



Funder experimentation with AI

EViR 22 January 2026

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tomstafford.github.io

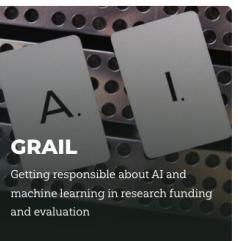
12 codesigned projects



Matthew
A study of cumulative advantages in funding allocation



Narratives
The uses and evaluation of researchers narrative CVs



GRAIL
Getting responsible about AI and machine learning in research funding and evaluation



Funder Data Platform
Supporting data-sharing to unlock insights into research funding



AGORRA
A global observatory of responsible research assessment



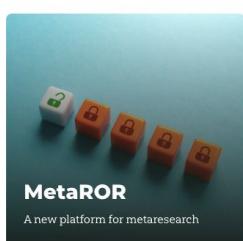
Undisciplined
Future models of funding and evaluating transdisciplinary research



Peer Review
RoRI Atlas of Peer Review



Portfolios
Research funding landscape analysis



MetaROR
A new platform for metaresearch



AFIRE
Accelerator For Innovation & Research Funding Experimentation

19 Core Partners



TRANS FORMING RESEARCH

EXPERIMENTS
SYSTEMS
PLATFORMS

The Research on Research
Institute Impact Report
(2023-2025)

<https://researchonresearch.org/roris-impact-what-weve-achieved-and-where-were-going/>

Forum

Sharing work by funders, for funders

Capacity building

Sprints on **AI/ML in reviewer selection**

Experiments

Distributed Peer Review, Partial Randomisation, Desk Rejection, and more!



These slides:
bit.ly/tomstafford

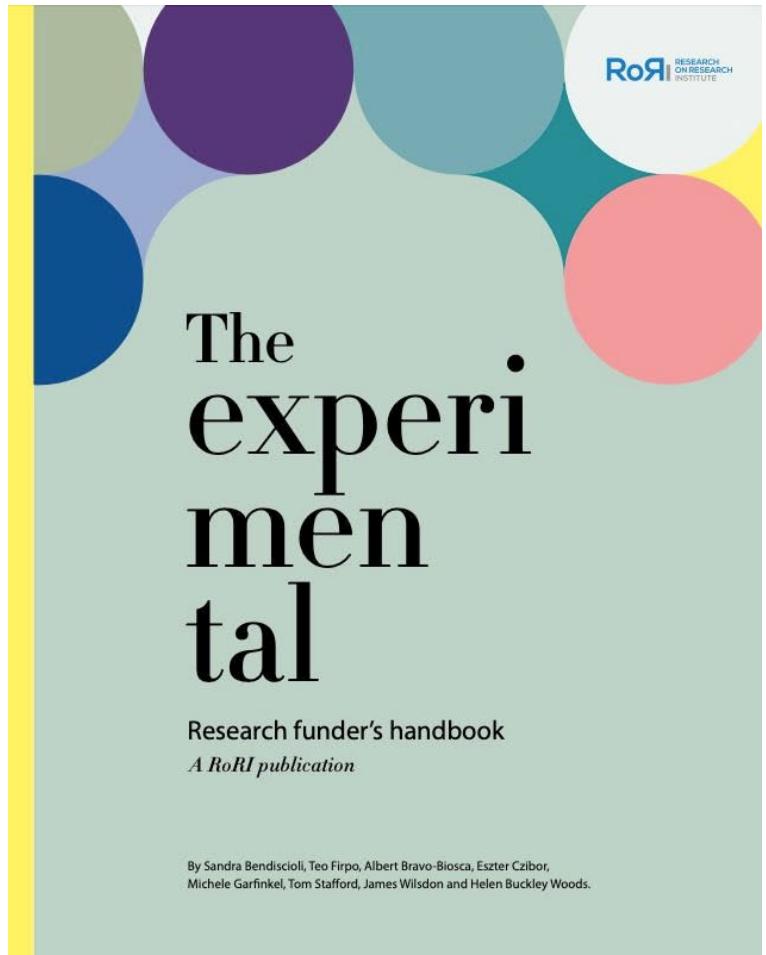
Our definition of experiment

Principled: a research design that allows inference about what causes what (before/after, shadow experiments, true experiment/RCT)

Planned: primary outcome measure and analysis plan declared in advance

Public: a commitment to sharing the results regardless of outcome

We can plan/run experiments



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The experimental research funder's handbook (Revised edition, June 2022, ISBN 978-1-7397102-0-0).

<https://doi.org/10.6084/m9.figshare.19459328.v2>

These slides:

bit.ly/tomstafford

RoRI's GRAIL project

GRAIL = Getting responsible about AI and machine learning (ML) in research funding and evaluation

A RoRI project running from 2023 to 2025

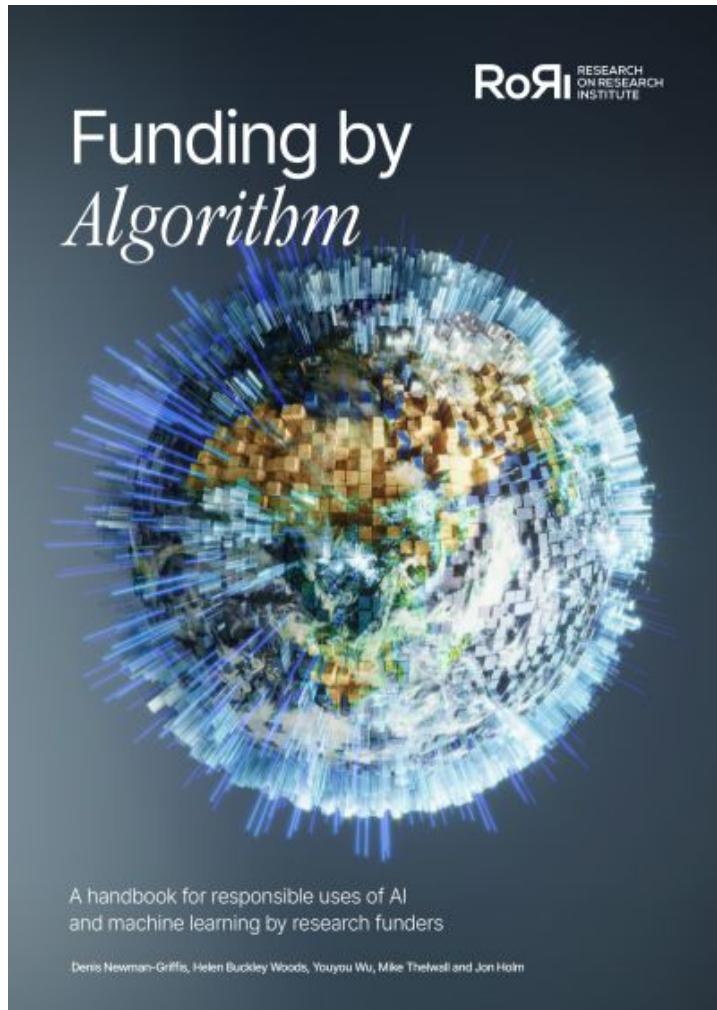
Goal: Understand how funders use AI/ML and build shared practices

Who:

- 35 delegates from 13 research funders
- 4 researchers



Funding By Algorithm



A handbook for
responsible uses of AI
and machine learning by
research funders

[link](#)

Sprint v1.0 - 20 x N America and European funders

AI in reviewer matching	3.8
AI in peer reviewing	3.5
AI for prioritising funding applications	3.3
AI in research assessment exercises	3.2
AI for applicant self-assessment	3.2
AI for navigating funding resources	3.0
AI in strategic planning	2.8

AI and Reviewer Matching in Research Funding: Three Case Studies

Inés Bouzón Arnáiz, Carla Carbonell Cortés, Alexander Hagemeijer, Anne Jorstad, Gabriel Okasa, Mike Thelwall, Niels van den Berg, Helen Buckley Woods

16/12/2025

Three case studies explore
real-world approaches and
trade-offs:

<https://tinyurl.com/y8a6vfdn>



**Swiss National
Science Foundation**



"la Caixa" Foundation



Research Questions

1. Can language models help match proposals to reviewers?
2. Is it feasible for something like a conference to adopt/adapt this technology?
3. Can it be done securely/privacy respecting?



Maybe - evidence for meaningful improvements beyond human matching



Definitely yes



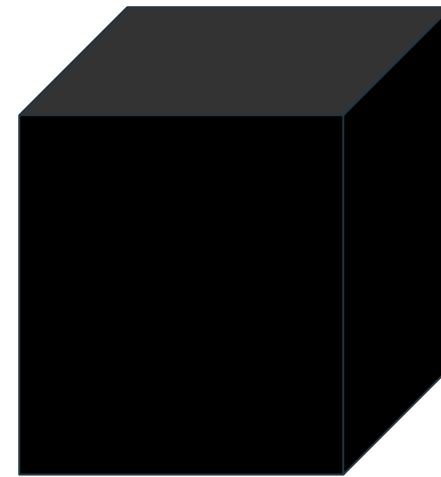
Definitely yes

Why AI specifically requires experiments

AI is novel & changing - our intuitions are poorly calibrated

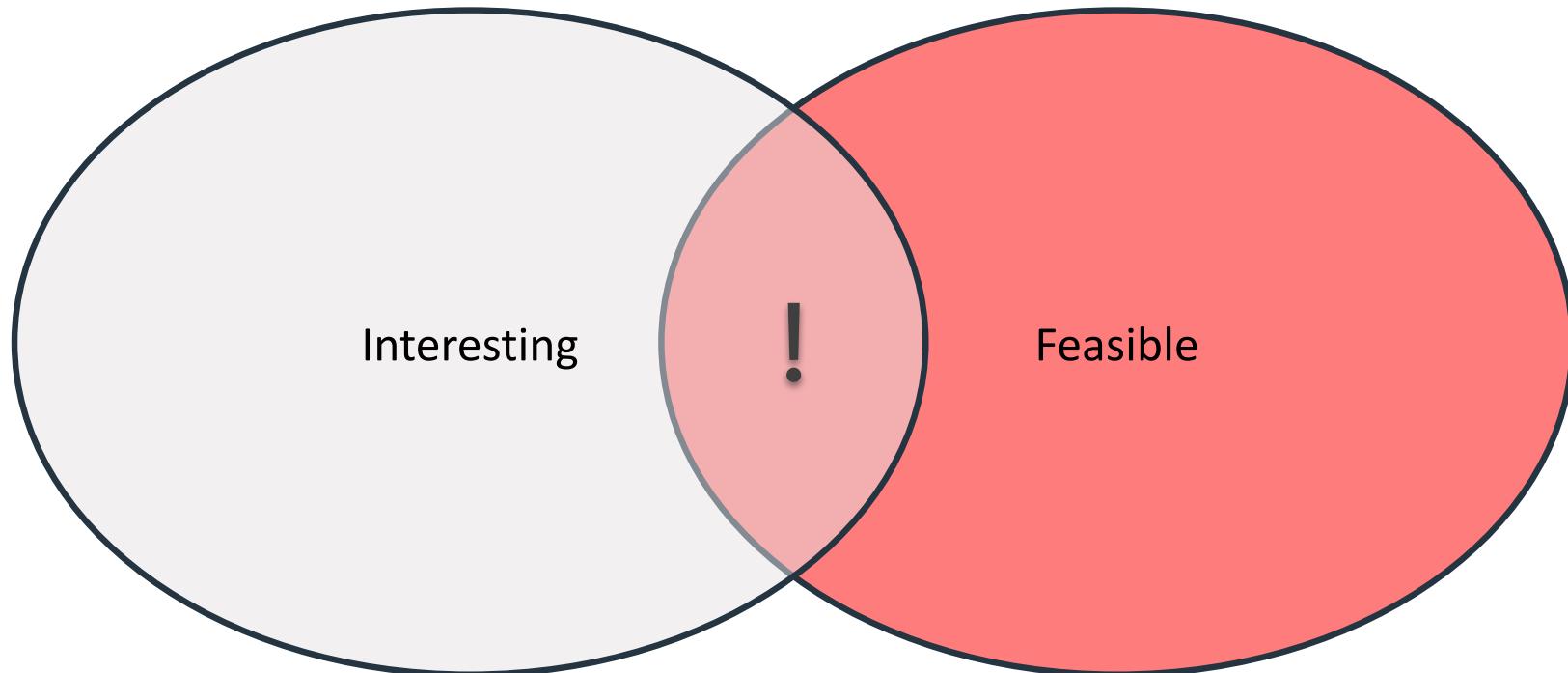
Specific areas of uncertainty

- Fluency
- Stochasticity
- Hallucinations
- Inscrutability
- Bias



Thinking about experiments

“The Art of the soluble”



Good outcome measures



A part of the fresco "Triumph of Galatea," created by Raphael around 1512 for the Villa Farnesina in Rome. [Art Images via Getty Images](#)

Assays and microscopes

Yes/No

but is it the
right
question



Close view

but what are
you looking for?

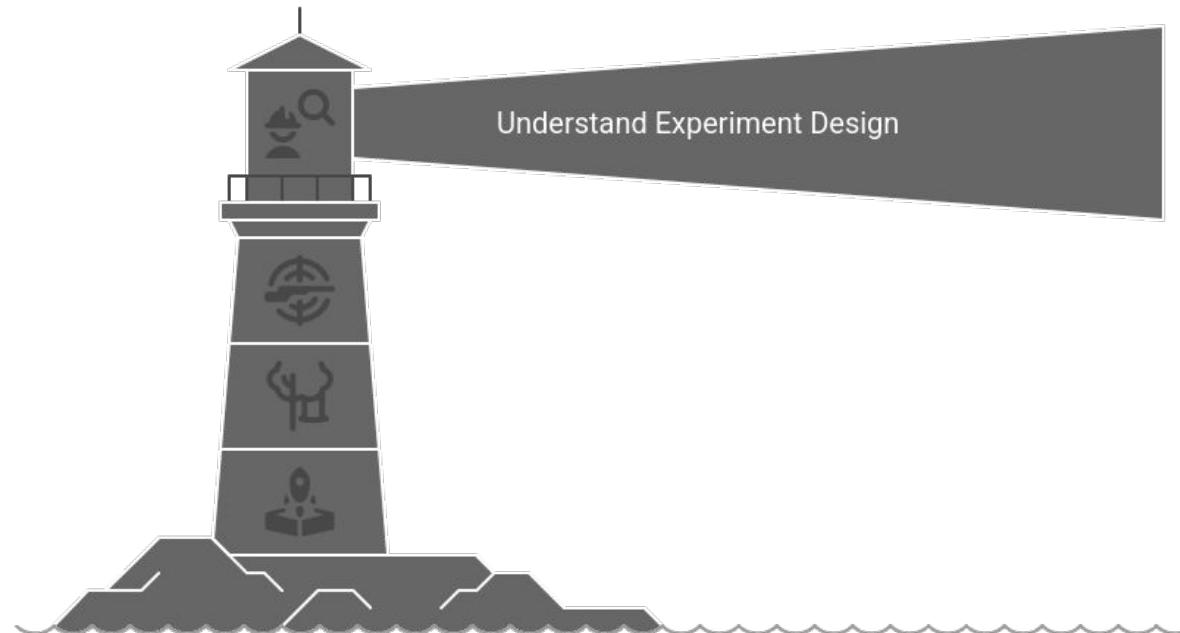


Image: [CC Wikimedia](#)

Just designing experiments is valuable



Becoming experimental



Made with  Napkin

Get in touch!

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END
(reserve slides
follow)

Other AFIRE experiments

Partial Randomisation Trials Catalogue

Funder	Dates
<u>Health Research Council of New Zealand</u>	2013-
<u>VolkswagenStiftung</u>	2017-2020
<u>Austrian Science Fund (FWF)</u>	2019-
<u>Swiss National Science Foundation (SNSF)</u>	2018-
<u>Novo Nordisk Fonden</u>	2022-2025
<u>British Academy</u>	2022-2025
<u>UKRI / NERC</u>	2022-
<u>Wellcome</u>	2023-
Nesta	2019-2020
University of Leeds	2023
UMC Utrecht/Ministry of OCW	2023

bit.ly/PRtrials



Desk Rejection Shadow Experiment

Can agency staff predict those proposals with the least likelihood of success?

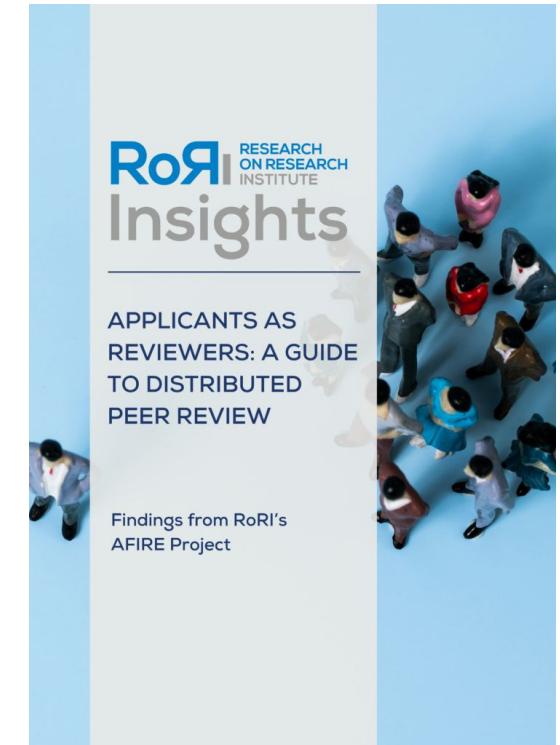
- a shadow experiment, not an intervention
- supports optimal use of external review
- UKRI leading participation
- recruiting schemes which will complete by end of 2026

Enquiries:

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Evaluating Distributed Peer Review at the Volkswagen Foundation

Anna Butters, Melanie Benson Marshall, Tom Stafford & Stephen Pinfield
(Research on Research Institute and University of Sheffield);
Hanna Denecke, Alexander Bondarenko, Barbara Neubauer, Robert Nuske
& Pierre Schwidlinski (Volkswagen Foundation)



VolkswagenStiftung

More on GRAIL & the GRAIL case studies

GRAIL activities

13 virtual workshops

Presentations / case studies

Q&A

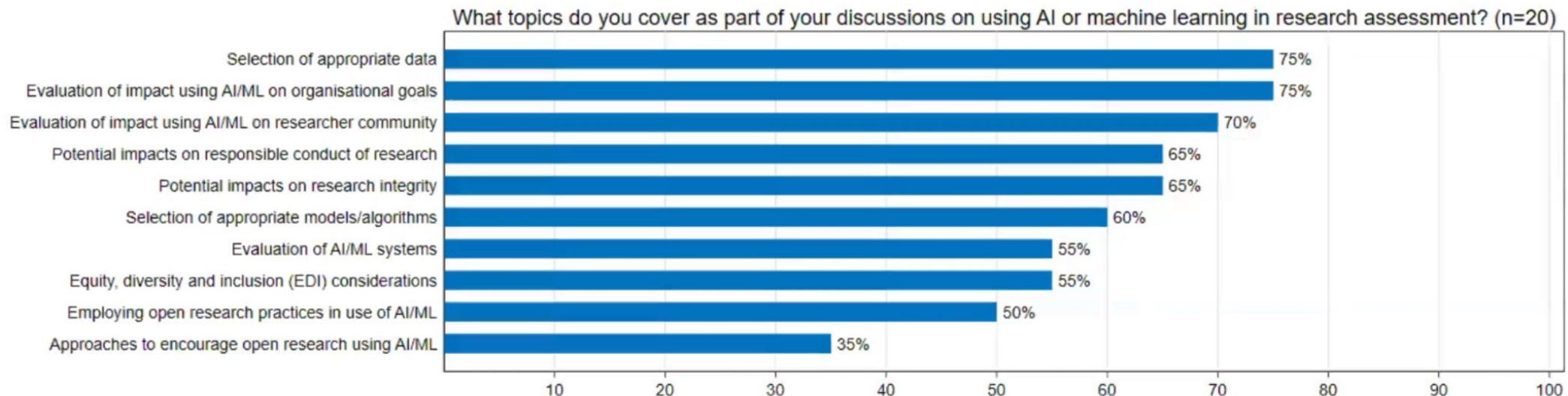
Group discussions

Topic
Guidelines for the use of generative AI in 7 research funding processes
Responsible AI principles for research 8 funders
9 Human in the Loop
Collaboration and reuse: tools, data, and 10 knowledge structures
Competencies and collaboration on AI/ML 11 applications
Impact assessment, documentation and 12 reporting, and transparency and reliability

GRAIL outputs

A curated library of AI/ML use cases

Survey: experiences with AI/ML



GRAIL insights: a wide range of AI use cases

Peer review

Handling applications

Tracking and evaluating research outputs

Assisting applicants

GRAIL insights: AI use cases

Peer review

- Matching proposals to reviewers [[Handbook case study 1](#)]
- Evaluating the quality of reviewers' comments
- Summarising and integrating reviewer comments

GRAIL insights: AI use cases

Handling applications

- Screening and prioritising applications [\[Handbook case study 2\]](#)
- Automatic tagging of proposals for topic/theme/SDGs
- Summarising / translating proposals
- Detecting duplicate / similar applications
- Verify eligibility

GRAIL insights: AI use cases

Tracking and evaluating research outputs

- Linking funded grant and research publications [\[Handbook case study 3\]](#)
- Linking funded grant and research impacts (patent/policy/media) [\[Handbook case study 4\]](#)
- Quality assessment of research publications [\[Handbook case study 5\]](#)

GRAIL insights: AI use cases

Assistance for applicants

- Chatbot for understanding funding calls
- Proposal writing assistant
- Proposal review assistant
- Self-evaluation of proposal

GRAIL insights: evaluation and experimentation

GRAIL has seen some excellent examples of experiments (a few among the participants)

A few suggested areas for evaluation in the handbook

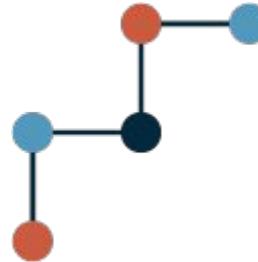
- AI in reviewer matching
- AI in producing peer review reports
- AI for prioritising funding applications
- AI in research assessment exercises
- AI for applicant self-assessment
- AI for navigating funding resources
- AI in strategic planning

GRAIL insights

More systematic experiments with AI/ML tools is needed

Small, focused experiments will help us move beyond anecdotes

Potential for multi-funder collaboration on experiments



Swiss National Science Foundation

Implementation

Since 2020 in the Life sciences (1000 proposals/year)

Fixed pool of reviewers

Full text of proposals

In house data team

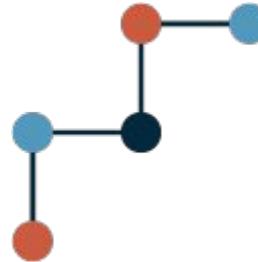
Considerations

Human in the loop (all matches reviewed)

Explainability (not generative)

Transparency (open, not commercial models)

Privacy (run locally)



Swiss National Science Foundation

Evaluation:

Informal: time saving

Formal: overlap with human matching (“in more than 8 out of 10 proposals, there was at least one reviewer suggested by the AI-assisted reviewer matching that was also manually assigned by the scientific officers.”)

Learnings

Demonstrate feasibility & efficiency *as a supporting tool*

Heterogeneity in performance

Integration with organisation requires as much attention/resource as technical implementation

Okasa, G., & Jorstad, A. (2024). The Value of Pre-training for Scientific Text Similarity: Evidence from Matching Grant Proposals to Reviewers. In Proceedings of the 9th edition of the Swiss Text Analytics Conference (pp. 89-101).



"la Caixa" Foundation

Implementation

Last 8 cycles of CaixaResearch Health call, also now Innovation call

Fixed reviewer pool

Co-designed/developed with external provider

Keywords (MeSH) from proposals sent to external provider, reviewer keywords obtained from pubmed, matches returned

Considerations

Time/workload saving,

Accuracy/fairness

Population balance (e.g. gender assignment)



"la Caixa" Foundation

Evaluation

10% of matches reviewed by human

Audit of % of reviewers who declare a lack of expertise on assigned proposals (stable at 20% per year)

Learnings

Successful for improving not replacing human intervention

Other uses of AI: detecting proposals with low probability of being funded, reviewing evaluators' comments, summarizing selected proposals to produce abstracts for the general public and summarizing evaluators' comments

Implementation

Tool available organisation wide

prophy.ai/ (previously Elsevier tool)

Proposals & applicant details uploaded, reviewer suggestions come back (no pool), used to augment existing reviewer search methods

Considerations

Prophy driven by OA sources

Motivations: Speed, widen reviewer pool, improve match quality

Evaluation

No formal evaluation - difficulties is assessing value for staff and in assessing quality of reviews resulting

Learnings

tool won't tell you reviewer quality, or timeliness

perceived to be successful (a useful tool, better than keyword only search)

external party easier than in house development



INSIDE THE FUNDING PROCESS: USING GENERATIVE AI TO ASSESS REVIEWERS' CRITERIA PRIORITISATION IN MULTI-STAGE APPLICATION ASSESSMENTS

PETER KOLARZ AND DIOGO MACHADO

DOI: 10.22163/FTEVAL.2025.710

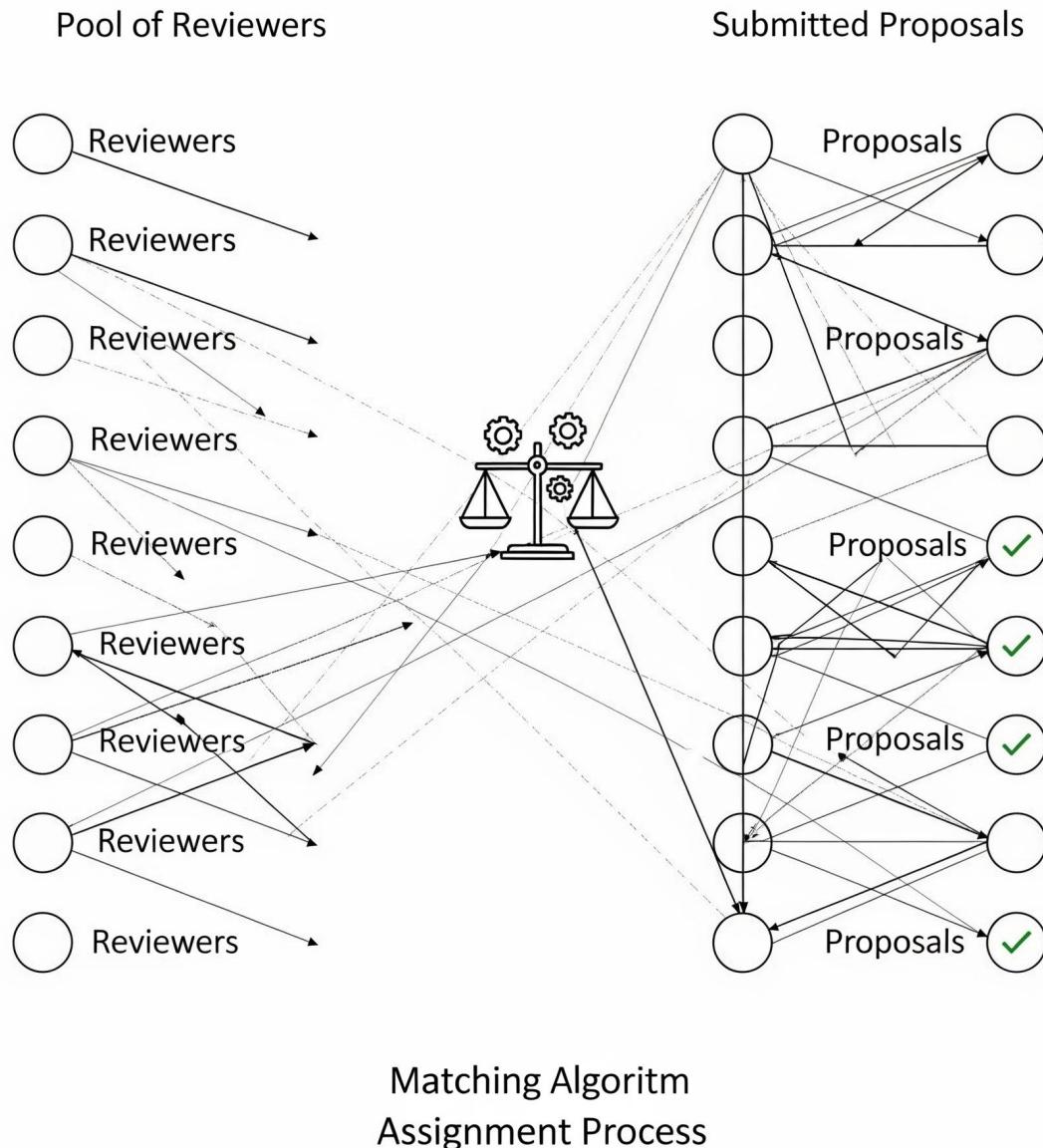
FWF Austrian
Science Fund

The Metascience 2025 conference experiment



Can AI be used for better matching
of proposals to reviewers? Feasibility
and formal evaluation with the
Metascience 2025 conference

Josie Coburn and Tom Stafford 2025-11-26



Finding (enough, good) reviewers is a conceptual and practical problem

- conceptual: what makes a reviewer good?
- practical: how do you get a reviewer to agree?

Reviewer-proposal matching
identified by GRAIL as a key area for
possible experiments

Many funders already exploring this

Algorithms need validation!

Meta-metascience

AFIRE Commitment: Observation is not enough - we have to try things!

- demonstrate feasibility
- opportunity for better causal inference

Metascience 2025 conference, London

- a chance to show we'll take our own medicine
- appropriate domain for demonstrating feasibility
- added value: validate by collecting reviewer self-perception of suitability

The “shadow” experiment

Consent from those submitting and reviewers
All analyses done after final programme decisions
All analyses local - no data left the conference
441 submissions: Title, Abstracts
25 reviewers: assigned to submissions via keywords
1,323 reviews

- for each we have a match scores & a reviewer suitability judgement
- (each proposal seen by 3 reviewers)

Research Questions

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Matching - via embedding

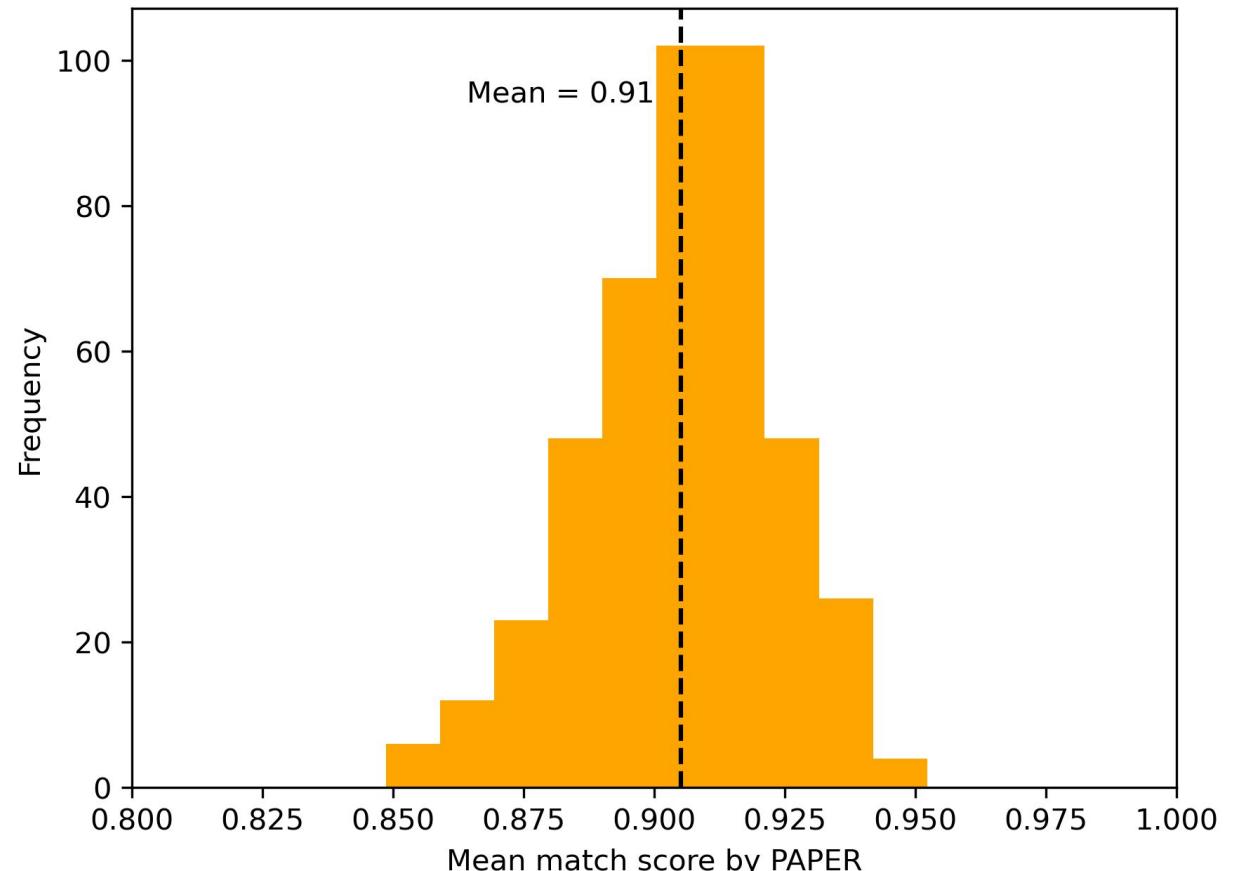
Reviewer keywords & proposal title+abstract -> embedding space

Code from SNSF:

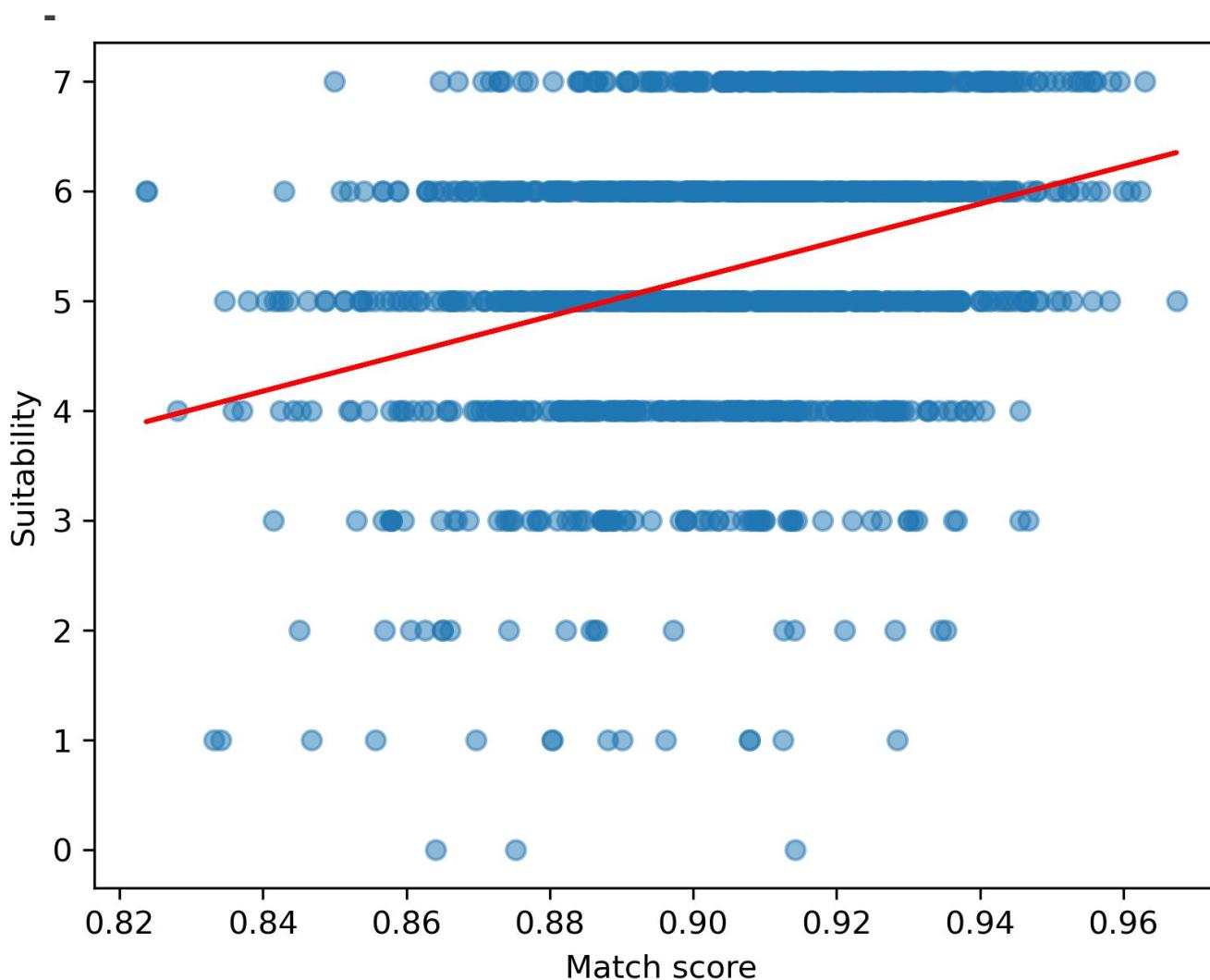
<https://github.com/snsf-data/snsf-grant-similarity>

- thanks to Gabriel Okasa and the SNSF data team!

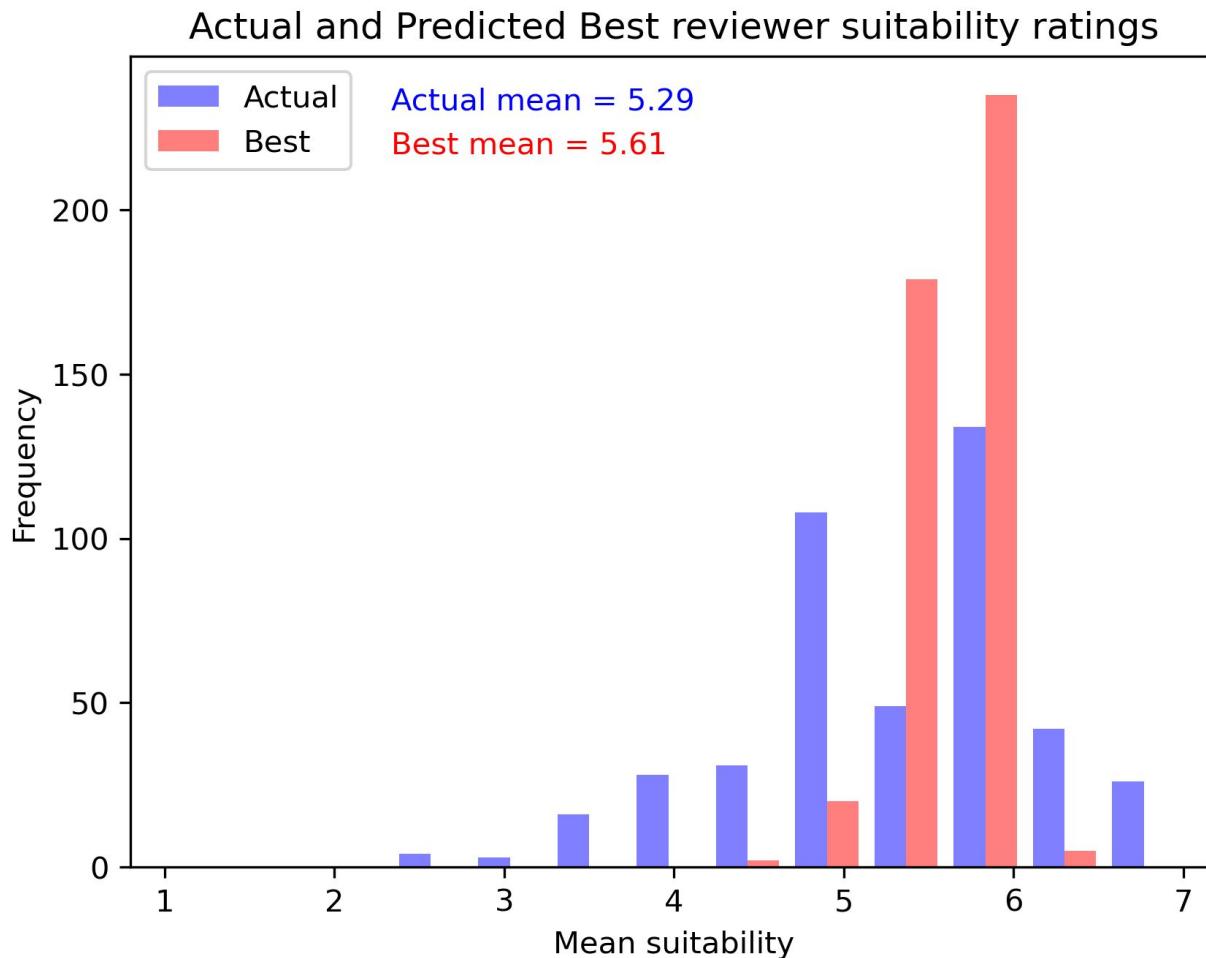
Model: [SPECTER2: BERT model pre-trained on scientific texts and augmented by a citation graph](#)



You can predict suitability from match score

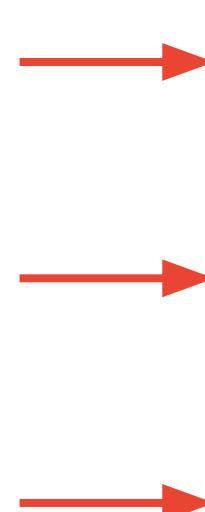


...and from this you can predict gain in suitability from using the optimal match



Research Questions

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Maybe - evidence for meaningful improvements beyond human matching

Definitely yes

Definitely yes

Thanks to all participants!