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Digging deeper into data citations: recognizing and rewarding data work

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Abstract

Citations and metrics are central features in evaluating academic careers. As researchers increasingly engage in open science, data citations have emerged as potential mechanisms for evaluating and rewarding data sharing and reuse in academic assessments. Despite this, we still lack critical information about the data citation practices and motivations of researchers themselves, information which is needed to contextualize the use of such metrics. Here, we present the results of a semi-structured interview study with researchers across disciplines exploring their data referencing practices and motivations, as well as how they would like their 'data work' (including data sharing) to be rewarded and evaluated. As a whole, our findings confirm a lack of standard practices for referencing data and provide new insights into the social and scientific reasons motivating data referencing. While our results show an overall skepticism toward the use of citation-based metrics in evaluations, they also suggest that researchers are caught between traditional and emergent modes of assessment for recognizing data work. Furthermore, we find that rather than valuing data citations as rewards, our participants value creating data objects which are useful for their (often small) research communities. Ultimately, we conclude that data work is a cornerstone of research practice which needs to be evaluated and considered, but one which also requires context-aware approaches.

Keywords: data reuse, open science, research evaluation, research data, data citation

1. Introduction

Academic publications and their associated metrics have been a mainstay in evaluating, recognizing and rewarding researchers' academic careers (Wouters 1999a). However, as many areas of the academy move toward more open ways of practicing research (Piwowar et al., 2018), there are calls for other outputs, such as research data, to be taken into account in systems of academic evaluation (Cabello Valdes et al., 2017; Alperin et al., 2020). The best way to do so remains an open question (Lowenberg et al., 2019), although data citations are often seen as a key mechanism for incentivizing, measuring and making visible data sharing and reuse (Parsons et al., 2019; Buneman et al., 2020).

The focus on data citations stands alongside a growing movement to de-emphasize the use of citation metrics in research assessments (COaRA 2022), or to do so in responsible ways which take into account the context of research (Wilsdon 2016). This movement toward responsible research assessment (RRA) is rooted in extensive work within science studies examining the literature citation practices of researchers and their motivations to reference things in particular ways (Tahamtan and Bornmann 2019). Foundational work in this area has led to viewing literature citation as being shaped by scientific norms (Merton 1973, 1988), socially constructed (Moed and Garfield 2004) and undertaken for a variety of reasons—not all of which are altruistic (Garfield 1965). This perspective has been central to developing nuanced citation metrics and entirely new modes of assessment such as narrative CVs (Bordignon et al., 2023), which attempt to make visible the context surrounding both the production and use of research.

We argue that data citation practices and motivations have not yet received the same level of scrutiny as those for literature citation. We need to know more not only about researchers' practices of referencing data, but also more about the motivations and contexts surrounding those practices. This is needed to understand the *meaning* of data citations and how they can best be used in responsible evaluative efforts.

Here, we contribute to this gap by presenting the results of a semi-structured interview study[1] with researchers across disciplines, to explore critical questions which are key to understanding the potential uses of data citations in academic evaluations. How and why do researchers cite data in their work? How are these practices and motivations related to those of referencing literature? Would researchers like their own data work to be rewarded and assessed, and if so, how?

We begin by examining the use of literature citation metrics in academic assessments and juxtapose that with the current state of data citations in research evaluations. We then analyze the data citation practices and motivations of our participants, how these motivations relate to those for (literature) citation more broadly, and participants' views about how 'data work' is (and could be) evaluated and rewarded. We conclude by discussing our findings in relation to the development of more context-aware data metrics which can be used to inform responsible research assessments.

2. Background: from literature citations to data citations

Much of research evaluation is based on practices centering around the production and use of literature, often as evidenced by citations (McKiernan et al., 2019). A rich body of work examining literature citation motivations, practices, and problems with citation indicators (e.g. Aksnes et al., 2019) has led to more nuanced ways of understanding and implementing such metrics. The same is needed to understand data referencing practices. As we work to gain insight into the practices and motivations for referencing data—which is a precursor to the development of responsible modes of assessment—we also need to understand how these data referencing practices are situated within existing ways of referencing other objects and within existing practices of research assessment. We therefore choose to situate our research within the existing work on literature citation, associated metrics, and their use in research evaluation.

2.1 Literature citation: practices and uses in research evaluations

The use of literature references in scholarly communication has been extensively studied. As a whole, this body of work reveals the complexity of the functions and scientific/social motivations underlying the act of citing (Wouters 1999b).

2.1.1 Literature citation practices and motivations

Two main theories of citation behavior have emerged within broader social theories of science: the normative theory and the social constructivist view (Bornmann and Daniel 2008). A key figure in normative theory is the sociologist of science Robert K. Merton, who proposed the existence of an ethos of science—an ensemble of values and norms considered binding for scientists (Merton 1973). From these norms arises "a composite cognitive and moral framework [that] calls for the systematic use of references and citations" (Merton 1988: 622). Merton further explained that by citing the work of others, researchers give credit to their peers:

> The reference serves both instrumental and symbolic functions in the transmission and enlargement of knowledge. Instrumentally, it tells us of work we may not have known before, some of which may hold further interest for us; symbolically, it registers in the enduring archives the intellectual property of the acknowledged source by providing a pellet of peer recognition of the knowledge claim, accepted or expressly rejected, that was made in that source. (Merton 1988: 622)

In contrast, the social constructivist view posits that researchers select specific documents to cite based on their own interests and objectives, with the aim of gaining a dominant position within the scientific field (Moed and Garfield 2004). Authors preparing papers tend to cite the 'important and correct' papers (Gilbert 1977: 116). This perspective aligns with sociologist Pierre Bourdieu's argument that new scientific knowledge is validated by citations from dominant scientists in the field, which are accorded greater weight than those from less prominent researchers (Bourdieu 1975; Bourdieu 2001).

These perspectives can be synthesized as follows: citations intersect with a rhetorical system for persuading others of knowledge claims and a reward system for allocating recognition and reputation (Cozzens 1989). This reward system is far from neutral, but rather has inequalities embedded within it. Such dynamics, that is the Matthew effect, where established scientists accumulate recognition to a greater degree than less prominent researchers (Merton 1973) or the Matilda effect, which describes how women scientists have been denied scientific credit (Rossiter 1993) have been well documented.

The motivations behind citations have also been the subject of extensive study (Moravcsik and Murugesan 1975; Gilbert 1977; Brooks 1986; Vinkler 1987; Case and Higgins 2000; Bornmann and Daniel 2008; Erikson and Erlandson 2014; Fazel and Shi 2015). One of the foundational works on this topic is that of Garfield (1965), who provided a comprehensive list of 15 major reasons for why researchers cite literature (Box 1).In a recent meta-synthesis of 38 studies on motivations for citing literature, Lyu et al. (2021) identified two main categories: 'scientific motivations' and 'tactical motivations'. Scientific motivations refer to citing with the aim of recognizing the intellectual influence of fellow researchers. This type of motivation includes, but is not limited to, citations to summarize the general background of the research topic; to compare current and previous contributions; to present the method or data source used; or to identify original publications in which the ideas or methods first appeared. Tactical motivations for citing are socially or strategically driven. Such motivations include the desire to conform to perceived academic norms or expectations, ie citing sources suggested by reviewerss or journal editors, as well as

Box 1 Motivations for citation proposed by Garfield (1965).

Motivations for literature citation

1) Paying homage to pioneers;
2) Giving credit for related work;
3) Identifying methodology, equipment, etc.;
4) Providing background reading;
5) Correcting one's own work;
6) Correcting the work of others;
7) Criticizing previous work;
8) Substantiating claims;
9) Alerting to forthcoming work;
10) Providing leads to poorly disseminated, poorly indexed, or uncited work;
11) Authenticating data and classes of fact—physical constants, etc.;
12) Identifying original publications in which an idea or concept was discussed
13) Identifying original publication or other work describing an eponymic concept or tem;
14) Disclaiming work or ideas of others (negative claims);
15) Disputing priority claims of others (negative homage).

using citations to advertise one's own competence and align work with influential researchers.

2.1.2 Literature citations in research evaluation

Research evaluation has traditionally relied heavily on citation metrics (Desrochers et al., 2018; Schimanski and Alperin 2018; Alperin et al., 2019; McKiernan et al., 2019; Jin and Jiang 2024), whether to assess individual researchers, research groups, institutions, or even to compare the scientific performance of countries (Moed 2005). However, a consensus on what the number of citations actually represents has yet to be reached (Lyu et al., 2021). Citation counts have been argued to indicate significance or quality (Cole and Cole 1973); importance or utility (Garfield 1979), or, more recently, 'impact'—an often vaguely defined concept (Martin and Irvine 1983; Aksnes et al., 2019).

This lack of consensus about what citation counts measure is only one of many limitations of citation indicators (Aksnes 2005). Indicators also have shortcomings in how they are conceptualized and applied, which affects their validity in measuring scholarly impact (Haustein and Larivière 2015; Larivière and Sugimoto 2019). Indicators have been shown to shape the behavior of researchers. Due to the prominent use of bibliometric indicators in assessments, researchers over-prioritize the number of publications, the impact of the journal, and research topics with higher citation potential, not hesitating to modify their research agenda to meet the expectations of evaluation agencies (Moher et al., 2016; Müller and de Rijcke 2017; Wang et al., 2017; Cañibano et al., 2018; Schimanski and Alperin 2018; McKiernan et al., 2019), to the potential detriment of research content (Robinson-Garcia et al., 2023). Other adverse behaviors, such as salami-publishing, self-plagiarism and honorary authorship (Martin 2013; Pontille 2016), also stem from this type of 'goal displacement' (Merton 1940).

As a result, there are increasing calls for reforms in research evaluation, such as changing how metrics are used (Rushforth and Hammarfelt 2023) and diversifying the scholarly activities and outputs included in evaluations (COaRA 2022; Robinson-Garcia et al., 2023). Recognizing a researcher's efforts to adopt open science practices such as sharing and reusing data is one example of such reform (Cabello Valdes et al., 2017; Dorta-González et al., 2021). How exactly to measure and integrate open science practices in research evaluations remains a subject of debate, in part because of a lack of understanding about data citation practices (Lowenberg 2022).

2.2 Data citation: practices and use in evaluations

Data citation is assumed to be an indication that data have been made available or 'shared' (either online or through other methods) and that data have been used in some way (Silvello 2018). Both data sharing and data reuse are highly contextual activities. These practices vary significantly across disciplinary communities and epistemic traditions (Borgman 2012; Gregory et al., 2020; Khan et al., 2023) as well as across career stages (Ninkov et al., 2024). Infrastructures, practices, and norms can differ even within the same community, depending on the specific project (Cragin et al., 2010; Wynholds et al., 2011). It is also worth noting that not all data can be made openly available. Some data will never be shared or will be made available under only certain access conditions, if at all (Rainey et al., 2023). At other times, sharing metadata rather than the data themselves is the most sensible way to practice open science (Verburg et al., 2023).

Similarly, it is unlikely that all available data will be reused (Federer 2019). Another key factor affecting both data sharing and reuse is the general lack of formal incentives for researchers to adopt open science practices, as academic reward systems are still very much centered on closed practices and publishing (Ali-Khan et al., 2017).

2.2.1 Data citation practices and motivations

Perhaps reflecting these complexities, the act of citing data is not yet well established within the scientific community (Peters et al., 2016; Ninkov et al., 2021), although it is more established in certain disciplines, such as the natural and life sciences (Peters et al., 2016) and the biomedical and physical sciences (Robinson-García et al., 2016; Park and Wolfram 2017). There is also a great diversity in the methods used for referencing data, which vary across disciplinary contexts (Belter 2014; Mayo et al., 2016; Park et al., 2018; Zhao et al., 2018). In addition to appearing in reference lists, data are mentioned in the body of publications, footnotes, supplementary material, figures, or acknowledgments (Mooney and Newton 2012; Park et al., 2018; Irrera et al., 2023).

Another approach for referencing data is to cite different 'data objects', such as databases, journal articles, and data papers (Sands et al., 2012; Jiao and Darch 2020). Gregory et al. (2023a) developed a taxonomy for discussing these various ways of referencing data: 'data citations' are located in reference lists; 'data mentions' refer to data objects throughout publications; and 'indirect data citations' pertain to referencing related publications rather than data themselves. Here, we add to this taxonomy and adopt the broader term 'data referencing' to indicate all ways of referring to data.

Although the diversity of modes for referencing data has begun to be documented, and in contrast to research on literature citation behaviors, we still do not know *why* researchers reference data in particular ways. Only a few authors have investigated the motivations underlying referencing data at all. Silvello (2018) draws on discourses advocating for data citation to propose six motivations for citing data: data attribution (acknowledging the contributions of those involved in creating and curating data), data connection (linking data with scientific papers), data discovery, data sharing (encouraging others to share data), data impact (enabling the creation of metrics), and reproducibility.

Lafia et al. (2023) conducted an empirical study based on the examination of texts to propose a typology of data references, highlighting the critical, descriptive, illustrative, interactive, and legitimizing functions that data references serve in scholarly publications in the social sciences. The critical function is employed by authors to facilitate comparison of their work and to acknowledge data limitations. Descriptive references are used to detail the composition and source of data. Illustrative references enable authors to provide context and to speculate on future applications of the data. Interactive references describe the processes of data analysis and manipulation. Lastly, legitimizing references are used by authors to justify data choices and to promote transparency in their methods.

A recent survey by Gregory and colleagues (2023a), explicitly asked a representative sample of authors by discipline about their motivations for citing data by providing participants with a pre-defined list of options. They found that researchers tend to cite data primarily out of a commitment to good research practices rather than because of external recommendations, such as those from journal publishers. Additionally, they noted that discipline-specific practices and academic norms, often rooted in long-standing traditions (e.g. the use of footnotes in the Humanities), significantly influence how data are cited.

2.2.2 Data citations in research evaluation

Data citations and metrics are an oft-discussed possibility for incentivizing, evaluating, and rewarding data sharing. Numerous surveys in recent years have reported that researchers view data citations as a preferred mechanism for recognizing data sharing efforts (Tenopir et al., 2020; Digital Science et al., 2022; Khan et al., 2023). Consistent with these results, 82% of the 2,492 respondents in the survey conducted by Gregory and colleagues (2023a) indicated that knowing the number of citations their data have received is important or extremely important. In addition, 70% of respondents in the same survey expressed interest in having detailed 'data narratives' that provide context for how their data has been reused (Ninkov et al., 2023).

Other possibilities have also been proposed as potential rewards for data sharing, although such measures have yet to be widely implemented or proven effective. These measures include the awarding of data badges by publishers and the use of altmetrics or usage metrics, such as views and downloads, as potential incentives for sharing data (Kidwell et al., 2016; Lowenberg et al., 2019; Konkiel 2020; Khan et al., 2023). These studies and approaches assume to some degree that data are shared *openly* and without restriction. Arguably, these types of indicators—citations and downloads in particular—will be more limited or irrelevant for data which are shared in more restricted ways, or in cases where only metadata can be made available.

Despite this seeming interest, and perhaps because of these complexities around openness, the development of metrics for shared data to support research evaluation is still in its early stages. The adoption of frameworks and workflows to inform the development of standardized metrics (e.g. the Counter Code of Practice for Research Data[2]) have been patchy by both data repositories and publishers (Puebla and Lowenberg 2024). A similar situation exists for guidelines for including open science activities and outputs in research assessment (Cabello Valdes et al., 2017) and expanding hiring, promotion and tenure policies. There appear to be a core set of institutions who are including open science and data metrics in such decisions, but for the most part, uptake remains low (Alperin et al., 2020; Puebla et al., 2024).

The limitations associated with the use of literature citations in research evaluation (Section 2.1.2), also raise questions about the implementation of metrics for data. The importance of contextualizing data citations by discipline to account for citing behaviors in fields (Ninkov et al., 2023), the need to understand the links between citations and data use (Lowenberg 2022), and possible manipulation of data metrics (Devriendt et al., 2023) all point to the need for further research in this space.

We further argue that we need to understand more about the data citation practices of researchers, including their motivations for referencing data as a way of contextualizing the meaning of data citations and metrics and their potential use in evaluative efforts. While surveys and document analysis can be helpful techniques in understanding these questions they also have their limitations. Surveys in this space (e.g. Gregory et al., 2023a) have relied on statistical analysis of pre-defined options, rather than allowing for more bottom-up responses and inductive analytical methods. Document analyses (e.g. Lafia et al., 2023) have relied on textual representations of citation intent, rather than engaging directly with researchers. Through conducting semi-structured interviews, grounded in examples of researchers' own referencing practices, we were able to have extensive conversations with researchers themselves. This allowed us to gain more insight into their referencing practices and attitudes about evaluating data work than what has been possible with more quantitative methods.

3. Methodology

The development of the interview protocol, recruitment and data analysis are described below.

3.1 Interviews

Our study is based on semi-structured interviews with 20 researchers across disciplines and includes those who self-identified as reusing or not reusing data (Table 1). We actively recruited participants who both reused and did not reuse data, as we hypothesized that they would have different perspectives about implementing data sharing or reuse metrics in academic evaluations. In actuality, many of those who self-identified as not reusing data prior to the interview were found to have reused data at least once and were therefore able to discuss their data referencing behaviors during the interview. Interviews were conducted by two authors (K.G. and E.R.) between September 2022 and March 2023 via Zoom and lasted approximately 1 hour.

Interview protocols were developed using an iterative process focusing first on researchers who reuse data and then making slight modifications for participants who do not reuse data (Gregory et al., 2023b). After the first two pilot interviews, slight changes to the question wording and ordering were made. As the meaning of the protocol and responses remained the same, all pilot interviews are included in our results. Building on the structure of the survey by Gregory et al. (2023a), questions were structured into three parts. First, we focused on participants' data reuse and referencing practices. In advance of the interview, participants were asked to bring a recent publication or manuscript to support concrete discussions about their own data work and citation practices. Using their example articles, we asked participants to show us how they referenced data, explain why they did so, and to describe their data work more broadly. In the second section, we asked questions about data sharing practices and participants' preferences for how they would like others to reference their own data. The final section of the interview protocol focused on research evaluation. Here, we asked questions about how researchers are currently evaluated and how (and if) data work should be considered in assessments.

The interview began with defining basic terms discussed throughout the interview to establish common terminology. Following Borgman (2015), we defined data as any entity used as evidence of phenomena for the purposes of research or scholarship. We also introduced the term 'data work' to broadly refer to a host of data practices, including collecting, managing, documenting, cleaning, and sharing data. Although we operated

Table 1 Participant demographics.

Participant	Discipline	Reuses data[a]	Career stage (years of working in academia)	Primary methods used in research
P01	Natural sciences	Yes	31+	Mostly quantitative
P02	Humanities	Yes	6–15	Mixed methods
P03	Social sciences	No	6–15	Mostly quantitative
P04	Medical and health	Yes	6–15	Mixed methods
P05	Natural sciences	No	0–5	Mixed methods
P06	Natural sciences	No	6–15	Mostly quantitative
P07	Humanities	Yes	0–5	Mostly qualitative
P08	Social sciences	Yes	0–5	Mostly quantitative
P09	Humanities	Yes	0–5	Mixed methods
P10	Natural sciences	Yes	0–5	Mostly quantitative
P11	Natural sciences	No	0–5	Mostly quantitative
P12	Medical and health	No	31+	Mostly quantitative
P13	Humanities	No	31+	Mixed methods
P14	Humanities	No	6–15	Mixed methods
P15	Natural sciences	Yes	16–30	Mostly quantitative
P16	Medical and health	Yes	6–15	Mostly qualitative
P17	Humanities	Yes	31+	Mostly qualitative
P18	Social sciences	No	16–30	Mostly qualitative
P19	Humanities	Yes	16–30	Mostly qualitative
P20	Social sciences	No	16–30	Mostly qualitative

[a] Participants classified themselves as reusing or not reusing data prior to the interview.

with this broad definition, the majority of the interviews focused on data sharing and management. We were careful to discuss what we meant by 'data sharing'. At the beginning of the interview, we told participants that while there are different interpretations of the term, data sharing "broadly means sharing data that you have created or collected. In our research, data sharing is typically thought to be done via an infrastructure, database, or data repository, but we also know that data sharing happens more informally, person-to-person." We did not specify whether data needed to be shared openly or not.

3.2 Participant recruitment and description

After obtaining ethics from the University of Ottawa Research Ethics Board (Ethics file number S-09-22-8451), we recruited a total of 20 researchers who participated in our interview study. Seven participants were recruited via convenience sampling, and 13 participants were recruited from respondents to an earlier survey (Gregory et al., 2023a) who indicated that they would be willing to participate in future research. We aimed to speak with participants across a variety of research domains as well as across career stages who either reuse data or do not (Table 1). A secondary inclusion criterion was to have a diversity of research methodologies present in the interview sample. Purposive sampling was used to select a diverse group of participants with seven participants from the Humanities, six with a Natural Science background, four from the Social Sciences and three participants from the Medical and Health Sciences.

3.3 Data and analysis

Interviews were recorded and transcribed using otter.ai, followed by manual correction and anonymization. We developed a codebook using a combination of deductive and inductive coding and analyzed coded transcripts using reflexive thematic analysis (Braun and Clarke 2006, 2019). Deductive codes closely mirrored the structure of the protocol. This initial codebook draft was then revised, enriched and expanded by inductive codes from reading a subset of transcripts. Some of the authors individually read a subset of transcripts to develop an initial set of inductive codes, which were collaboratively discussed and defined. The transcripts were read and re-read by two authors (K.G. and S.H.) to finalize the codebook. The same two authors then applied relevant codes to all transcripts for the thematic analysis. In order to ensure consistency between the two coders, six transcripts were selected to be coded by both authors independently at the beginning of the coding process. Results were then compared and any discrepancies discussed and resolved before each coded half of the remaining transcripts. Results and coding notes were compared after the coding process was completed.

4. Findings

Here, we present findings about participants' data citation practices (Section 4.1) in order to gain more insight into the meaning of data references and citations, as well as their perceptions about evaluating, recognizing and rewarding data work (Section 4.2).

4.1 Data citation practices

This section presents researchers' data citation/referencing practices and motivations, some of which are shaped by external factors, such as journals' and publishers' guidelines or policies.

4.1.1 How do researchers cite or mention data? Why do they do so?

Researchers reference data using multiple strategies. They do not always use a citation in a reference list, but rather mention data throughout publications, for example in various sections of manuscripts, in footnotes, or in appendixes, as also observed in other studies (Parket al., 2018; Zhao et al., 2018, Mayo; Gregory et al., 2023a). We also find that participants reference data for a variety of reasons. Descriptions of *why* participants reference data were often entangled with descriptions of their broader citation strategies. We therefore summarize their reported *motivations* for referencing data in Table 2 and their *strategies* for referencing data (Box 2), drawn from results reported throughout the findings. We

Table 2 Motivations mentioned by participants for referencing data compared to existing typologies for motivations for citing literature and proposed functions of data citations.

Participants' motivations for referencing data	Motivations for citing literature	Proposed functions for citing data
Show that data had been used in a publication	Scientific (Lyu et al., 2021)	Critical function (Lafia et al., 2023)
Because it is best practice and needed for ethical research	Tactical (Merton 1973; Lyu et al., 2021)	–
As a thank you to data creators or data sources	Tactical (Lyu et al., 2021)	–
Crediting work of individual data creators	Scientific (Garfield 1965; Lyu et al., 2021) Tactical (Lyu et al., 2021)	Data attribution (Silvello 2018)
Demonstrate trust or reliability in data source	Scientific (Garfield 1965; Lyu et al., 2021) Tactical (Lyu et al., 2021)	Legitimizing function (Lafia et al., 2023)
Describe data handling, data curation, data sources, data limitations (often in methods)	Scientific (Garfield 1965; Lyu et al., 2021)	Critical function (Lafia et al., 2023) Descriptive function (Lafia et al., 2023) Interactive function (Lafia et al., 2023)
Make it possible to find and trace data	Scientific (Garfield 1965; Lyu et al., 2021)	Critical function (Lafia et al., 2023) Connection (Silvello 2018) Data discovery (Silvello 2018)
Provide context to the study or research project	Scientific (Garfield 1965; Lyu et al., 2021)	Illustrative function (Lafia et al., 2023) Connection (Silvello 2018)
Build on own past work (self-citation)	Scientific (Lyu et al., 2021) Tactical (Lyu et al., 2021)	Critical function (Lafia et al., 2023) Legitimizing function (Lafia et al., 2023)
Draw attention to their own data, encourage use of data which they have shared (self-citation)	Tactical (Lyu et al., 2021)	–
Instructed to by publisher or recommendation from data repository	Tactical (Lyu et al., 2021)	–
Could have legal repercussions if they do not correctly attribute the data	Tactical (Lyu et al., 2021)	–

Box 2 Participants' referencing strategies describing the broad method used to reference data and where in a publication those references occur.

Referencing strategies
Appendix lists
Acknowledgements
Methods (very common)
Abstract
Multiple places throughout a single article
In syllabi
In reference lists
In footnotes
Via in-text mentions
Providing links to websites in text or footnotes
Listed as obtaining data via personal communications

further relate and compare our findings to documented classifications for motivations for citing literature and proposed functions of data citations (Table 2). Doing so helps to identify similarities between literature citation motivations and to verify proposed motivations for referencing data.

Nearly all participants expressed a need to formally acknowledge data if they were used in any way within a paper; many seemed aghast to think that people would not reference data if they had been used, as that would be unethical behavior. Some reported referencing data in the acknowledgment section of a paper in order to thank an individual, institution, or data source for providing access to (restricted) data. This was also done to show that data originated from a government body in order to back up the trustworthiness or reliability of data.

> We thank the Ministry of Gender, Children and Social Protection, [reading directly from Acknowledgement section] "for granting us access to the data. In addition, we are grateful to all children who participated in the study." So mostly, when we use those [data], we acknowledge them in the acknowledgement section, to let them know we had the data from a government institution. (P14)

Numerous participants reference data in the methods section of papers in order to provide detailed descriptions of the context about the study and data processing, including details about data handling or data curation. Some participants referred to data in numerous places of a publication for different reasons, for example explaining data limitations in Section 5.

> I mention it here in the abstract, and then [.] right here in the methods. So this is where I talked about it. So I cite it one, two, three [.] times there [.]. I talk about it, like, how it was curated, and everything like that [.] and yeah, it's in the reference list. (P16)
>
> *[later in interview]*
>
> A couple times I've cited it in the discussion just commenting on [.] issues with it. Like if there were problems or limitations that I saw, then I would cite it there. (P16)

Another participant described the importance of regularly speaking about data throughout an article. Rather than referencing data using a standardized citation strategy or style, for example using footnotes, the norm in their research community is to regularly acknowledge and discuss data, in part because of the nature of the data which are reused.

My field is pretty vague in how it references data. And I think that stems from the type of data we use, like popularity charts. When you say "so and so peaked at number one on the Billboard chart this week," it's like, what else do you need? (P2)

Participants reported trying to make the provenance of data visible to others and to act according to best practice, although 'best practices' vary by discipline, methodologies, and community norms. While a natural scientist using mostly quantitative methods reported including a data citation with a DOI in a reference list (P6), a historian documented the source of their data (a handwritten translated text) as a 'personal communication' using a footnote, because:

At least in my field of study, it's not common to reference personal communications in the reference list, because only published works are welcome there. (P14)

Sometimes these norms and ways of referencing do not translate well to individuals outside of a particular community, making it difficult for interdisciplinary researchers to understand and trace data.

They [computer scientists] use a lot of data. As a matter of fact, in any given proceedings or journal article, they might be using a lot of datasets to check a model's validity or something like that. But they use these really crude acronyms to reference the data, and then you can't really find a reference to where to find it. (P8)

Some data references are mentions or citations to participants' own data, code, or previous publications. These 'self-citations' are made in order to build on participants' past work, but also to provide context, for example descriptions of tools and scripts, that are needed to work with and understand data. Some participants cite their published data in order to draw attention to the data, to make data more visible and findable, or because they believe sharing data could be good for their reputation. It is not always obvious how best to integrate self-citations (and their motivations) into existing writing styles and norms.

What we did here, it's a pioneer project. I'm quite sure that it adds to my reputation. I'm right now writing an article on this topic [.] I wrote something like three sentences saying, "You can use these data, and we'll be happy to share them. And you know, these data are so unique". And so she [editor] said, "Don't do it," you know, "that's bad style". So I basically put it in a footnote. (P10)

4.1.2 What data objects do researchers cite or mention? Why do they do so?

Researchers refer to a variety of data objects when they cite or mention data. This has also been observed in other work (Jiao and Darch 2020; Gregory et al., 2023c). Our results contribute to this work by further documenting participants' motivations for referencing these particular types of data objects (Table 3).

4.1.2.1 Referencing data sources or collections

Numerous participants, across demographic characteristics, reported referencing data sources, such as databases, data collections, or websites. A primary motivation for doing so was to provide information about where data could be found and accessed if needed. This was done to demonstrate the provenance of data (namely where data were from), which could also signal the trustworthiness of a data source.

Participants' uses for data influence what they reference. If participants use an entire collection of data, for example to conduct computational analysis on a set of political speeches, they reference the data source. If, however, they are using a particular part of the data, for example a quote from a particular speech to provide context, they will also cite the individual dataset.

I've done a lot of work with the State of the Union addresses. And that's pretty easy to cite, because even though that's a collection of a bunch of otherwise independent [things] [.] it's kind of a collection of things that themselves could be cited. [.] So it'll be one citation for the whole collection and then we'll cite the individual things, like speeches, as to the extent that we paraphrase or quote them directly in the body of the paper. (P8)

This highlights the challenge of being able to reference data at the appropriate levels of granularity to indicate how they are used, as well as the role that the size of data plays in how data are referenced. For participants who use computational methods, for example to analyze multiple datasets across different sources, it would be unwieldy and awkward to provide long lists of data citations in a publication. Rather, data sources are listed in an appendix.

I have an appendix, and I don't provide a bibliographic citation, because we're talking like fifty-two playlists a year for twenty years. Instead, I just indicated in the data sources at the end, like where the data came from. I didn't provide a bibliographic citation in the more traditional sense, but I indicated where all of the data sets came from. (P2)

Access restrictions are another reason that participants described for referencing data sources. If data are restricted or under embargo, participants provide a link to databases or sources where data can potentially be found.

The challenge with this data that we use, it was restricted. We couldn't share. The data is not available to the public [.] So [for] that one, we try to share the link to where we can get to the repository, so that people could find access to the data themselves. (P14)

4.1.2.2 Referencing associated articles

Many participants cite articles associated with data. The availability and accessibility of data can be a factor in using an article citation to refer to data. If data are not available digitally but are rather accessed through personal communication, citing an article can feel like the 'most professional' option.

Table 3 Data objects referenced by participants and their motivations for referencing these objects.

A single data object is referenced	Motivations for referencing the data object
Data or dataset	• In order to enhance findability of data • In order to provide context to data • In order to follow best open science practices
Source of data or a data collection (e.g. a database, data repository, or website)	• In order to provide a way to access data if needed • Because data themselves are closed data within a proprietary database or under embargo • In order to demonstrate the trustworthiness of the data used • Because they used the entire data collection • Because they used a series of related data commissioned by an organization • Because the size of the data used was too large to document individual datasets
Particular section of data	• Because they are only using a particular part of the data (e.g. quoting a speech directly)
Publications associated with the data	• Because when data are not available, articles seem to be the most professional thing to reference • In order to recognize the work and interpretations of the original authors • In order to provide context for own work • In order to describe data collection methods in more detail • Because researchers' data are the publications • In order to enhance the findability of data by providing a 'breadcrumb' trail • Because it is often easiest to reference an article
More than one data object is referenced within the same publication	**Motivations for referencing these data objects**
Referencing a large combination of data objects	• When data are not available, they reference whatever objects are available
Referencing the data and an associated publication	• In order to recognize the work and interpretations of the original authors • In order to provide context for own work • In order to describe data collection methods in more detail • In order to enhance findability
Citing data in a reference list and providing a link to GitHub	• Because the format of a data citation alone is not enough for tracking the provenance of a dataset • Because other platforms offer unique affordances for data
Referencing a physical object (e.g. in a museum) and a representation of that object (e.g. a photograph)	• Because different objects are owned and created by different people • Because they are different, yet related, objects
Referencing multiple datasets or data sources within a single publication	• Because participants used multiple data, which are located in different places

> The original data producer has not made the data available on the web, through some sort of a repository or on their GitHub, and I have it because I asked for it. In which case, I have nothing to cite but the article where they used it. [.] I guess I could come up with some sort of a citation that it's a personal-correspondence [.] but I haven't done that. It feels more official in that particular scenario, to cite the article. (P8)

Article citations provide the necessary context for understanding data and a means for honoring the original data interpretations and work of the article authors. Even if data are too large to be included in a single article and are instead part of a community data archive, as in the case of astronomy research, it is seen to be important to acknowledge the contributions of individual authors.

> So, the authors might show one example of it [the data] in a paper and they'll say, for the rest of the stuff, go to this data archive, and then we'll go to get those. But we want to cite the author himself or herself, rather than just SIMBAD [Set of Identifications, Measurements and Bibliography for Astronomical Data] or wherever. (P1)

When published texts are data, as in philosophy or the history of technology and design, there is no visible difference between a data citation and a literature citation. Texts may be used in different ways within a publication, but it is not possible to distinguish this by looking at a reference list alone.

Such cases can be extremely complex, particularly in collaborative work, where multiple teams work together but collect data independently, as in multi-sited comparative case studies. A senior social scientist described a process where internal reports were analyzed as data and cited in resulting team publications. Publications themselves were then recoded and analyzed in another round of data analysis.

> There were three reports on each case. It was a literature review, a pilot, and then a substantive summative report. And we agreed that those would remain confidential within

> the team, but every team member can draw from them. And they [the summative reports] are cited in both the monographs. Over and above that, there are a set of journal articles that were published based on this same data. I coded those [articles] as well, and treated them as data, I suppose. (P20)

4.1.2.3 Referencing multiple objects in combination

The above results begin to demonstrate that our participants often reference more than one object when referring to data. This is done when data are not readily available online or when multiple sources (including people) are consulted. Providing 'breadcrumbs' to assist others to locate data was an important citation motivation for many participants; however, a citation alone (either to data or an article) is not always sufficient for others to be able to access and use data. One participant, for example described their practice of providing a data citation with an additional link to their GitHub repository, which contained a detailed description about the steps needed to access restricted data.

Participants reference multiple objects and repositories due to the unique affordances of particular platforms. A senior chemistry researcher described posting data and code in two places and referencing both in an article. They referenced a GitHub repository due to the platform's ability to document, change, and make data more usable; they also cited a 'cloned' version stored in Zenodo, which offered the capability of obtaining a DOI for the data and code.

> Because you can't cite GitHub, we've also echoed it [the data and code] to the Zenodo website. And so basically, that's a time capture of the GitHub repository at a submission time. And the nice thing about that is you get a DOI number which is citable! Yay! So you can get credit for it. We like both because if we discover a bug, there's a really nice bug reporting system for GitHub. And it's sort of easier just to make a copy and clone it and play with it. And then if you have suggested changes, you can push it back to this website. So we like having both. (P15)

Humanities researchers conducting historical research, for example in art history, reference both original artifacts as well as representations of those artifacts, such as photographs or illustrations. The ownership of the objects, ie by a museum, needs to be recognized, as does the ownership or creation of a photographic representation of that object.

> A typical photo caption reads "Albert Bierstadt, XX sketchbook, private collection, artwork in the public domain, photograph provided by Heritage Auctions". A lot of these things are way out of copyright, and museums are trying to assert rights to the things that they own [.] So, art historians are supposed to consider both the right of the object itself for the owner of the object- what collection it's in, who is its owner- and the owner of the photograph, and they get separate credits, absolutely. Those are two different things that you're having to credit. (P17)

4.1.3 Role of publishers and data repositories

Participants' referencing practices are shaped by publisher's policies. Factors such as space limitations in reference lists or the use of existing citation styles and formats (e.g. using footnotes for referencing) influence how our participants refer to data. New policies regarding data sharing also change how participants reference data. One participant described how they referenced a data article, a practice which was instigated by a new policy which allowed co-submission of a data article with a journal article.

Different publishers have different policies and enforce them with varying levels of rigor. Participants change their practices depending on the policies at different submission venues; in some research communities, firm standards have yet to be developed and researchers feel as if they are left to figure things out on their own.

> It's not super clear how exactly that [data] should be referenced in the reference list. [.] We did our best to figure it out, and we didn't get any comments. So, I don't even know if the journal really cares all that much. Or if they just assume that we know what we're doing. (P10)

Even when policies for referencing data at repositories are in place, participants experience tension between recommended formats for citing data and their own intuition about what would be useful for future readers who may wish to locate and access the data.

> I remember thinking that this citation felt wrong. But at the end of the dataset [it says] this is how you're supposed to cite it. So I was like, "Okay, this is how I'm supposed to cite it". But I remember clearly thinking this doesn't seem like there's enough information, so I was like, "Should I put the website?", but no it doesn't really say to. (P16)

Although researchers want to follow publisher policies and recommendations from data repositories, they also want to do so in ways which respect data creators. This is visible in an example of a researcher who cited a data repository, as an article had not yet been published. The researcher double-checked their citation with the data creator before publication of the article.

> They [the editor] asked, "Are you sure this is the right citation?" [.] And then in that case, I just went back to the researcher, and I was like, "Is this right? Is this how you want me to cite it? What do you think?" And they [the author] confirmed. (P16)

4.2 Evaluation, recognition and reward of data work

4.2.1 Rewarding data and data work

4.2.1.1 Data as standalone outputs

Nearly all participants stated that 'data work'—from documenting to sharing to analyzing data—takes up a large portion of their research time. In part because of the significant amount of work required to share data and make them understandable, some believe that data should be seen as being equal to other forms of research output, namely publications. At the same time, our results suggest differences in this perspective within disciplines based on methodological approaches.

> The amount of work and research that goes into carefully curating these datasets to be able to analyze in this way is 75% of the project. But my perception, again, could be

> wrong, is that folks in my field [.], the musicology side of the field, just don't see it as research and so they don't regard it on the same level. Whereas in Digital Humanities, they totally get how much work it is […]. I would like the creation of and production of datasets to be treated at the same level as, you know, the publication of a peer-reviewed article. (P2)

Even though some participants wish that data were seen as standalone research outputs, this does not often match their reality. This is in part driven by a product-based mentality, for example in sociology, where articles and books are seen as typical products, but creating data and software is "at best, [.] looked at positively. But [.] in probably virtually no case is it evaluated as equally as, like, an article." (P8)

It is also difficult for some researchers to separate 'their data' from other research outputs and activities. This was clear, for example for participants whose data *are* literature, as in philosophy. Another participant explained that various research processes—including synthesis, analysis, and writing—cannot be meaningfully separated from data. For them, highlighting data as a separate entity is simply too reductive.

> To me, it's part of the whole process. But if [.] colleagues of mine would only have data as their outputs it's too easy. Part of the challenge in every field is to synthesize something from the data [.] and to come up with original ideas [.] hypotheses that fit the data, etc [.] Just outputting data is not a merit, I think; it's part of it. (P19)

4.2.1.2 Value lies in usefulness to (small) communities

Data recognition and reward are embedded within participants' communities, often very small research communities, rather than broader disciplines. Numerous participants reiterated that the true value of 'data work' lies in creating something that is useful to these local communities. Making something useful—either a database, a code package, an instrument, or a shared dataset—is seen positively, particularly in more 'informal' evaluations from peers which contribute to establishing a person's reputation in a field.

> As well as the evaluations of your department is the evaluation of your peers in the field. And those evaluations are very different. There's no formal evaluation, but your standing in the community is I think, if you do build an instrument, you do collect data and you do share it, you're regarded much better than someone who just keeps it to themselves. (P1)

This reputational value that is accrued through sharing data (and associated code or resources) is seen as being something separate from data citations. Sharing data aids the community and can demonstrate other data-related skills or forms of service; this can enhance a researcher's reputation, even if it does not lead to citations.

> His GitHub repository's a big part of his resume, so when you look at him, you go, boy, this is a serious scientist. They write their own workup code, they're posting patches to major software packages. This is a heavy hitter. This is someone I want on my team. [.]
> This code will be a major resource because he shows you exactly how to do it and there you have the example datasets, so you can start by reproducing his work. Not sure that'll ever be cited, but it could well help a lot of people. So yeah. So [it is] reputation. Street cred, we call it. (P15)

4.2.2 Data citations, metrics and alternative rewards in academic assessments

For some, part of the reason for this separation between reputational value and data citations appears to be because academic assessments focus on publications and associated literature citations. Assessment practices therefore predetermine how data and data citations are viewed and given value.

> Interviewer: If you produce a dataset and you produce an article is that an equal contribution?
> P10: I guess I must not see it that way because I don't really care about being cited for data, but I would want someone to cite my paper [.] maybe it's because I don't really think that a hiring committee would care as much that I had a cited dataset.

Many reported that academic assessments relied on publications, literature citations, and grant procurement. Such factors were often seen to be checkboxes or evaluation criteria to be met, rather than being 'rewards' or 'incentives'. One senior researcher explained the mere fact of having something listed as an evaluation criterion may in fact decrease researchers' internal motivations.

This reflects an overall skepticism among our participants about the use of metrics or citations (for either literature or data) in academic evaluations. They were concerned about embedded biases, potential gaming of metrics, or the possibility that introducing data metrics into assessments would lead to more work for researchers, who would then need to track and include such metrics in tenure or grant applications. One participant mentioned that evaluators may not have the necessary expertise to evaluate the quality of data, which would also complicate their inclusion in assessments.

Some participants proposed alternative means for recognizing and rewarding data work. Rather than seeing data citations as a potential form of academic currency, they advocated using monetary currency as a form of reward.

> I think a cash bonus from the National Science Foundation would be nice. I'm like semi serious there. It's a [.] ton of work to package this all up. And so getting a little boost would be nice or, you know, a prize would be nice. So it's not going to be citations, but [.] something that would enhance your reputation a little better. (P15)

Co-authorship on datasets emerged in some interviews as a potential way of rewarding collaborative data work. At the same time, this idea raised concerns, particularly for collaborations involving people outside of the academic system, for example clinicians or photographers for whom co-authorship may not be as meaningful. We also observed that there were not many instances of co-authored data in the examples participants discussed in the interviews, even for very collaborative projects.

5. Discussion

This paper presented the results of a semi-structured interview study investigating researchers' practices and motivations for referencing data. We further explored how researchers perceive the evaluation of their 'data work,' paying special attention to the role that data citations and metrics play (or could play) in evaluative processes. We now conclude by discussing our findings along two lines: (i) the meanings of data citations and (ii) the use of data citations and metrics in research assessments. We then conclude by considering ramifications for assessing data work in research assessments.

5.1 Data citations: more than meets the eye

Our results demonstrate that data references represent much more than just indications of use. As with literature citations, we find that participants refer to data for both 'scientific' reasons (e.g. to recognize intellectual influence) and 'tactical' reasons, which are more social or strategic (Table 2; Lyu et al., 2021). Some referencing motivations could be considered to be both scientific and tactical, such as crediting the work of individual data creators or demonstrating the reliability and trustworthiness of data sources. We also note that many of our participants' motivations corresponded with those originally proposed by Garfield (1965) for literature citations, for example enabling traceability, providing context, giving details about data creation or collection. This perhaps demonstrates an overlap in literature and data referencing behaviors (van de Sandt et al., 2019; Gregory et al., 2023a) and highlights that the inherently instrumental and symbolic functions of referencing literature (Merton 1988) also apply to referencing data.

The complexities of the motivations underlying the act of referencing data are also visible in our comparison with proposed typologies for citing data (Table 2; Silvello 2018; Lafia et al., 2023). In line with the work of Lafia et al. (2023), participants reference data for critical/legitimizing reasons to facilitate findability and descriptive/interactive functions to provide details and context, which are needed to understand and reuse data (Faniel et al., 2013; Koesten et al., 2021). Notably missing from these two typologies, but present in our findings, are motivations that could be thought of as being more tactical or social in nature. These include participants' descriptions of referencing to draw attention to their own data or because of the threat of possible legal repercussions if they did not properly reference data.

Some of these tactical motivations can also be thought of as being altruistic in nature—for example referencing as a 'thank you' or because doing so is the hallmark of good, ethical research (Gregory et al., 2023a). Our findings further show the importance of individual relationships in decisions about how to reference data (Section 4.1.2). Participants followed disciplinary norms and guidelines to reference data sources, for example, but they also took care to either credit individual authors or check the reference format with data creators. This demonstrates a commitment to act in ways which respect individuals, but also a knowledge of the importance of attribution within academia.

Referencing data is a socially constructed process, one which is shaped by guidelines from repositories and publishers and disciplinary norms around both data and citation practices (Park and Wolfram 2017; Khan et al., 2023). Our participants discussed for example the impact of space limitations in reference lists or the use of existing citation styles and recommended formats from repositories on their data referencing practices. Participants reported changing their referencing practices depending on the policies at different submission venues. These practices reflect an evolving publishing landscape, with some publishers enforcing strict rules about data sharing and attribution, while others have none or merely encourage data availability statements (Vines et al., 2013; Colavizza et al., 2020; Gomes et al., 2022), which are not always helpful for accessing data (Tedersoo et al., 2021).

Adding new insight, our findings further show that what and how people reference is influenced by the *nature of the data* themselves (e.g. the type of data being referred to) and the *uses* people have for data, such as using an entire collection for computational analysis versus using a portion of a dataset to add nuance to an argument. This underscores the importance of having data be citable at different levels of granularity (Mathiak and Boland 2015; Buneman et al., 2020) to accurately reflect different uses.

5.2 Using data citations and metrics in research evaluations

The complexities and social situation of the data referencing practices observed in this study, as well as the diversity of those practices (Section 4.1.2; Park et al., 2018; Irrera et al., 2023), suggest the need for including nuanced metrics, aside from raw counts of data citations, in research evaluations. Our findings provide a starting place for thinking about how to do this, by examining what is valued by researchers themselves (Section 4.2). Many of our participants believe that data should be considered to be valuable (standalone) research outputs, although our findings also point to differences in this perspective across disciplines and methodological approaches (Cragin et al., 2010, Wynholds et al., 2011).

Rather than valuing data citations as a reward for data work (as proposed in Dorta-González et al., 2021), our findings show that many participants value making something *useful* for their research communities, for example a shared database, a code repository, or a dataset. This type of data work often was seen to have a 'reputational value' which circulated among the community—a value that would not necessarily be reflected in citations alone. These results bring nuance to the importance given to data citations documented by others (Tenopir et al., 2020; Digital Science et al., 2022; Khan et al., 2023) and also suggest a tension. Perhaps one of the reasons that data work is seen to have intrinsic value to a community is precisely because citations have yet to be integrated into formal assessments. Researchers therefore may not (yet) be experiencing the same goal displacement which occurs when citations become the focus rather than academic or community value (Merton 1940; Campbell 1979).

Another potential tension hinted at throughout our results is that different levels of openness and ways of sharing data impact referencing practices. We see that restricted access data are used and referenced, for example by citing data sources or data themselves, sometimes with detailed descriptions about how to access the data. While they are used, it could be that restricted access data will not be used (or accessed) as much as openly available data. We also see instances of indirect references to data that were obtained through personal contacts. Here, the data reference was arguably not a reward for open science practices but rather was made because it was scientifically necessary. This suggests that not all (indirect) data references will indicate open science practices, such as sharing data via a repository. It also suggests that some modes of data sharing and reuse will not be captured by analyzing data references (Federer 2019).

Our participants are keenly aware of the use of literature and citation metrics in research evaluations (Alperin et al., 2019; Jin and Jiang 2024). While our results show an overall skepticism toward the use of citation-based metrics in evaluations (Müller and de Rijcke 2017), they also suggest that researchers are stuck between traditional modes of assessment and ones which could recognize data work. This highlights the persistent problem of changing entrenched cultures of research assessment (Robinson-Garcia et al., 2023). Many concerns raised by our participants about using metrics for data in assessments also mirrored existing evaluation structures and practices, such as their worries about the extra work involved in tracking metrics to include in tenure or grant applications. This further points toward a more general need for less burdensome methods of assessment (Rushforth and Hammarfelt 2023).

6. Conclusion: towards context-aware ways of assessing data

While our results provide insight into various practices for referencing data and their use in research evaluations, they also raise persistent and difficult questions. What are context-sensitive ways for evaluating data work? What would truly meaningful data metrics look like? How can the pitfalls of literature citation metrics be avoided? Various recent efforts highlight the need to consider the *values* behind open science activities when considering how they can be monitored and evaluated (UNESCO 2023). While our results underscore the importance of understanding what is of value to local research communities; institutional values also need to be considered (Puebla et al., 2024) as standardized data metrics (be they quantitative or qualitative) are developed.

In line with others, we argue that such metrics should be broad enough to encompass a variety of different open science values from different epistemic traditions and offer ways to create and contextualize narratives around data practices and research contributions (Puebla and Lowenberg 2024). While some experiments think about how database work could be captured and transformed into existing bibliometric indicators, for example the h-index (Buneman et al., 2020), we see more promise in assessment approaches emerging from the RRA movement, such as the use of narrative CVs (Varga and Kaltenbrunner 2024). Our results point to the need to consider the deeper meanings (scientific as well as social) behind referencing data. Narrative approaches to assessment could help to make visible both the context needed to understand shared data (Faniel et al., 2019) as well as the service-oriented contributions of data work which our results reveal. In this format, researchers could include descriptions of their data work, how and why data were shared in particular ways, and their own assessment of how their data (and associated outputs) are useful for a particular community.

Perhaps more radically, we could also move to thinking about how to create meaningful spaces for data interaction, which could capture different signals of data reuse to consider in research evaluations. Creating forums for conversation and collaboration in data repositories, as in Kaggle, where communities can ask questions and work on data together, could support both the collaborative nature of (some) data work and provide insight into the usefulness of shared data (Koesten et al., 2025).

Other recent work within RRA calls for separating the production of publications from individual research assessments (Waltman 2025). While we see this as an interesting approach for publications, we also believe that we are in an earlier stage for data, where there is still a need to encourage the production and sharing of (open) research data. Given the diversity of data practices and the varying levels of openness which are possible for data, it could be interesting to consider indicators which separate data production/sharing and data use. Rather than working towards metrics such as the h-index where these practices are combined, assessments could take into account metrics only for sharing, for example the presence or DOIs in trusted repositories. This could be done for data which are openly available or under different access restrictions; at the same time, researchers should not be penalized if they work with data which they cannot (openly) share. Rather than focusing only on data sharing, responsible data work could also be recognised and rewarded. This could be evidenced through data documentation or consultations with data stewards, for example.

Ultimately, data work is a cornerstone of research practice which needs to be evaluated and considered. It is also nuanced and complex, and any indicators which are developed need to respect this complexity.

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Notes

1. Some of the initial results were described in a research in progress paper (Gregory et al., 2023c).
2. https://www.countermetrics.org/coprd/

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