document).

A primary goal of CONP's technical evaluation phase is to ensure the interactive functionality of each notebook, which itself facilitates other scientists' evaluation of the content. Unlike resources that may be shared as supplemental material in the appendix of a traditional paper, CONP notebooks feature indeed interactive visualizations. Each reader can engage with and assess figures and computations on their own, modifying their parameters and observing how the outputs vary as a result: "The beautiful thing about them [i.e., the notebooks] is that they run in a web browser…You can take a look at the outputs, the values, the images, the plots, and you can be modifying these in real time to observe how different modifications affect your findings" [#1]. Overall, the interactivity of notebooks was viewed as addressing a key weakness of the research process:

> "Does the typical figure printed on paper really help you understand much?…Just keep in mind how much code and how much data goes behind this figure. But then, at the end, here we are. We just printed it and we showed it to you, and you're supposed to make sense of it and cite it in the future…So I think what we've got here is a failure to communicate"
>
> [#18]

By offering full access to computational scripts, the notebook enables the end-to-end reproduction of research through the removal of "the overhead that comes with accessing other labs' data and running their analysis code" (CONP internal document). In making pipelines available for verification and/or reuse, the goal was not for "every reader…[to] go over the code…for each paper they read. However, anybody who has ever tried to replicate a paper will appreciate the[se] additional functionalities…[which] save invaluable time and resources" (CONP internal document).

The sharing of intermediate resources via CONP notebooks raises significant evaluation concerns, which CONP addressed by adding an additional layer of technical evaluation prior to the traditional peer review process. Furthermore, ensuring the interactivity of the notebooks is itself meant to help researchers engage more deeply with and evaluate one another's work.

4.2.2. *TCGA: centralizing and aggregating quality controls*

TCGA was guided from the start by concerns about the quality of data its scientists were producing and sharing, and the traditional processes of evaluation that occur after the submission of outputs for publication were considered insufficient to ensure the desired level of quality. TCGA thus centralized the processes of quality control and relied on the participation of large numbers of leading researchers as ongoing evaluators.

TCGA was designed so that teams of researchers at Sequencing and Characterization Centers (referred to here as "Centers") would assemble genomic data using samples of human tissue ("specimens") that were collected from biobankers and other scientists across the community. The production of data thus involved the transformation of a finite, material resource (i.e., tissue samples) into a reusable, digital resource (i.e., genomic data). At the start of the project, TCGA leadership chose to take full control of this process, including sample collection and processing. Specifically, all tissue samples that were used in the project went through a centralized processing facility that performed quality control, extracted biomolecules (e.g., DNA and RNA), and distributed those biomolecules to each Center for analysis. According to one TCGA scientist, this choice was "very contentious" since "every group wanted to process their own [samples]" [#H]. But, according to one of the directors, "I thought it was the only way to do it where we really had the controls we needed. And so that part of the project was somewhat top down, and that was not really done in science" [#Q]. Reflecting further on the project, the same leader noted:

> "People asked me, 'What is so special about TCGA? What made that dataset what it is?' And my answer is one word: quality. That was it. That's the whole secret. We organized the quality metrics for the project, everything from the samples to the way that nucleic acids were extracted, to how the samples were shipped, how they were received..."
>
> [#D]

Because scientists collect tissue samples for different purposes following a variety of protocols, what is considered a quality sample in one context may not be suitable in another. Thus, when the TCGA project began, it was extremely difficult for program officers to find enough samples that met TCGA quality criteria in terms of size, content, and preparation. Locating and obtaining samples took much longer than anticipated, and the already funded Centers had nothing to analyze at the start of the project. Although some of the scientists involved at this point thought that the program's quality criteria were too stringent, and they wanted to get the project started with whatever samples were available, others emphasized the concern that because TCGA data would become the basis of further scientific research, "bad" data could lead to bad results and misguided clinical practices. As one TCGA leader explained,

> "I mean, it would be unethical to spend taxpayers' dollars analyzing crap. And it would be further unethical to generate data that was artefactual, irreproducible and put that in the medical scientific literature for other people to waste money on… to carry on research that was ill founded just simply based on bad specimens at the very beginning. Bad specimens, bad data, more bad data."
>
> [#P]

To ensure the quality of genomic data, alongside the centralized processing of samples TCGA Centers managed and stored all generated data in a single, central repository. Centralized data management facilitated quality control by highlighting inconsistencies between data produced at different Centers. When TCGA scientists began compiling and collectively reviewing data, they would look for aberrations that might have been caused by problems with a particular technology or protocol, which allowed them to iteratively refine and improve their process. As sequencing and other technologies became increasingly advanced throughout the duration of the project, TCGA members sought to stay up to date, again, for the purpose of producing quality data. The benchmarks for quality thus changed over time and relied, in part, on researchers' expertise.

The emphasis on quality in TCGA shaped its engagement with the traditional peer review process. To facilitate the publication process, TCGA established a publication agreement with the journal *Nature*. According to the initial agreement, TCGA was not supposed to submit any of the first ten marker papers for consideration to journals other than *Nature*, while editors at *Nature*, who were familiar with the TCGA project, were meant to guide each marker paper through the review process. Researchers within the TCGA network understood that the objective for each marker paper was a submission to *Nature* and that publication was "extremely likely" [#S].

TCGA's agreement with *Nature* involved an understanding that TCGA scientists would not be asked to perform additional experiments or data collection during the review process. Data production had been officially completed at that point, and TCGA researchers had not been funded to do additional experiments. The agreement also served to ease the challenges faced by reviewers in evaluating TCGA data, which was a new form of data produced on a large scale with little to compare to. Essentially, the process was meant to give reviewers a certain level of confidence in the validity of the data knowing that it had been produced and vetted by a large number of leading scientists. As one leader explained:

> "It's interesting when you're reviewing something that original. It makes it a bit more streamlined because, you know, you don't have a lot of… competing kind of data that's going to say, oh, maybe this isn't true. So, you know, I think… the reviews were not routine… they were stringent, but they were not… the kind of stringency you would see for an individual investigator, for example, or a group of 3 or 4 folks. When you've got, you know, 300 people on a paper, it becomes pretty hard not to say, well, you know, amongst these 300 people… if there's [something] very much wrong with this data, we would have found it"
>
> [#K].

Although the novelty of the TCGA approach was part of what initially made marker papers suitable for publication, once various components of the approach, such as sequencing technologies and protocols, became more common, marker papers needed to present more novel contributions. Nevertheless, only one out of the first ten marker papers was rejected for publication in *Nature* (Sheth et al., 2016).

While establishing what counted as "good" data was not always clear-cut, TCGA sought to define and meet high standards for quality. The centralization of sample processing and data management was driven by this goal. Moreover, the project aggregated a large number of scientists, who contributed to evaluating the quality of shared resources prior to and in lieu of the traditional assessment processes.

5. Discussion

Our comparative analysis of the governance mechanisms used to address the limitations of authorship and evaluation norms for the sharing of intermediate resources in CONP and TCGA reveals two distinct forms of governance: "distributed" in CONP and "layered" in TCGA. CONP's distributed governance is characterized by conceptions of authorship as "atomized" and of evaluation as "functional;" within TCGA's layered governance, authorship is instead seen as "tiered" and evaluation as "quality-based" (Fig. 2). In the following subsections, we discuss these two forms of governance, comparing their varying understandings of authorship and evaluation. We then consider the broader implications of our study beyond the cases of CONP and TCGA, providing policy recommendations that may enhance collaboration and openness in scientific research.

5.1. *Authorship in distributed vs layered governance*

By promoting decentralized access to intermediate resources, and by elevating such resources to the status of citable research objects, CONP's distributed governance is characterized by an atomized model of authorship. Over time, CONP established a socio-technical system wherein each individual involved in the creation and curation of data and code is acknowledged, as are those who use that data and code to develop new findings. This system allows data creators to determine which portions of their data to share and under what conditions, thereby further incentivizing sharing practices. The allocation and specification of credit to the creators of intermediate resources was also facilitated by the development of the CONP notebook. This novel manuscript format discloses the specific datasets and pipelines that are employed in any

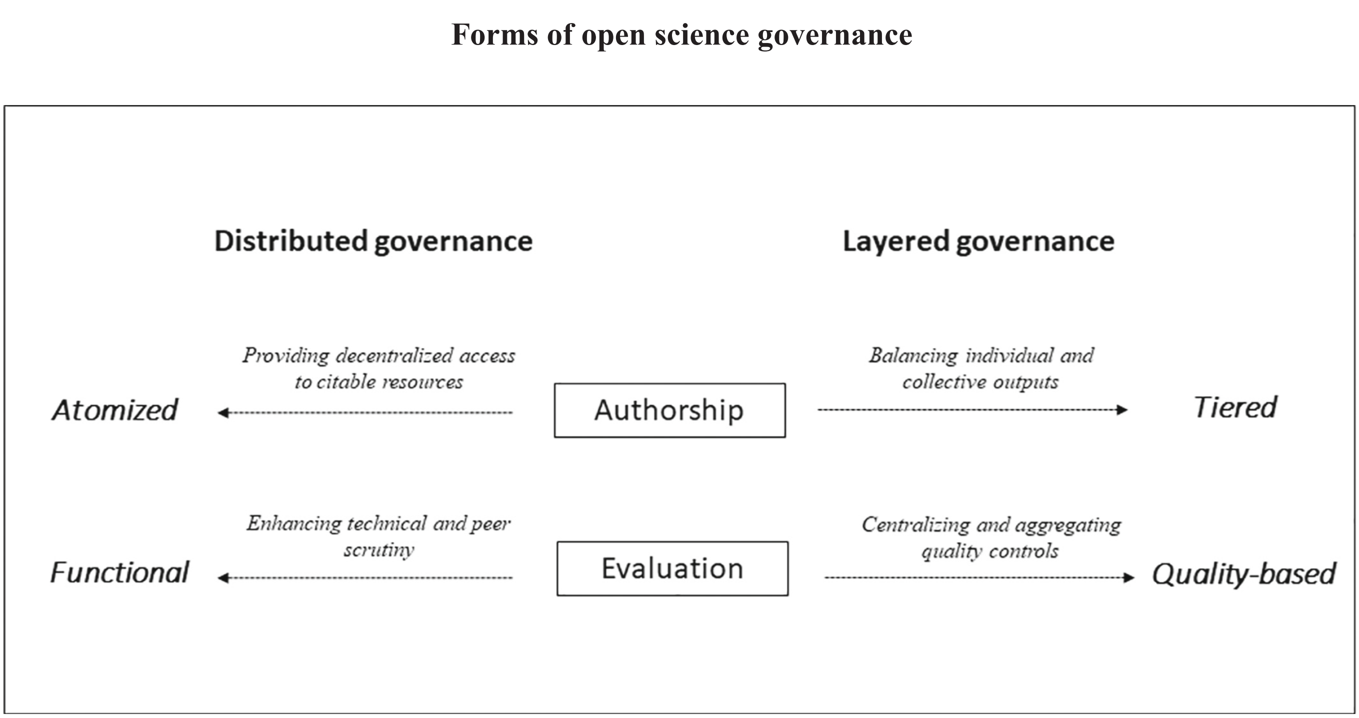

Fig. 2. Forms of open science governance.

given study, thereby clarifying each contributor's role.

CONP's atomized model of authorship helps to address the complexities of credit allocation in collaborative efforts. As prior research has shown, traditional norms of authorship tend not to recognize adequately the individuals who contribute to the creation of intermediate resources (Biagioli, 2003; Rennie et al., 1997), which may hinder sharing (Campbell et al., 2002; Derrick, 2015) or promote “strategic withholding” behaviors (Nelson, 2016). To address these challenges, the atomized model disaggregates the traditional notion of authorship by recognizing the distributed and diverse contributions made throughout the research process.

In contrast, TCGA addressed the limitations of traditional authorship norms by balancing collective recognition with the need to credit individuals. TCGA's layered governance is indeed characterized by a tiered model of authorship, which reflects a variegated conception of credit that includes collective, mixed, and individual forms of authorship.

When TCGA leadership decided that the sole author of its publications (i.e., “marker papers”) would be “The Cancer Genome Atlas Research Network,” it established a collective form of scientific authorship. Including all participants in TCGA's collective authorship helped acknowledge the wide range of efforts and forms of labor required to produce an extensive dataset. In some ways, TCGA's collective authorship mirrors the publication practices of other scientific disciplines, such as high-energy physics, where hundreds of authors are often listed on a single paper (Knorr-Cetina, 1999). Unlike publications with hundreds of authors, however, in TCGA, the collective itself was considered an author. This allowed TCGA to later develop an additional, mixed authorship model, where “The Cancer Genome Atlas Research Network” was listed alongside individual scientists who made significant contributions to a particular paper, which fostered a process for allocating credit that was simultaneously inclusive and specific. TCGA's tiered conception of authorship is also reflected in the pairing of marker papers authored by the collective and follow-up papers authored by individual scientists. This approach helped to avoid the “erasure of the individual as epistemic subject” (Knorr-Cetina, 1999, p. 166) often seen in disciplines like high-energy physics. Instead, TCGA struck a balance between the individual and the collective through its orchestration of marker and follow-up papers, which helped the consortium effectively distribute credit across its participants.

Atomized and tiered models of authorship have different implications. The atomized model challenges the conventional hierarchical structures of scientific collaboration by recognizing that each contributor, regardless of the stage and type of their contribution, plays a critical role in the production of knowledge. Thus, this model contributes to democratizing the research process, empowering scientists with fewer resources or less technical expertise. Moreover, it encourages researchers to openly build on each other's data and code, thereby leveraging the collective expertise of the broader field to accelerate research progress. This approach aligns with broader movements towards the decentralization of knowledge production (Beck et al., 2022; Leone et al., 2021), where the boundaries of expertise are fluid and collaboration across teams and disciplines is seen as the prime mover of scientific advancement. In this sense, atomized authorship can be understood as a response to the increasingly complex and interdisciplinary nature of contemporary scientific challenges, where the integration of diverse inputs is essential for meaningful progress.

Conversely, the tiered model of authorship represents a more stratified approach to credit allocation that reflects the persistence of traditional academic structures, even within large collaborative endeavors. This model acknowledges the necessity of collective effort in the production of large datasets and foundational research resources while simultaneously preserving the notion of individual authorship as a core currency in academic career progression (Dasgupta and David, 1994). Although building a comprehensive resource for cancer genomics was thought to be unattainable through distributed individual efforts alone, the goal of TCGA was not to replace the traditional, individual-level form of collaboration. Instead, its aim was to complement and support the work of individual researchers, functioning alongside and in service of their contributions. The tiered model can thus be seen as an attempt to reconcile the demands of collective science with the enduring institutional pressures of individual achievement and recognition.

5.2. Evaluation in distributed vs layered governance

Distributed and layered forms of governance not only differ in their authorship models but also in their approaches to scientific evaluation. In CONP, the concept of evaluation takes on a distinctly functional connotation, which entails primarily the technical review of CONP notebooks. This technical review process focuses on the validity, operability, and interactivity of the notebooks, and ensures that the underlying pipelines are concise, well-documented, and organized in a coherent directory hierarchy, with automated tests in place for verification. By implementing a specific review system for these technical aspects, CONP extends evaluation beyond the traditional scientific peer review process, ensuring that the resources employed in any given study are usable and interoperable.

Significantly, CONP's new technical review not only seeks to ensure that all steps in the coding process are thoroughly documented and accessible—an essential component of reproducible computational research (Sandve et al., 2013)—but also promotes peer scrutiny by guaranteeing the interactivity of the notebooks. Once a notebook is made available online following a successful technical review, other researchers can engage with, verify, and build upon the underlying data and code. This real-time access to resources facilitates an ongoing peer evaluation process, allowing readers to delve deeply into the study's research process, replicate analyses, and adjust parameters to test the robustness of the results. Such scrutiny promotes transparency and reproducibility, which are key features of credible research (Leonelli, 2023; Munafò et al., 2017). Moreover, it contributes to mitigating the challenges faced by traditional peer review systems, in which the complexity of reviewing data and code can significantly extend review cycles, especially when reviewers lack the programming and software engineering skills necessary for effective code assessment (Wurzel Gonçalves et al., 2023).

In contrast, TCGA placed a strong emphasis on quality as the cornerstone of its evaluation framework, recognizing that scalable and impactful cancer research requires not only large volumes of data but also data that is meticulously vetted for accuracy and consistency (Leonelli, 2018). Indeed, while quality concerns were integral to the development of CONP as well, TCGA established stringent rules and standards to ensure the reliability and rigor of its data from the outset, overseeing the collection of tissue samples and the production of genomic data to guarantee that they met high-quality benchmarks before any further research could proceed.

In addition, TCGA's quality-centric approach incorporated further layers of evaluation by involving some of the most respected scientists in the field. By aggregating the expertise of these leading researchers, TCGA enhanced the likelihood that the data and findings produced were of the highest standard. The involvement of top-tier scientists provided ongoing quality checks throughout the research process, ensuring that potential issues were identified and addressed as they arose. This form of quality control also had implications for the peer-review process, easing the challenges faced by reviewers in evaluating TCGA data, which was a new form of data produced on a large scale with little to compare to.

Both TCGA and CONP redefined the criteria and stages at which scientific evaluation occurs, contributing to the evolving standards of what constitutes “good research” (Gläser, 2007). CONP's functional evaluation shifts the focus to ensuring the usability and operability of shared resources, thus addressing the critical need, already highlighted by Dasgupta and David (1994), for developing universally applicable tools for future research. This approach to evaluation acknowledges the complexities and opportunities inherent in digital and computational science, where the value of research increasingly depends on the ability to reproduce and build upon digital resources. In contrast, TCGA's model, with its strong emphasis on quality control, prioritizes the integrity and reliability of data from the outset, reflecting a focus on the quality and integrity of the data as the prime driver of large scientific collaborations.

5.3. Implications for open science initiatives beyond CONP and TCGA

The limitations of the traditional norms of authorship and evaluation that were evident in both CONP and TCGA are not unique to the disciplines of neuroscience and cancer genomics, and the mechanisms developed to address these limitations may be applicable to other open science initiatives. In a survey of 1564 researchers across the natural sciences, human sciences, social sciences, humanities, engineering, and agriculture, for example, Fecher et al. (2015) found that the primary barrier to sharing (80 % of respondents) was "other researchers could publish before me." Similarly, in their survey of 173 innovation management researchers, Barczak et al. (2022) found that when researchers viewed a particular dataset as a competitive advantage over other researchers, they were less likely to share that resource. These findings highlight the limitations across disciplines of the traditional norms of authorship; in the context of these norms, intermediate resources are often viewed as assets to be protected. Barczak et al. (2022) also found evidence that researchers who express concerns about potential embarrassment or reputational damage due to flawed code or data are less likely to share, which demonstrates the limitations of traditional norms of evaluation.

Although differences remain in resource sharing practices across disciplines (particularly between those that involve human subjects and those that do not: see Tenopir et al., 2015), the persistence of common challenges suggests the potential for common solutions. In developing mechanisms to facilitate the sharing of intermediate resources, CONP and TCGA emphasized various types of exchanges that resonate with the generalized, direct, and reputational sharing systems identified by Shibayama and Lawson (2021) in their survey of scientists in biology, chemistry, engineering, economics, and business (Table 2). By advocating for notebooks as a standard manuscript format, CONP worked to cultivate a generalized exchange culture within the neuroscience field. This approach encourages researchers to share data and materials by default, thereby fostering a more open scientific environment. At the same time, CONP's atomized authorship model aims to mitigate the free-rider problem that is often associated with generalized sharing. Specifically, this model provides a reputational reward system, allowing researchers to obtain recognition for the resources they share. Moreover, the elevation of data and pipelines to citable research objects alleviates the risk of overwhelming scientists with the task of processing reputational information. By attaching DOIs and DATS model files to shared resources, CONP surfaces every contributor's role in their creation and curation, thus automating the recognition process and avoiding the challenges of an informal reputation system.

TCGA addressed the free-rider problem typically associated with generalized sharing by emphasizing direct exchanges. This is evident in the practice of including everyone involved in data sharing and processing as authors on marker papers. Inclusion as an author was often seen as an incentive for participation. Program directors, for example, used the promise of authorship to encourage biobankers to contribute samples. In other words, they exchanged authorship for samples. Although inclusion on a network-authored marker paper was part of a direct exchange for some (e.g., biobankers), for others, network authorship was more along the lines of reputational rewarding, with their contribution being acknowledged in the Author Information section. However, since assessing the extent of the contribution of every person listed in the Author Information section would likely overwhelm the reward system, the strategy of balancing individual and collective contributions helped mitigate the challenges of purely reputational

Table 2
How governance mechanisms in CONP and TCGA address common barriers to sharing.

Barriers to sharing intermediate resources	Governance mechanisms	Models of authorship and evaluation	Working features
Researchers are concerned about not receiving credit for and losing control of the resources they have created (Tenopir et al., 2015)	Providing decentralized access to citable resources (CONP)	Atomized model of authorship	Combines generalized exchange with reputational exchange (Shibayama and Lawson, 2021) while addressing their limitations: Generalized exchange promotes sharing as a default but raises the issue of free-riding. Reputational exchange helps with the issue of free-riding but raises the issue of overwhelming scientists with the task of processing reputational information. *Providing decentralized access to citable resources* addresses this issue by automating attribution while allowing researchers to maintain control over shared resources.
Researchers and resource creators require options for both individual and collective credit (Knorr-Cetina, 1999)	Balancing individual and collective outputs (TCGA)	Tiered model of authorship	Combines direct exchange with reputational exchange (Shibayama and Lawson, 2021) while addressing their limitations: Exchanges that are direct for some and reputational for others help mitigate the issue of free-riding but raise the issue of overwhelming scientists with the task of processing reputational information. *Balancing individual and collective outputs* helps address this issue by combining both inclusive and specific forms of credit allocation.
Reviewers are unable to scrutinize large amounts of shared data and code (Wurzel Gonçalves et al., 2023)	Enhancing technical and peer scrutiny (CONP)	Functional model of evaluation	Adds a technical review process to the traditional peer review system while facilitating new forms of interactive peer evaluation.

(continued on next page)

Table 2 (*continued*)

Barriers to sharing intermediate resources	Governance mechanisms	Models of authorship and evaluation	Working features
Shared resources may not be usable by other researchers (Dasgupta and David, 1994)			*Enhancing technical and peer scrutiny* ensures the usability and operability of intermediate resources, mitigating the challenges of scrutinizing large volumes of resources.
Creators of intermediate resources are concerned about sharing inadequate resources (Tenopir et al., 2020; Fecher et al., 2015) Low-quality resources may lead to faulty results (Leonelli, 2018)	Centralizing and aggregating quality controls (TCGA)	Quality-based model of evaluation	Emphasizes and highlights quality control mechanisms throughout the research process. *Centralizing and aggregating quality controls* ensures that only rigorously vetted, high-quality data is shared.

rewarding systems. TCGA's tiered authorship model thus includes multiple forms of reward, acknowledging all contributors equally in network-authored marker papers, yet providing them with the possibility to earn additional credit through mixed-author or follow-up papers.

Overall, despite some variance, the scientists surveyed by Shibayama and Lawson (2021) reported drawing on sharing systems that resonate with the governance mechanisms we found in CONP and TCGA. This suggests that the mechanisms implemented in CONP and TCGA, and the authorship and evaluation approaches they reflect, may find application across disciplines, although they may vary depending on context. CONP's atomized authorship, for example, may encourage sharing in disciplines in which losing control of data is a primary concern. In their 2015 study, Tenopir and colleagues found that there were no significant pairwise differences across a wide variety of disciplines for the question "I would be more likely to make my data available if I could place conditions on access." It is thus possible that providing decentralized access to citable resources, which is a key feature of CONP's atomized authorship, may help alleviate barriers to sharing in these cases. It is also possible that TCGA's quality-based evaluation mechanisms may be helpful in cases where researchers are concerned about sharing inadequate or faulty resources. According to Tenopir et al. (2020), "When asked what would increase their confidence in using data collected by others, the vast majority (82.1%) of respondents thought it most important to see written details about collection and quality assurance methods accompanying the data." This suggests that it may be important to emphasize and highlight quality control mechanisms in open science initiatives, especially where scientists are concerned about being "criticized or falsified" (Fecher et al., 2015).

5.4. Implications for management and policy

Our in-depth examination of different forms of open science governance and their specific understandings of authorship and evaluation provides key insights for managing scientific collaboration and resource sharing in an era where the scale and complexity of ongoing challenges require innovative approaches. Our findings suggest that policy recommendations to increase openness in science should transcend the level of the individual scientist, accounting for broader organizational dimensions. That is, besides looking at the behavior of individual scientists, policy recommendations should focus on the governance of scientific collaboration, paying attention to differences in goals, scale, and context.

Policy designers should also keep in mind that different forms of governance offer unique advantages and challenges in advancing scientific knowledge. CONP's distributed governance model, for example, embodies a more open approach, harnessing the collective expertise spread across the increasingly digital neuroscience field and emphasizing the value of sharing throughout all research stages and in relation to all intermediate resources. In contrast, TCGA's layered governance model highlights the effectiveness of centralized collaboration in developing datasets suited to addressing today's biomedical challenges. Accordingly, CONP has evaluated its own approach in a way that aligns more closely with a broader shift towards open neuroscience (Harding et al., 2023), while TCGA's approach has been articulated as a "how-to" for similar collaborative projects (Sheth et al., 2016).

Both forms of governance also present challenges. CONP's distributed governance requires substantial coordination, as its decentralized nature may lead to reduced oversight and, consequently, inconsistencies in the quality of shared resources. In contrast, TCGA's layered governance may unintentionally create a divide between consortium members and outsiders, as consortium members typically use data for publications before it is made available to others. This can hinder wider participation and collaboration, while CONP's model fosters a more equitable distribution of resources across the entire field.

Overall, both CONP's and TCGA's approaches to governance highlight the critical role of the tools and practices scientists adopt to coordinate their day-to-day activities. Examples in these cases include the association of intermediate resources with DOIs and DATs model files, the creation of DataLad datasets, and the centralization of quality controls. In other open science initiatives, the tools and practices of scientific collaboration will likely remain central to the promotion of openness.

Moreover, our findings shed light on the significance of science communication media in fostering open science collaboration. CONP notebooks underscore a shift from static documents to interactive science communication tools that enable real-time and deeper engagement with the research process. Likewise, the move in TCGA from traditional single-authored papers to network-authored, mixed, and follow-up papers demonstrates how the collective production and dissemination of high-quality, widely accessible research outputs can still accommodate individual recognition. This hybrid approach ensures that large collaborative efforts can effectively complement, rather than eclipse, individual contributions. These changes—from traditional manuscripts to interactive notebooks and hybrid publication formats—are not merely technological advancements but reflect a fundamental rethinking of how science is conducted and credited, underscoring the need for policymakers to explore more collaborative and open formats for scientific communication.

Finally, our findings suggest that policy recommendations should incentivize additional evaluation practices that take place before the submission of scientific work for publication. Both CONP and TCGA feature the emergence of non-conventional forms of pre-submission peer review. In CONP, this occurs through engagement with notebooks available online, allowing scientists to evaluate the validity of each other's resources. In TCGA, this was achieved by enforcing stringent quality controls on the data produced and involving leading scientists in the consortium, which not only increased confidence in the validity of the data but also allowed for ongoing updates to definitions and approaches to quality control. Overall, these cases demonstrate that the governance of shared resources requires rethinking how and when evaluation takes place, going beyond the traditional peer-review process.

5.5. Limitations, future research and conclusions

While our study provides valuable insights into the governance mechanisms of open science consortia, several limitations must be acknowledged. One key limitation is that our analysis is based on qualitative data from two specific fields, neuroscience and cancer genomics. These fields have particular governance challenges due to the nature of the resources they employ, such as high volumes of complex genomic data, brain imaging data, and computer code. Although we explained how the governance mechanisms employed in CONP and TCGA may well find broader relevance, their specific applicability has yet to be empirically tested. Future research should focus on conducting surveys in fields including and beyond neuroscience and cancer genomics as a way to assess the broader appeal of these governance mechanisms. Different fields employ different types of intermediate resources, relying on data and research materials that might differ in format, scale, and complexity. By expanding the scope of this research, we could better understand how governance models might be adapted or transformed to suit different scientific disciplines, ensuring that open science initiatives can thrive in various research environments.

Other key areas for further investigation include the impact of the governance mechanisms employed by open science consortia on fostering interdisciplinary collaboration. A crucial objective of this line of research would be to explore how the sharing of intermediate resources influences the mobilization of scientific efforts across disciplinary boundaries. Additionally, it would be beneficial to examine the long-term sustainability and adaptability of open science consortia, particularly in response to emerging scientific challenges and technological advancements. Understanding the implications of resource sharing for early-career researchers and underrepresented groups in science could also yield important insights into creating more inclusive and supportive research environments.

Overall, the insights we obtained from our examination of CONP and TCGA underscore the significance of adaptable and flexible strategies tailored to the unique needs and objectives of each scientific collaboration. With the trend towards open science continuing to shape expectations across disciplines, embracing these lessons is key to building more open, collaborative, and resilient scientific collaborations.

CRediT authorship contribution statement

Ellen Abrams: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Paolo V. Leone:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alberto Cambrosio:** Writing – review & editing, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Samer Faraj:** Supervision, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

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Data availability

The data that has been used is confidential.

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