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# Challenges and opportunities with data sharing

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<http://cos.io/>



JOHN TEMPLETON  
FOUNDATION

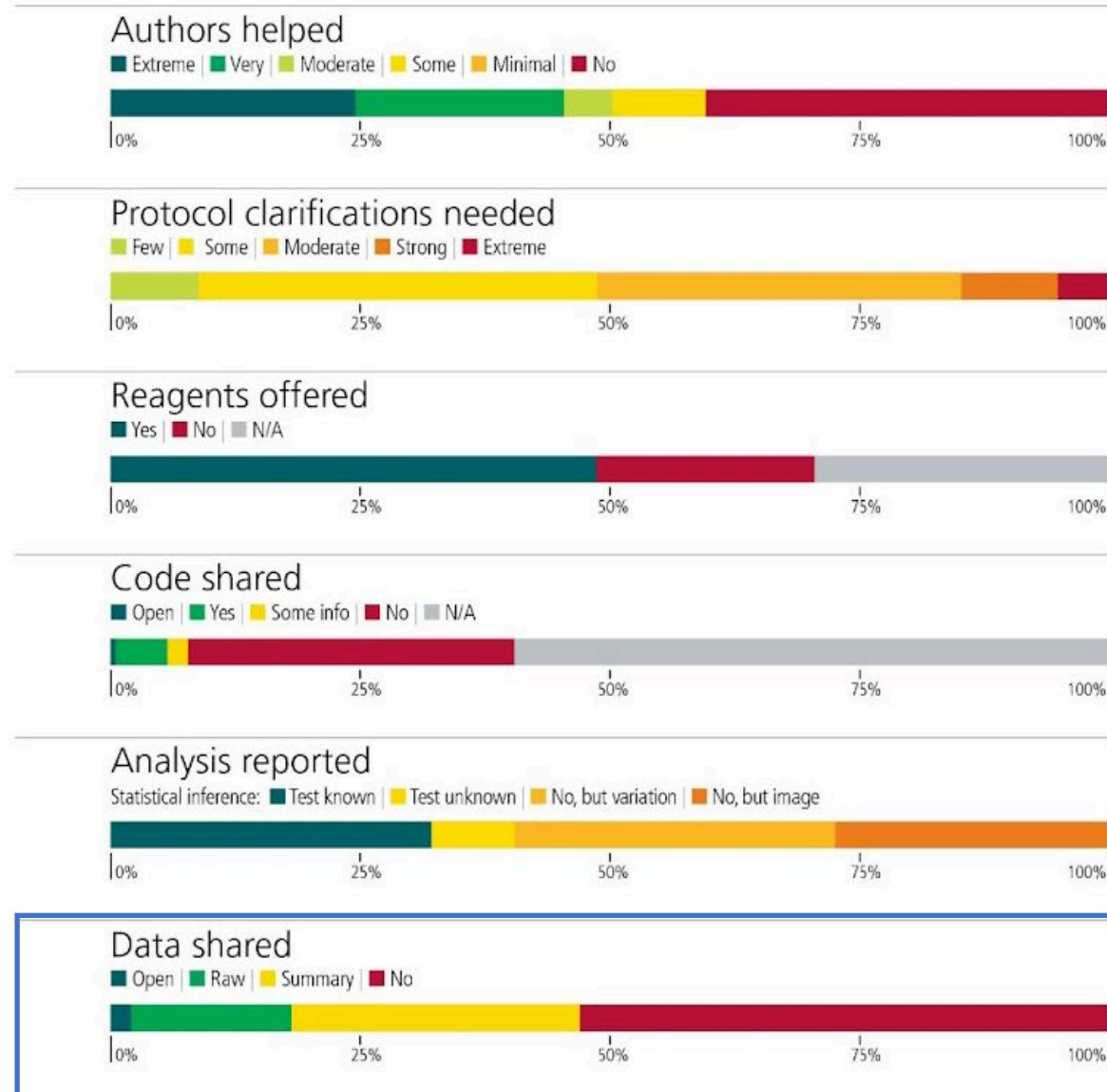


# Outline

- Rates of data sharing
- Attitudes of authors towards data sharing
- Behaviors of data sharing
- FAIR data sharing
- Challenges of data sharing
- Opportunities

# How often were data shared?

**DESIGNED**  
193 experiments

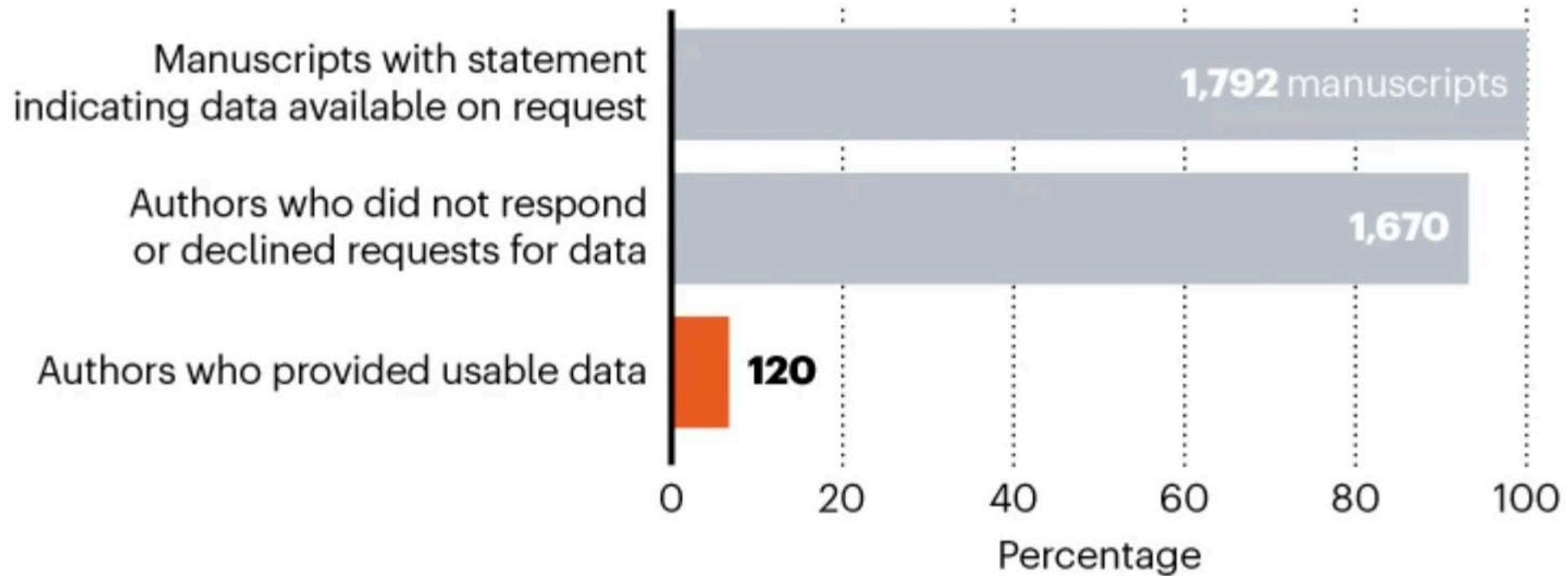


2% had open data; after requests 16% shared raw data

# How often were data shared?

## DATA-SHARING BEHAVIOUR

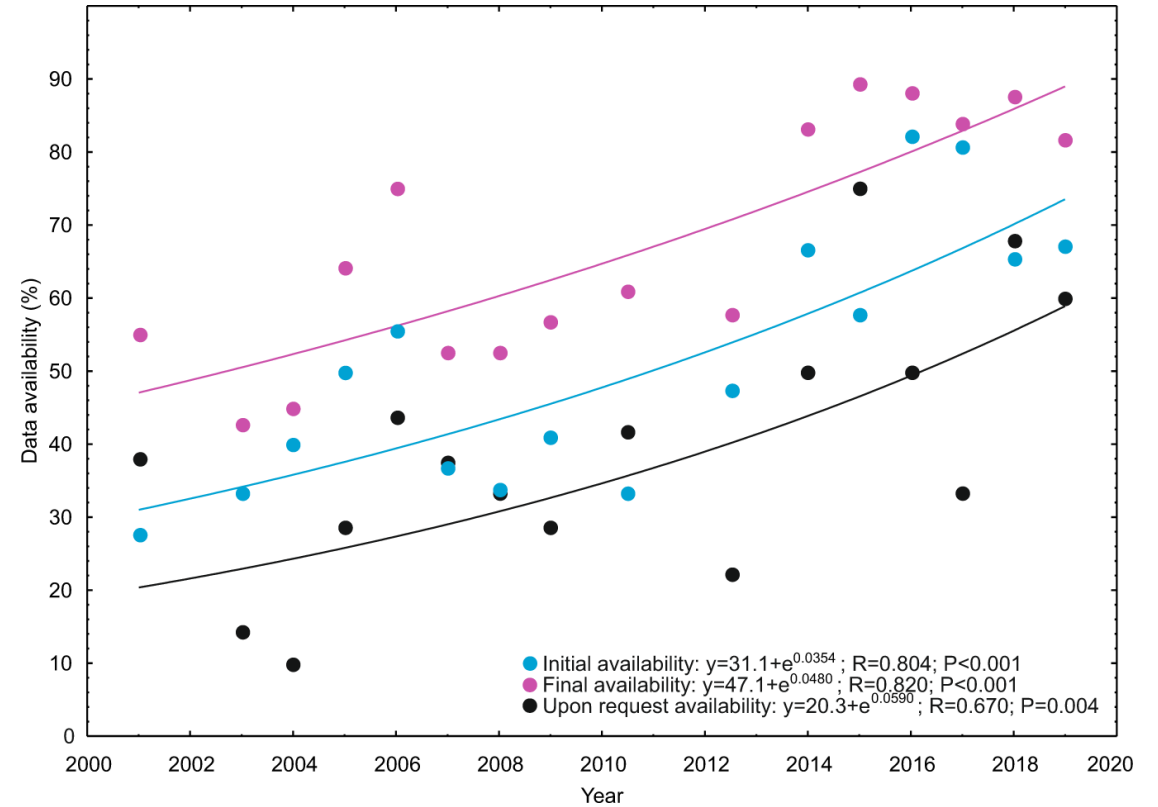
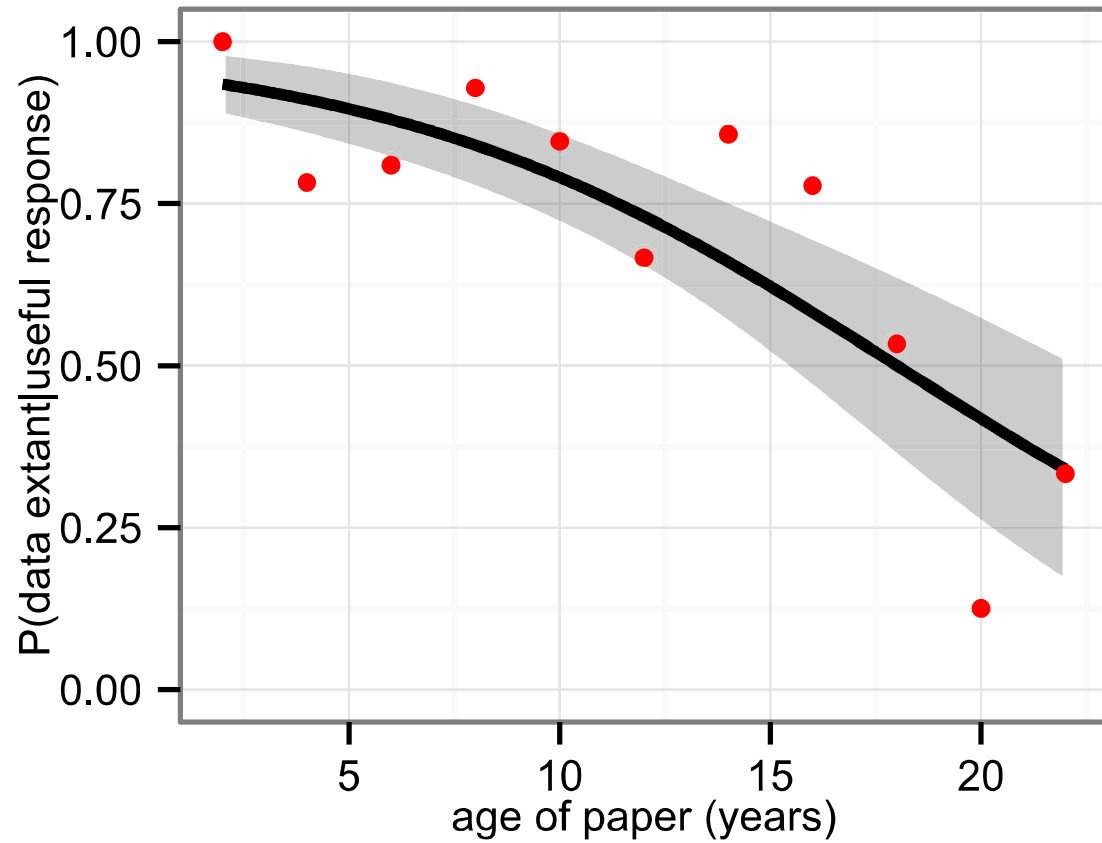
Of almost 1,800 manuscripts for which the authors stated they were willing to share their data, more than 90% of corresponding authors either declined or did not respond to requests for data. Only about 7% of authors actually handed over data.



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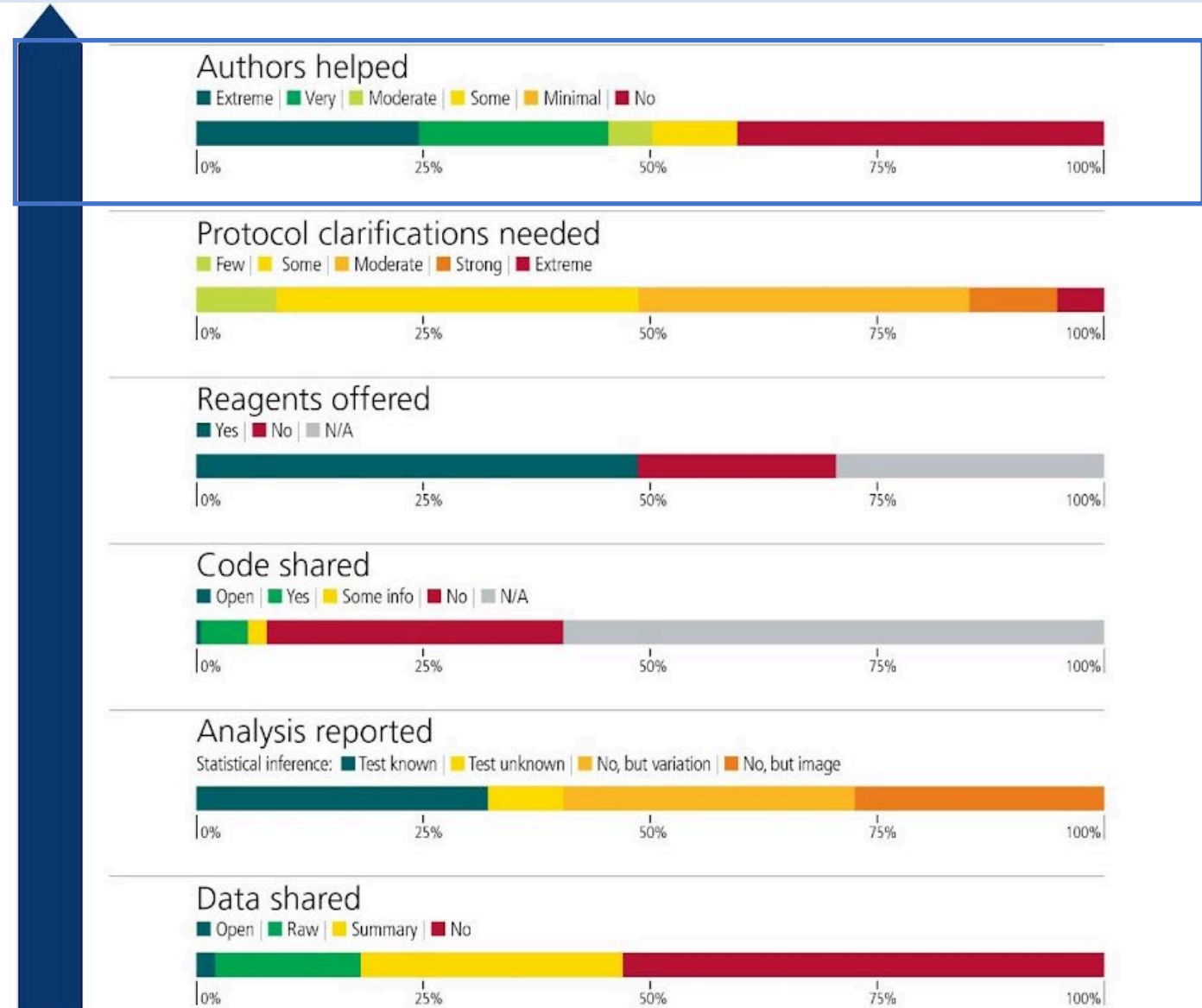
\* 381/3,556 articles linked to data in online repositories (10.7%)

# Data access declines with age



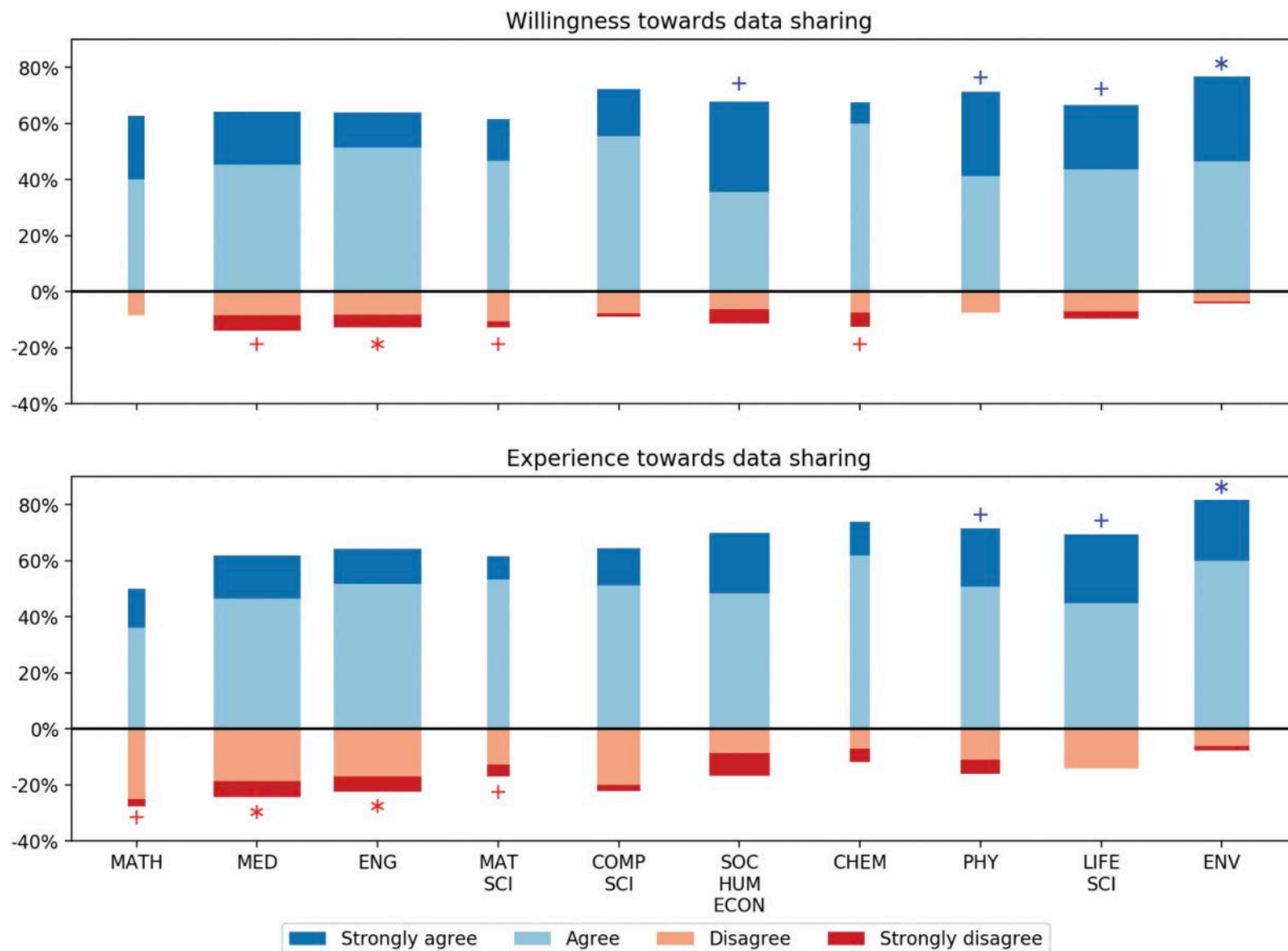
# How often was help provided?

**DESIGNED**  
193 experiments



41% extremely/very helpful, 32% not at all helpful/no response

# Attitudes towards data sharing by discipline

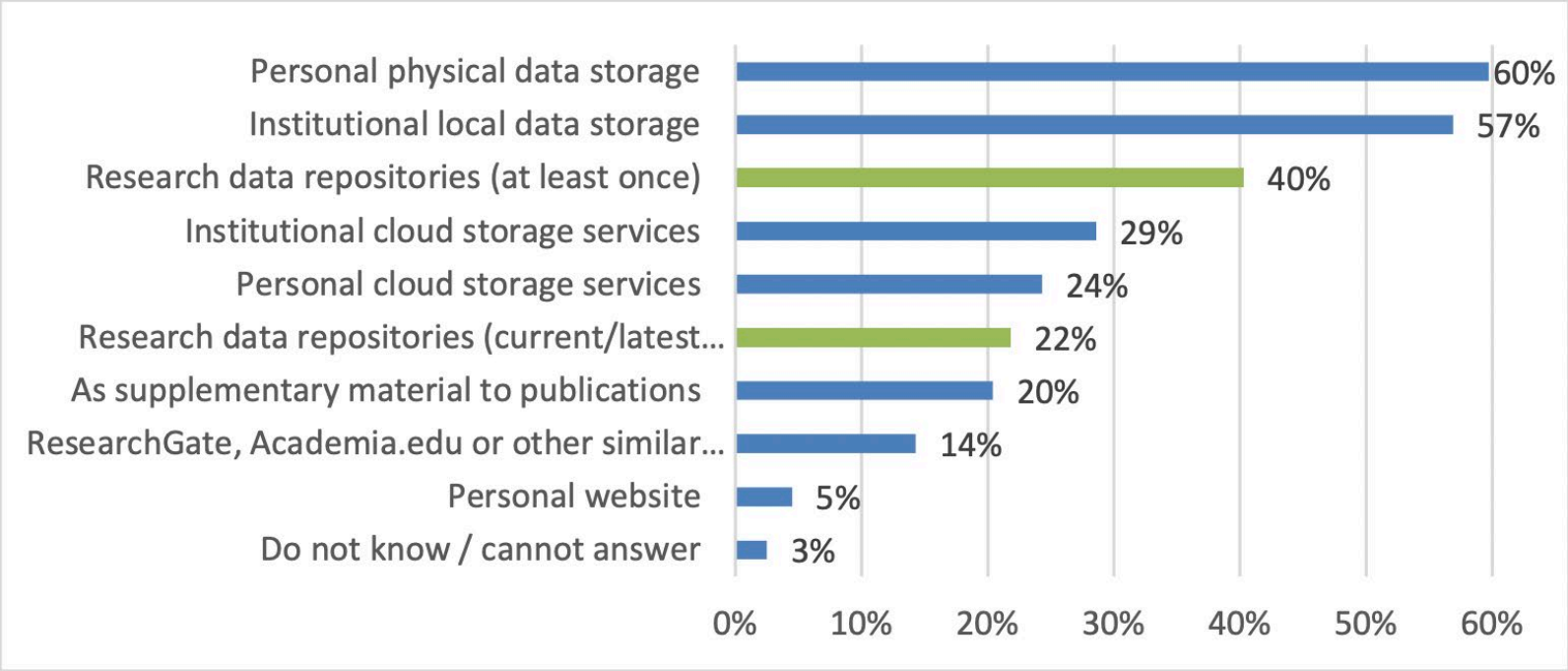


# Data sharing behaviors

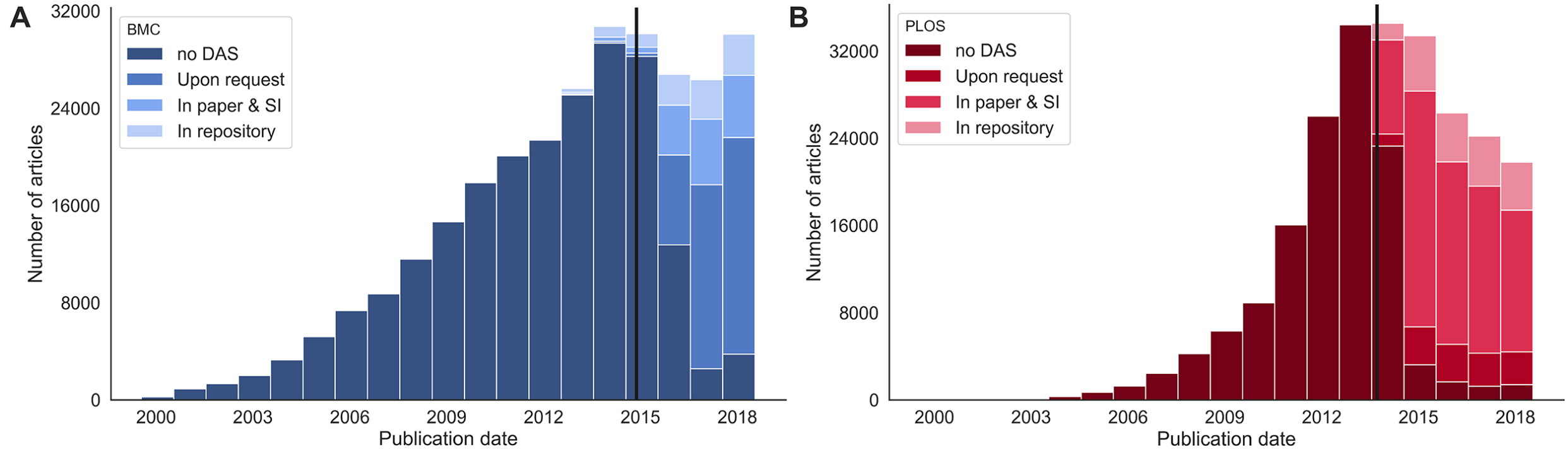




# Where do researchers store their research data?

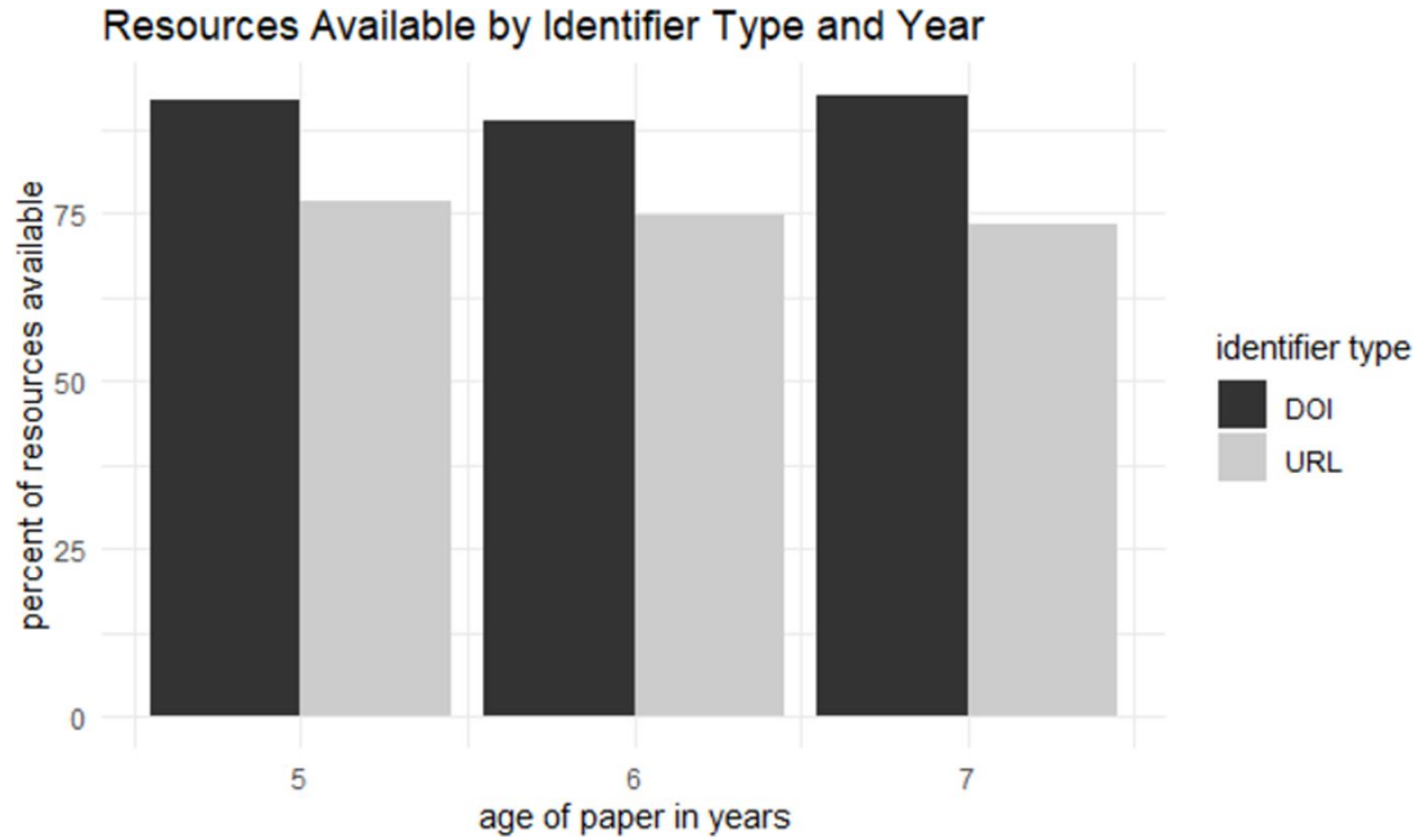


# Data Availability Statements Over Time

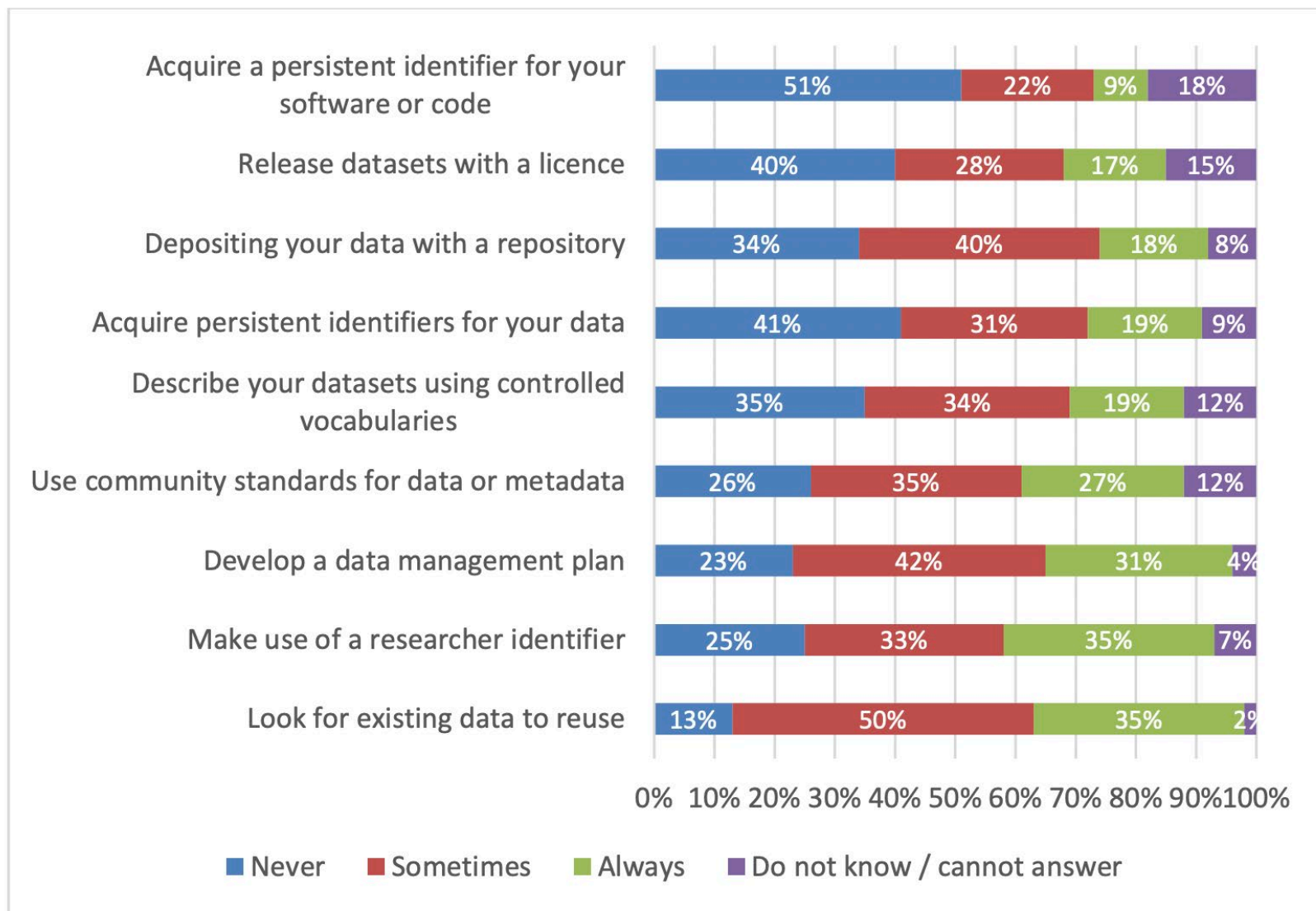


Correlation of up to 25.36% more citations for articles that share their data in a repository

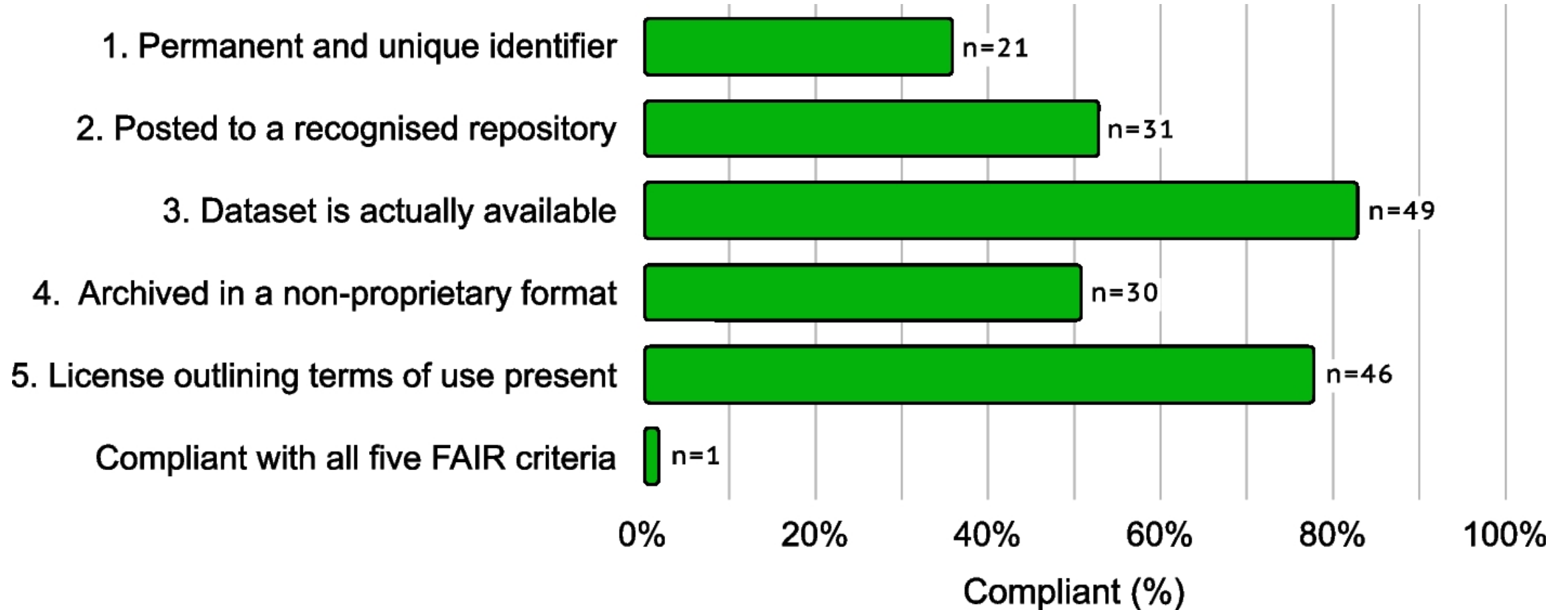
# Resource availability with identifier



# Frequency of carrying out specific FAIR-related activities



# FAIR assessment of 59 studies



# Likely cost of not having FAIR research data

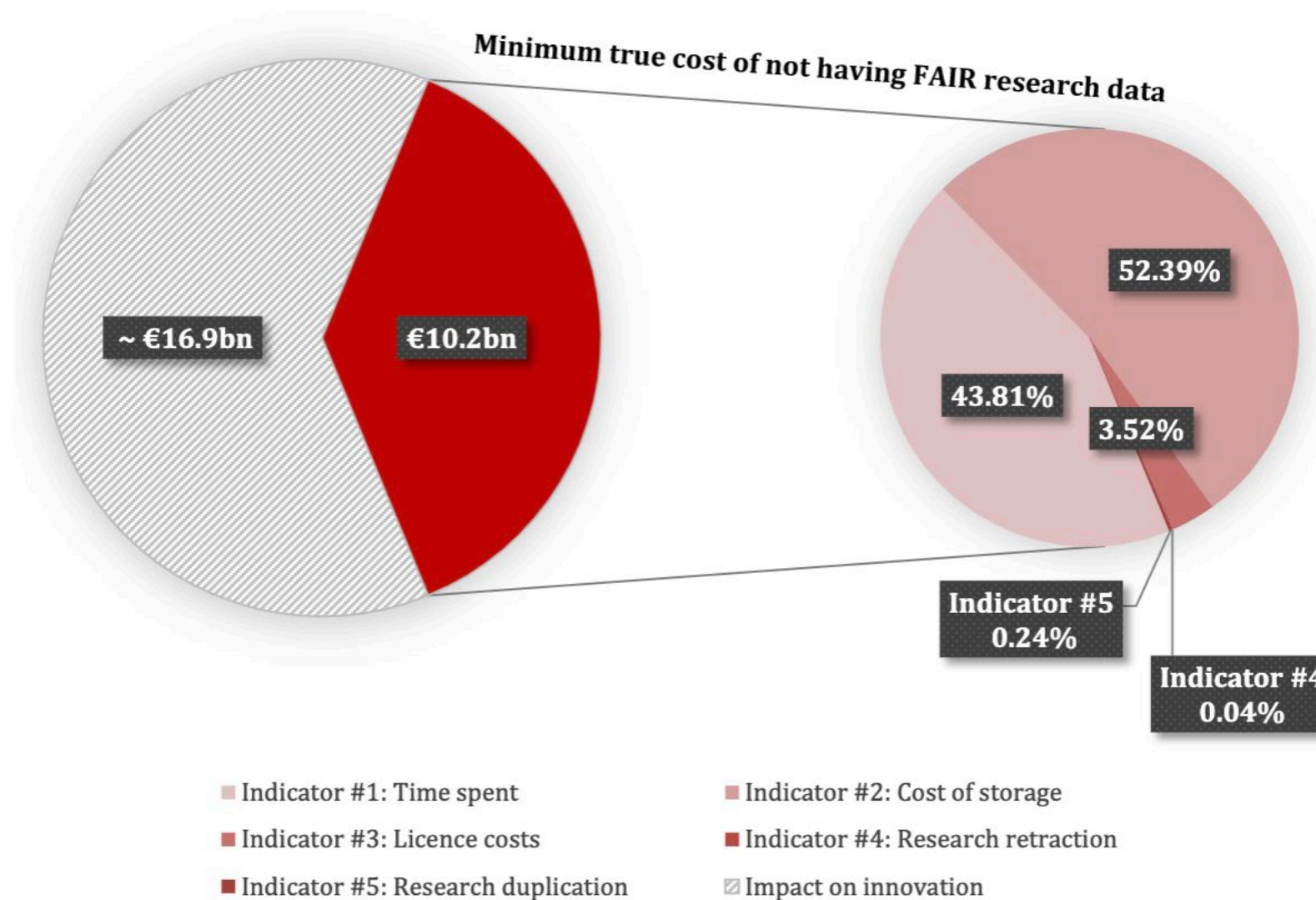
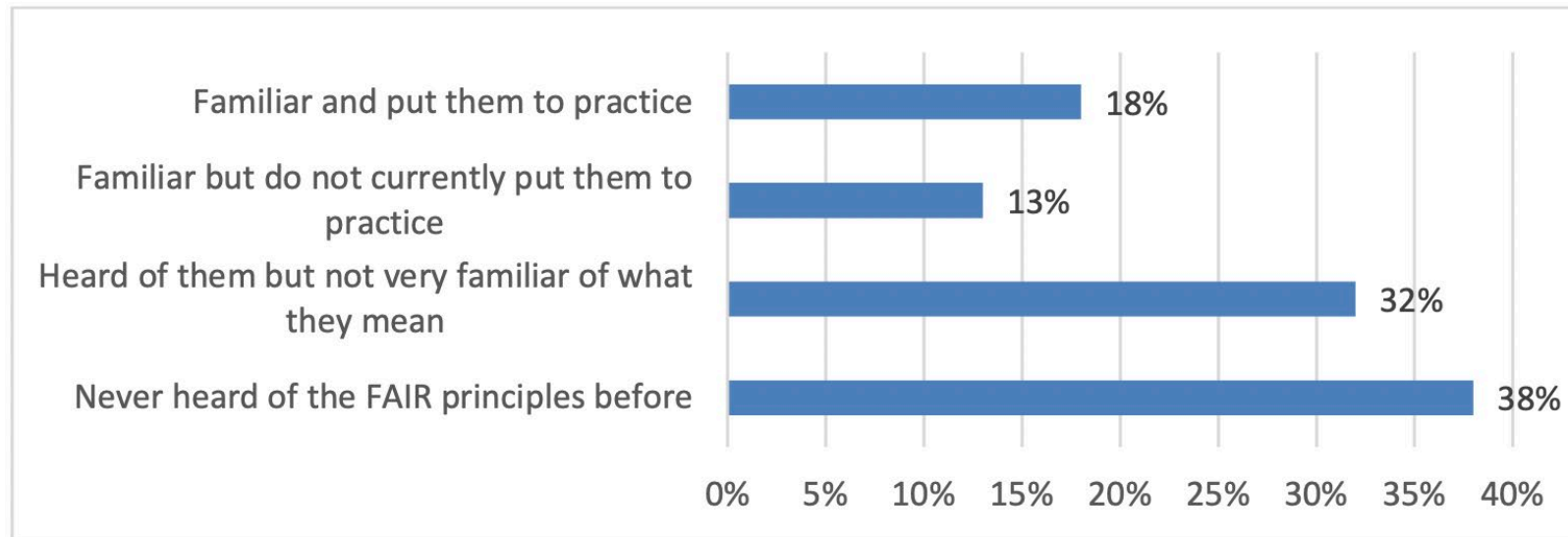
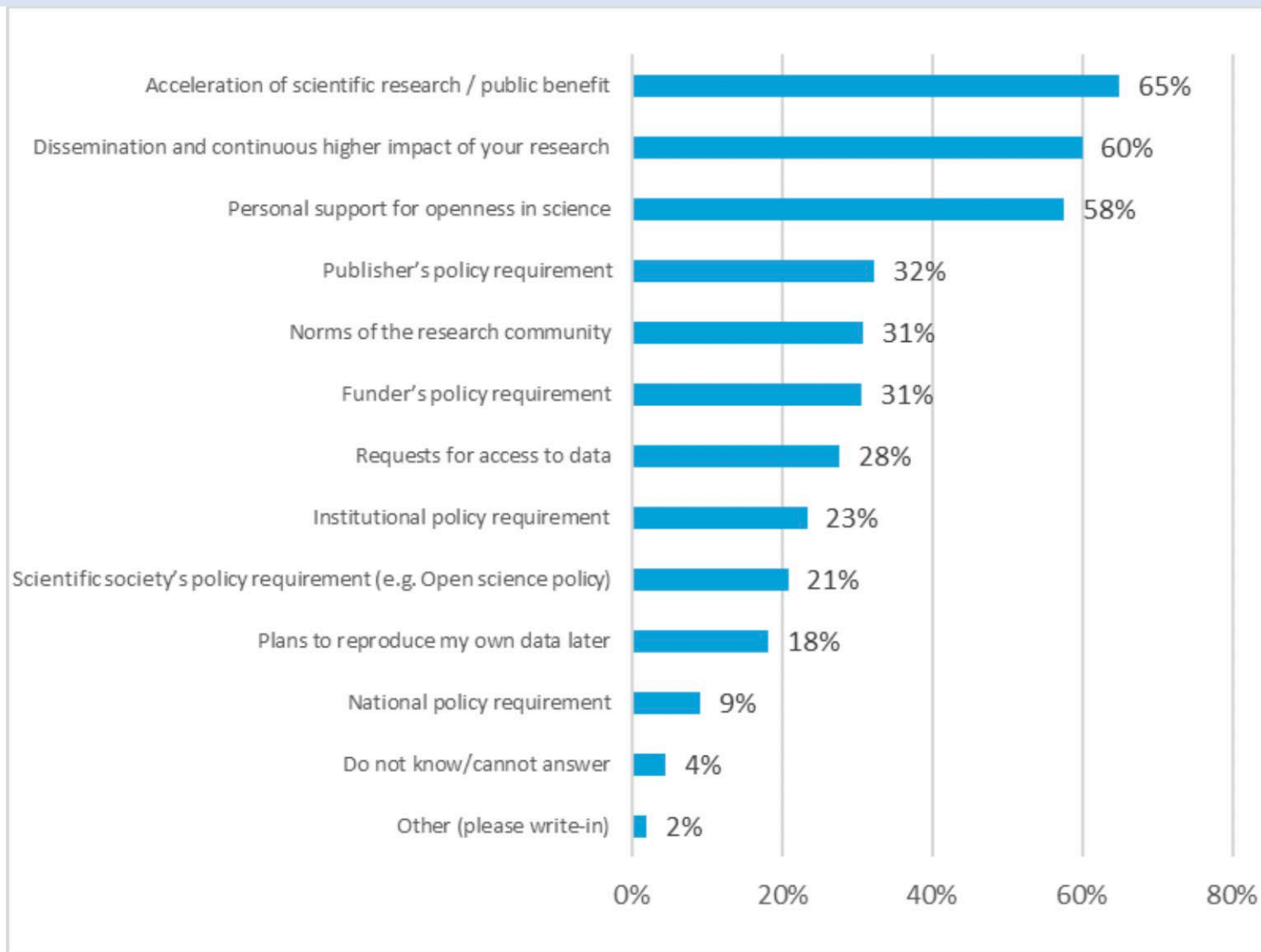


Figure 5: Cost breakdown

# Familiarity with the FAIR principles



# Why do researchers store research data in repositories?

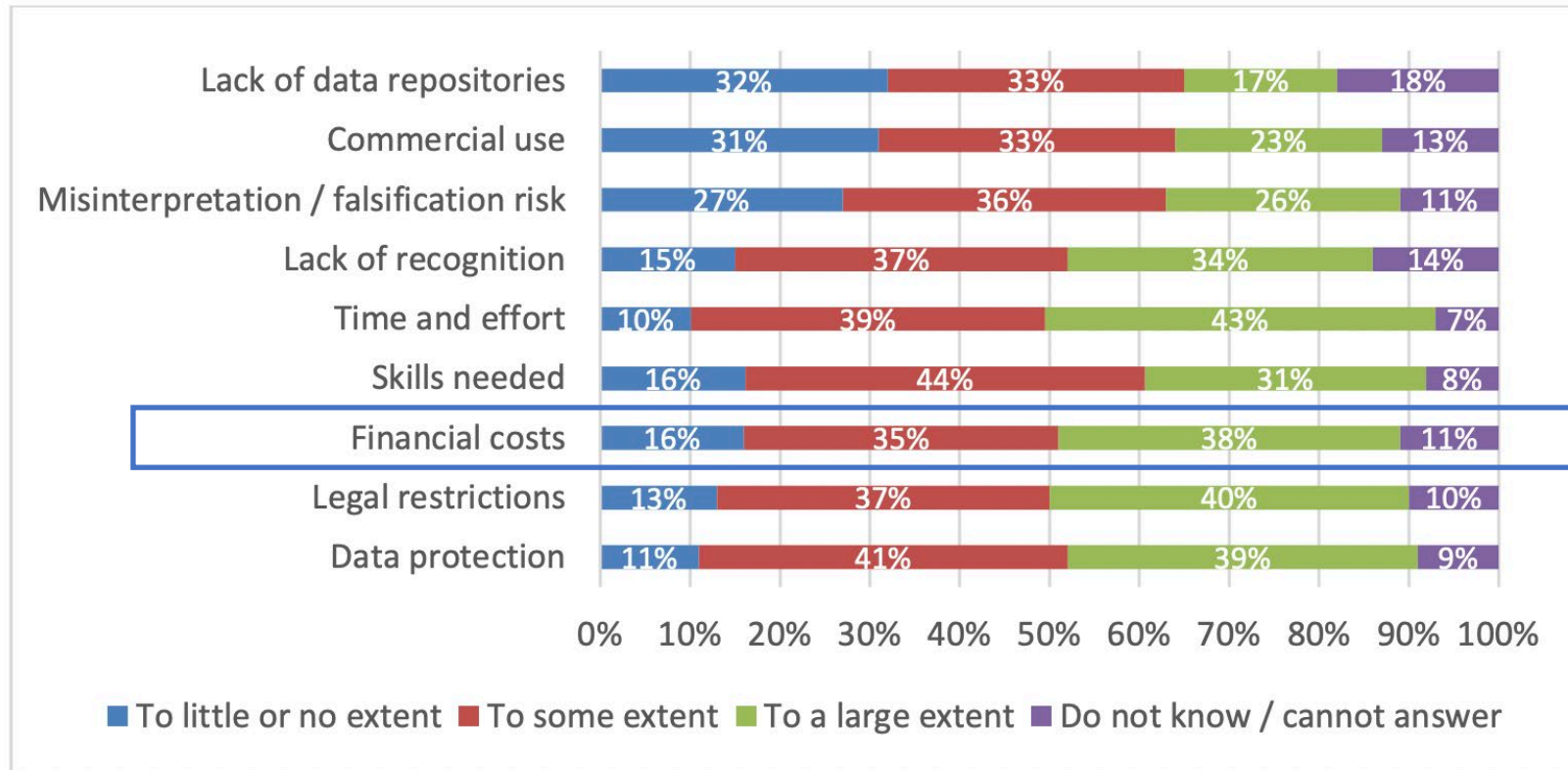




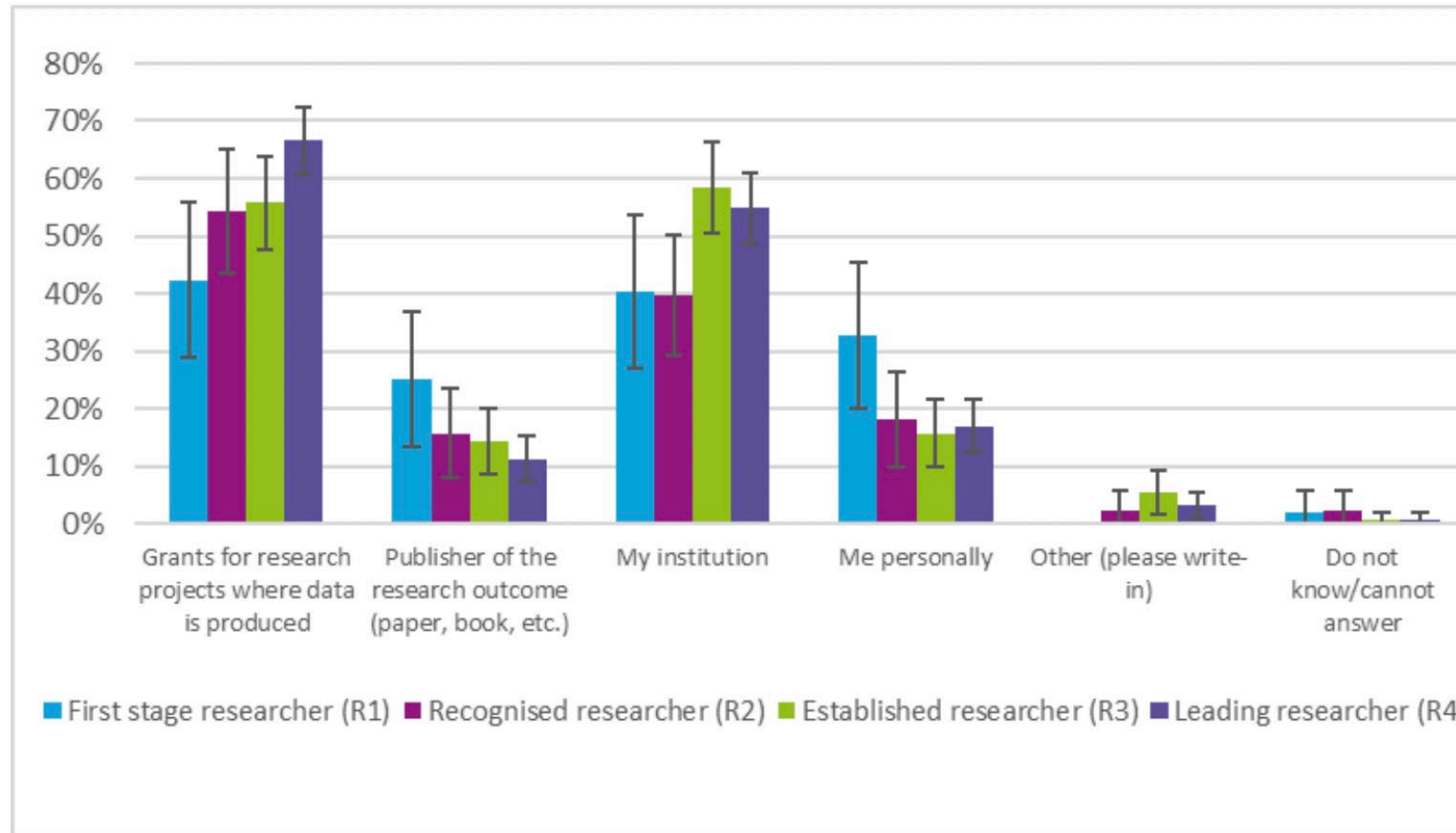
# Key barriers

	To a very large extent	To a large extent	To a moderate extent	To a small extent	To a very small extent	Not important in / applicable to my field of research
<b>Pressure to publish for career advancement (N=1,245)</b>	<b>30%</b>	<b>28%</b>	18%	10%	8%	6%
<b>Lack of overall recognition given to research practices that promote reproducibility (N=1,243)</b>	<b>20%</b>	<b>32%</b>	22%	11%	8%	8%
<b>Extensive time and effort required to make research reproducible (i.e. describing, sharing, preserving data and methodologies, etc.) (N=1,267)</b>	<b>16%</b>	<b>34%</b>	28%	10%	8%	5%
Lack of unified guidelines and commonly accepted standards for reproducible research practices (N=1,245)	16%	28%	26%	14%	9%	8%
Insufficient attention is paid to reproducibility-related topics during training and professional development (N=1,246)	15%	28%	29%	13%	8%	6%
Lack of access to the data used or generated by the original research (N=1,239)	17%	26%	23%	15%	11%	7%
Methods require tacit knowledge or particular technical expertise that makes them difficult for others to reproduce (N=1,205)	15%	28%	25%	13%	10%	9%
Focus on reproducibility is not incentivised by home research institutions (e.g. through hiring, tenure, promotion, etc.) (N=1,212)	16%	26%	23%	14%	12%	9%
Lack of journal policies promoting good reproducibility practices (N=1,215)	13%	25%	27%	15%	12%	8%
Research funders do not provide enough incentives to make research reproducible (N=1,218)	13%	23%	25%	15%	16%	9%
Selective reporting of results (including p-hacking / HARKing, lack of reporting of negative / null results) (N=1,058)	11%	25%	23%	15%	10%	16%
Legal or ethical restrictions (e.g. on data sharing) (N=1,264)	16%	19%	19%	14%	16%	16%
Original findings not robust enough (i.e. due to poor research design, statistical analysis, lack of verification or peer-review, etc.) (N=1,200)	10%	23%	28%	17%	13%	9%
Lack of publication of research protocols (N=1,198)	8%	23%	27%	19%	10%	13%
Lack of pre-registration of studies (N=1,058)	5%	15%	21%	20%	15%	24%

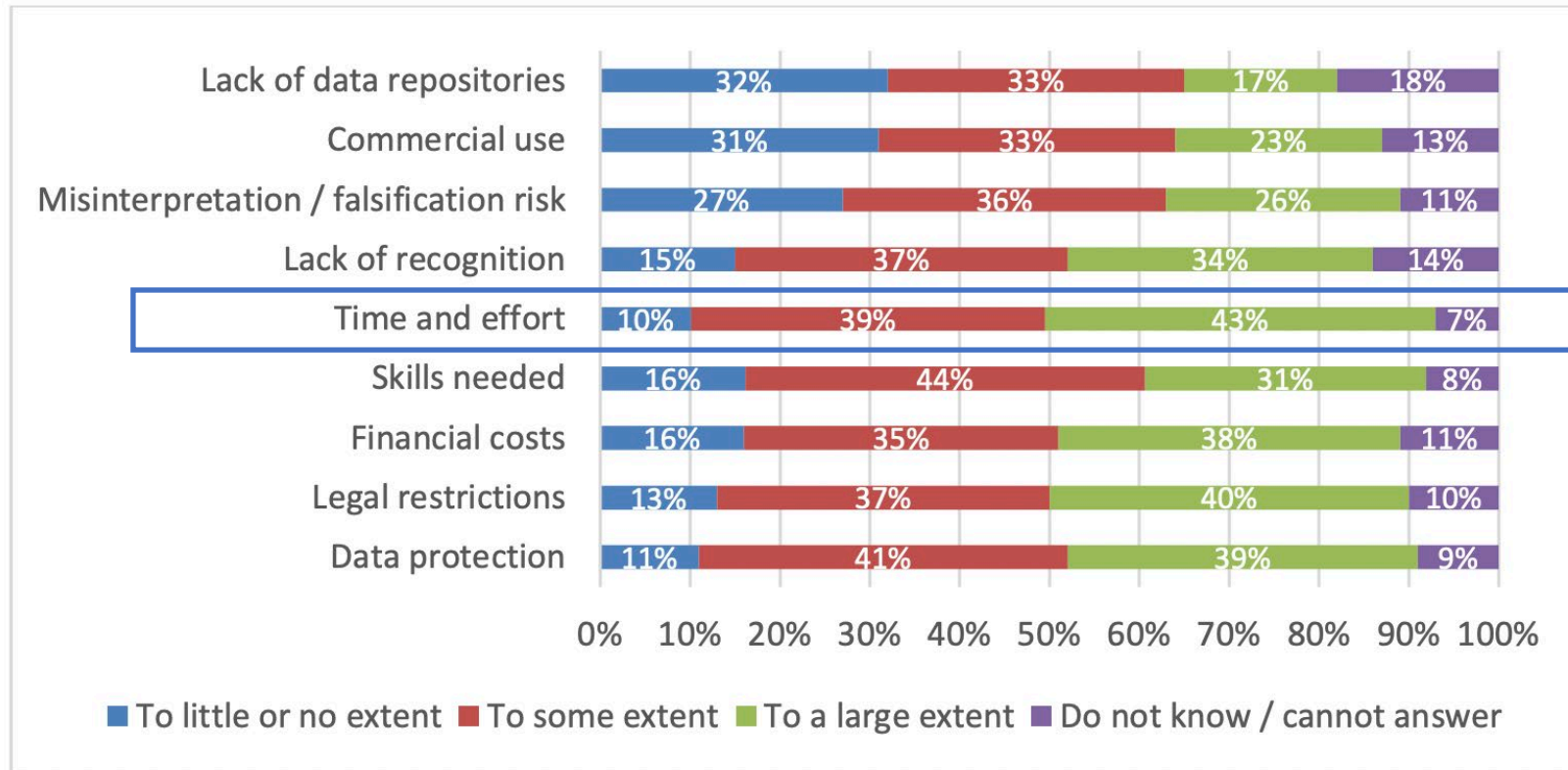
# Obstacles to the management and sharing of research data



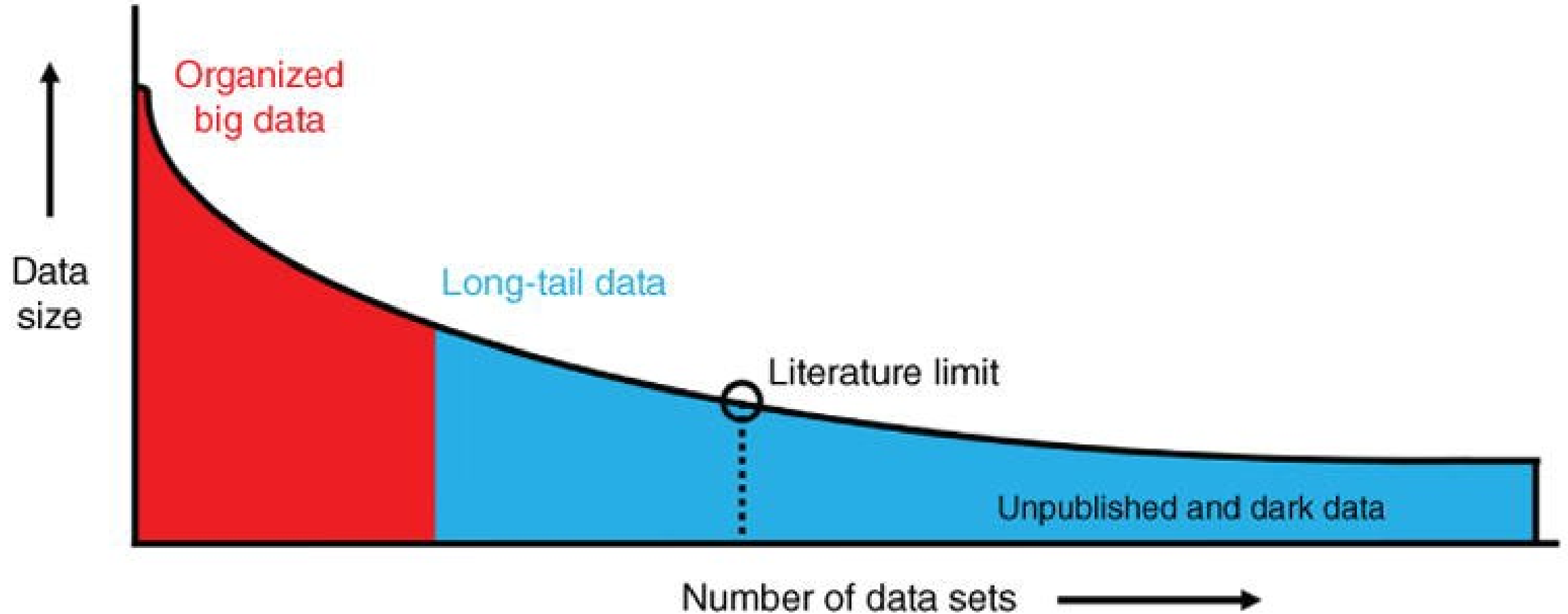
# Ways in which research sharing costs were covered



# Obstacles to the management and sharing of research data



# The long tail of data



# Many standards



search through all content

SEARCH

LOGIN

STANDARDS

DATABASES

POLICIES

COLLECTIONS

ORGANISATIONS

ADD CONTENT

STATS

**A curated, informative and educational resource on data and metadata standards, inter-related to databases and data policies.**

We guide consumers to discover, select and use these resources with confidence, and producers to make their resource more discoverable, more widely adopted and cited.

RESEARCHERS

DEVELOPERS & CURATORS

JOURNAL PUBLISHERS

LIBRARIANS & TRAINERS

SOCIETIES & ALLIANCES

FUNDERS

# Automate processes?

## Automated metadata extraction: challenges and opportunities

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Data Lifecycle and Scalable Workflows Group  
Oak Ridge National Laboratory

Kyle Chard and Ian Foster

Department of Computer Science, University of Chicago  
Data Science and Learning Division, Argonne National Laboratory

October 07 2022

### Automated metadata annotation: What is and is not possible with machine learning

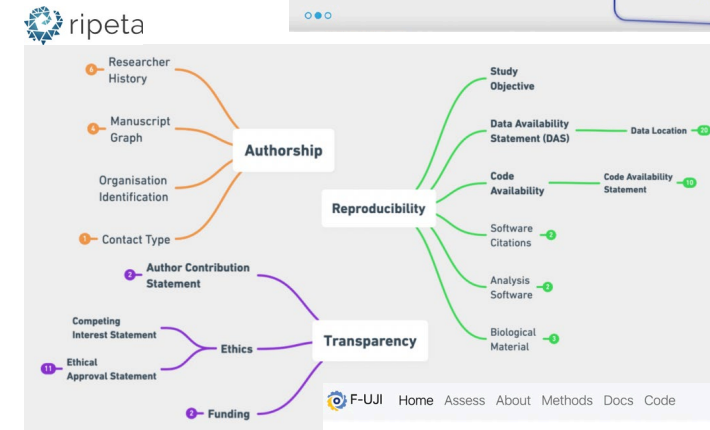
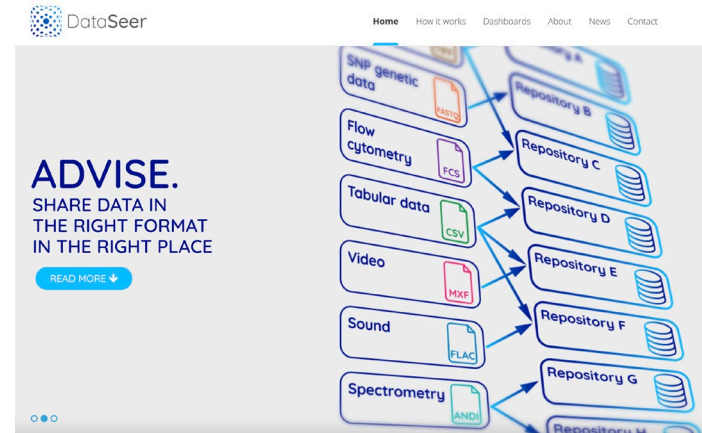
Mingfang Wu, Hans Brandhorst, Maria-Cristina Marinescu, Joaquim More Lopez, Margorie Hlava, Joseph Busch

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Author and Article Information

Data Intelligence 1–17.

[https://doi.org/10.1162/dint\\_a\\_00162](https://doi.org/10.1162/dint_a_00162) Article history



## Experience: Automated Prediction of Experimental Metadata from Scientific Publications

STUTI NAYAK, AMRAPALI ZAVERI, PEDRO HERNANDEZ SERRANO, and MICHEL DUMONTIER, Institute of Data Science, Maastricht University, The Netherlands

### Advancing smart building readiness: Automated metadata extraction using neural language processing methods

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F-UJI is a web service to programmatically assess FAIRness of research data objects at the dataset level based on the FAIRsFAIR Data Object Assessment Metrics

[Click here to assess a dataset](#)

## Summary

- FAIR data sharing in repositories helps with data transparency, reproducibility, reuse, and impact
- Researchers need help – unaware of FAIR practices and challenges in time, effort, and cost of data sharing
- The ‘long-tail’ of data complicates this further with many options
- Education, support, and workflows/tools to help automate process are potential opportunity areas



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