

Machine learning tools are now available for use in Cochrane reviews! Try them out and discuss how they should and shouldn't – be used

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Declaration of interests and funding

- James Thomas is co-lead of the Cochrane 'Transform'
 project, which is implementing some of the technologies
 discussed here. He also directs development &
 management of EPPI-Reviewer, the EPPI-Centre's
 software for systematic reviews.
- Parts of this work funded by: Cochrane, JISC, Medical Research Council, National Health & Medical Research Council (Australia), Wellcome Trust. All views expressed are my own, and not necessarily those of these funders.





Objectives

- Demonstrate the range of machine learning tools which Cochrane authors can use in their reviews
- Try out machine learning technologies
- Discuss their use in Cochrane reviews

Links to tools: http://eppi.ioe.ac.uk/ (under 'resources' tab)





Automation in systematic reviews – what can be done?

- Study identification:
 - Assisting search development
 - Citation screening
 - Updating reviews
 - RCT classifier
- Mapping research activity
- Data extraction
 - · Risk of Bias assessment
 - Other study characteristics
 - · Extraction of statistical data
- Synthesis and conclusions



What is a classifier?





What does a classifier do?

- It takes as its input the title and abstract describing a publication
- It outputs a 'probability' score between 0 and 1 which indicates how likely the publication is to being the 'positive class' (e.g. is an RCT)
- Classification is an integral part of the 'evidence pipeline'





Pre-built or build your own

- Pre-built
 - Developed from established datasets
 - RCT model
 - Systematic review model
 - Economic evaluation
- Build your own

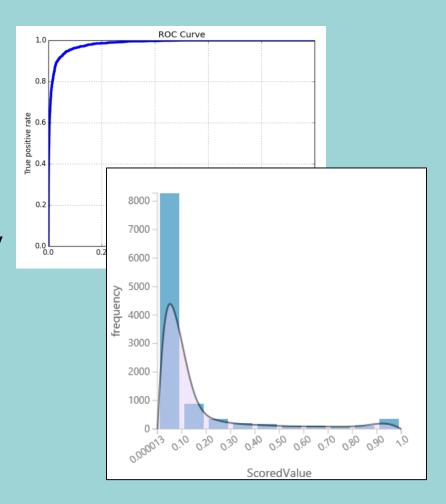






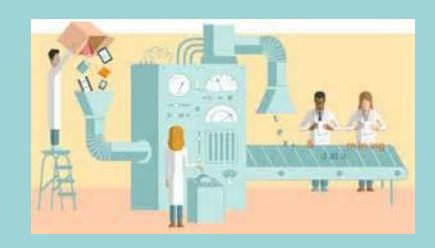
Pre-built classifier

- An RCT classifier was built using more than 280,000 records from Cochrane Crowd
- 60% of the studies have scores < 0.1
- If we trust the machine, and automatically exclude these citations, we're left with 99.897% of the RCTs (i.e. we lose 0.1%)
- Is that good enough?
- Systematic review community needs to discuss appropriate uses of automation





Demo - RCT classifier *EPPI-Reviewer 4*



http://eppi.ioe.ac.uk/eppireviewer4/





Testing three models for TRoPHI register of controlled trials

N=9,431 records	Pre-built RCT classifier		Build your own classifier			
			Best		Second best	
	RCTs	NonRCTs	RCTs	NonRCTs	RCTs	NonRCTs
Precision = relevant items scored 11-99/total number of items scored 11-99	12%	3%	17%	5%	12%	4%
Recall = relevant items scored 11-99/all relevant items	99%	86%	99%	99%	99%	100%
Screening reduction	43%		58%		41%	

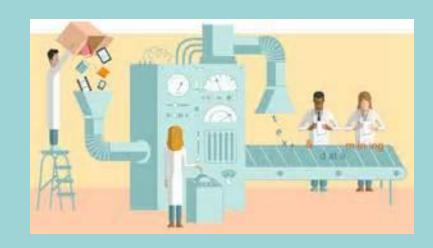


Build your own classifier





Demo - DIY classifier EPPI-Reviewer 4



http://eppi.ioe.ac.uk/eppireviewer4/



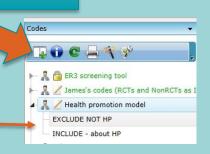


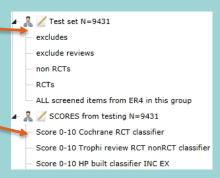
How to build your own

To build a classifier you need a **development set** of known includes and excludes

To test the classifier you need a **test set** of includes and excludes

- 1. Create codesets
- i) include and exclude codes for the development set
- ii) a test codeset
- iii) a score codeset





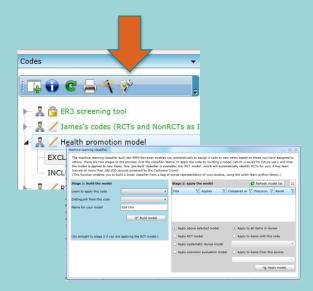
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2. **Click** on the spanner 'classifier' icon to get the Machine building classifier menu

Build the model.
 Apply the include code from exclude code.
 Name the model.



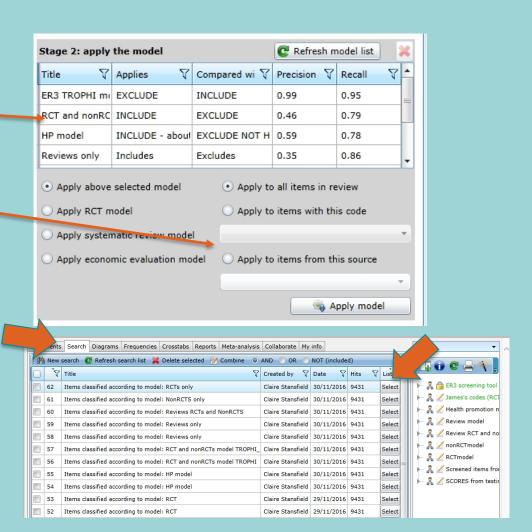
Stage 1: build the model			
Learn to apply this code	Includes		
			V
Distinguish from this code	Excludes	_	
Name for your model	Edit title	╝	
	Build model		
(Go straight to stage 2 if you are			



Go to stage 2

- 4. Select a model
- 5. **Select** the items to apply to the model ___

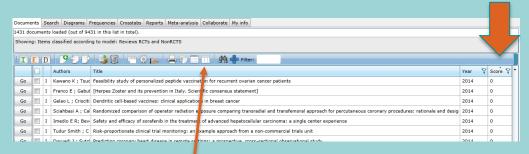
- 6. **Choose** the Search tab for the results.
- 7. Click 'Select'



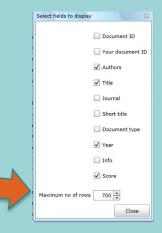


The results are displayed.

A Score tab has appeared. The items are ranked from 0 to 99

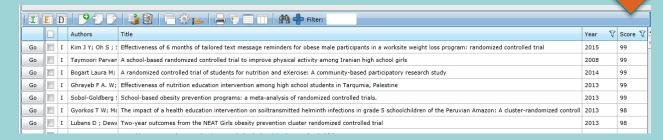


- 8. Click on the Column icon.
- 9. **Change** the maximum no. of rows to 4,000.

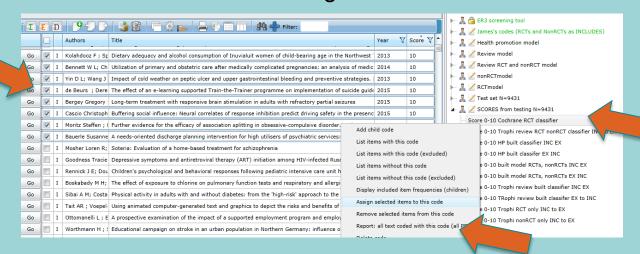




10. Click on score. This orders items by score

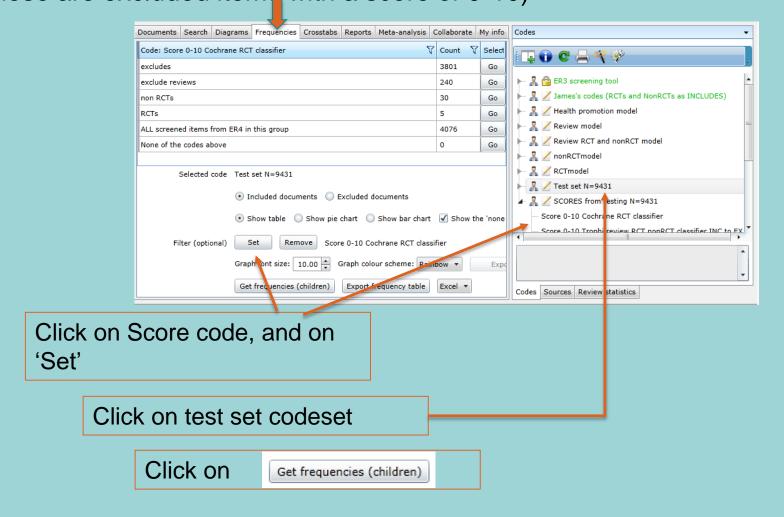


11. for each page of citations, highlight the items coded 0-10 (Ctrl and drag with mouse) assign to the score code (left click on code and click 'Assign selected items to this code')





12. Use the **frequency tab** to compare results for the code (these are excluded items with a score of 0-10)



Study identification

RESEARCH

O'Mara-Eves et al. Systematic Reviews 2015, 4:5

http://www.systematicreviewsjournal.com/content/4/1/5

Using text mining for study identification in systematic reviews: a systematic review of current approaches

Alison O'Mara-Eves¹, James Thomas^{1*}, John McNaught², Makoto Miwa³ and Sophia Ananiadou²

Background: The large and growing number of published studies, and their increasing rate of publication, makes the task of identifying relevant studies in an unbiased way for inclusion in systematic reviews both complex and time consuming. Text mining has been offered as a potential solution: through automating some of the screening process, reviewer time can be saved. The evidence base around the use of text mining for screening has not yet been pulled together systematically; this systematic review fills that research gap. Focusing mainly on non-technical issues, the review aims to increase awareness of the potential of these technologies and promote further collaborative research between the computer science and systematic review communities.

Methods: Five research questions led our review: what is the state of the evidence base; how has workload reduction been evaluated; what are the purposes of semi-automation and how effective are they; how have key contextual problems of applying text mining to the systematic review field been addressed; and what challenges to

Citation screening

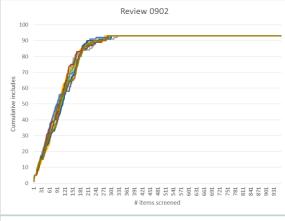
- Has received most R&D attention
- Diverse evidence base; difficult to compare evaluations
- 'semi-automated' approaches are the most common
- Possible reductions in workload in excess of 30% (and up to 97%)

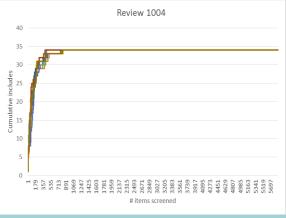
Summary of conclusions

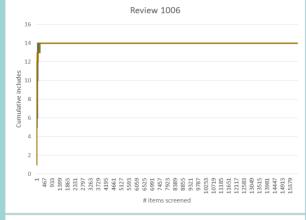
- Screening prioritisation
 - 'safe to use'
- Machine as a 'second screener'
 - Use with care
- Automatic study exclusion
 - Highly promising in many areas, but performance varies significantly depending on the domain of literature being screened

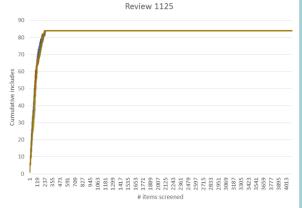


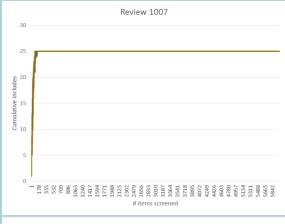
Does it work? e.g. reviews from Cochrane Heart Group

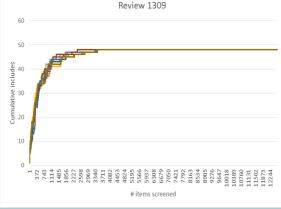






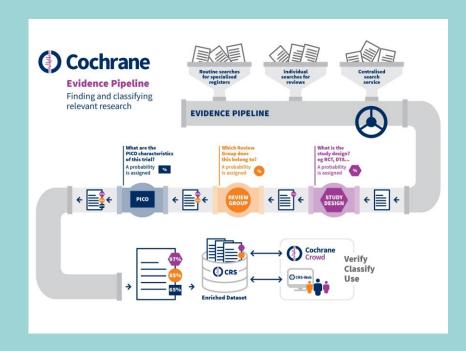








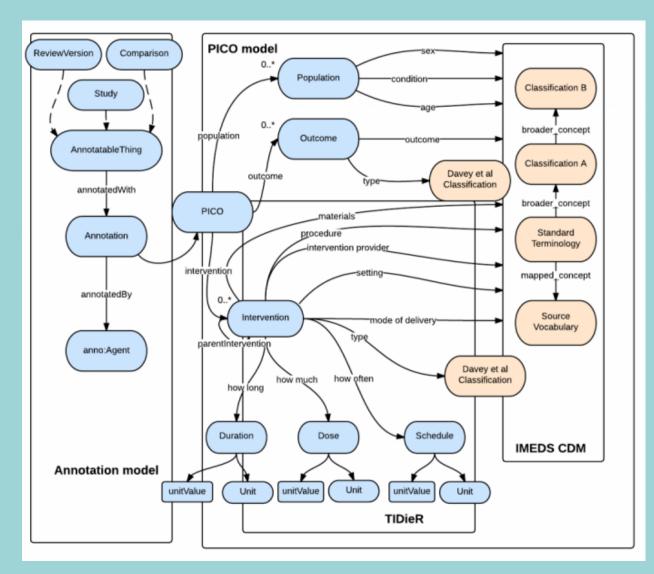
Cochrane Evidence Pipeline



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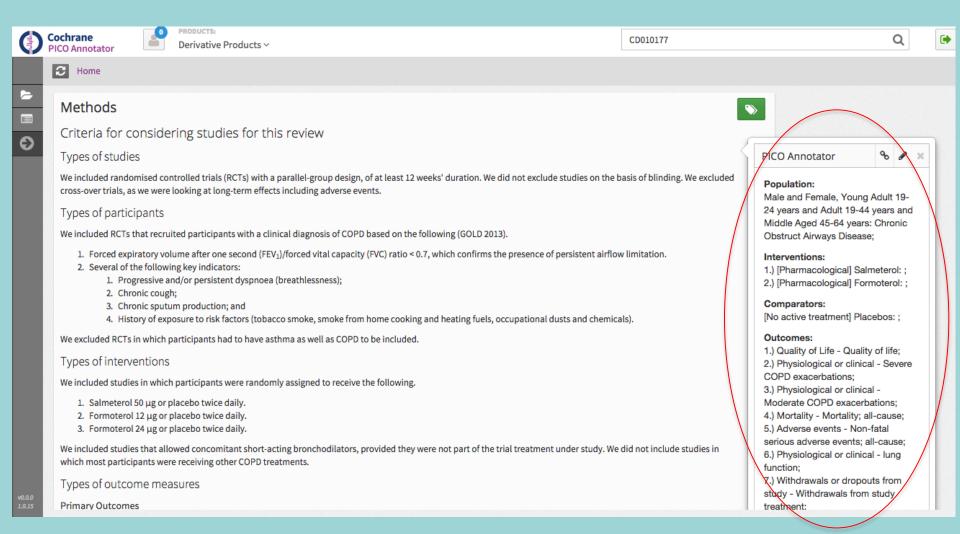


A PICO 'ontology' is being developed in Cochrane

... and is being applied to...



... all Cochrane reviews and all the trials they contain



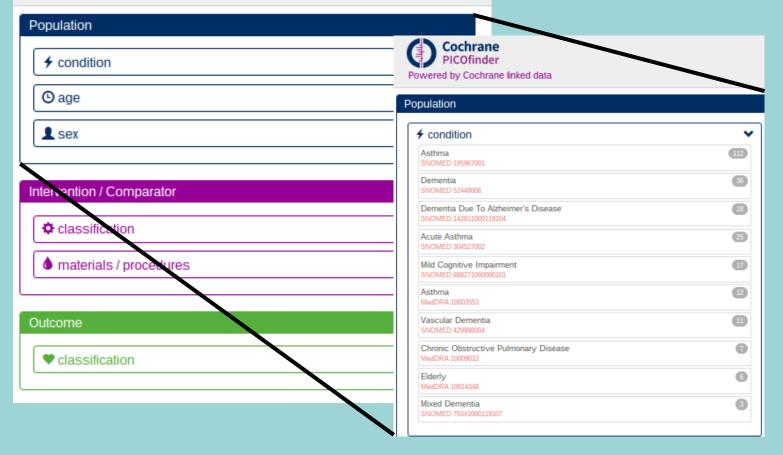
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Cochrane
PICOfinder
Powered by Cochrane linked data

... Boolean searches are replaced by the specification of the 'PICO' of interest

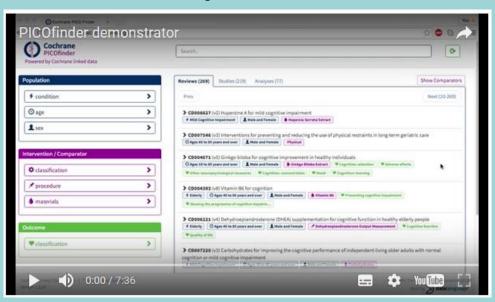






PICOfinder

https://youtu.be/WtqAnL6QPt4

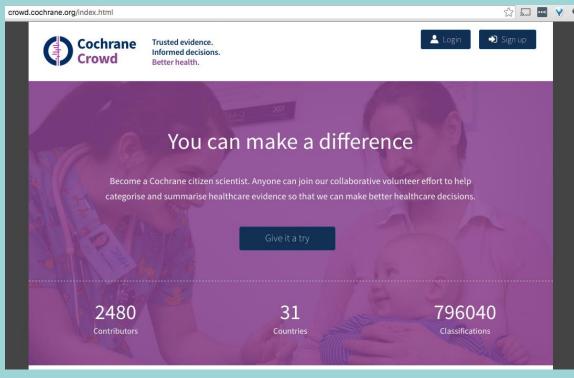


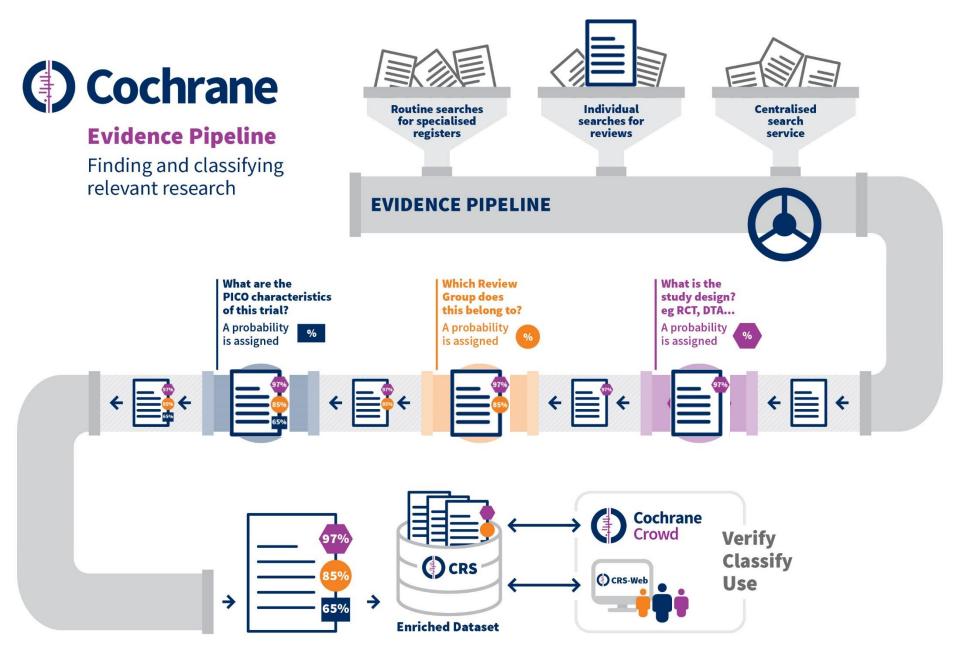


Through a combination of human and machine effort the aim is to identify and classify ALL trials using this system.

Identifying studies for systematic reviews* will then be a simple process of specifying the relevant PICO

* Of RCTs



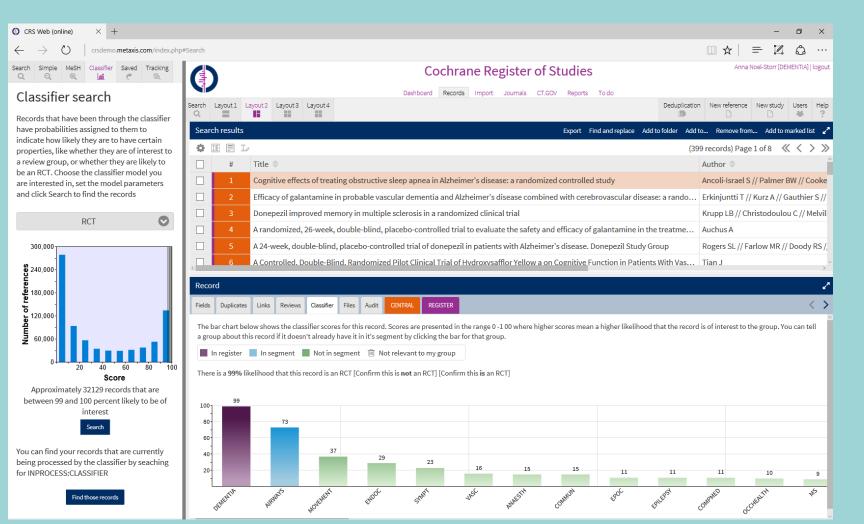


http://community.cochrane.org/tools/project-coordination-and-support/transform





CRS-Web









Mapping research activity

- It is possible to apply 'keywords' to text automatically, without needing to 'teach' the machine beforehand
- This relies on 'clustering' technology – which groups studies which use similar combinations of words
- Very few evaluations
 - Can be promising, especially when time is short
 - But users have no control on the terms actually used

Original Article

Research Synthesis Methods

Received 23 November 2012.

evised 21 March 2013

Accepted 21 April 201

Published online in Wiley Online Library

(wileyonlinelibrary.com) DOI: 10.1002/jrsm.1082

'Clustering' documents automatically to support scoping reviews of research: a case study

Claire Stansfield,*† James Thomas† and Josephine Kavanagh†

Background: Scoping reviews of research help determine the feasibility and the resource requirements of conducting a systematic review, and the potential to generate a description of the literature quickly is attractive.

Aims: To test the utility and applicability of an automated clustering tool to describe and group research studies to improve the efficiency of scoping reviews.

Methods: A retrospective study of two completed scoping reviews was conducted. This compared the





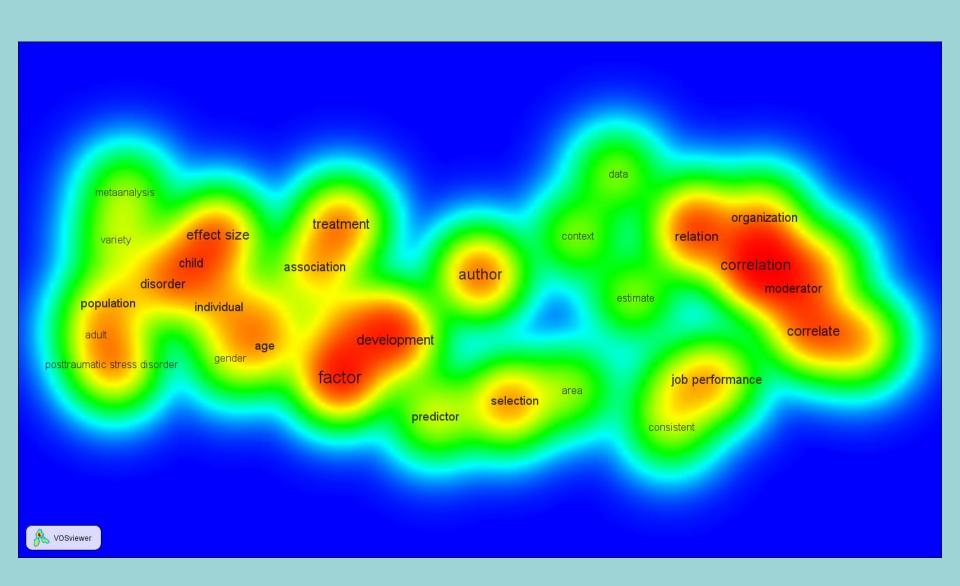
Technologies for identifying subsets of citations

- Different families of techniques
 - Fairly simple approaches which examine term frequencies to group similar citations
 - More complex approaches, such as Latent Dirichlet Allocation (LDA)
- The difficult part is finding good labels to describe the clusters
 - But are labels always needed?
- Visualisations are often incorporated into tools

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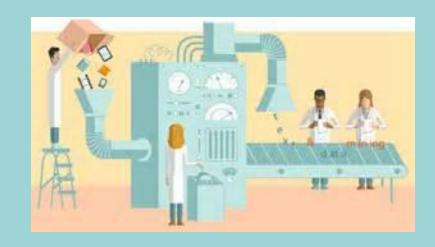








Demo – Topic modelling pyLDAvis



http://eppi.ioe.ac.uk/ldavis/index.html#topic =6&lambda=0.63&term=

Data extraction; synthesis and conclusions

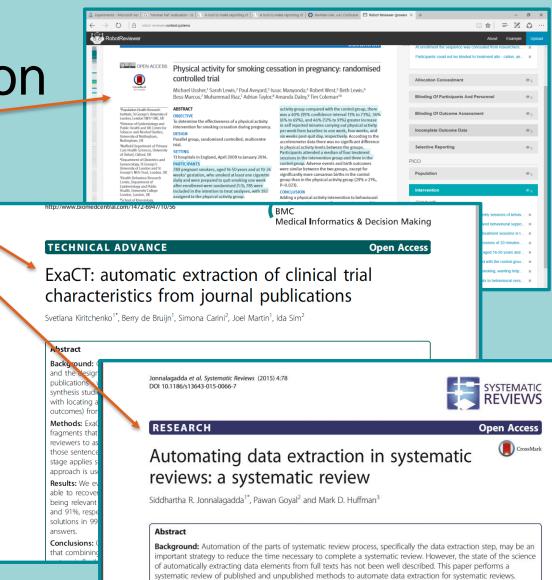






Data extraction

- RobotReviewer can identify phrases relating to study PICO characteristics
- ExaCT extracts trial characteristics (e.g. eligibility criteria)
- Systematic review found that no unified framework yet exists
- More evaluative work is needed on larger datasets
- Further challenges include extraction of data from tables and graphs



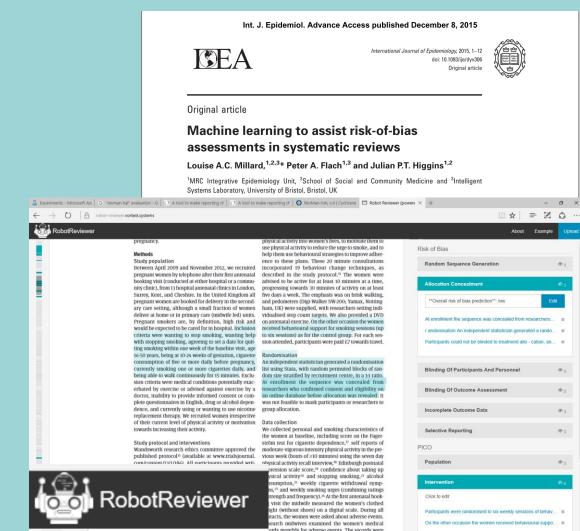
Methods: We systematically searched PubMed, IEEEXplore, and ACM Digital Library to identify potentially relevant





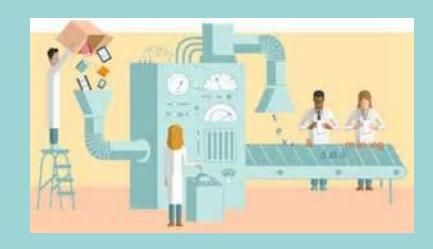
Risk of Bias assessment

- Emerging area; e.g.
 - RobotReviewer
 - Millard, Flach and Higgins
- Tools can accomplish two purposes:
 - 1. identify relevant text in the document
 - 2. automatically assess risk of bias
- Can perform very well though authors do not yet suggest well enough to replace humans





Demo - Data extraction RobotReviewer



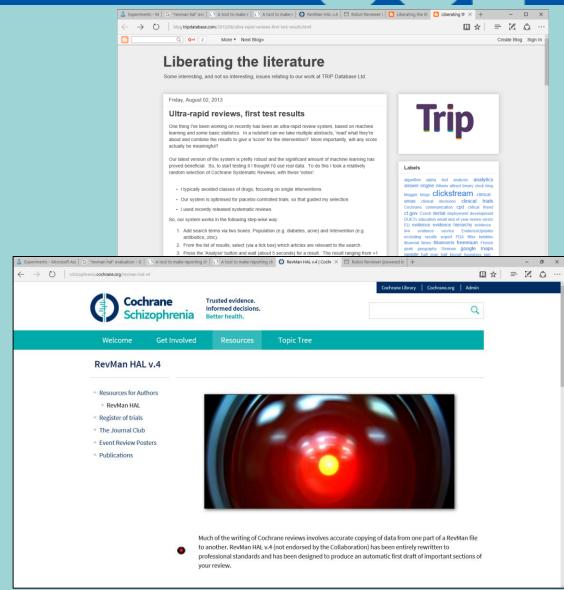
https://robot-reviewer.vortext.systems/



LUCL

Synthesis and conclusions

- Summarisation and synthesis of text is an active area for development in computer science
- Many hurdles to overcome before this technology can be used routinely
- Some systems automate parts of the process









The wider picture: part of a wider evolution of systematic review methods

- Systematic reviews (as currently known) might change quite substantially
- From 'search strategy' to PICO definition
- From 'data extraction' to structured data (and IPD)
- We may choose to link trial data in new ways (e.g. via IPD to patient medical records)
- The 'systematic review' will become a matter of ascertaining the validity and utility of combining particular sets of studies at particular points in time, rather than the tedious trawling for, and extraction of, data – that they currently entail



Discussion and experimentation: in small groups:

How can Cochrane reviewers take advantage of the efficiencies these tools offer?

What methods and processes will need to be developed? How can we build an evidence base around them?

What are your concerns?

Are there other limitations?

Links to tools: http://eppi.ioe.ac.uk/ (under 'resources' tab)

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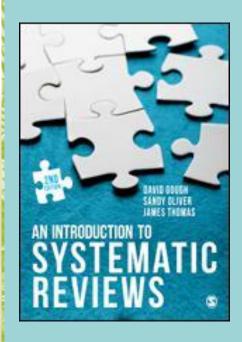


Thank you

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The EPPI-Centre is part of the Social Science Research Unit at the UCL Institute of Education, University College London



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