Current Strategies for Updating Systematic Reviews

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Center on
KNOWLEDGE TRANSLATION FOR
DISABILITY & REHABILITATION RESEARCH
at American Institutes for Research

Using New Tools and Technologies to Maintain Our Living Map of COVID-19 Research

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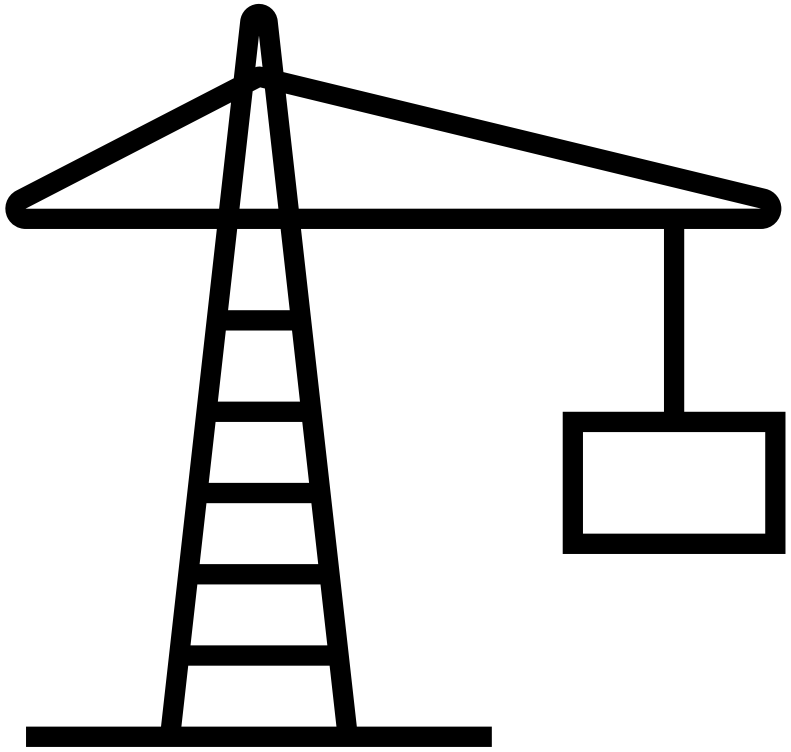
Evidence for Policy & Practice

Under construction



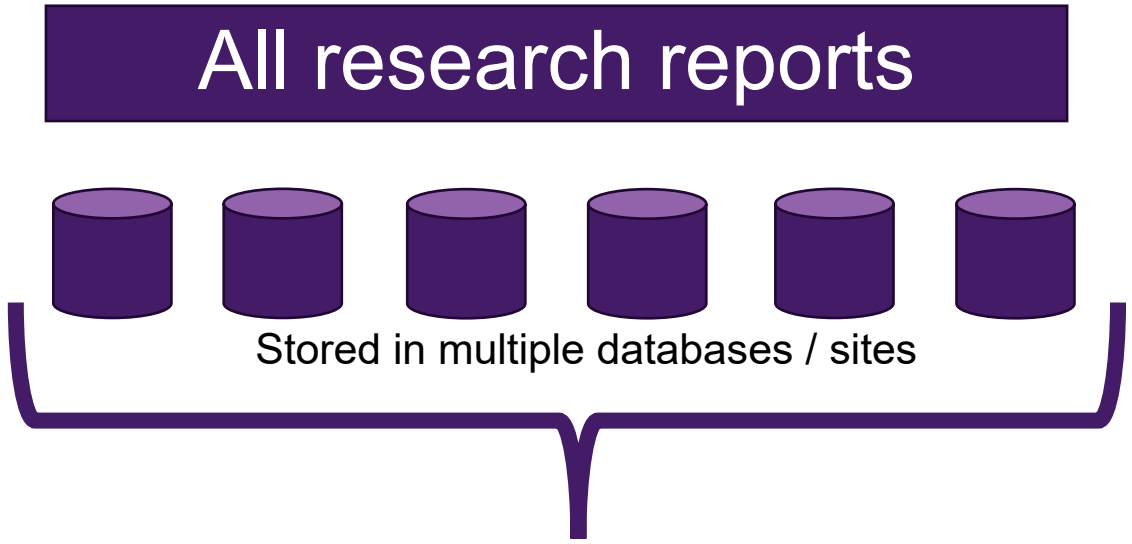
Outline

- A new search paradigm for updating systematic reviews and maps?
- Case study: the COVID-19 map of research maintained by EPPI-Centre, University College London and CRD, University of York

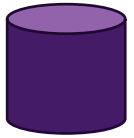
A new search paradigm?

- Two enablers:
  - Increasingly open bibliographic data
  - New automation technologies and tools

Finding eligible studies



Boolean searches retrieve most likely relevant into local database

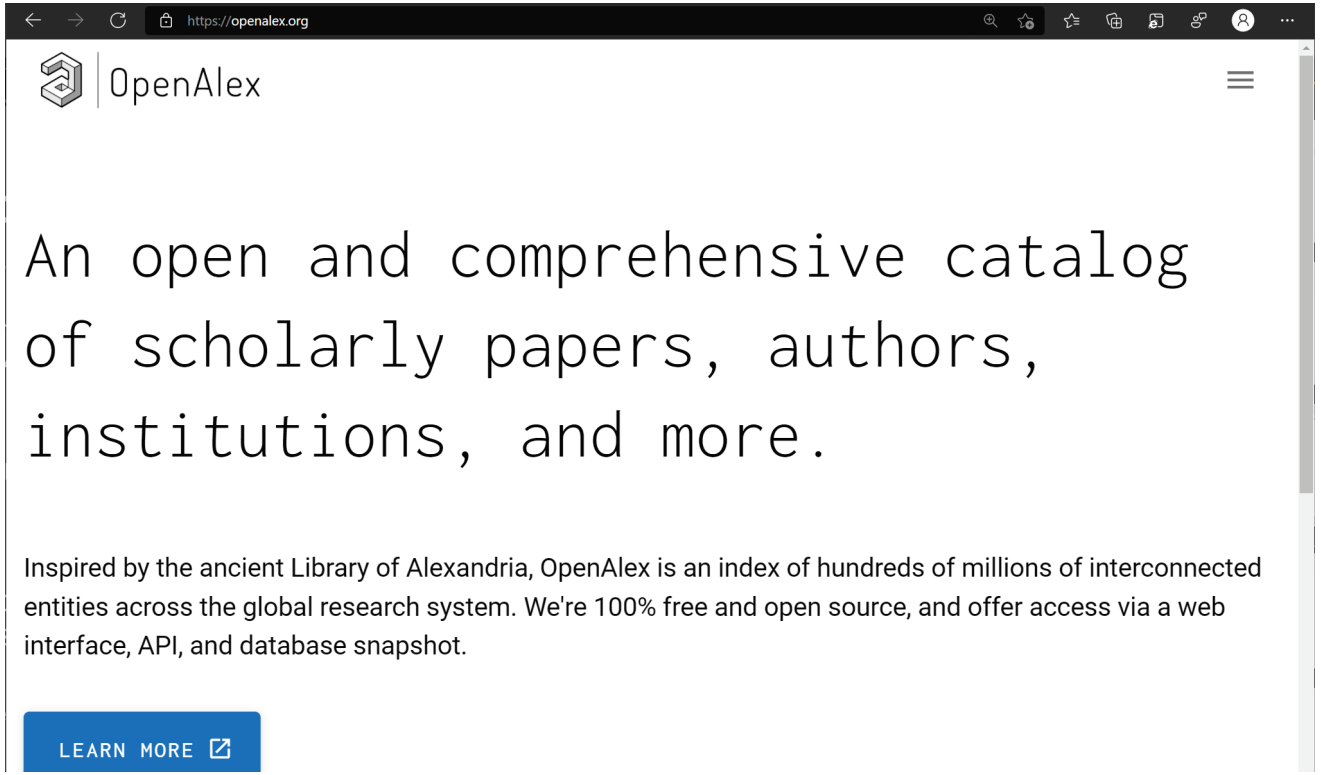


Records deduplicated and manually screened for eligibility

Why is it like this?

- Various organisations have indexed research in their area.
- It costs money to index research.
  - The business model (thus far) has been to charge for access to bibliographic databases.
  - There's been financial benefit to keeping a monopoly hold over the content of databases (i.e. you can't find a given set of records by searching elsewhere).
- This has led to the picture we see of numerous, subject-specific databases jealously guarding their content (and charging £££ for access).

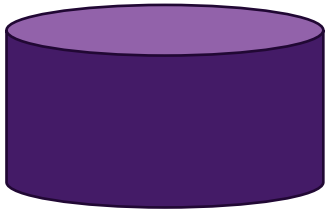
Movement towards open and more comprehensive sources



- Open Alex / CrossRef / Dimensions… (Google Scholar to some extent) are publishing bibliographic data at scale.
- Microsoft Academic – now discontinued – played a major role.
- Bibliographic data are becoming *commoditized* (you can get the same content from multiple sources).
- You can ingest (essentially) ALL the world's published research into a local database.

Commoditized bibliographic data can be aggregated / stored by anyone

All research reports

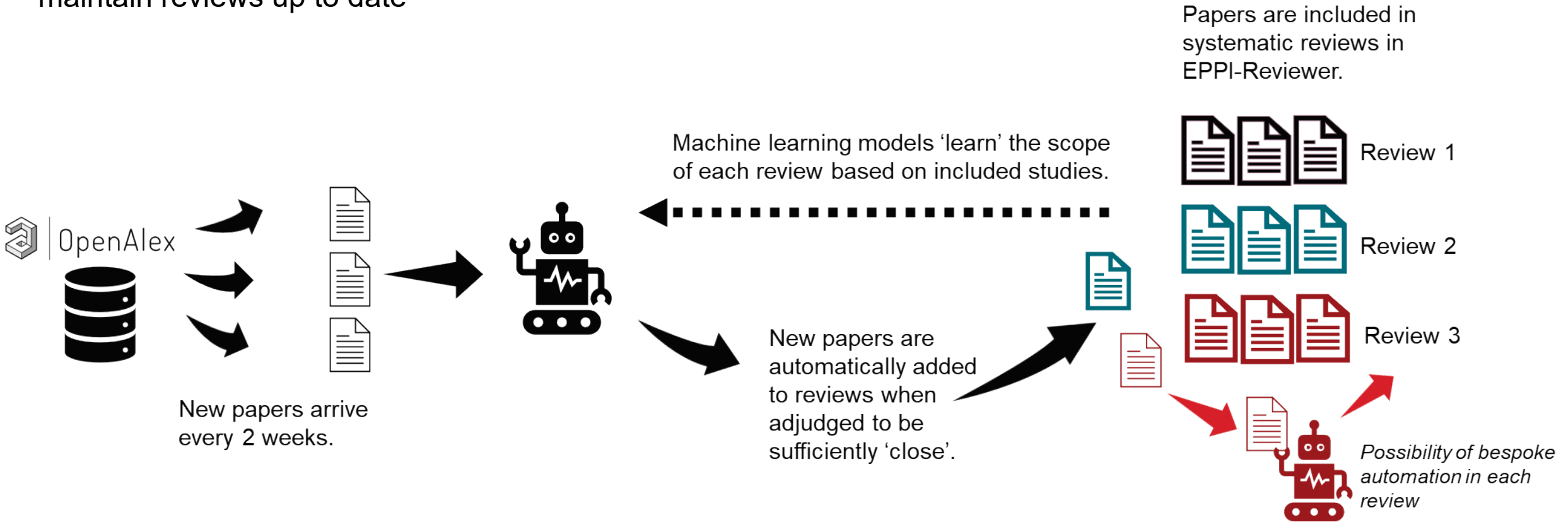


Stored in comprehensive repositories

What is the best way to find eligible studies?

Continuous update of reviews in EPPI-Reviewer

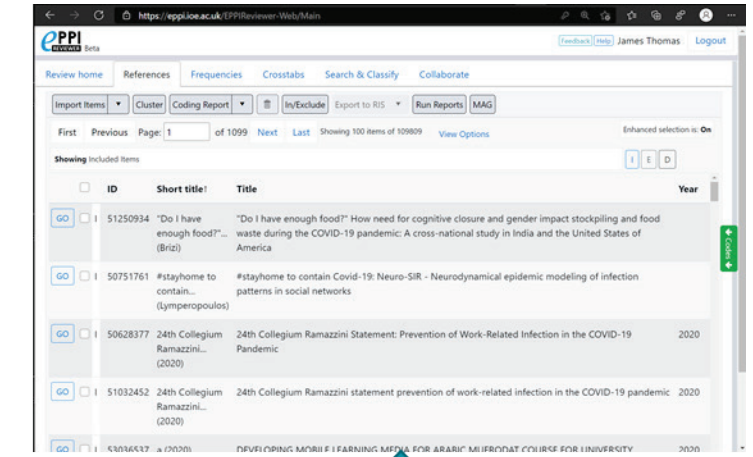
Main aim: to maintain a ‘surveillance’ of the literature as it emerges to maintain reviews up to date

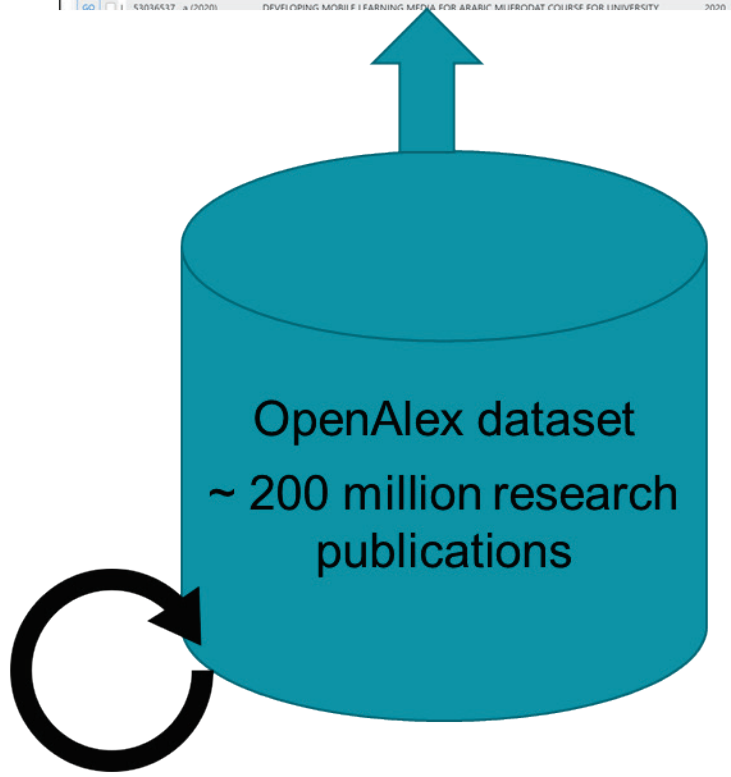


Our case study

- The EPPI-Reviewer platform contains a local copy of the OpenAlex* dataset
- It's updated every 2 weeks
- Between 400k and 2m new records arrive each update
- We can find research using machine learning and Boolean searches

How can we use this new resource to maintain our COVID-19 map of research?





*We originally started this work using Microsoft Academic which closed at the end of 2021. OpenAlex builds on Microsoft Academic and aims to be a 'drop-in' replacement.

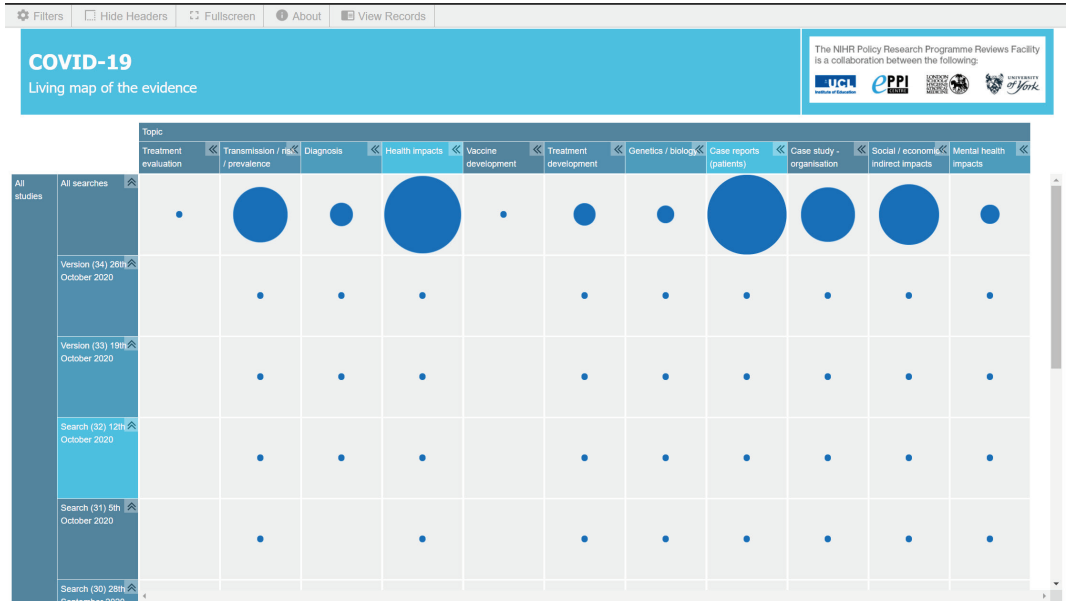
Overarching research questions

Are all the studies we need for systematic reviews indexed in OpenAlex (MAG)?

Can we ***efficiently*** identify the studies we need for systematic reviews using OpenAlex (MAG)?

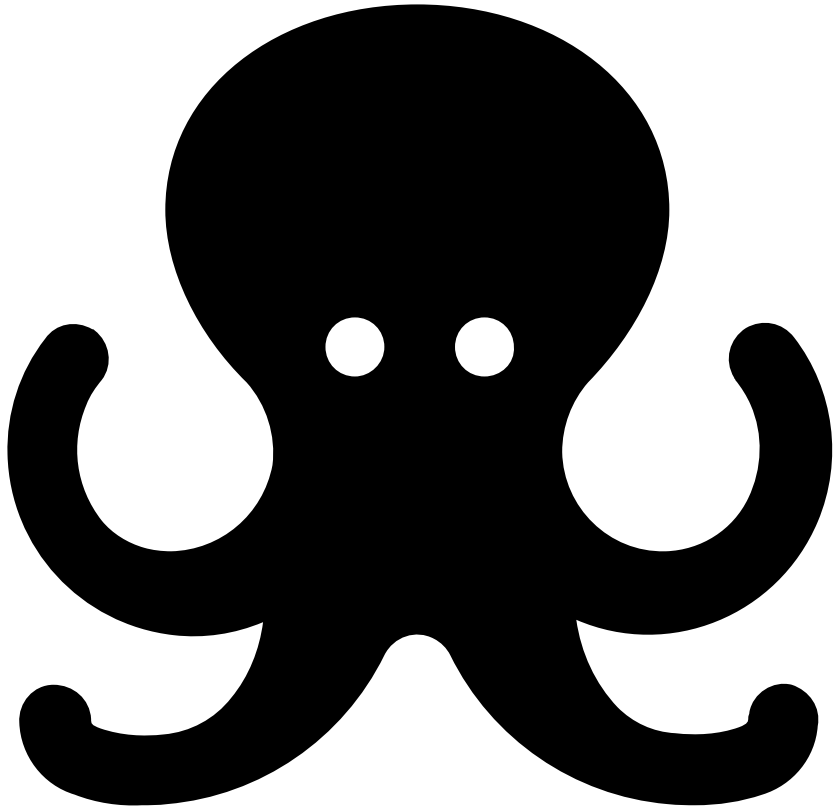
COVID-19 map of research activity

- Updated weekly
- To start with, was populated via searches of Embase and PubMed
- Comprehensive
- Large team
- A lot of work!



The Octopus Study

- Aim: to undertake a cost-effectiveness study of different options for maintaining the COVID-19 map
- Lots of data in map; added detailed time-on-task data for team
- Collected data for 4 weeks of map updates (June / July 2020)
  - Compared
    - Embase / PubMed search sources
    - MAG / OpenAlex as a single search source
    - Different machine learning options



8-arm CEA: Components of study identification workflows

Study Arm	Intervention / Comparator	Automation in Workflow	Boolean MEDLINE + Embase Searches	MEDLINE-Embase De-duplication	Automated MAG Update Search	Binary ML Classifier	Manual Screening	Priority Screening	Fixed Screening Target N = 1,500 records	Target Recall
1	Comparator A		●	●			●			1.0
2	Comparator B		●	●			●			0.95
3	Comparator C		●	●			●		●	0.95
4	Intervention A	●	●	●		●	●			0.95
5	Intervention B	●	●	●		●	●	●	●	0.95
6	Intervention C	●			●		●			1.0
7	Intervention D	●			●	●	●			0.95
8	Intervention E	●			●	●	●	●	●	0.95

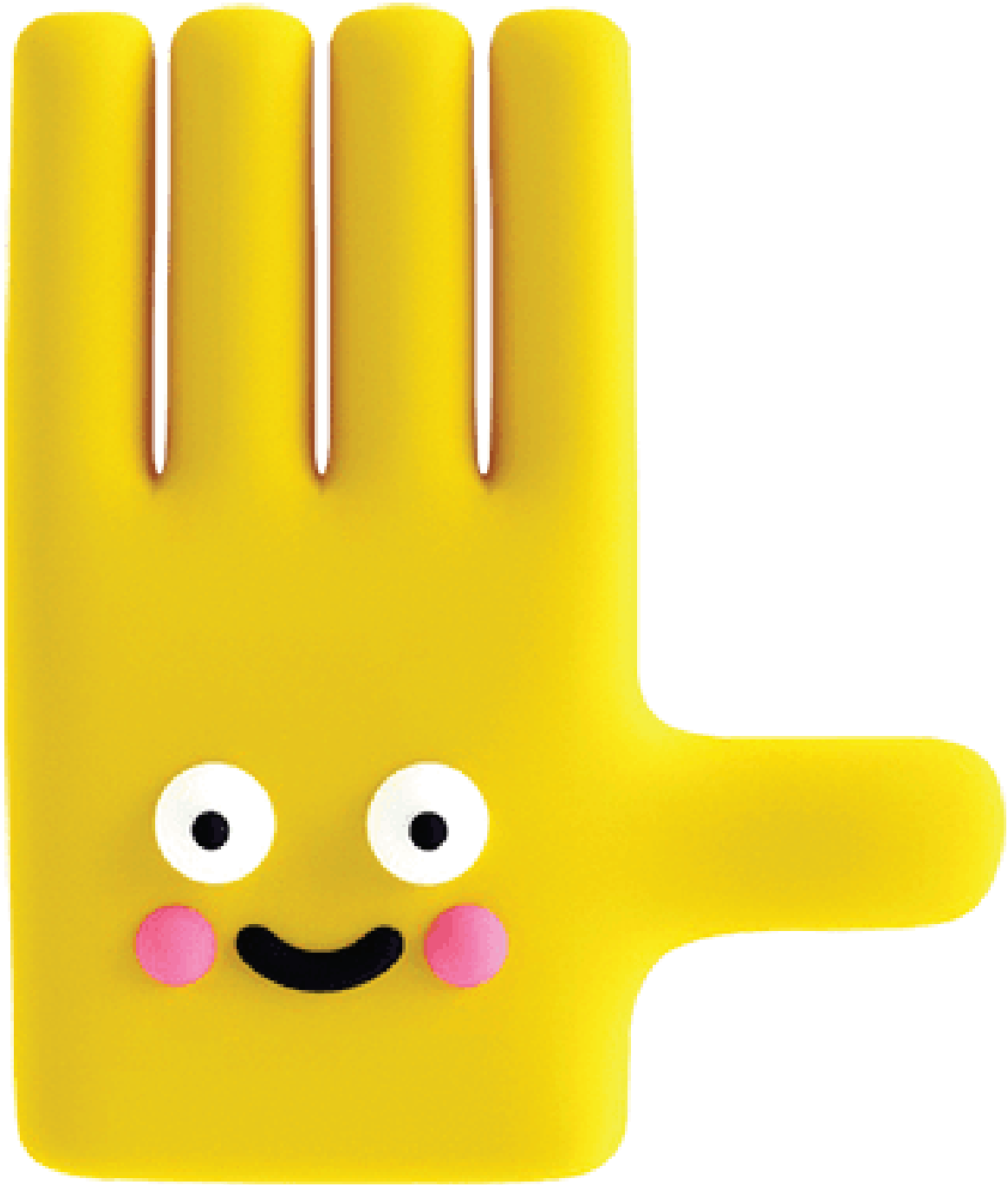
Octopus study: results

	Arm 1	Arm 2	Arm 3	Arm 4	Arm 5	Arm 6*	Arm 7*	Arm 8*
	Comparator A	Comparator B	Comparator C	Intervention A	Intervention B	Intervention C	Intervention D	Intervention E
Gold standard included	4378	4378	4378	4378	4378	4378	4378	4378
Medline-Embase unique included	65	65	65	65	65	65	65	65
MAG unique included	743	743	743	743	743	743	743	743
Medline-Embase + MAG common included	3570	3570	3570	3570	3570	3570	3570	3570
Screened-coded	9180	8722	6000	6315	6000	8639	7898	6000
Included	3635	3455	2392	3468	3441	4313	4104	4104
Target recall vs Source(s) included	1	0.95	0.95	0.95	0.95	1	0.95	0.95
Recall vs Source(s) included	1.00	0.95	0.66	0.95	0.95	1.00	0.95	0.95
Cumulative Recall vs Gold standard included	**0.83**	**0.79**	**0.55**	**0.79**	**0.79**	**0.99**	**0.94**	**0.94**
Cumulative Precision vs Gold standard included	**0.40**	**0.40**	**0.40**	**0.55**	**0.57**	**0.50**	**0.52**	**0.68**

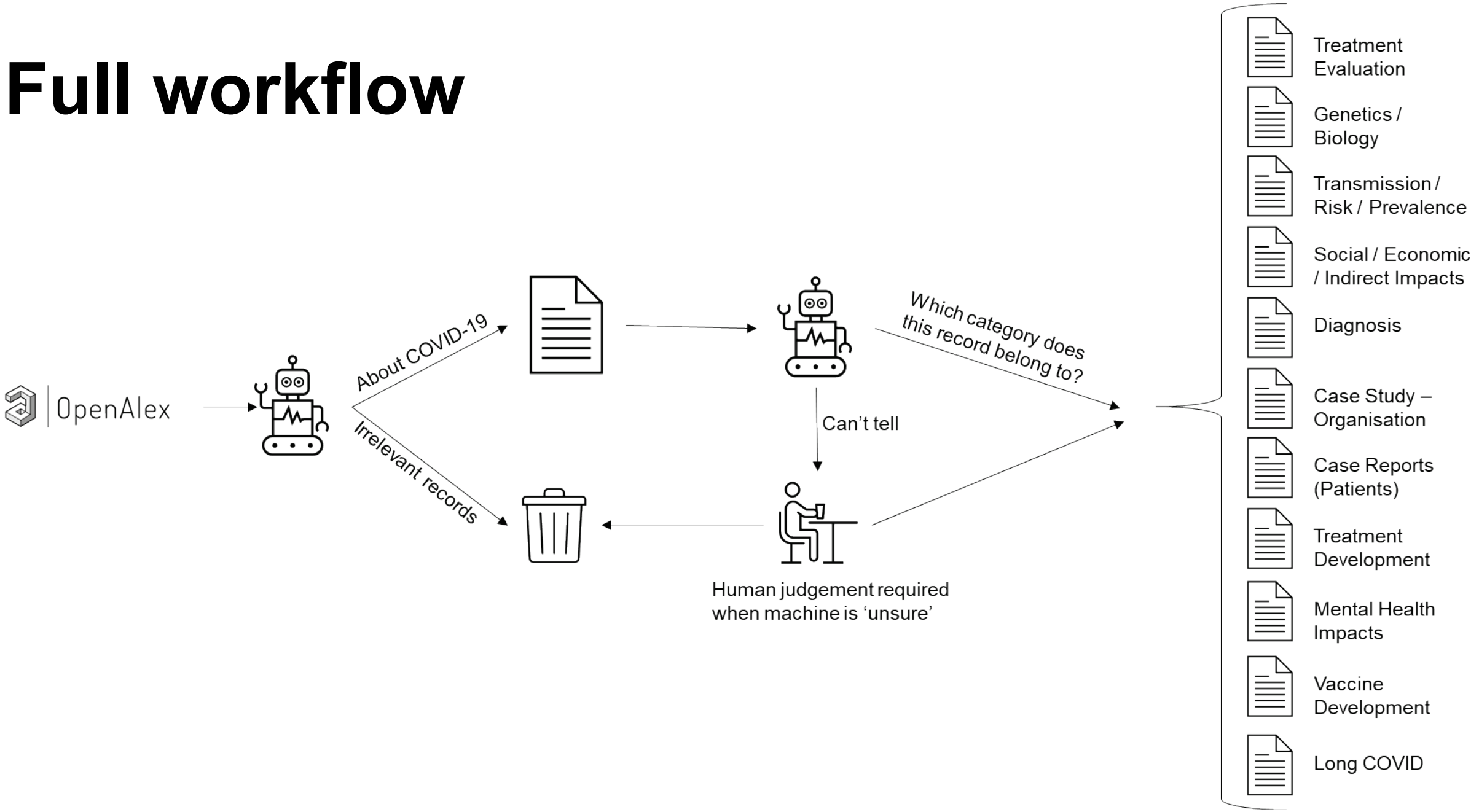
For full results, please see https://wellcomeopenresearch.org/articles/6-210/v1.

Further automation …

- The map contains ~100k records manually categorized into 12 domains (diagnosis, health impacts, treatment evaluation…)
- We have plenty of training data for more refined machine learning
- We now use a BERT model in addition to the previous machine learning to put research into categories automatically
- A second model identifies research on long COVID

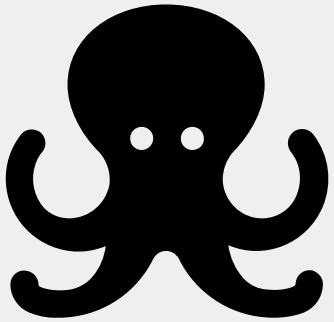


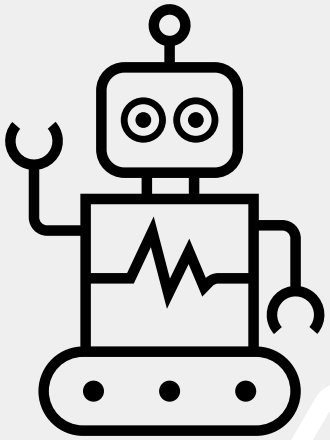
Full workflow



Conclusions

- We conducted a detailed study examining the costs and benefits of two different search sources together with automation options.
- Our traditional search sources had lower recall than expected.
- OpenAlex / MAG contains more research that is not indexed in Embase / PubMed than expected.
- Thanks to a lot of training data, we can also classify a large proportion of records automatically.
- With automation, we can obtain a higher recall at lower cost than our initial workflow.
- We are currently evolving the workflow with a view to maximising the efficiency gains from automation.





Thank you

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Thank You!

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