

The Impact of Digitalisation on Science: Workflows, Outputs, and Trust

Tandem Talk

Dr. Felix Bach¹, Dr. Linda Nierling²

Dr. Christian Bonatto¹ Minella, Angelina Sophie Dähms²

(1: FIZ Karlsruhe, 2: KIT)

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Agenda

1. **Introduction to DiTraRe (Leibniz Science Campus)**
2. **Short history of digitalisation in science**
3. **AI in science: public trust & research integrity**
4. **Use case example: Smart Labs & AI**
5. **Conclusions & open questions**

Digital Transformation of Research

In **DiTraRe** we investigate the effects and potential of the digitalisation of scientific work with a focus on:

- collection of research data,
- organisation of knowledge & use of AI,
- handling of sensitive data,
- publication cultures.

Based on specific questions (**use cases**), **research clusters** develop solutions and **dimensions** work on cross-cutting topics.

In this talk we focus on 2 of our dimensions (**reflection & resonance**, **tools & processes**) and 1 **research cluster** “**smart data acquisition**” with the use case

“**chemotion electronic lab notebook**”



Short history of digitalisation in science



Leibniz ScienceCampus
Digital Transformation
of Research

1703 **Leibniz** develops the **Logical Machine**, binary number system. Publishes *Explication de l'Arithmétique Binaire*

1936 **Alan Turing** publishes "On Computable Numbers", introducing the **Turing machine**

1938 - 1977 **Introduction of computers and application in Research**

- 1938-1941 First computers by Konrad Zuse: Z1 (1938, binary mechanical), Z3 (1941, first digital computer).
- 1945 Von Neumann Architecture
- 1975 First Personal Computers: Altair 8800 (1975) Intel's 8080 processor, Apple I (1976), Commodore PET (1977), ...
- 1977 First computational DNA sequencing

1970s-1980s **Networking & the Internet and early internet protocols.**

- 1969 ARPANET goes online, connecting four U.S. universities (UCLA, Stanford, UCSB, University of Utah).
- 1983 Internet (TCP/IP protocol) is standardised.
- 1989 WWW: Tim Berners-Lee launches the **World Wide Web**, revolutionising **information access** (web browsers...)

1990s **Open Science movement** - enhances transparency and accessibility. e.g.: 1991 arXiv.org starts

- 2001 Open Knowledge, platforms like **Wikipedia** democratise knowledge and enable **collaborative** content creation.

2000s **Digitisation of Libraries starts**

- 2002 Internet Archive's Million Book Project starts (still relevant: Websites and data disappear - e.g. now in the US)
- 2004 Google and major libraries begin **digitising books at scale** (Project Gutenberg already started in 1971)

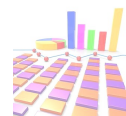
2000-2010s **Data-Driven Research advances**

- 2000 Cloud computing and **Big Data** infrastructures transform data storage and analysis.
- 2008 CERN's Large Hadron Collider produces vast datasets.
- 2009 Jim Gray's **Fourth Paradigm** describes the era of **data-intensive scientific discovery**.
- 2014 Research Tools like Electronic Lab Notebooks (ELNs) improve structured data acquisition and reproducibility.

recent years **Artificial Intelligence (AI) & Machine Learning (ML) become central to scientific data analysis**

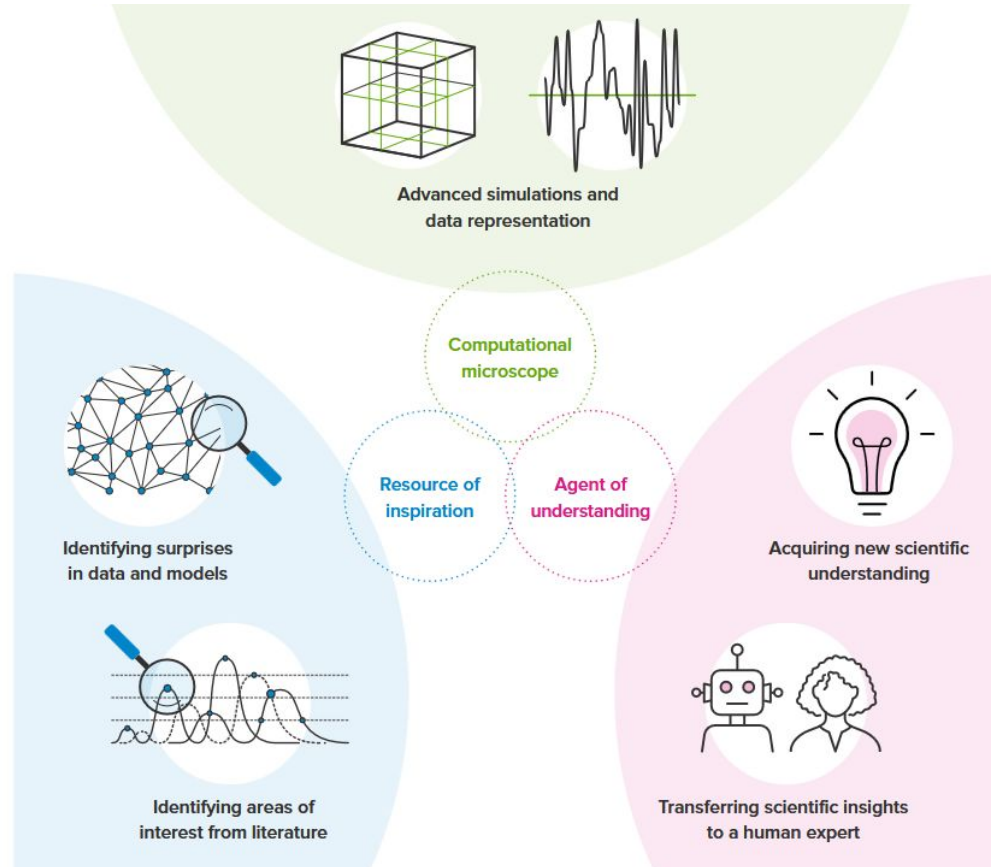


open science



Short history of digitalisation in science

**Today: Potential
contribution of AI
to scientific
understanding**



From: The Royal Society
(2024): Science in the age
of AI: How artificial
intelligence is changing
the nature and method of
scientific research., p. 31

Public trust & research integrity

■ Digitalisation of research affects how science is conducted but also how it is perceived

- Transparency, data openness, and the potential for reproducibility enhance public trust.
- The reliance on black-box AI systems and large-scale datasets raises concerns about the reliability and accessibility of scientific findings

■ (Generative) AI challenges workflows, infrastructures and outputs in science

- New chances for knowledge generation and processing
 - Increased efficiency and productivity in scientific working practices with various possible applications
 - Potentials in training small data sets, LLM-based knowledge extraction from data bases, easier programming tools
- But:
 - Technical limits: Transparency and traceability: detection, authentication, “hallucinations”
 - Social changes: AI-literacy of researchers & potential loss of competences
 - Legal issues: Data protection, limits of regulation
 - Ethical questions: Overreliance, spread of false information, biased knowledge, source misrepresentation

■ Challenges on two levels → focused on in this talk

- Trust in science from the public
- Research integrity within science



Public trust & research integrity

Trust in science from the public

- Narratives of low public trust in scientists, but no empirical evidence, e.g. by recent international 68-country survey
 - In most countries, scientists and scientific methods are trusted.
 - Factors e.g. being male, conservative, science-populist attitudes, are correlated with lower trust
- Four components of trust in scientists: competence, **integrity**, benevolence and **openness**
 - Public perception of integrity is high → **risk of erosion by AI in science?**
 - Public perception of openness is lower → **how to deal with it in case of AI & open data?**
 - receptive to feedback, transparent about funding and data sources
 - communicating about science with the public, avoiding top-down communication
 - encouraging public participation in genuine dialogue, insights and needs of societal actors

Public trust & research integrity

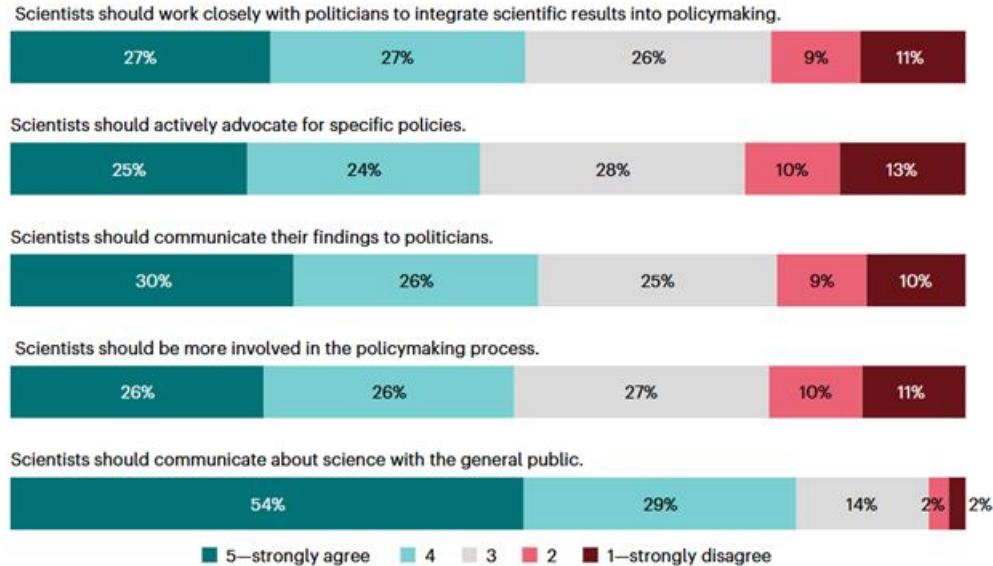


Fig. 4 | Normative perceptions of scientists in society and policymaking. Normative perceptions of scientists in society and policymaking using weighted response probabilities.

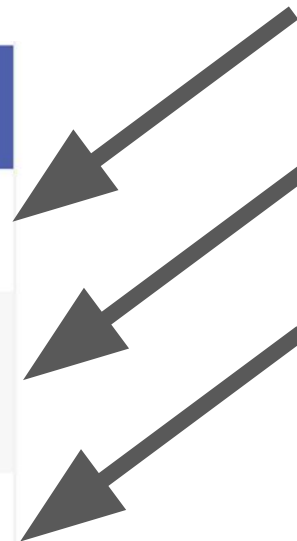
Cologna, V., Medreertertere, N.G., Berger, S. *et al.* Trust in scientists and their role in society across 68 countries. *Nat Hum Behav* (2025).
<https://doi.org/10.1038/s41562-024-02090-5>

Public trust & research integrity

Trust in science from the public - Open Science

Table 1. Survey questions (Study 1).

ID	Wording	Response format	M	SD	Positive responses (%)
SQ1	How important do you think it is that scientific results are made available to the public free of charge (e.g., on the Internet)?	7-point scale, <i>not important at all</i> to <i>very important</i>	5.96	1.19	87.2
SQ2	How important do you think it is that the following scientific results are made available to the public free of charge (e.g., on the Internet)? <ul style="list-style-type: none">• SQ2c: Study materials, datasets, and analysis code of individual studies	7-point scale, <i>not important at all</i> to <i>very important</i>	5.09	1.32	64.3
SQ3	My trust in a scientific study increases when I see scientists publicly sharing their study materials, their datasets, and their analysis code.	7-point scale, <i>do not agree at all</i> to <i>fully agree</i>	5.25	1.26	74.0



Public trust & research integrity

Trust in Science from the public - Open Science and AI

- Measures for trust in open data using AI
 - Improve reproducibility of AI-based research
 - requesting the use of reproducibility checklists and data sharing protocols
 - supporting the development of community and field-specific reproducibility standards
 - Invest in open repositories
 - sharing of datasets, software versions, and workflows
 - development of context-aware documentation that enable the local adaptation of AI models across research environments
 - Trustworthy use of sensitive datasets
 - relates to people (e.g. health information, demographics, location, etc.).
 - trusted and secure research environments that enable sensitive data sharing (--> *other use case*)

The Royal Society (2024): Science in the age of AI:
How artificial intelligence is changing the nature
and method of scientific research., p. 13;

Public trust & research integrity

Research integrity within science: National guidelines (DFG)

- **“The use of generative models** in the context of scientific work **should by no means be ruled out** in view of the considerable opportunities and development potential. However, their use requires certain binding framework conditions in order to ensure good scientific practice and the quality of scientific results.”
- **“Transparency and traceability** of the research process and the knowledge gained for third parties are essential basic principles of scientific integrity. This value system continues to provide valuable guidelines for dealing with generative models.”
- **“Scientists should disclose whether and which generative models they have used**, for what purpose and to what extent, **when making their results publicly available in the interests of scientific integrity.**”
- **“The influence of generative models on the sciences and the DFG's funding activities can currently only be partially recognised. In order to illuminate the opportunities and challenges, it is necessary to gather and share experiences with the use of generative models. Only this will enable a discursive and science-based process.”**

Public trust & research integrity

Research integrity within science: International guidelines



Guidance for generative AI in education and research



“...the usage processes should ensure humans’ interactive engagement with GenAI and higher-order thinking, as well as human accountability for decisions related to the accuracy of AI-generated content, and their impact on human behaviours” p. 29



“Large Language Models (LLMs), such as ChatGPT, do not currently satisfy our authorship criteria”



ELSEVIER

“Where authors use generative AI and AI-assisted technologies in the writing process, these technologies should only be used to improve readability and language of the work.”

“...publishers and researchers at all stages of their careers are essential in shaping the discussion on AI and how it can serve the public interest in research.” (EC 2024, S.4)



UNESCO (2023): <https://www.unesco.org/en/articles/guidance-generative-ai-education-and-research>

EC (2024): https://research-and-innovation.ec.europa.eu/document/2b6cf7e5-36ac-41cb-aab5-0d32050143dc_en

Elsevier (2025): <https://www.elsevier.com/about/policies-and-standards/the-use-of-generative-ai-and-ai-assisted-technologies-in-writing-for-elsevier>

Springer (2025): https://www.springer.com/gp/editorial-policies/artificial-intelligence--ai-/25428500?srltid=AfmBOopzRsbwsT9pkaJbJPXq-IWMhiA8NQI_Gp9swQ5mEadFkJefQP1

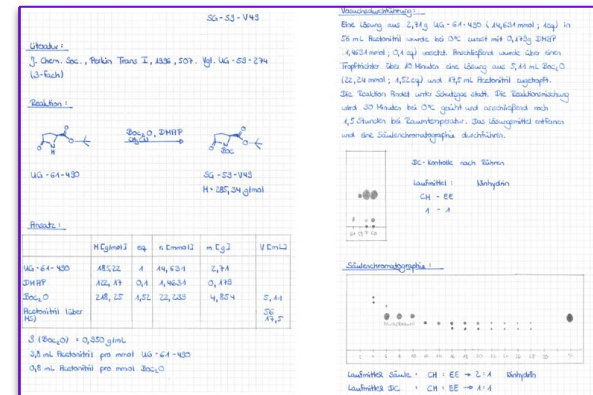


iPhone 15 Pro
2.147 GFLOPS
3.78 GHz CPU Speed

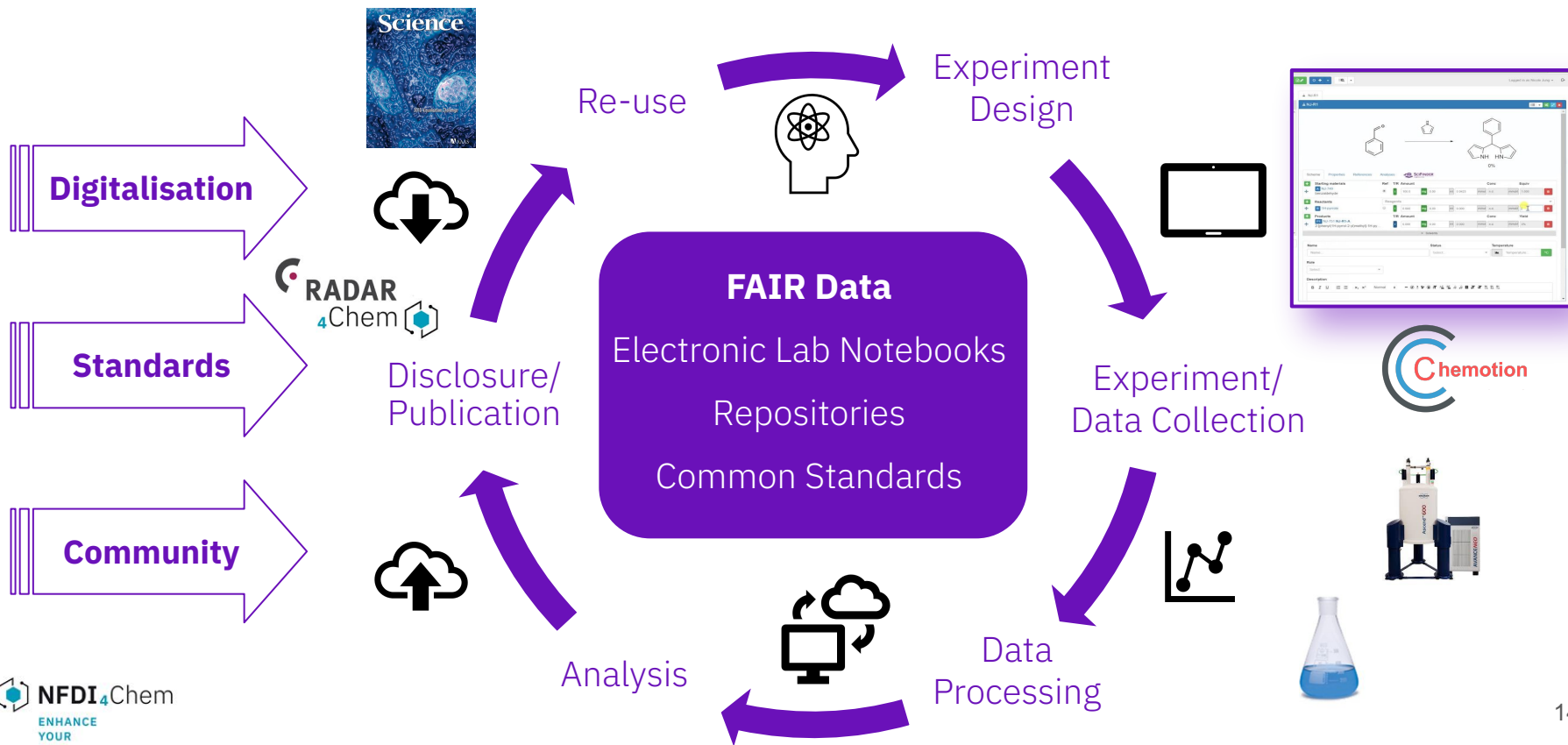
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ENHANCE
YOUR
DATA.

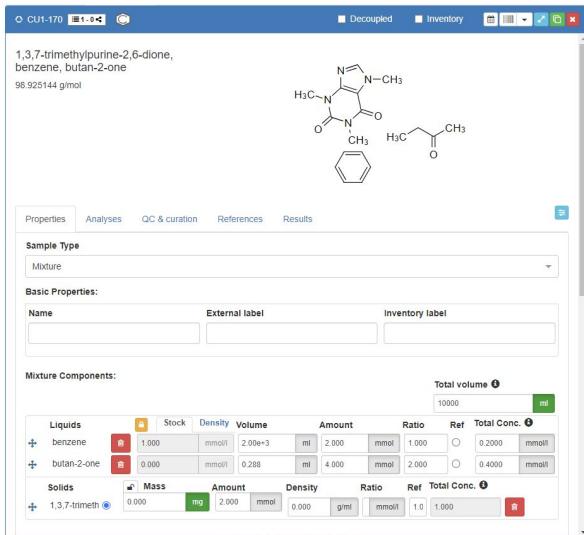


Use Case: Chemotion - Workflow



Use Case: Electronic Lab Notebook

Chemotion ELN: A Major Digitalisation Achievement (NFDI4Chem, KIT-IBCS)



1,3,7-trimethylpurine-2,6-dione,
benzene, butan-2-one
98.925144 g/mol

Properties Analyses QC & curation References Results

Sample Type
Mixture

Basic Properties:

Name External label Inventory label

Mixture Components:

Total volume 10000 ml

Liquids	Stock	Density	Volume	Amount	Ratio	Ref	Total Conc.
+	benzene	1.000	mmol/l	2.00e+3	ml	2.000	mmol
+	butan-2-one	0.800	mmol/l	0.288	ml	4.000	mmol

Solids

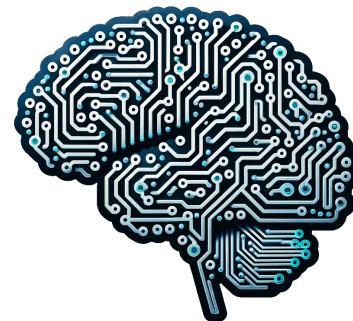
Mass	Amount	Density	Ratio	Ref	Total Conc.	
+	1,3,7-trimeth	0.000	mg	2.000	mmol	0.000

- Standardisation & Interoperability
- Improved Reproducibility
- Automated Data Logging & Organisation
- Enhanced Collaboration
- FAIR Principles Compliance
- Regulatory & Compliance Benefits

4. AI use in Chemotion ELN

Potential AI Benefits for Data & Metadata Curation in Chemotion

- Automated Metadata Extraction
- Smart Data Classification & Tagging
- Predictive Data Cleaning & Error Detection
- AI-Assisted Data Retrieval & Querying
- Machine-Generated Reports & Insights



Reflections – AI in Open Research Data



- Strengthening Open Data
 - AI improves metadata quality, small dataset utilisation, and collaboration.
 - Acts as a virtual research assistant.
- Human-AI Collaboration
 - Defining the role of human verification in research.
 - Limits of "human-in-the-loop" approaches?
- Changing Knowledge Processes
 - Shift from control knowledge → translational knowledge.
- Standards & Governance
 - Guidelines vs. AI progress – addressing the Collingridge dilemma.
 - Bottom-up vs. top-down: Who should drive AI standards?
- Implementation Challenges
 - Ensuring scalable, effective AI integration in research.

Conclusions

■ Opportunities

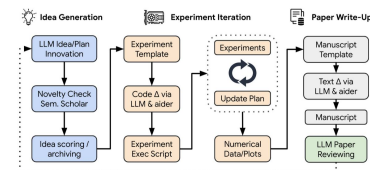
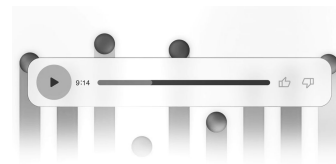
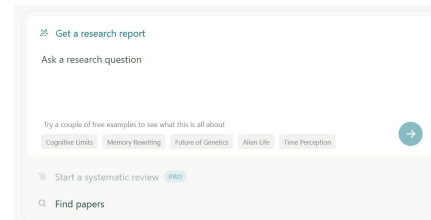
- **AI-based research assistant** (e.g. Elicit)
- **Conversational access to science** by AI summarised texts & podcasts (e.g. Google Notebook LM)
- Full replacement of scientific discovery: “The **AI scientist**” (e.g. Sakana AI)

■ Challenges

- **Research integrity** within science → continuous development
 - **Explainable AI/human in the loop**: transparency but limits of human verification → **Bias** remains
 - Role of **guidelines** - limits of guidelines
- **Trust in science** from the public → increase of openness
 - **Communication** formats with the public on genAI use in science & open research data
 - Inclusion of **stakeholders** in the assessment process (e.g. publishers, funding, data & rights protection)

■ Risks

- **Disappearance of Data** hosts & access to tools may be limited → <https://safeguarding-research.discourse.group/>
- Limits of co-hosting data in Europe → not all data can be covered
- Source of genAI data → trustworthiness of national tools (e.g. Open AI vs. Deep seek)



Further questions?

Please contact us:

Dr. Felix Bach

FIZ Karlsruhe

Leibniz Institute for Information Infrastructure

felix.bach@fiz-karlsruhe.de

&

Dr. Linda Nierling

Institute for Technology Assessment and Systems Analysis (ITAS)

Karlsruhe Institute of Technology (KIT)

linda.nierling@kit.edu

and the **DiTraRe team**



ditrare@fiz-karlsruhe.de

www.linkedin.com/company/ditrare

sigmoid.social/@DiTraRe

