Data sharing: an integral part of research practice?

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Abstract: Sharing research data is now recognised as an integral part of scientific work and as a service to the public, contributing to the development of knowledge and the transparency of research. However, as many studies have shown, data sharing policies and practices vary widely across disciplines, countries; and funding bodies, and ultimately depend on the motivation and attitudes of individual researchers. The author focuses on researchers' attitudes to data sharing, drawing on an extensive literature review of data sharing studies. The author describes the factors that influence researchers' data sharing at an individual level, and the motivations and barriers that prevent effective access to data.
Keywords: data sharing, attitudes, barriers to data sharing, motivation

1. Introduction

Data sharing is not a new issue related to the boom of digital technologies in the last three decades, but it has been discussed since the 1960s, as shown by examples of studies from the social sciences (e.g. Wollins, 1962; Craig and Reese, 1973).

The most commonly reported benefits of data sharing are the ability to reproduce or verify research, the availability of publicly funded research to the public, which allows other researchers to ask new questions, and scientific progress (Borgman, 2012). Data sharing contributes to the transparency and trustworthiness of science (Abele-Brehm et al., 2019), supports better decision making in both government and business (Darby et al., 2012; Hate et al., 2015), saves time and money by avoiding repetitive experiments (Chawinga and Zin, 2019; Wu and Worrall, 2018), and helps the public understand science (Darby et al., 2012). Despite these widely recognised benefits and pressure from research stakeholders to make data publicly available, there are still many factors that hinder data sharing at individual, institutional and international levels (Chawinga and Zin, 2019). In this study, the author focuses on the individual level, and through a qualitative review of empirical studies, seeks to categorise

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the factors that influence data sharing, both positively and negatively, and to provide a framework of motives and barriers for further research.

2. Literature review

There is a need to identify and address the motivations and barriers to data sharing, given the significant benefits of data sharing on the one hand, and the reluctance of researchers to share data openly on the other. One of the first large-scale studies on data sharing practices, conducted by Tenopir et al. (2011), showed that researchers were willing to share data under certain conditions, including formal acknowledgement of the data producer, formal citation of the data, and also the possibility to retain some control over data use, which can be materialised in a data sharing agreement or in the review and approval of the secondary analysis results. The barriers identified in this study, namely lack of time, lack of funding, lack of infrastructure and lack of standards for data sharing, have been consistently identified in the subsequent research (Tenopir, 2015) up to the present day.

In order to clarify the factors influencing data sharing, several frameworks have been proposed. Three of them are mentioned here, as they provided inspiration for the subsequent work. Based on the literature review, Fecher et al. (2015) divided the factors into six groups, i.e. data donor, research organisation, research community, norms, data recipient and data infrastructure. Based on the theory of knowledge infrastructure and the theory of remote scientific collaboration, Jeng et al. (2016) built a profiling tool to capture data practices specifically in the social sciences. However, it is more oriented towards real practices and behaviour, and the motivation and barriers form only a minority of the items (i.e. motivation, individual characteristics, data sharing norms). De Souza et al. (2021) created a framework for data sharing perspectives and attitudes using institutional theory and the theory of planned behaviour. Their framework, which is still in a proposal stage, is organised into three dimensions: institutional, which includes cognitive, normative and regulative indicators; researcher, which includes career, resource and social indicators; and analysis, which lies in between.

Chawinga and Zin (2019), in their systematic review of papers on data sharing, present the challenges of data sharing in three levels: individual, institutional and organisational. At the individual level, two demographic factors (age, seniority) and three others (control over data, lack of time and data misappropriation) are mentioned. At the organisational level, data sharing skills, availability of data sharing compensation, and organisational policies, and at the international level, international research policies, publisher and funding agency policies, rights management issues, ethical and legal standards, interoperability issues and research data infrastructure. Several important themes related to the challenges of data sharing also emerged from the metasynthesis by Perrier et al. (2020), which focused exclusively on qualitative studies. This perspective is important as the focus is on discovering how researchers perceive the data sharing landscape, without giving them pre-determined answers that would channel their thoughts. The issues that influence data sharing either positively or negatively include, unsurprisingly, misuse of data, protection of intellectual property, privacy and ethical issues, control of data, work culture, concepts related to the feasibility of data sharing (infrastructure, time and skills), and benefits to society and to the researchers themselves.

3. Methods

Data collection methods. Web of Science and Scopus were chosen to identify studies because of their multidisciplinary nature. The author performed the search using a fairly broad search strategy (see Table 1), which yielded 556 and 806 results respectively. The records were loaded into MS Excel for de-duplication, leaving 880 records. After checking the titles for relevance, the author excluded 734 records and proceeded to obtain the full text of the remaining 146 papers. The full texts of 4 articles were not available to the author, and a further 62 articles were excluded after reading the full texts because of language barrier or because they a) did not report the results of original studies, b) were either reviews or opinion papers, c) did not mention the motivation for sharing and/or barriers to sharing data. The author also conducted a Google Scholar search, which identified a further 3 studies not included in the previous searches. A total of 83 studies were included in the analysis.

Table 1. Overview of search strategies

Web of Science	("data sharing" OR "open data") NEAR/3 (research* OR scientist*) AND (attitude* OR behavior OR factor* OR motiv* OR barrier* OR inhibit* OR concern* OR fear* OR influenc* OR incentiv* OR practice) (Topic)
Scopus	(research* OR scientist*) W/3 ("data sharing" OR "opendata") AND (attitude* OR behavior OR factor* OR motiv* OR barrier* OR inhibit* OR concern* OR fear* OR influenc* OR incentiv* OR practice)

Data analysis methods. The author developed a data extraction form with predefined data elements as described by McKibbon (2006), including author and title of the paper, date of publication, country and discipline of participants, data collection and data analysis methods used in the studies. When reading the articles, the author focused on the incentives, motives, fears and barriers associated with data sharing. Thematic coding was used to describe these (for the list of codes see supplement]. After the first round of coding, the resulting codes were unified, and all articles were re-coded. The codes were then grouped into categories at a higher level of abstraction and finally a framework was constructed to show them in relation to each other. The list of codes together with corresponding references and the list of all studies included in the analysis are available as a supplement material.

4. Results

Overview of studies. Of the included studies, 58 used quantitative data collection methods, 20 were qualitative and 5 studies used both types. Details of study designs are given in Table 2. The most commonly used background theory was the theory of planned behaviour, used 11 times, while institutional theory was used 5 times. Twenty-five studies included researchers from multiple disciplines, while the others concentrated on one or two disciplines, some of which were very narrow, such as earthquake engineering (Wu and Worrall, 2019), plant phenotyping (Ugochukwu and Phillips, 2022), and human movement research (Obiora, 2022).

Table 2. Data collection methods of included studies.

Data collection method	No of studies
Survey	59
Interviews	23
Focus groups	6
Documents analysis	2
Observations	2
Randomized controlled trial	2
Secondary analysis	2
Archival notes	1
Case study	1
Data platforms examination	1
Group discussion	1
Vignettes	1
Website analysis	1

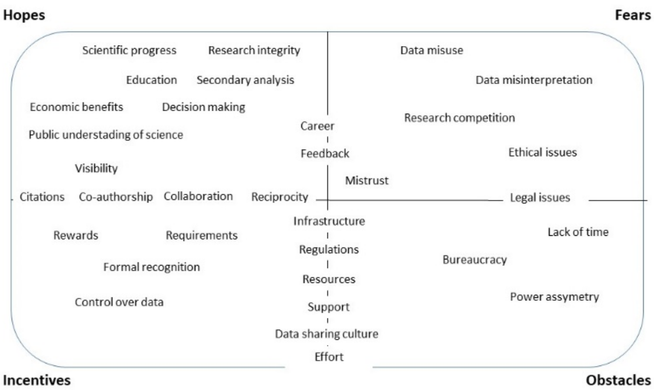
Demographic factors. There are a number of demographic factors that have been suggested to influence data sharing intentions and behaviours, namely age, career stage, discipline and gender, but the nature of the influence varies widely and often the conclusions are based solely on descriptive statistics, so the author does not include them in the proposed framework.

Data sharing. According to several recent studies, the percentage of researchers who either share or are willing to share data is promising, although the meaning of data sharing in individual studies varies and does not always mean sharing data openly. According to Klingner et al. (2023), 45% (N=218) of German neurologists share data publicly, the most recent large study by Tenopir et al. (2020) reports 87% (N=2184) of researchers from different disciplines willing to share, Saeed and Ali (2019) say 55.4% of social scientists and 53.4% of life scientists share data. However, the survey instruments are very different, which prevents any attempt at meta-analysis that would shed more light on the data sharing landscape.

HIFO framework. During the coding and analysis, a certain framework emerged, which is called HIFO, according to the four main groups of codes: hopes, incentives, fears and barriers. As with many attempts at categorisation, these groups are not disjunctive and some categories can be included in more than one group, depending on the perspective, as can be seen in Figure 1.

Hopes are understood as positive outcomes or experiences that researchers hope to achieve by sharing data, either for themselves, for the scientific community, or for the public, e.g. transparency of research, acknowledgement or recognition. Starting from the highest level, the benefits to society fall into three main categories. Data sharing brings economic benefits as it means better use of resources spent on research by avoiding duplication of research. Better decisions can be made by governments and businesses on the basis of the wide range of data available, and the public can also monitor the policy-making process and hold government to account. Finally, opening up data can contribute to a better public understanding of science.

Figure 1. HIFO framework



The benefits to the scientific community are many: from the outset, data sharing has been seen as a major contribution to scientific progress, facilitating multidisciplinary collaboration and inspiring researchers in other fields. First and foremost, data sharing means increasing the integrity and transparency of research and better policing of questionable scientific practices. The availability of data for secondary analysis allows new questions to be asked, results to be compared and large datasets to be better analysed. It contributes to educating and inspiring young researchers.

What the researcher can hope for partly creates a subset of both hopes and incentives. For example, citations or co-authorship can be either a hope or an incentive in communities with a strong data sharing culture where such practices are common. The same is true of collaboration, which increases the likelihood of publication. By making their data available, researchers can hope for greater visibility, even media interest, and feedback or validation of their results. On the other hand, the possibility of receiving feedback also creates the fear that errors in the research will be discovered and that reputations and careers will be damaged as a result.

Incentives are those external stimuli that cause or would cause researchers to share their data and are institutionally or socially based. Most of the categories of codes that fall into this group can work both ways, as both supporting and limiting factors. This is particularly the case for infrastructure, resources, regulations, support in general, formal recognition and the culture of data sharing. While existing or available infrastructure, a strong data sharing culture or formal recognition are important enablers, their absence is often cited as one of the main barriers to data sharing.

Other important incentives come in the form of requirements, which exist at three levels - institutional pressure, journal requirements and funding agency requirements, the last two being the most prominent. The intersection with the group of hopes was mentioned above, the common categories being citations, co-authorship and reciprocity. The possibility of having control over the data, through measures such as data sharing agreements or other types of contact with the user, the timing of data release, the possibility of restricting or setting conditions on data use, and the review of secondary analysis results, also supports data sharing. The last category of incentives involves trust between the donor and the recipient of the data, either at an interpersonal or community level, which can compensate for the lack of formal agreements.

On the other hand, fears and obstacles are barriers to data sharing. **Fears** can be defined in this case as reactions to potential threats associated with data sharing, i.e. what researchers fear might happen to themselves or others (research participants) if their data are shared. At the personal level, it includes the above-mentioned fear that others will uncover weaknesses in the original research and data, or that the alternative hypotheses will lead to rejection of the original results. The fear most frequently mentioned in the papers over the whole period is the fear of data misuse, followed by the fear of misinterpretation. Data misuse and misinterpretation are closely linked to several ethical concerns, most commonly privacy and potential harm to participants from misuse of sensitive data, but also disregard for context and local norms. Researchers are also concerned about a number of legal issues, not being sure whether they have the right to share data, or whether the sharing of data does not infringe the intellectual property rights of others, or whether their intellectual property rights will not be compromised.

A very rich category of fears is a category referred to as research competition, which is mainly related to making the most of the data for publications and includes fear of losing exclusivity or lead in research, fear of being scooped, and fear of theft and plagiarism.

Finally, **obstacles** are understood to be of an objective nature, independent of the researcher. Some of these have already been mentioned as the flipside of incentives, e.g. lack of infrastructure, resources or recognition, perceived effort to collect and share data, and a weak culture of data sharing. Other important barriers include lack of time, bureaucracy associated with data sharing, the data itself and power asymmetry. This last theme emerged with more contributions

from low- and middle-income countries and represents the perceived inequality in access to resources and infrastructure for research on the one hand, and the equality of access to the collected data required, for example, for publication in certain journals, on the other, and also borders on the issue of misuse of data.
The proposed framework reflects the characteristics of factors influencing data sharing intentions and behaviours from different perspectives. Each of the four quandrants can be described in terms of subjectivity/objectivity, nature of influence on data sharing, dependence on more or fewer actors, and difficulty to address (see Figure 2).

5. Discussion

Demographic factors such as age and career stage have been deliberately left out of the framework, as the evidence for their influence is often contradictory. While Chawinga and Zin (2019) conclude that younger and early career researchers are more reluctant to share, a finding further supported by Dorta-Gonzales et al. (2021), this is not the case, for example, for the study in Malaysia (Hodonu-Wusu et al., 2020) or Campbell et al. (2019), and the same is true for other factors in this group.

Figure 2. Dimensions of HIFO

Hopes Subjective Based on emotions Depend on more actors Positive influence	**Fears** Subjective Based on emotions Depend on more actors Negative influence More difficult to address
Objective Based on rationality Depend on less actors Positive influence **Incentives**	Objective Based on rationality Depend on less actors Positive influence Easier to address **Obstacles**

In this section selected categories will be discussed, that have proven to be a lasting topics of the data sharing motives and barriers discussion. Most of them fall into the fears quadrant of the framework. The label for this category was inspired by the work of Abele-Brehm et al. (2019), but together with Stieglitz et al. (2020) they can also be described as uncertainty factors, where the threat is not yet identified or realised. Uncertainty is also manifested in the fact that the codes that belong to this category and occur consistently throughout the observation period (e.g. Darby et al., 2012; Hate et al., 2015; Tenopir et al.;

Krahe et al., 2023) have no clear definition. Data misuse is one of the most prominent concerns that has not changed over time, but in most papers it is simply referred to as data misuse without further clarification of the meaning of the term. This can be partly attributed to the 'inheritance' of items in surveys, but the qualitative studies do not provide more help. Data misuse is often perceived as a potential risk rather than an experienced problem, and includes both intentional and unintentional misuse (Jao et al., 2015). The few authors who describe data misuse in more detail refer to it as the use of data for purposes for which it is not suited, or to justify arguments that the contributor would find unacceptable, or the use of data in a way that was not originally agreed or understood (Jao et al., 2015), which may result in harm to the data contributor or participants (Hate et al., 2015). It is often mentioned in the context of data misinterpretation, which is also mostly undefined. Ethical and legal issues are also sources of anxiety and uncertainty and are often mentioned as such broad concepts. In the case of ethics, some authors specify them as problems with sensitive data, threats to the privacy of participants and potential harm to them (e.g.Hate et al., 2015; Cheah et al., 2015), legal concerns are mostly attributed to uncertainty about intellectual property rights and authorship (e.g. Al-Ebbini et al., 2020; Melero and Navarro-Molina, 2020; Zuiderwijk and Spiers, 2019). More obvious is the fear of research competition, which includes the fear of losing either the opportunity to make the most of the data for publication (e.g., Al-Ebbini et al., 2020; Bezuidenhout and Chakauya, 2018) or the lead in research (e.g., Fiialka et al., 2022; Majid et al., 2018). The problem with this category of factors is the subjectivity and emotionality that, combined with uncertainty about the potential threats, makes them the most difficult barriers to address, but more in-depth research into them could help in overcoming them.

Lack of time and effort are borderline concepts between fears and barriers, as decisions to share or not share data are often based on the belief that it is either worth the time and effort or not. These two factors are often combined into the perceived effort factor, which has been shown to have a negative impact on data sharing (e.g. Harper and Kim, 2018; Kim, et al. 2018).

Moving to the positive side, let us discuss the hopes and incentives. Apart from the benefits to science and society, citations and collaboration are the most cited incentives or hopes, depending on the perspective (either the researcher hopes to get more citations by sharing data, or he/she can be sure to be cited due to a strong data sharing culture). It is strongly related to the prevailing data sharing culture and depends on whether sharing is expected, seen as important, and whether other researchers participate in data sharing (Harper and Kim, 2018), creating the so-called normative pressure that Kim (2017;2018; etc.) has explored in several of his studies. The requirements of journals and funding agencies, which also help to create a culture of data sharing at the disciplinary, national or even international level (Chawinga and Zin, 2019), can then be seen as pure incentives.

With the exception of power asymmetry (Abebe et al., 2021; Hodonu-Wusu 2020), no new concepts have emerged from this review compared to the systematic reviews by Chawinga and Zin (2019) and Perrier et al. (2020), so its value lies mainly in the rearrangement of topics, which should help to frame the research more thoroughly and address the issues appropriately. So far, the HIFO has not been empirically tested, similar to the framework of de Souza et al. (2021), with which it shares several concepts but differs in their arrangement and detail. It does not aim to cover the whole landscape of data sharing like Fecher's (2015) framework, but focuses more on motives and barriers.

Limitations. This review does not aim to be a meta-synthesis or systematic review for several main reasons. On the one hand, the search was limited to Web of Science, Scopus and Google Scholar, so it cannot be said to be exhaustive. On the other hand, the concepts related to the motivating and inhibiting factors of data sharing identified in the selected studies tended to repeat themselves, only the wording used differed. Therefore, the process reached the level of thematic saturation, defined as a point when, according to Urquhart, there are increasing instances of the same codes but no new ones (Urquhart, 2013). As can be seen in the table, the studies have different research designs, which makes the results incomparable. Even within the group of quantitative studies, comparability is limited by the different types of questions used in the surveys and the many different angles from which data sharing is considered, such as attitudes towards data sharing, existing data sharing practices and behaviours, or asking about hypothetical data sharing situations. The author also fully agree with Thoegersen and Borglund (2022) who found in their meta-evaluation that there is a lack of common understanding of data sharing and explicit definitions of data sharing across studies, with data sharing concepts used in the included studies ranging from open data sharing via repositories to data sharing including sharing within one's own research group. There is also great variability in how the positive and/or negative factors influencing data sharing are labelled.

6. Conclusion

Despite the undisputed benefits and promising numbers of researchers that share or want to share data, data sharing is not as widespread as it could be for a variety of reasons. In this study, based on a qualitative review of primary studies, the author sought to develop a framework that captures the incentives and barriers to data sharing in a holistic way and reflects the characteristics of factors influencing data sharing intentions and behaviours from different perspectives. The aim was not to propose solutions to problems, but to provide a framework for in-depth research into the motivations and barriers to data sharing.

Supplemental material. List of codes together with references of all included papers is available at https://doi.org/10.5281/zenodo.7876975.

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