# The Field-Specificity of Open Data Practices

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**Abstract:** Increasingly, researchers are expected to make their research data openly available. However, scientific fields differ in their research practices and norms for sharing research data publicly. We provide quantitative evidence of differences in data practices and the public sharing of research data at a granularity of field-specificity that is rarely reported in open data surveys. Based on a survey of 8,822 researchers at German Universities, we find considerable variation, within and across disciplines, of data practices and rates of open data sharing. For experimentally oriented subject areas we further observe a relationship between data self-sufficiency and public data sharing which likely reflects a link between data sharing and the epistemic specificity of data. Our findings underline that in order to quantitively assess and evaluate rates of public data sharing, a better understanding of the embedding of public data sharing into field-specific research practices is needed.

#### **1. Introduction**

The public sharing of research data is not a new phenomenon. For example, star catalogues have been publicly shared by astronomers since ancient times, enabling scientific discoveries, such as the discovery of the precession of the epinox by Hipparch in the 2<sup>nd</sup> century B.C. (Goldstein & Bowen 1991). With digitization and the advance of the Internet, the technical capabilities to make research data widely available have vastly increased, triggering a movement to make the public sharing of research data a new standard for publicly funded research (Kroes, 2012; Holdren 2013; OECD 2015; CNRS 2016; Wellcome 2017, Commission Recommendation (EU) 2018, G6 2021).

To inform research policy and other stakeholders about the state of public data sharing, a growing number of survey studies has sought to quantify the extent to which researchers embrace the idea of public sharing and follow suit in their practices. However, the coverage in terms of disciplines and countries as well as sample sizes differ widely between these survey studies, as do the ways in which the phenomenon of sharing research data is operationalized. Consequently, the empirical evidence about different forms of sharing, across disciplinary or (inter)national contexts, is still sketchy. Some general trends about the state of data sharing, however, seem fairly well supported: that there exists a gap between support for the idea of public data sharing, and actual practice (e.g. Ambrasat & Heger 2020, Zhu 2020, Tenopir 2020, Nicholas et al. 2020, Fecher 2017), and that a number of hindrances exist that either delay or entirely prevent the public sharing of data, such as the effort involved in preparing data for sharing, the sensitivity of data, or concerns about a lack of control over the (re)use of the data by others (see e.g. Campbell et al. 2002, Tenopir 2011, 2015, 2020, Zhu 2020, Nicholas et al. 2020, Aleixandre-Benavent 2020).

The degree to which sharing practices differ between disciplines and research fields, however, have received only scant attention. Whereas most surveys apply some sort of field classification, most multidisciplinary surveys use rather coarse classifications (e.g. Goodey 2022, Stuart et al. 2018, Fecher et al. 2017) or use this information merely to describe the overall composition of their sample rather than a systematic analysis of field differences (e.g. Aleixandre-Benavent et al. 2020; Choi & Lee 2020). A rare exception are the studies by Thursby et al. (2018) on pre-publication disclosure of results, and Kim & Stanton (2012) on

public sharing of research data upon publication of results. Their statistical analysis confirms the existence of field differences in rates of sharing, and both studies agree that the strength of sharing-supporting norms in a field correlates with the reported sharing. However, neither study examines the underlying reasons why sharing supporting norms emerge more strongly in some fields than in others.

One hypothesis is that field-specific norms of sharing are the result of field specific epistemic practices (Steinhardt et al. 2022, Thursby et al. 2018, Velden 2013), i.e. the specific way of how knowledge is produced in a field: the empirical objects that are studied, the methods used, and the theories developed, which in turn influence data practices – the type of data and how they are produced and used (Borgman 2012). To further explore the field-specificity of public data sharing and how it is linked to the underlying research practices in a field, we examine the data provided by the *DZHW Science Survey* (WiBef), a large survey of over 8,000 researchers at German universities. It offers data on data practices and data sharing at a much finer resolution than most multidisciplinary open data surveys provide, bringing us closer to the level of analysis required for investigating links between epistemic practices and data sharing.

# 2. Data and Methods

## 2.1. The data source

The data we use is from WiBef, a representative tri-annual trend study about the German Science System covering a variety of topics. The data collection was conducted between November 2019 and February 2020. The questionnaire was sent to a total 60,002 researcher from German universities, 52,769 of the emails were delivered. The 8,822 received valid responses represented a 16.72% response rate. For more details about the overall survey design see Ambrasat et al. (2020).

In this study we evaluate the information collected through a survey instrument that asked a set of questions about the role that research data plays in a respondent's research practice, which included a question about the public sharing of research data.

## 2.2. Survey instruments

Information about the *field affiliation* of researchers was collected using a two-level classification covering humanities & social sciences, engineering, life sciences, and physical sciences. The questionnaire offered respondents 10 disciplines to choose from, and within each discipline, one to eight different subject areas, such that in total 39 subject areas are distinguished. This relatively fine-grained classification is largely based on the field classification used in 2016-2019 by the German Research Foundation (DFG), with some small modifications. The subject areas correspond to review committees in the DFG grant review system (so called 'Fachkollegien').

In the following analysis we will distinguish *data practices* with regard to the role that data play in the practice of research, namely whether researchers produce data themselves (alone or in a team), use data from third parties in their research, or do not work with data at all.

Discipline	Sample size	Subject area	Sample size
Social and Behavioural Sciences		Educational Sciences	344
		Jurisprudence	139
	1968	Psychology	473
	1908	Social Sciences	62
		Economics	38
		Other	(
Humanities		Fine Arts, Music, Theatre and Media Studies	197
		Linguistics	304
		Literary Studies	270
		Philosophy	111
		History	294
		Religious Studies, Jewish Studies	24
		Social and Cultural Anthropology	7:
		Theology	11:
		Other	4
Engineering Sciences	1383	Heat Energy Technology, Process Engineering	154
		Materials Science, Materials Engineering	11'
		Mechanical Engineering, Production Technology	27
		Electrical Engineering, Computer Science,	
0 0		Systems Technology	629
		Construction Engineering and Architecture	204
		Other	
Medicine	507	Human Medicine	47
		Veterinary Medicine	3
		Other	
Biology	1025	Zoology	11
		Basic Biological and Medical Research	408
		Microbiology, Virology and Immunology	18
		Biochemistry	14
		Plant Sciences	15
		Other	15
Agricultural, Forestry,			
Horticulture	127	Agricultural, Forestry, Horticulture	12
	1 n/1	Astrophysics and Astronomy	6.
Physics		Condensed Matter Physics	203
		Optics, Quantum Optics and Physics of Atoms,	148
		Molecules and Plasma	140
		Particles, Nuclei and Fields	10.
		Statistical Physics, Soft Matter, Biological	9(
		Physics, Non-linear Dynamics	
		Other	14
Mathematics	397	Mathematics	39
Geology	474	Geology	47-
Chemistry	576	Chemical Solid State and Surface Research	6
		Molecular Chemistry	12
		Physical and Theoretical Chemistry	14
		Analytical Chemistry, Method Development	6
		(Chemistry)	0
		Biochemistry	10
		Polymer Science	6
		Other	1
No assignment			29
Total			882

# Table 1. Sample sizes by discipline and by subject area.

The *rate of sharing research data publicly* is determined by the proportion of respondents in a subject area who affirm that they make research data that they collect or produce 'publicly available to other scientists, regularly or occasionally.'

# 2.3. Realized field-specific sample sizes

Different from surveys that work with convenience or snow-ball samples, the stratified, random sample of the WiBef can be considered representative of researchers at German Universities. An overview over the achieved sample sizes of the different disciplines and subject areas is given in Table 1.

Due to the stratification of the sample by level of seniority and the variance of response rates by level of seniority, we apply a weighting scheme that adjusts observed proportions by respective weights in order to increase the representativeness of results for the targeted population (see Ambrasat et al. 2020). The data structure regarding level of seniority before and after weighting is shown in Table 2. All results reported in the results section are calculated after weighting of the data.

Seniority level	Professor	Postdoc	PhD Student	Total
Weights	0,854	0,578	1,704	Mean = 1
Sample structure				
- before weighting	1721	4216	2885	8822
- after weighting	1469	2437	4916	8822

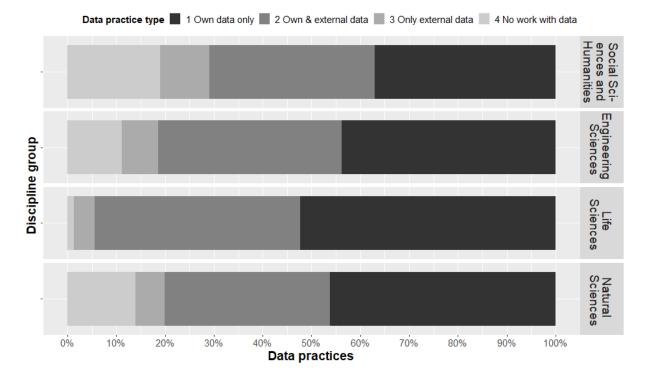
## 3. Results

## 3.1. Variation in data practices

Figure 1 compares data practices between Humanities & Social Sciences, Engineering, Life Sciences, and Natural Sciences. It shows that in each broad disciplinary grouping a large majority, over 75% of researchers, work with data. We see that the Life Sciences are highly empirically oriented: only 2% of researchers do not work with data. Next are Engineering and the Natural Sciences, with 11%, respectively 14% of researchers saying that they do not work with data. The highest proportion of researchers who do not work with research data is reported for Humanities and Social Science (approx. 20%).

Moving to a more fine-grained resolution, at the level of subject areas (figure 2), we find stark differences in data practices, even within the same discipline.

We can now identify distinctively 'data distant' fields, such as Philosophy, Literary Studies, Theology, Mathematics, and Jurisprudence, where most researchers do not work with data. At the other end of the spectrum, we have strongly empirically oriented subject areas, such as Agriculture, Polymer Science, Zoology, Biochemistry (Biology), and Psychology, where almost everyone (>99%) reports to be working with research data.



# Figure 1: Data Practices by High-Level Disciplinary Grouping

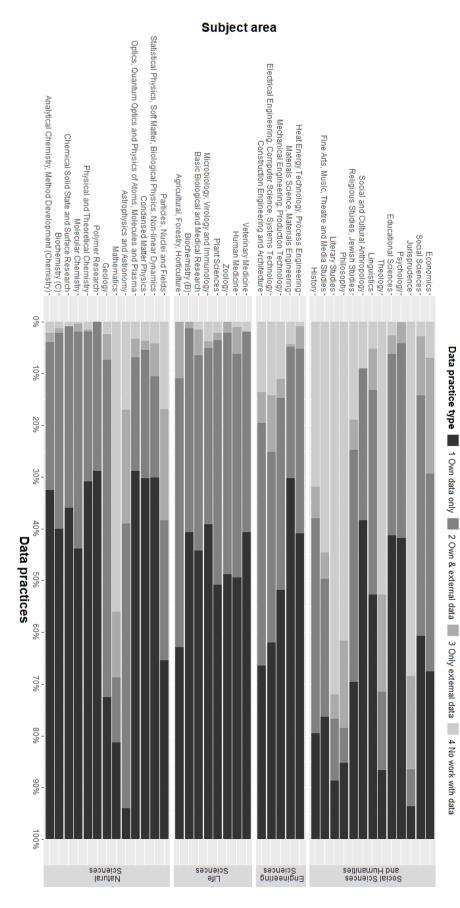
Among empirically oriented subject areas where a large majority of researchers work with data, we find differences regarding whether data from third parties are used, or whether researchers rely exclusively on data they produce themselves.

If we label researchers who work exclusively with their own data (i.e. produce data and do not work with data from third parties) as **'data self-sufficient'**, we find in most disciplines subject areas where a majority of researchers is data self-sufficient: in Humanities (Social And Cultural Anthropology), Social and Behavioural Sciences (Psychology, Educational Sciences), Engineering (e.g. Materials Science & Materials Engineering), Medicine (Veterinary Medicine), Biology (e.g. Biochemistry, Microbiology, Virology & Immunology), Chemistry (All Subject Areas), and Physics (e.g. Condensed Matter Physics).

In other subject areas the majority of researchers are '**data combiners**'<sup>1</sup>, i.e. researchers who produce data themselves and use data provided by third parties. This is the case in Geosciences, Agricultural, Forestry & Veterinary Medicine, and Astronomy & Astrophysics.

Further, we note that some of the empirically oriented subject areas have a comparatively large fraction of researchers (15-25%) who we may refer to as **'data consumers'** because they do not produce data themselves, but instead exclusively rely on data provided by third parties (Astronomy & Astrophysics, Particles, Nuclei & Fields, and Economics).

<sup>&</sup>lt;sup>1</sup> We have to interpret the label of 'data combiners' with caution, in so far as these are researchers who have specified that they produce data themselves (or in a team) and that they use data in their research that has been provided by a third party. This does not necessarily imply that they combine own and third-party data within the same research project.



# Figure 2: Data Practices at Subject Area Level

#### 3.2 Variation in public data sharing

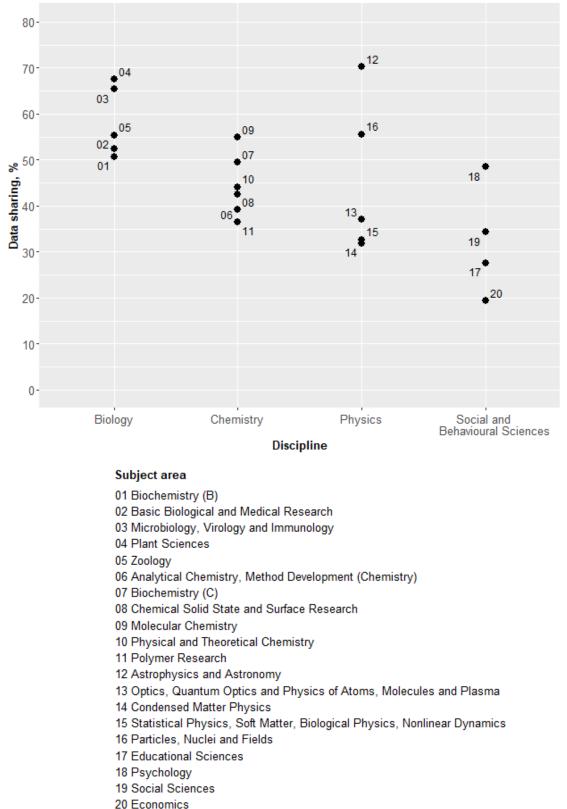
To probe the connection between research practices and the public sharing of research data, we select four disciplines: Biology, Chemistry, Physics, and Social & Behavioural Sciences<sup>2</sup> for closer examination where most researchers produce data and hence face the question of whether to publicly share this data or not.

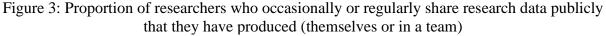
Table 3 and figure 3 show the rates of public data sharing for the subject areas in the selected disciplines. They reveal considerable variation across and within disciplines. The rates of public data sharing range from 70% in Astronomy & Astrophysics at the high end to 19% in Economics at the low end. The within discipline variation between subject areas is highest in Physics and Social Sciences, and lower in Chemistry and Biology.

Discipline / Subject area	Rate of public sharing
Biology	
01 Biochemistry (B)	51%
02 Basic Biological and Medical Research	52%
03 Microbiology, Virology and Immunology	65%
04 Plant Sciences	67%
05 Zoology	55%
Chemistry	
06 Analytical Chemistry, Method Development (Chemistry)	39%
07 Biochemistry (C)	49%
08 Chemical Solid State and Surface Research	42%
09 Molecular Chemistry	55%
10 Physical and Theoretical Chemistry	44%
11 Polymer Research	37%
Physics	
12 Astrophysics and Astronomy	70%
13 Optics, Quantum Optics and Physics of Atoms, Molecules and Plasma	37%
14 Condensed Matter Physics	32%
15 Statistical Physics, Soft Matter, Biological Physics, Non-linear Dynamics	33%
16 Particles, Nuclei and Fields	56%
Social and Behavioural Sciences	
17 Educational Science	28%
18 Psychology	48%
19 Social Sciences	34%
20 Economics	19%

Table 3. Rates of public sharing by subject area.

 $<sup>^2</sup>$  In the analysis that follows, we omit Jurisprudence (formally grouped into the social sciences by the DFG classification), due to its very low rate of data production. The reported public sharing rate among the data producers in this subject area is 0%.





However, the disciplinary affiliation of subject areas tells only part of the story of their epistemic practices. To learn more about the dependency of rates of public sharing on epistemic practices, we juxtapose in figure 4 the public data sharing rate among data producing scientists in a subject area with the rate of data self-sufficiency among them. Data self-sufficiency may serve – in first approximation – as indicative of an experimental research orientation. Research that is experimentally oriented generates data under controlled conditions to address a specific research question. Such data are epistemically highly specific, produced by the researchers themselves in custom made experimental set-ups, rather than obtained from a third party (Borgman 2012).

In figure 4 we can identify a large group of subject areas (**Group I**) that displays a linear association between rate of data self-sufficiency and rate of public sharing. Then there is a second group of six subject areas that are outliers in so far as that they deviate in one or the other way from group 1 (**Group II: subject areas 03, 04, 12, 17, 19, 20**).

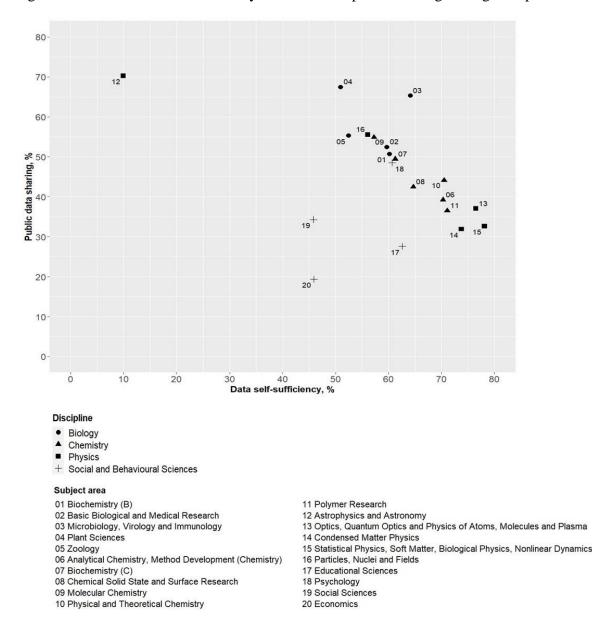


Figure 4: Rate of data self-sufficiency versus rate of public sharing among data producers

**Observations regarding Group I** (linear trend): All subject areas in this group have a pronounced rate of data self-sufficiency (> 50%), suggesting a high relevancy of experimental methods. We observe a linear trend for this group: the more data self-sufficient, the lower the rate of public sharing of research data. Three subject areas in Physics occupy the low end of this spectrum, with high data self-sufficiency, and public data sharing below 40%. At the upper end of the spectrum, we find subject areas with higher rates of public sharing, and lower rates of data self-sufficiency. Among them are subject areas such as Molecular Chemistry, and Basic Biological & Medical Research, which produce (and use) data such as genetic sequences and molecular structures, which are stored and made available in global databases. Whereas experimental data from custom made experiments often is scientifically exploited after its original analysis and considered of limited re-use value (Akmon 2014), molecular structures and genetic sequences are forms of data that are highly standardized and have great re-use value for scientific research (Borgman 2012). The lower rate of self-sufficiency along with the higher rate of public sharing could be indicative of a mutual interdependency of researchers in these subject areas regarding data they produce and use.

**Observations regarding Group II** (**'outliers'):** This group of subject areas shows a disparate pattern. We can distinguish two subgroups: three Natural Science subject areas with an extremely high rate of public data sharing  $\geq 65\%$ ). The second subgroup consists of three subject areas in the Behavioural & Social sciences that expose a low rate of public data sharing (< 35%).

Among the three natural science subject areas, Astronomy & Astrophysics is set apart by an extremely low rate of data self-sufficiency. It is a distinctively observational field, unified by a common type of empirical data: electromagnetic radiation reaching Earth from the sky. Combining digital observational data from various sources is a frequent practice (Genova 2018, Hoeppe 2014), which would align with the low rate of data self-sufficiency reported here. In Plant Sciences a great diversity of sources of empirical data exists, such as genetic analyses, lab based or field-based experiments, and observational fieldwork. The data self-sufficiency and the rate of public data sharing reported for this subject area likely represent an aggregate that conflates a wide range of epistemic practices and types of data shared. Finally, Microbiology, Virology & Immunology combines a relatively high rate of data self-sufficiency of > 60% with a high rate of public data sharing. This suggests a proliferation of research data, possibly through high-throughput genome sequencing (Connor et al. 2016, Loman & Pallen 2015), and could be indicative of a division of work in this subject area in that a section of researchers is primarily engaged in the production of research data, without the use of third party data, which is then publicly shared and re-used by others.

The three Social & Behavioural Science subject areas in group II, by contrast, are characterized by a low rate of public sharing, below 35%. The subject area of Educational Sciences is an interesting case because it is characterized by a higher level of data self-sufficiency, above 60%, than the other two subject areas in this subgroup, Social Sciences and Economics. In these latter two subject areas most data producers also use data provided by third parties. Major sources of data used in these fields are social and economic statistical data provided by state authorities or large-scale survey projects (Hessel et al. 2019; Einav & Levin 2014). In the subject area of Social Sciences, the sharing of survey data is rather institutionalized, with institutions collecting and making survey data available under a range of access conditions, including public sharing. This applies mostly to quantitative data however, as the public sharing of qualitative data through publicly accessible repositories is only in its infancy. Notably, researchers in Economics who produce data report a lower rate of public sharing compared to Social Sciences

which may have to do with an increasing role of private sector data that is acquired for research through data sharing agreements that limit distribution (Einav & Levin 2014).

## 4. Discussion

Our analysis shows strong variation of data practices and rates of public sharing at the subject area level, across and within disciplines. The observed association between public data sharing rates and data-self-sufficiency suggests the relevance of epistemic practices such as experimental orientation, the specificity of data produced, and the need to combine data from diverse sources, for explaining rates of public data sharing.

This study is only a starting point for quantifying differences in data sharing between research fields. Research is highly diverse in its epistemic practices, and what constitutes data, how these data can be made available and (re)used, differs widely (Steinhardt et al. 2022, Leonelli & Tempini 2020, Kurata et al. 2017, Borgman 2012). Underlying this diversity is a variety of different 'data economies' – social systems of research data production and use that get supported by different forms of exchange and accompanying norms for data sharing. Therefore, to evaluate and compare rates of public sharing we need to consider the underlying epistemic practices, which are insufficiently operationalized by the discipline classifications systems used in most open data surveys (Gläser 2018). Even a field classification at the level of granularity used here, is bound to conflate different methods of data production and different types of data that come along with rather different opportunities and limitations for re-use.

# **5.** Conclusions

A field-comparative analysis of survey data collected from researchers at German Universities in 2019/2020 shows variation of data practices and rates of public sharing of research data across and within disciplines. Among empirically oriented sciences, we find a large group of subject areas with an association between data self-sufficiency and rates of public data sharing. The variation of sharing rates and its interdependency with epistemic practices suggests that to collect meaningful data for comparative and evaluative assessments of the state of open data, we need to go beyond mere field classifications and develop more sophisticated instruments to capture relevant dimensions of epistemic practices and the data economies that support them.

## **Open science practices**

The survey instrument of the DZHW WiBef survey can be downloaded from: <u>https://doi.org/10.21249/DZHW:scs2019:2.0.0</u>. This way the way the survey data has been generated is more transparent. Further a method report is available that gives detailed insight in how the survey was designed and conducted (Ambrasat et al. 2020). The actual survey data itself is also available for further research, via the FDZ-DZHW data repository. It and can be accessed upon application for analysis via remote desktop free of charge (see Ambrasat, et al. 2022). The limitation of being restricted to analysis via a remote desktop is deemed necessary by the creators of the survey to protect the anonymity of the survey participants who shared extensive and detailed information in the survey.

#### Acknowledgments

We are indebted to the 2019/20 WiBef team, Jens Ambrasat and Christoph Heger, for sharing the data from the core questionnaire that provided the basis for the field-comparative analysis in this study. We thank Nathalie Schwichtenberg for thoughtful feedback in various stages of the instrument design and data analysis. We thank Laura Mages, who supported us as a student assistant in the initial, exploratory analysis of the survey data.

#### Author contributions

Theresa Velden conceptualized the paper, participated in the formal data analysis, and in the writing of the paper. Anastasiia Tcypina has participated in the formal data analysis, prepared the visualization of results, and participated in the writing of the paper.

#### **Competing interests**

No competing interests.

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