Data Sharing Frames: How Scientists Understand the Work of Sharing Scientific Data

Completed Research Paper

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Abstract

The curation of data is fundamental to their wider dissemination and use. This paper investigates the frames of workers who perform data curation in scientific contexts. We view data curation as a sense-making practice, where workers collaborate to disseminate meaningful data to a broad set of prospective users. Previous Information Systems investigations have suggested that data-related activities are dependent on workers' understanding of their local work context. We expand this with an evolving and long-term view. We use a stepwise-deductive induction method to examine how scientists understand the work involved in curating scientific data for public sharing. We draw on frames as the theoretical lens of the study that enables us to identify three data sharing frames – the object, curation, and aligning frames – as important frames that shape how scientists curate data for public sharing. Our analysis provides a deeper understanding of the nuances of managing scientific data for public access. Our main contribution is the articulation of an evolving and long-term view of how workers approach their tasks in getting data ready for long-term public use.

Keywords: Data Curation, Data Sharing, Data Governance, Sensemaking Frames

Introduction

IS research have begun to examine broader aspects of data governance (Brous et al., 2020; Mikalef et al., 2020). Such studies have theorized data governance as an inherent problem of collective action that depends on heterogeneous actors adopting collaborative strategies, and have examined data curation as an everyday manifestation of data governance in local practices to achieve data quality, filter out irrelevant data, and ensure privacy (Parmiggiani and Grisot 2020). Scientists are increasingly mandated by funding agencies to share their research data publicly. The idea of open access to publicly funded research data, while admirable, is an unresolved concept in practice. Within Information Systems (IS) studies, such data issues related to curating data for further uses are a central theme (Aaltonen et al., 2021; Alaimo &

Kallinikos, 2022; Jones, 2019; Mikalsen & Monteiro, 2021). What is (relatively) new in such studies is the data curation work to prepare scientific data for long-term public access (Parmiggiani et al., 2022, 2023).

The existing discourse on big and open data is also accompanied by the expectation that an increase in amount of data will lead to opportunities to develop more and better knowledge. However, this is problematic especially in contexts where there are discrepancies in labeling, and also because the reliability of data from public sources may be compromised in unfamiliar contexts. For example, the assertion that:

> *X can access battery data from online databases and perform algorithmic analysis to model battery behaviour and improve battery system design.*

is significantly weakened by the following account:

> *X thought she had obtained battery data from an online database, but upon further reflection, she realized that the data were not reliable because the labels were significantly different from those she is used to in her daily work.*

In this alternative version, X's confidence in the reliability of the data is shaken by the unfamiliar labelling and subsequent realization of inconsistency. This intrusion of social factors, such as "upon further reflection" and "significantly different from what she is used to", disrupts the previously established logical framework of systematic data use. These social factors highlight the nuanced interplay between technical capabilities and the human context and illustrate that neglecting accounts of human intervention in data-related activities, such as data sharing can pose a significant challenge to integrate data from multiple sources into a coherent aggregate.

Again, accessing and using scientific data in a specific lab, manufacturer or niche application may require less data curation work in curating data that are clear for others to understand. However, in relation to large-scale and distributed settings (i.e., engaging with the whole scientific community – as well as the general public), scientists undertake a wide array of activities and develop methods that are aware of standardization needs and unknown reuse contexts (Parmiggiani et al., 2023). For example, when a scientist in a battery lab in Oslo, Norway, refers to a dataset with the English word "battery", they are likely referring to a battery cell. However, a scientist in a battery lab in Trondheim, Norway, might use the same term to refer to data from a battery pack. Also, in some countries, the data might be labelled with a synonym such as "accumulator" or in a language other than English. These variations underscore the importance of comprehensive data curation strategies that go beyond local nuances to promote effective communication and knowledge sharing in an increasingly interconnected global scientific landscape.

Research into sensemaking frames has shown that local actors' understandings and meanings influence their daily actions (Davidson, 2006; Weick, 1995). Different frames by workers could lead to overestimation or underestimation of the potential impact of ongoing digitalization programs (Orlikowski & Gash, 1994). Different frames also pose a major challenge to defining the necessary governance and organizational standards and make it difficult to agree on a common vision or future roadmap for long-term research infrastructures, slowing the development of the potential benefits of ongoing digitalisation. The frames of local workers can thus provide important insights for IS.

Given the presence of such contextual factors, no data sharing program can be successful without careful attention to the different frames of workers who curate data for their wider dissemination and use. Research will benefit from understanding the work of scientists who prepare data that are clearly understood by prospective users. As this work ensures that data can be appropriately linked and become part of big data aggregates – which in turn serve as an empirical resource to explore new correlations support machine learning algorithms, and ask ambitious and innovative questions (Leonelli & Tempini, 2020). This work, which is often invisible and outside scientists' formal job description ensures that data are reliable, relevant and more useful to prospective users (Engesmo & Panteli, 2020).

Insights into how scientists, in specific contexts, prepare data for public access can inform a richer understanding of data governance in distributed data sharing infrastructures and open such practices to more rigorous scrutiny (Parmiggiani et al., 2023; Parmiggiani & Grisot, 2020). The investigation of workers' frames is also about bringing scientific thinking and scientific work into local work practices. Moreover, IS researchers are encouraged to study phenomena that dynamically evolve and mutate as people engage with them (Bailey et al. 2022; Monteiro et al. 2022).

Against this background, we ask *how do scientists frame their curation work when sharing*[1] *data?* To address this, we draw on the 'frames' perspective (Davidson, 2006; Orlikowski & Gash, 1994; Weick, 1995). The concept explores how people's views on technologies, processes and policies shape their practices, including their attitudes, behaviors, and decision-making. This lens is useful to gain insights into scientists' own understanding of their data curation practices in relation to data sharing. Failure to pay attention to and understand these frames may lead to undermining the role of scientists in data sharing infrastructures and further compromise the ambitions of data sharing policies.

Using a stepwise-deductive induction approach (Tjora, 2019), we empirically investigate how scientists from the Norwegian node of the European Long Term Ecological Research (eLTER) network understand the work to publicly share ecological data over long time periods. We analyze questionnaires, interviews, field notes, and documents to understand the meanings given by scientists to data sharing. We contribute to IS by providing insights into the salient practices influencing data sharing by articulating three work frames carried out by scientists – that detail how scientific data are prepared for long-term public access.

The rest of our paper is organized as follows: Section 2 develops our understanding of the concept of data as relational and derived through situated practices of data curation. Section 3 presents the theoretical lens that informed our study. Section 4 provides an overview of the context of our case and a description of our research methods. Section 5 presents our empirical findings, which are organized around three frames of work developed during the data analysis. The discussion in Section 6 highlights our findings and draws on existing IS literature to discuss the theoretical contribution of our work; further in this section we reflect on the implications of our study for practitioners and IS research. In Section 7, we conclude with limitations and future work.

Conceptualizing Data and Data Curation

In this section, we explore the intricate interplay between data as a resource and the curation strategies employed to shape them into valuable assets for current use and future endeavors. By exploring these concepts, we navigate the complexities of managing data in data infrastructures, shedding light on the methods, challenges, and importance of carefully curating data for public use.

Jones (2019) reminds us that data are brought into being as a consequence of work practices. Producing and using scientific data depends on the accuracy and completeness of the recording process and on the reliability of the data management tools, and processes (Jones, 2019; Orlikowski & Scott, 2016). Producing and using data is challenged by several social and technical factors. These include errors in the data production process, network or communication breakdowns, intentional, or accidental changes to the records, or errors and damage to the records. The risk of such errors is greater when the data production process depends on humans, but this risk is not eliminated when the processes are automated (Jones, 2019).

Data provenance concerns the history or lineage of data (Karasti et al., 2018). Provenance information documents the origins, transformations, and changes that data have undergone from their creation to their current state (Leonelli & Tempini, 2020). Data provenance has been shown to play an important role in documenting contextual factors that influence data production and use. Well-documented data provenance can provide useful information for prospective users to form their own opinions about the relevance and reliability of data (Borgman et al., 2015). It provides a detailed record of the data sources, the processes applied to them, and all intermediate steps (Lingel, 2016). Data provenance helps establish the authenticity, reliability, and quality of data and enables prospective users to trace how data were generated, manipulated, and shared (Borgman et al., 2015; Karasti et al., 2006; Leonelli, 2016). This can be crucial in various future use settings such as scientific research, regulatory compliance, and auditing. Data curation plays a crucial role in ensuring that data and their provenance are well documented, maintained, and accessible throughout their lifecycle (Parmiggiani et al., 2023; Ribes & Polk, 2014).

[1] We use data sharing not to mean exchanging data with others, which will suggest a 'give-and-take' activity but instead we focus in this study on data sharing as giving data to others. This work as 'framed' by scientists is not a one-time handoff of data to others, but will continue so that the data will be accessible and clear to prospective users in the near and distant future. Hence the evolving and long-term perspective.

In our study we define data curation as the activities associated with preparing and caring for data (Karasti et al., 2006; Parmiggiani et al., 2023) to fit existing datasets or create new datasets (Leonelli, 2019b). It involves various activities in systematic data management, including the collection of data, their validation, cleaning, organization, storage, release, and archiving. The goal of data curation is to preserve data and their provenance in a well-organized and structured manner so that they remain accurate, accessible, and usable over long periods of time (Ribes & Polk, 2014).

Ongoing digitalization has enabled data curation in a variety of contexts. In telecommunications, for example, data are curated and packaged into commodities that are later combined into innovative products (Aaltonen et al., 2021). In the offshore oil and gas industry, data are curated and used to interpret hydrocarbon reservoirs (Mikalsen & Monteiro, 2021). From these studies, scientists cope with understanding the methods and technologies to prepare data for further uses.

In the sciences, scientists often operate in changing technologies and empirical demands of data sharing policies over extended periods of time (Leonelli, 2019b). By examining closely, the instances of data curation in science and viewing them through the eyes of the scientist, we aim to provide insights into the problems and relationships in sharing data, and how scientists deal with these problems and relationships.

Theoretical Lens

To explore how scientists understand the work involved in sharing data, we adopt the theoretical lens of frames. The concept has been used to explain internal, self-conscious and cognitive processes of individual sensemaking (Weick, 1995). It has also been used in strategic processes of evoking meaning in line with existing cultural categories of understanding and as a basis for mobilizing support and gaining legitimacy (e.g. Creed, Langstraat, and Scully 2002). An initial area of research in which frames have been used extensively is in cognition and decision-making by individuals in organizations. Here, researchers demonstrate the importance of understanding the 'frames of reference' through which individuals review and filter their environment (March & Simon, 2005). The overarching assumption is that individuals in organizations cognitively recognize regularities in their environment and condense these into much less detailed cognitive constructs that then guide their decisions and actions (Shrivastava & Schneider, 1984).

Building on these studies, Orlikowski and Gash (1994) introduced technological frames to characterize the mental constructs through which individuals perceive and interpret technology (Orlikowski & Gash, 1994). The literature on technological frames examines how individuals' cognitive frames influence their attitudes, behaviors, and decision making in relation to patterns of technology use within an organization (Anthony, 2018), technology implementation (Young et al., 2016) and technology development (Seidel et al., 2020). There is also a wealth of research on the conflicts that can arise when different frames are in play for different user groups within an organization (Barrett et al., 2013; Mazmanian, 2013).

The literature also highlights different types of technological frames. These include instrumental frames, where people view technology as a tool for achieving specific tasks or goals (Dzhengiz & Hockerts, 2022; Gao & Bansal, 2013). Social frames emphasize the impact of technology on interpersonal relationships and social dynamics (Hervieux & Voltan, 2018). Cultural frames emphasize the role of technology in shaping traditions, language, and forms of expression (J. L. Bailey, 2009; Creed et al., 2002). Economic frames focus on the financial impact of technology, including a technology's potential to drive innovation, create jobs, and influence economic growth (Dzhengiz & Hockerts, 2022). Political frames deal with issues of surveillance, censorship, and distribution of technological resources (J. L. Bailey, 2009; Creed et al., 2002). Ethical frames address moral considerations associated with technology, including questions about its impact on human rights, social justice, and the environment (Dzhengiz & Hockerts, 2022). Dogmatic frames address people's rigid and inflexible way of perceiving or interpreting technology (Dzhengiz & Hockerts, 2022). Following these studies, we examine the frames of individuals who curate data for sharing and refer to this as data sharing frames. As we will show in the later sections, data sharing frames focus on data management strategies for shaping data. Data sharing frames, then, is about data curation considerations to share data that are clearly understood by prospective users. The concept of data sharing frame is in line with calls made by IS researchers to critically evaluate how we approach and think about data, their provenance, privacy, and related organizational practices (Lyytinen & Grover, 2017; Mikalsen & Monteiro, 2021; Parmiggiani et al., 2022).

In what follows we describe our research setting and the methods that informed this study.

Research setting

In 2002, the European Commission created a coordinated data sharing mechanism to strategically connect and integrate data from distributed research institutes in European countries. This mechanism is called the European Strategy Forum for Research Infrastructures (ESFRI). ESFRI regularly publishes and updates a policy roadmap that reflects the strategic objectives of the European Commission.

In 2018, the Integrated European Long-Term Ecosystem, critical zone, and socio-ecological Research (eLTER) network was added to the ESFRI Roadmap. eLTER currently comprises 26 national networks. These national networks include eLTER-Portugal, eLTER-Norway and other national nodes spread across Europe. Together, the national networks consist of about 550 local research institutes that are taking up the challenge of collecting, aggregating, preserving, and disseminating ecological data to understand the long-term and complex interactions between humans and nature. ESFRI therefore promotes data sharing policies and roadmaps, and these ambitions are mirrored at eLTER national and local networks.

The goal of eLTER is to provide the public, including citizens and experts with access to data from its 550 research institutes. In particular eLTER seeks to offer harmonized and standardized data, services and training useful in joint efforts to find sustainable solutions to major societal challenges (eLTER, 2022). Despite their crucial role in this data sharing program, there is little visibility in ESFRI's roadmap on data and data management practices of scientists.

Ecological data are not fully standardized across research institutes in eLTER-Norway, and their formats vary considerably depending on how a project is organized and funded. As well there are variations in technologies available and the natural elements being observed at research institutes. Research institutes in eLTER-Norway monitor air quality, fauna and flora in fresh and salt forests, and Arctic tundra. Research institutes are usually located near the environmental phenomena to be measured and some research institutes are closed during the coldest months.

The institutes usually combine analog and digital technologies to measure various ecological parameters and to clean, analyze, and store the data. Institutes employ a variety of professionals, all of whom contribute to data curation through their daily work, such as environmentalists, chemists, biologists, zoologists, or physicists. These professionals are sometimes employed by research institutions or funded by grants. Interns, bachelor's, and master's students also often spend a few months doing ecological studies as part of their training. Institutes also often employ (either permanently or temporarily through projects funded by the Norwegian Research Council or the EU) software developers, data scientists, and systems engineers who program open access web portals, Internet-of-Things (IoT) sensor networks and develop software and databases for data storage and analysis. Finally, maintaining data centers, and other data collection and analysis devices requires the work of several craftsmen, and some volunteers. The amount of time these individuals spend at a research institute depends on their duties. These various professionals perform some form of data curation. For example, *data collection* may be performed by biologists and chemists, *data cleaning* by data scientists and engineers, *database management* by software engineers, *data entry, updating and analysis* by students, and *maintenance of the data center and equipment* by craftsmen. For this reason, we use all of these professionals in our data sources and analysis as "scientists" to ensure consistency.

Data Sources

During the period February 2020 to March 2022, we worked with three local research institutes in eLTER-Norway. We used questionnaires, semi-structured interviews, and field notes to understand the meanings given by scientists to data sharing. We also analyzed, for this study, white papers, and documents from eLTER, ESFRI and the Norwegian Research Council to understand the perspective of coordinators of the eLTER Data Sharing program. This helped us to identify and explore the data sharing regulations conveyed by coordinators, and how these ambitions are understood and executed by scientists responsible for the stewardship and local management of primary data.

We first sent out an online questionnaire to sixteen scientists to which we received five responses. The responses gave us an overview of how data are handled by scientists. In the questionnaire, we asked respondents for an opportunity to visit their local sites to further understand their data management activities. We were invited to three research institutes, one in Trondheim and two in Oslo. We visited these institutions to talk to the respondents on site. We spent about twelve hours at each site. We observed scientists in the field, offices and in their laboratories. Scientists also showed us the technologies that they used in their work. We also conducted a total of fourteen semi-structured interviews. This number was based on the availability of interviewees during our visit. We also attended one of the eLTER data management meetings where scientists in the eLTER network discussed challenges and trends in data management. For this study, we also used data from two workshops organized by eLTER on the specifics of data management. Here, scientists took turns demonstrating to us (participants of the workshop) how they work with software tools such as R, Python and Excel, to manage data for immediate use and future sharing.

Preparations for sharing data in eLTER began in 2020 and implementation is ongoing. eLTER data sharing is expected to begin operation by 2026. Participants' responses are informative as they shed light on how scientists understand and interpret their current data management practices as a foundation for the growth and future of data sharing. The understanding and meaning that scientists place on data sharing is important because it shapes their work practices, which become embedded in organizational processes. Such embedded practices are particularly difficult to change later (Monteiro et al., 2014). Table 1 provides an overview of our data sources.

Data Sources	Number
Online Questionnaire	5 Scientists
14 Semi-structured Interviews (Approx. 45 to 60 minutes)	14 Scientists
Observation and fieldnotes	4 days at 3 environmental research institutes (Approx. 12 hours, 1 day equals approximately 3 hours) 1 day at a meeting to discuss challenges, opportunities, and trends for data management and education in eLTER (Approx. 6 hours, 1 day equals approximately 6 hours) 2 days at a workshop on eLTER data management (Approx. 12 hours, 1 day equals approximately 6 hours)
Documents	Strategy reports by EU, ESFRI and the Norwegian Research Council, White papers, and guidelines for establishing data infrastructures. Official descriptions, standards, and guidelines for data sharing by the eLTER network

Table 1. Data Sources

Data Analysis

We followed a stepwise-deductive induction approach (Tjora, 2019) to analyze our data. The approach begins with raw data and moves towards theories through incremental deductive feedback loops. It has similarities with Glaser's Grounded Theory emphasis on inductive conceptualization (Glaser, 2002) but takes a step back with a fundamental agreement in scientific-theoretical terms (Tjora, 2019), ensuring that themes have stricter agreement to extant theories. We explored respondents' interpretation of data sharing, with a focus on their data management practices. The data were first examined to identify statements or actions that reflected meanings – understandings, assumptions, expectations, and knowledge – about data sharing and its impact on scientific work, data curation and the larger eLTER network. This was done by reading and sorting participants' own words into categories. We followed this with comparing the categories to see if they reflected common themes in extant literature. After this, the data was re-explored and re-coded to ensure our themes connected with and contributed to existing literature. This iterative exploration resulted in a set of constructs that we considered core to answering our research question. Our constructs were labelled in two iterations. For example, in one iteration we identified our frames as data, data management and data infrastructure however these terminologies could have potential conflicts with those used in extant literature (see, for example, (Karasti et al., 2018)). We thus renamed our constructs differently as object frame, curation frame and aligning frame because these communicated more clearly the frames within which scientists understood their work in curating data for long term sharing.

Findings

In this section, we present the emergent themes that underpinned our study: object frame, curation frame and aligning frame. These are also summarized in Table 2. Within the object frame, scientists frame data sharing in terms of the properties of data. This frame allows scientists to determine the strategies to adopt to plan for the high variability of data types and formats. Within the curation frame, scientists frame data sharing in terms of the actual work involved in resolving data issues. This frame allows scientists to resolve situated local data issues. Within the aligning frame, scientists frame data sharing in terms of the collaborative efforts to address various standardization issues across the network.

Themes	Categories	Excerpts From Data (Examples)
Object Frame: Scientists understand data sharing in terms of the characteristics of the data to be disseminated	Variability and quality of data	*"We have many different types of datasets. Some studies may have huge amounts of datasets, but not a great diversity, a 'deep database', like the remote sensing." (Scientist 1)* *"My team and I work a lot on projects involving forest and soil data collection. Examples of data not collected by sensors include measurements of tree diameter and height growth, soil and humus samples, and various geophysical variables" (Scientist 2)* *"We deal a lot with quality control of data. You know if the data is to be shared then it has to be given in a way that anyone that sees it can trust it" (Scientist 1)* *"The data should be fit for its intended uses in research, and decision making…." (Scientist 12)*
	Planning for data requires time and effort	*"It takes a lot of time to describe data in a way that others can understand" (Scientist 19)* *"We have no guidelines yet for doing that [describing data]" (Scientist 13)*
	Funders and Regulators dictating type and form of data work	*"It depends on the project… We sometimes exchange data with our network partners only. So, not all our data are open to the public" (Scientist 5)* *"In that project, there was this expectation that the data is managed and documented well then made readily available to the public" (Scientist 9)* *"If I'm going to make a report for Popular Science and a report for the Norwegian government, I need to translate the species from Latin names to Norwegian names. I collaborate with my team members to do the matches. It's often a matter of not just matching the species but ensuring that the species that were first reported are the correct scientific name that's currently in use for that species because they change over time as a species are reclassified. So, we collaborate to make sure that we're actually using the exact and the most up to date, species name. So those things are typical data wrangling issues" (Scientist 13)*
Curation Frame:	Procedures for data collection	*"We plan for non-reproducible observational data, and also experimental and modelling data" (Scientist 11)*

Scientists understand data sharing in terms of the work to resolve problems related to formal plans, curation models, and situational data curation needs		*"There are plans and procedures for collecting sensor based and manual data" (Scientist 8)*
	Overseeing collection of seasonal data	*"Part of my work is overseeing the ongoing recording and updating of data sets as they are collected and accumulate over time" (Scientist 1)* *We sometimes retrieve old datasets from scientist personal computers and format them well [contemporary digital form] into our shared database and interview them [scientists] to understand the context [i.e., how the data collection was done]" (Scientist 16)*
	Focus on long-term data description	*"For someone outside our station or for someone a few years from now, say 30 years from now, or even 100 years from now, it matters more and more that we document data context" (Scientist 12)*
	(Re)Using long-term data	*"Data is managed in a way that can first and foremost support immediate analysis and local use" (Scientist 4)* *"I believe Open Data can result in analysis of previously accrued data in conjunction with other long-term datasets" (Scientist 10)*
Aligning Frame: Scientists understand data sharing as working collaboratively to minimize disruptions to ongoing science and data sharing caused by changing technologies, data, and standards.	Awareness of diversity in data management	*"Local research institutes are diverse and do not always fit standardized data and metadata templates" (Program coordinator)* *"I'm not sure what you mean by open data sharing. Like do you mean stuff like Open Access? Or do you mean like the actual data?... I haven't like shared them anywhere outside our project..." (Scientist 6)*
	Aligning data sharing technologies with local ecological research	*"I think it's important that open data sharing is driven by research, that we [scientists] are always looking at whether the technologies we want to implement really support [ecological] work in the field." (Scientist 14)* *"We have to search for own funding and align ourselves to eLTER open data sharing policies." (Scientist 3)*
	Participating at the network-level	*"We participate in network-level activities to learn together" (Scientist 4)* *"Part of my work has been to make them [scientists, data curators and everyone at the local institute] to be aware that we are also benefiting from sharing the data. It has been quite a bit of a long road to get people to that point, but we're almost there now. [...]." (Scientist 17)*

Table 2. Emerging Themes

The Object Frame

Respondents understand data sharing in terms of the characteristics of the data to be made publicly available. It is often generally assumed that data submitted to publicly accessible portals are of the same format, well organized, error-free, and well-documented. In practice, however, there are diverse forms of data including long-term observations. Sometimes labels and code names may change over time, which requires scientists to resolve such changes. In the excerpt below Scientist 13, informs us about the work in ensuring that scientific data labels are not only matched correctly but also updated according to the most recent labels:

> *"If I'm going to make a report for Popular Science and a report for the Norwegian government, I need to translate the species from Latin names to Norwegian names. I collaborate with my team members to do the matches. It's often a matter of not just matching the species but ensuring that the species that were first reported are the correct scientific name that's currently in use for that species because they change over time as species are reclassified. So, we collaborate to make sure that we're actually using the exact and the most up to date, species name. So those things are typical data wrangling issues" (Scientist 13)*

Sharing data also requires scientists to assess the varying formats of scientific data in structured and unstructured form including graphs, emails, portable documents, photos, videos, physical samples, experimental setups, and sounds files. Different local research domains with a given institute have many different data formats, scientific procedures, and data collection routines to study a given environmental phenomenon. For example, if a project team at is studying bird species in a particular region, they may collect optical data using cameras, others may use sensor devices to collect acoustic data, and still other institutes may use both methods:

> *"We have many different types of datasets. Some studies may have huge amounts of datasets…." (Scientist 1)*

Such data heterogeneity is worsened by missing data values:

> *"We deal a lot with quality control of data. You know if the data is to be shared then it has to be given in a way that anyone that sees it can trust it." (Scientist 1)*

The different data at research sites are also not yet fully digitized or well-described with contextual information. Some data are found in binders of paper as these sources are still very relevant to scientists. Scientists acknowledge the time and effort required to digitize and describe data:

> *"It takes a lot of time to describe data in a way that others can understand" (Scientist 19)*

Some scientists understand that releasing data is not just about static data that do not change over time, but also about seasonally accrued data collected and disseminated by other scientists. Seasonally accrued data in local institutes are subject to various types of revisions and changes.

Data are also sometimes safeguarded when intellectual property rights are at stake. This raises the question of which technologies and databases to use and whether to open access to primary data by creating a dedicated public portal for data sharing, using publicly available portals, or opening private or project-specific internal portals of a local institute, which could lead to organizational privacy concerns. Scientists understand that disseminating ecological data comes with the requirement that data be made accessible if no legitimate considerations stand in the way of their accessibility, i.e., "as open as possible, as closed as necessary". Sometimes regulators and funders dictate the type and form of data to be shared:

> *"In that project, there was this expectation that the data is managed and documented well then made readily available to the public" (Scientist 9)*

Regardless of what a team decides, all data and metadata must be well organized, error-free, well-documented and comply with the standards of the eLTER network. This requires a lot of human expertise.

> *"We have no guidelines yet for doing that yet. We meet and discuss these issues on a project basis." (Scientist 13)*

In summary, the heterogeneity of scientific data is a prominent feature of the eLTER network. Through the object frame, scientists understand and develop cognitive perceptions around the characteristics of data, which leads to opportunities to plan the work needed to create and share data. If scientists were to assume that scientific data were consistent and homogeneous, they would simply adopt automated approaches to collect and share data to publicly accessible portals. The object frame shows how scientists focus instead on ways to organize the heterogeneous forms of data to be shared. An important outcome of the object frame is that an assessment of the characteristics of scientific data provides an opportunity to plan how to manage the various forms of scientific data..

The Curation Frame

In local research institutes, scientists develop data management plans to collect and share data. Observational data are usually not easy to reproduce. Once the data are lost, potential knowledge that could have been gained from them is permanently lost. Scientists therefore plan for and document any changes during ongoing collection of observational data:

> *"We plan for non-reproducible observational data, and also experimental and modelling data" (Scientist 11)*

Scientists are mandated by their funders to produce data management plans[2] (DMPs) when applying for project funding. A DMP is a formal document outlining how project data will be collected, organized, and shared both during a research project and after the project is completed. Although scientists strive to follow the rules in such documents, they end up carrying out several activities outside of these documented plans and procedures. This perspective reflects what we call a curation frame, where scientists understand data sharing in terms of balancing requirements of formal plans with empirical contingencies that accompany everyday data management:

> *"Part of my work is overseeing the ongoing recording and updating of data sets as they are collected and accumulate over time" (Scientist 1)*

Scientists may intervene and make changes to data in ongoing sampling procedures by adding or deleting study parameters. Further, there can be alteration of habitats due to natural factors or changing environmental conditions, that create data anomalies. Scientists sometimes analyze the data while performing observational data collection. Such arrangements are usually flexible to the changes in the field or laboratory and allow for new factors to be considered during data collection. On the one hand, this allows for analysis of and reflection on the data to begin in the field or laboratory. On the other hand, such flexibility poses challenges for structured data management and documentation of updated or changed procedures while data collection continues. If important procedures are not properly documented, this poses a threat to adequate curation of data and other contextual information relevant for understanding shared data. As a result, relevant information needed by prospective users to make sense of the shared data is compromised. For scientists, this means going back in time to understand and restore historical datasets. In the excerpt below Scientist 16 tells us how her task to retrieve data required her to interact with colleagues to understand the context within which those data were produced in order to describe and format them meaningfully:

> *"We sometimes retrieve old datasets from scientist personal computers and format them well [in contemporary digital form] into our shared database and interview them [scientists] to understand the context [i.e., how the data collection was done]" (Scientist 16)*

Scientists understand that managing scientific data by adding contextual information is a crucial aspect of long-term data sharing because:

> *"For someone outside our station or for someone a few years from now, say 30 years from now, or even 100 years from now, it matters more and more that we document data context" (Scientist 12)*

In summary, data management plans that document how project data will be managed and shared during and after the completion of a project play a crucial role in eLTER's data sharing program. However, if scientists assumed that releasing scientific data is tied to DMPs, they may only consider data curation models or routinized approaches to obtaining and disseminating ecological data. The curation frame suggests instead key considerations made by scientists to augment this process. These include recovering relevant contextual data, usually through informal interactions and interviews with scientists. The curation frame shows how scientists focus on situated ways to redefine their curatorship activities in practice in ways that enhance the reliability and relevance of shared data. An important outcome of the curation frame is

[2] Examples of data policy by funding agencies: https://www.ukri.org/publications/esrc-research-data-policy/ and https://www.esfri.eu/esfri-roadmap

the recognition that data management should not be seen as a mechanical sequence of plans, models, and rules, but also a series of situational decisions.

The Aligning Frame

Like many data sharing programs, the eLTER network aims to grow: to provide data that will support policy and science in the long term. Scientists are aware of their role in collaborating and ensuring that data management, local science conduct and data sharing align to ensure the continued growth of the eLTER data sharing network. We call this the aligning frame.

Local research institutes work on diverse projects. The domain-agnostic data generated by each project across the eLTER network do not always fit existing data and metadata templates:

> *"Local research institutes are diverse and do not always fit standardized data and metadata templates" (Program coordinator)*

Scientists are therefore involved in network-level efforts, where they learn the different local data management and science study cultures distributed within the network to align their data standards, labels, and code names, etc., with the growing eLTER network.

In doing so, the aligning frame brings to the fore cultural and socio-technical issues related to standardization, integration, and interoperability of shared data. This represents another important dimension of the eLTER network to shape the future of data sharing within the network, because:

> *"...the common elements of [local research institute] governance: their funding and their management [must] guarantee long-term sustainability..." (Document, ESFRI)*

In most cases, scientists have to search for their own funding and align themselves to eLTER data sharing policies. Scientists also ensure that data produced at the local level first enrich their scientific investigations and supports science on the ground. As a result, new data sharing technologies that can have an impact on local scientific work may be approached with greater caution by scientists.

> *"I think it's important that open data sharing is driven by research, that we [scientists] are always looking at whether the technologies we want to implement really support [our] work in the field." (Scientist 14)*

An awareness and recognition of the importance of data sharing and collaborative data management is not currently evenly spread:

> *"I'm not sure what you mean by open data sharing. Like do you mean stuff like Open Access? Or do you mean like the actual data?... I haven't like shared them anywhere outside our project..." (Scientist 6)*

This has led to education about the importance of data sharing and the role of scientists in collaboratively managing data:

> *"Part of my work has been to make them [scientists, data curators and everyone at the local institute] to be aware that we are also benefiting from sharing the data. It has been quite a bit of a long road to get people to that point, but we're almost there now. [...]." (Scientist 17)*

In summary, scientists' approach data sharing in a way that connects data management with ongoing scientific work and contribute to the broader eLTER data sharing infrastructure. This is often done through network-level forums and awareness-raising, training, and education workshops that are based on the realities and needs of each site and reflect the history and specificities of local science conduct and data management. Scientists see how others within the network are doing, either as a contrast or as a stimulus for improvement. The aligning frame thus highlight how scientists collaboratively contribute to the growing eLTER data sharing network. An important outcome of the aligning frame is the recognition to develop a data sharing infrastructure with continuity.

Discussion and Implications

Our study has aimed to examine scientists understanding of data curation for the purpose of data sharing. With the increasing pressure on scientists by funding agencies, to comply with data management policies, this study is both relevant and timely. As such, we conducted this study to empirically analyze how scientists frame their work when sharing scientific data to the public. We focused not on the digital technologies and resources for sharing science data or their effects but rather on the work processes involved (Schlagwein et al., 2017). Our findings, brief as it may be, points to the significant amount of work involved in sharing scientific data – as well as the many unresolved challenges and failures that plague this process. We have also shown why this work is important for long-term continuity of data sharing.

We contribute a data sharing frame to IS literature, which comprises three understandings of the work needed for disseminating science data publicly. First is the object frame, where scientists understand shared science data in terms of the characteristics of the data to be shared. This frame is important for identifying efficient ways to plan for scientific data production, use and sharing. For example, homogeneous data sets may require a more automated approach than heterogenous data sets. Data that are static or hardly change over time may require less work than dynamic data that change seasonally or annually. Awareness of the object frame can lead to a more complete understanding of the nature of data and open their data management needs to more rigorous scrutiny.

Second is the curation frame, where scientists understand shared scientific data in terms of the situated work practices to solve problems related to formal plans. In light of increasingly automated approaches to data collection, such as the use of Internet-of-Things sensors to monitor the Arctic seafloor (see, e.g., (Parmiggiani, 2017)), the question is whether science will move toward complete automation or rather that automation becomes an extension of manual ongoing techniques. For example, manual data collection is a common practice in science and analysis usually begin in the field or laboratory. Data collection is therefore a matter of the scientist and their understanding and relationship to the data and the environment in which the data are collected. Pushing for routinized data collection schedules or automated methods risks marginalizing other approaches. Awareness of the curation frame can lead to a better understanding of the flexibility of scientific work and its associated challenges for structured data flow into shared databases.

Third, is the aligning frame, where scientists understand shared science data in terms of the collaborative work to align emerging data, methods, technologies, and standards, and minimize disruption to ongoing science. For example, as the eLTER data sharing network grows, it will face issues related to addressing data interoperability problems at the international level. How to connect the various interdependent domains of science, including individual laboratories, collaborative repositories, regional or national archives, and network standards, will require crucial human work. Awareness of the aligning frame can lead to an understanding of the various local science activities and data management needs and provide opportunities to regulate and fund their common elements and build a data sharing infrastructure with continuity.

Taken together, these frames answer *how scientists frame their curation work when sharing data*. We used data sharing in this study not to mean exchanging data with others, which will suggest a 'give-and-take' activity but instead focused on data sharing as "giving data to others". Our proposed data sharing frame is illustrated in Figure 1., below:

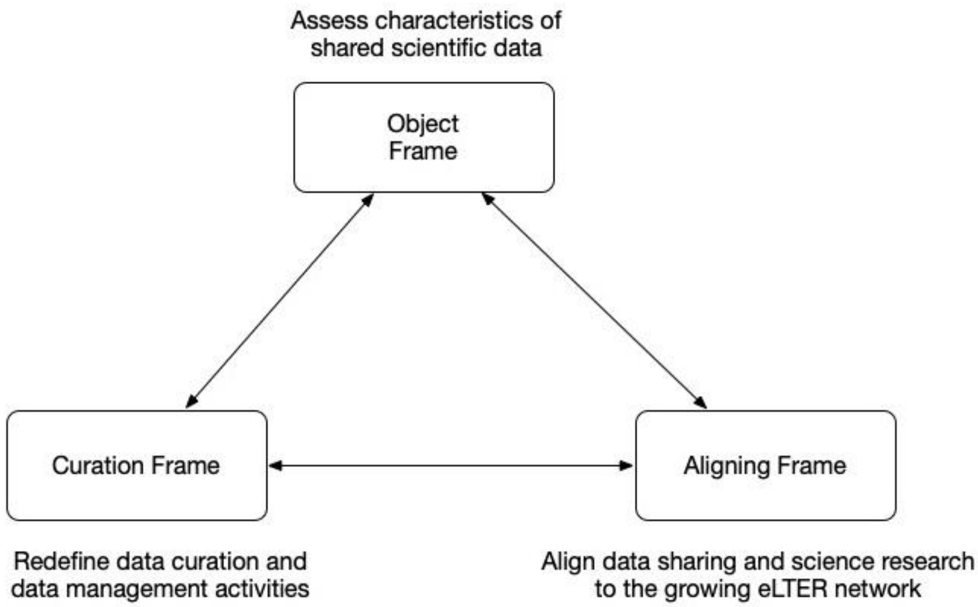

Figure 1 Data Sharing Frames: How scientists frame the work of sharing data

Our proposed data sharing frame fleshes out an understanding of the work needed to share scientific data publicly over longer time periods. The key point we are making is that this work is carried out because scientists pay attention to and understand that this is important if future users, several centuries later will find, access, understand and (re)use shared data. Our findings are in line with existing IS studies on data as a phenomenon shaped by their provenance – that is, by the methods, procedures, and technologies used to generate, clean, and disseminate the data (Barley & Bechky, 1994; Mikalsen & Monteiro, 2021; Parmiggiani et al., 2022; Porter, 1996). Our work is also in line with Porter's (1996) work on the pursuit of objectivity in science and public life (Porter, 1996). Without this work, science data risk becoming mere signs or symbols that have little or no meaning to future (re)users.

As IS scholars have pointed out practice-oriented perspectives risk becoming near-sighted in the sense of downplaying broader historic and institutional contexts that go beyond the "here and now" (Ribes & Finholt, 2009). Issues of long-term and continuity repeatedly come to the fore in our analysis. We suggest that ongoing datafication is likely to face challenging issues of longevity and continuity, especially in the context of data curation issues. Our work contributes a "long-now" perspective (Ribes & Finholt, 2009) on the work practices performed today with the view to share science data over longer time periods for future generations. Research on frames emphasizes that people view technologies, processes, and policies through different lenses influenced by their social, cultural, and personal contexts (Davidson, 2006; Dzhengiz & Hockerts, 2022; Orlikowski & Gash, 1994). We extend this understanding to the idea that frames for data sharing evolve over the long term. Data sharing frames are inherently not static, but rather dynamic and subject to change as people's understanding of their data, technologies, work processes, and policies change over time.

Our study has implications for data governance in distributed data infrastructures. Data governance comprises strategies to harness the potential of data throughout their lifecycle (Khatri & Brown, 2010; Otto, 2011; Parmiggiani & Grisot, 2020). The challenge for IS literature has been to specify how practices by local actors dynamically shape data infrastructures (Parmiggiani & Grisot, 2020), and to conceptualize data governance in a way that more sustainable approaches to governing long-term infrastructures can be realized (Ribes & Finholt, 2009). Given data sharing frames, researchers are encouraged to not only develop frameworks and strategies for governing data, but also to show the actual data handling practices of local actors in specific technology use contexts. These may include the methods, capabilities, and knowledge that are developed now and, in the future to handle data (Leonelli, 2019a). This may unearth local actors' perspective in various contexts and inform an approach to organizational data governance that is oriented more toward inclusion and collaboration.

Our analysis can be used to argue that characterizations of Open Science agenda (Karasti 2010) brings new salience to scientific practice which have always been vital to successful empirical research, and yet have often been overlooked by policy-makers, funders, publishers, philosophers of science and even scientists themselves, who in the past have tended to evaluate what counts as 'good science' in terms of its products including: new claims about phenomena or technologies for data collection and analysis rather than in terms of the processes through which such results are eventually achieved. These aspects include the processes involved in valuing data as a key scientific resource; situating data in a context within which they are generated, interpreted reliably; and credit mechanisms so that data sharing is supported and regulated in ways that are conducive to the advancement of both science and society.

Given that data sharing frames can lead to understanding local actor's behaviors and cultures of data management, organizations, particularly those involved in distributed and long-term sharing of science data can adopt this perspective to understand the role of its members toward managing common elements of the distributed data management cultures. For practical purposes, organizations are encouraged to schedule time and identify local contexts within which data management activities occur so that they can learn from mistakes and help shape data-related projects and outcomes. Organizations are also encouraged to be aware of the different actor groups, recognize the importance of mutual respect for these roles, and find opportunities to learn about and empower marginalized groups.

Conclusion

In drawing attention to the gulf between the way science data are commonly presented and the way that they are produced and disseminated in practice, our aim is not to dismiss the significance or potential of opening access to science data to transform organizations and society. Rather we aim to encourage a richer awareness of the complexities of data and of the often-unrecognized articulation work that is involved in making them accurate and meaningful for future use. Knowledge of this work, moreover, should encourage greater recognition of the social processes that shape data and of the scope for intervention to influence their production and use (Jones, 2019).

By connecting the research streams on data curation, sensemaking frames and data governance we hope to have opened up opportunities to understand how connecting these streams of literature can provide a better understanding of the nature of data – including their production, use and management in specific contexts. Although we foreground our analysis in the practice-oriented literature in IS, we recognize that our work has the potential to contribute to discussions on "openness", a phenomenon characterized by transparency, access, participation, and democracy (Diriker et al., 2023; Schlagwein et al., 2017). Our study opens up the agenda for future research in this area. For researchers interested in Open Data there are interesting opportunities to examine the democratizing effects of using publicly accessed science data, how heterogeneous science data sets are managed for open sharing in specific local contexts, how curators anticipate future reuses of open data, and how data owners and data users balance the intricacies of formal plans and empirical contingencies. Our future work will examine the practices that actors use to resolve tensions in data management plans.

In closing, it is our hope that our contribution of data sharing frames articulated in the three frames of work practices may provide a fertile breeding ground for pursuing a research program that often "gets under the hood" in IS through practice-oriented studies.

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