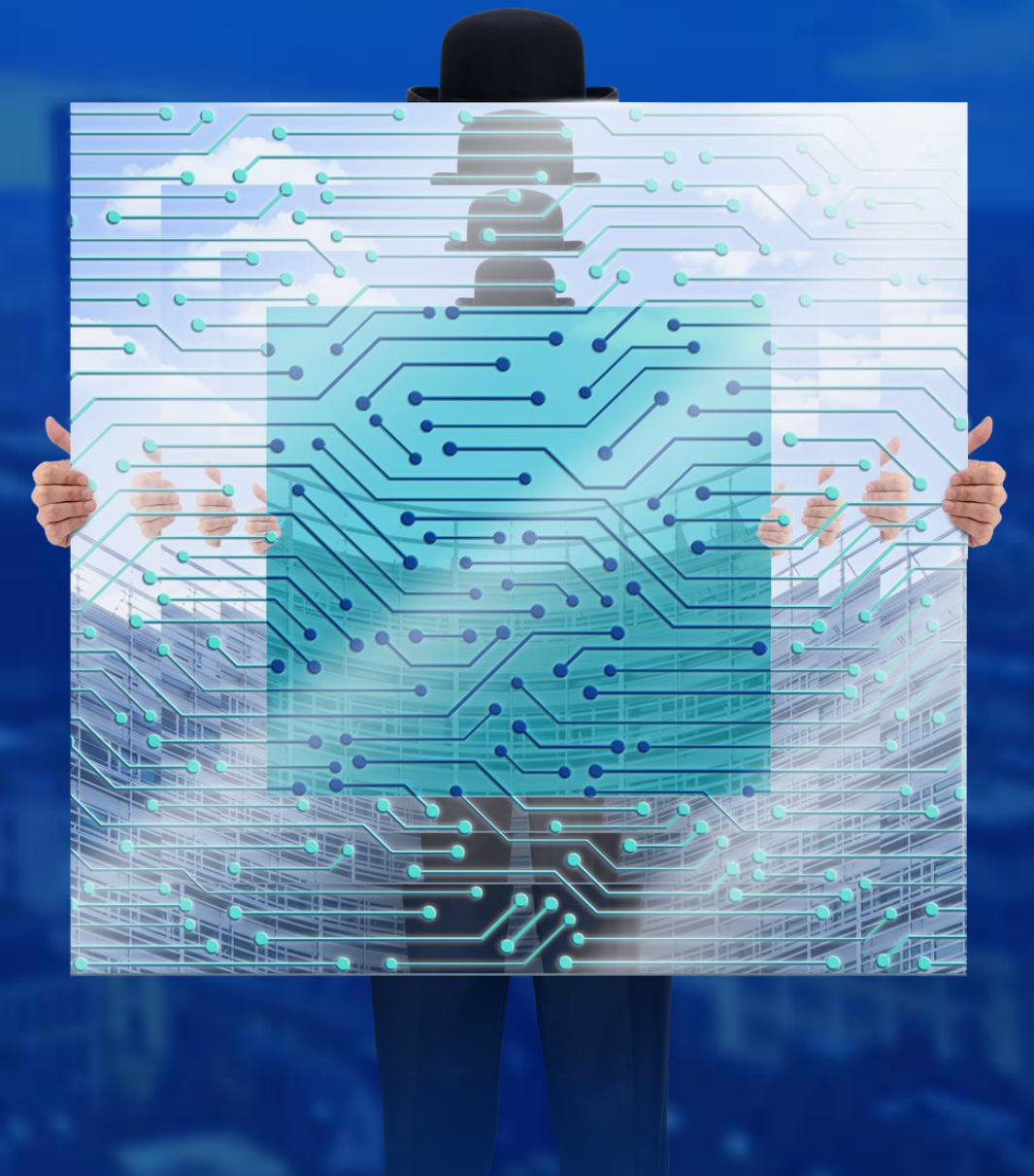


Can AI, Data and Robotics Research be Open and Accessible to All? Exploring the challenges

*From the perspective of open research data
management*



What does a research data officier do?

Data Management Helpdesk ☺
Boosting compliance with:

- FAIR data principles
- Open Science guidelines
- Stakeholders demands
- Applicable regulations or standards

All along the data life cycle of their projects



Open data, open source, and AI

Open science means more research outputs online...
... and more training material for machine-learning models

-> Boosting open science **supports** innovation capabilities in AI, even outside academia

Open data, open source, and AI

Open science means more research outputs online...
... and more training material for machine-learning models

- > Is OS enough?
- > Will research be ever really open?

Technical challenges

Financial challenges

Systemic challenges

Technical challenges

Just because a dataset is open does not mean it is:

Easy to find

Directly reusable

Formats & metadata,
provenance

Of good quality

Technical debt

Compliant

True anonymity vs big data

Non-fraudulent

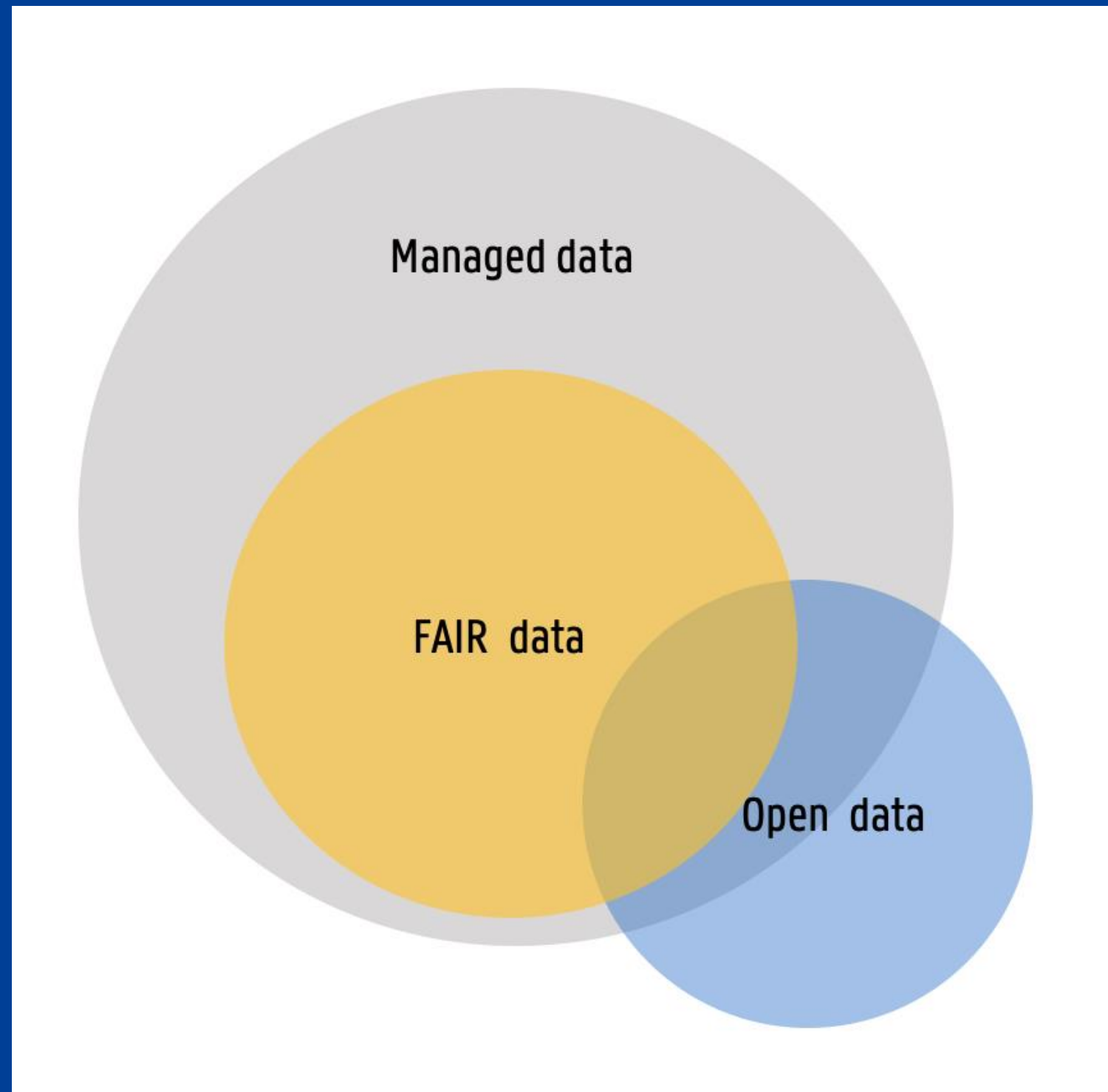
LancetGate

Technical challenges

Shifting the norm to the FAIR data principles helps addressing some of these challenges

- > **Awareness** in research communities
- > **Tools and support** available in RPOs

Technical challenges



Findable

Data repositories with machine-readable metadata, including a DOI

Accessible

Standardized retrieval protocol (such as « log in and download »)

Interoperable

Non-proprietary format, standard vocabularies, references, languages

Reusable

Sufficient documentation for autonomous reuse, including non-experts, open licence

Technical challenges

Just because a piece of code is open does not mean it is:

Portable

Well-documented

Years and layers of decision-making

Model-data blur

Of good quality

Technical debt

Generalisable

Verification vs hope for re-use and co-dev

Lawfully reusable

What really is an open source licence?

Technical challenges

Some of the FAIR principles can support open source too

Journal policies and good practice guides

Producing truly open code takes **skills and time**

Technical challenges

Case study: re-using social network data for AI-based research

How to collect?

Tools, method, selection/rejection criteria? Quality control? Need for inter-disciplinarity (IT, law, numerical humanities, ...)

How to reuse?

Ethical considerations: consent, sensitivity, illegal content, ...
Technical considerations: storage security, volume vs cost, duration ...

How to publish?

Legal considerations: freedom of speech, copyright, privacy protection, true anonymity, social network policies...

Financial challenges

Indirect, non-negligible costs

Human resources for maintenance and user support

Often poorly recognised tasks in research careers

Cumulative **data storage** vs digital sobriety

Article Processing Charges for open science papers are a major barrier to OS culture in general

In 2022, cumulated ULiège expenses in APC = 460k€ for 238 articles

Systemic challenges

Can science ever be truly open?

Terrorists will use it	We'll get spam	It's too big	It's not very interesting
Thieves will use it	I don't mind, but someone else might	We will get too many enquiries	Lawyers want a custom License
There's no API	Poor Quality	There's already a project to...	We might want to use it in a paper
It's too complicated	Data Protection	People may misinterpret the data	What if we want to sell it later

#opendataexcuses

Systemic challenges

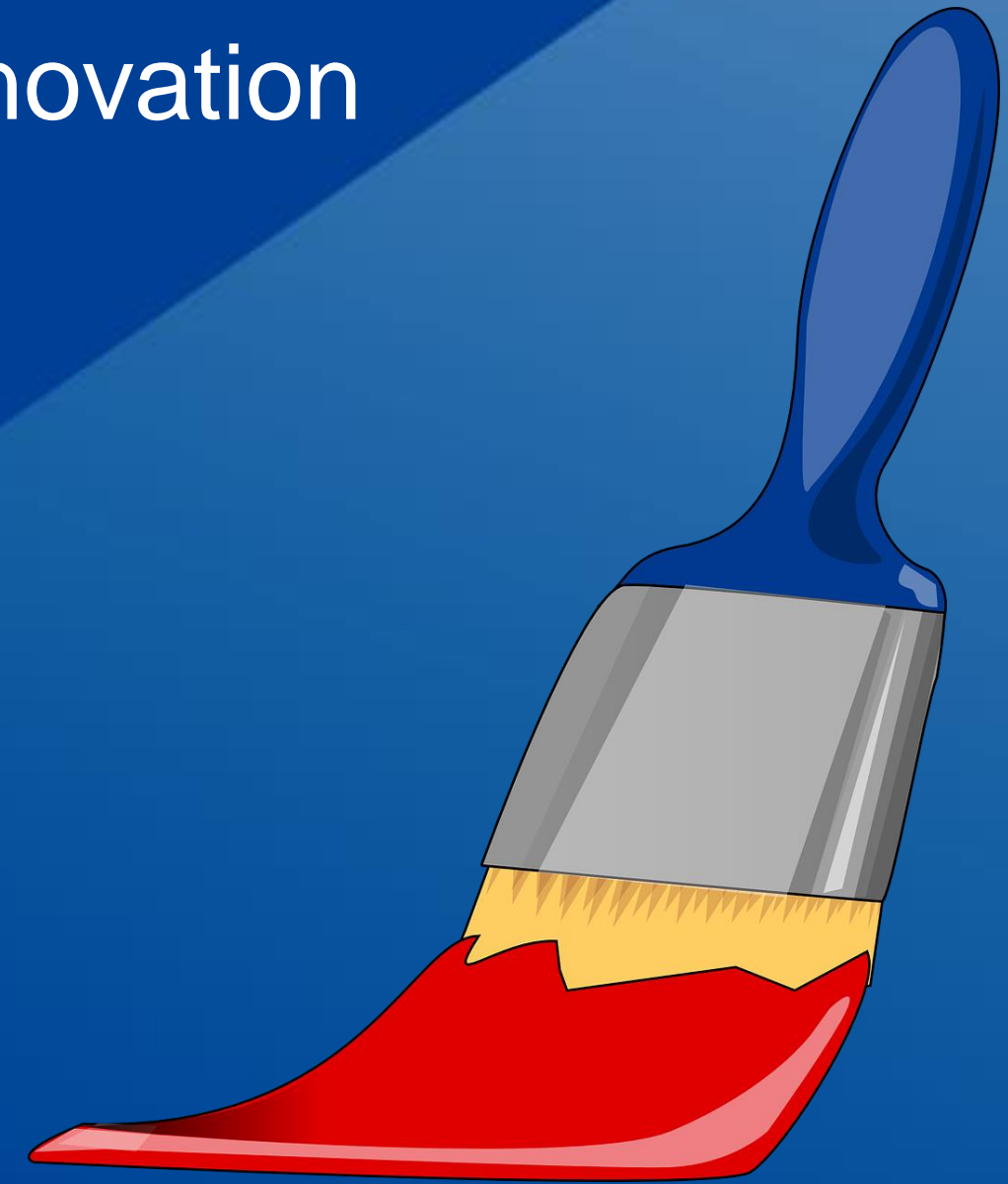
Biases in open science culture impact AI innovation

Positivity bias

Negative results are seldom published,
painting a **too positive picture**

- > Skewed training datasets
- > Skewed ML model

e.g. enhancing chemical properties of material



Systemic challenges

Biases in open science culture impact AI innovation

Lack of bibliodiversity

Metrics culture effectively silences a whole facet of scientific productions

- > Global North over-represented
- > Gender, ethnic, linguistic biases

- > Vendor lock-in, limited publication models

Systemic challenges

Research communication remains a market, research outputs are managed **more as commercial goods** than as a public good.

Its biases are carried out in machine-learning models that are trained on this improper representation.

A **deeper shift** of publication strategies needs to be incentivized towards truly reusable research.

So what do we do ? A culture shift

AI in and of itself might just help detect and discuss such biases 😊

“By analysing big data, researchers have confirmed deeply rooted intersectional inequalities in science production and publishing. And they have a fairly good understanding of how various dimensions of diversity, from gender and racial or ethnic composition to interdisciplinarity and geography, relate to outcomes”

Broader scope is key to the future of ‘science of science’. Nat Hum Behav 6, 899–900 (2022).
<https://doi.org/10.1038/s41562-022-01424-5>

So what do we do ? A culture shift

Top-down initiatives from big stakeholders

Since the Jussieu Call and the DORA manifesto

EOSC: a diversity of services and infrastructures, supporting OS in all its forms

Open and FAIR as norm for € grants, FNRS/ FWO, ...

CoARA: RPOs are committing to steer away from metrics-based evaluations



So what do we do ? A culture shift

Bottom-up initiatives:

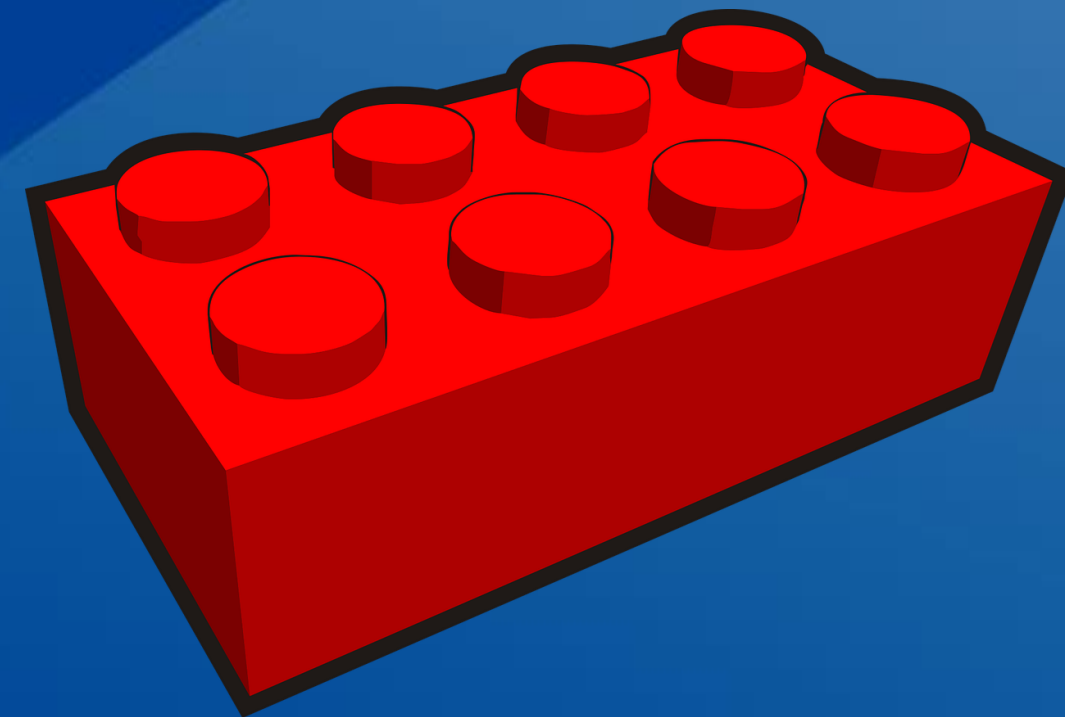
Sector-level guidelines

Such as TOP or EQUATOR guidelines

Belgian Reproducibility Network

Flemish Research Data Network

FWB Data Ambassadors



Hold your institution CoARA accountable

Challenge publication culture towards truly open science

Acknowledgements

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