

# Opportunities for AI-enabled scientific knowledge exploration, analysis, and discovery

**Karin Verspoor**

Executive Dean, School of Computing Technologies,  
**RMIT University**

Fellow, **Australasian Institute of Digital Health**

Deputy Director, **ARC Training Centre in Cognitive  
Computing for Medical Technologies**

Honorary Professor, **The University of Melbourne**



ARC TRAINING CENTRE  
IN COGNITIVE COMPUTING  
FOR MEDICAL TECHNOLOGIES

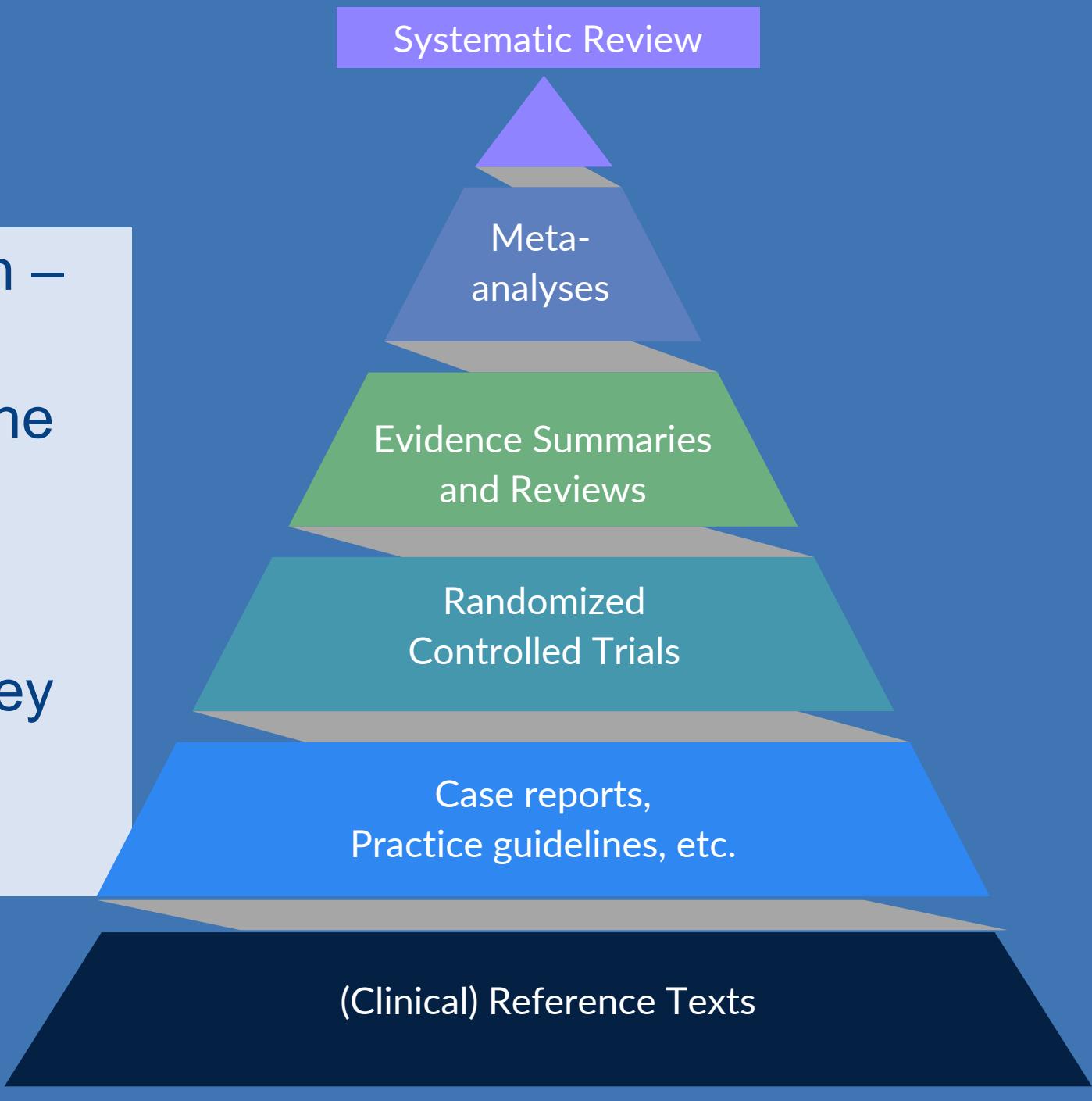


# Research Literature

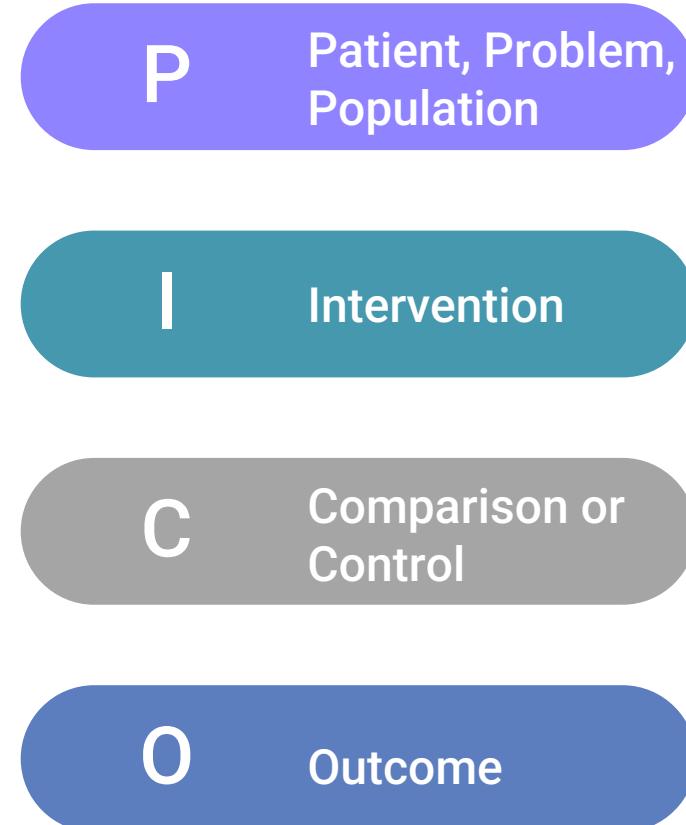
Systematic Review

**Evidence** derived from research – and published in the scientific literature – is considered to be the **gold standard** for knowledge, particularly in medical practice.

Research literature is also the key source of **knowledge** driving scientific progress.



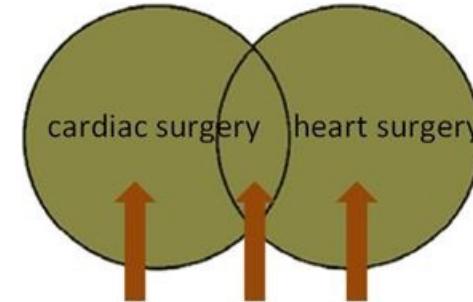
# Clinical Randomised Control Trial Structure



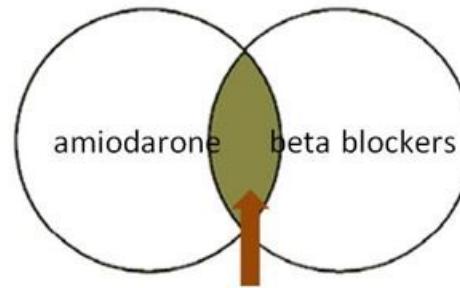
“To assess the effects  
of [intervention]  
compared to  
[comparison/control] for  
[condition/problem] in  
[population] in [context]  
on [outcomes].”

# Structured querying of biomedical literature

Using **OR** lets you broaden your search by combining synonyms to appropriately cover a concept. This search will retrieve articles containing each term separately, as well as both terms together.



Using **AND** lets you narrow your search and is used to combine concepts. This search will retrieve articles containing both terms only.



## Search Process

Define main **concepts** in search topic.  
Focus on key terms, phrases, synonyms or variants.  
Add in **MeSH terms** to constrain results.  
....  
Select and read papers.  
“Snowball search” to find papers citing relevant papers.

```
("Alzheimer Disease"[mh] OR "alzheimer's"[tiab] OR "alzheimer"[tiab] OR ad[tiab] OR "alzheimers"[tiab] OR "alzhiemer"[tiab] OR "alzhiemers"[tiab] OR "alzhiemer's"[tiab] OR "cognition disorders"[mh] OR cognitive[tiab] OR cognition[tiab] OR "dementia"[mh:noexp] OR dementia[tiab])
```

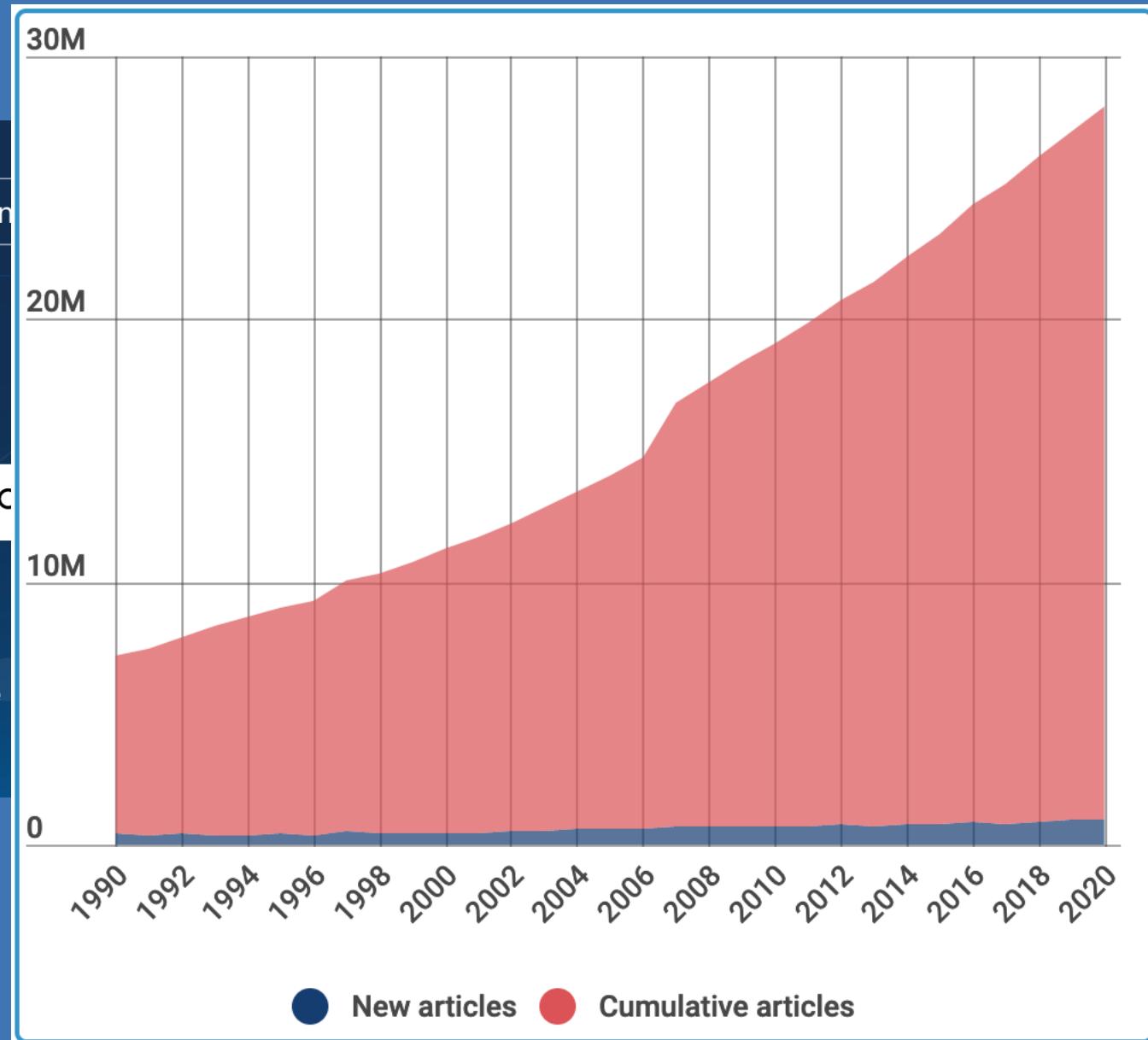
# The research literature is huge and growing



2024

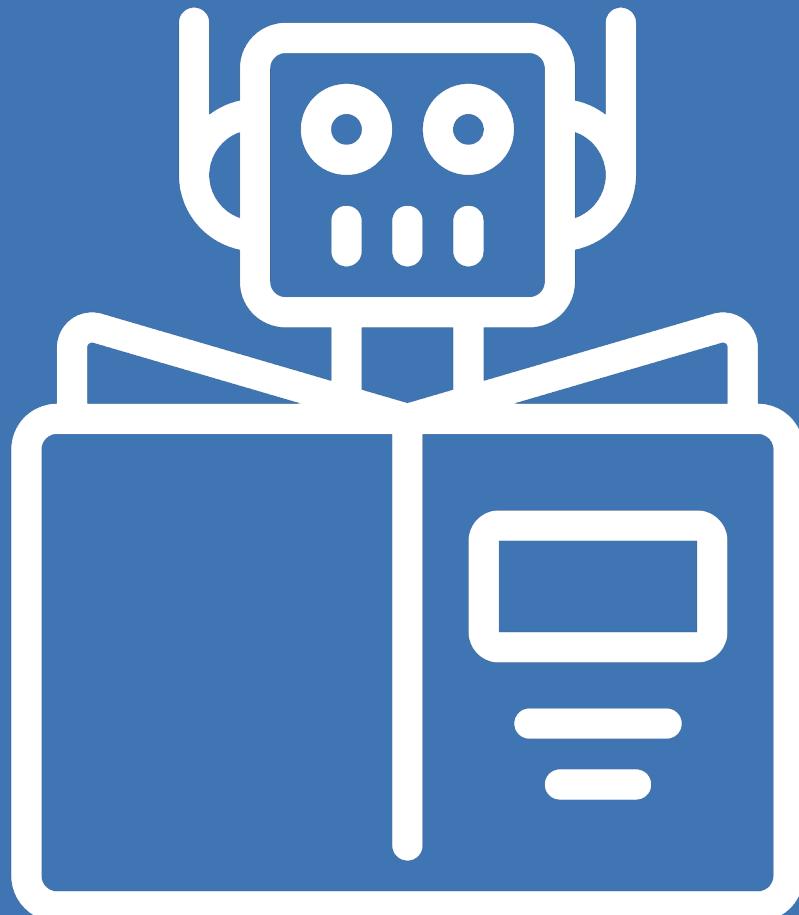
Advanced

PubMed® comprises more than 37 million citations for biomedical literature from MEDLINE, life science journals, and some books. Citations may include links to full text content from PubMed Central and publisher web sites.

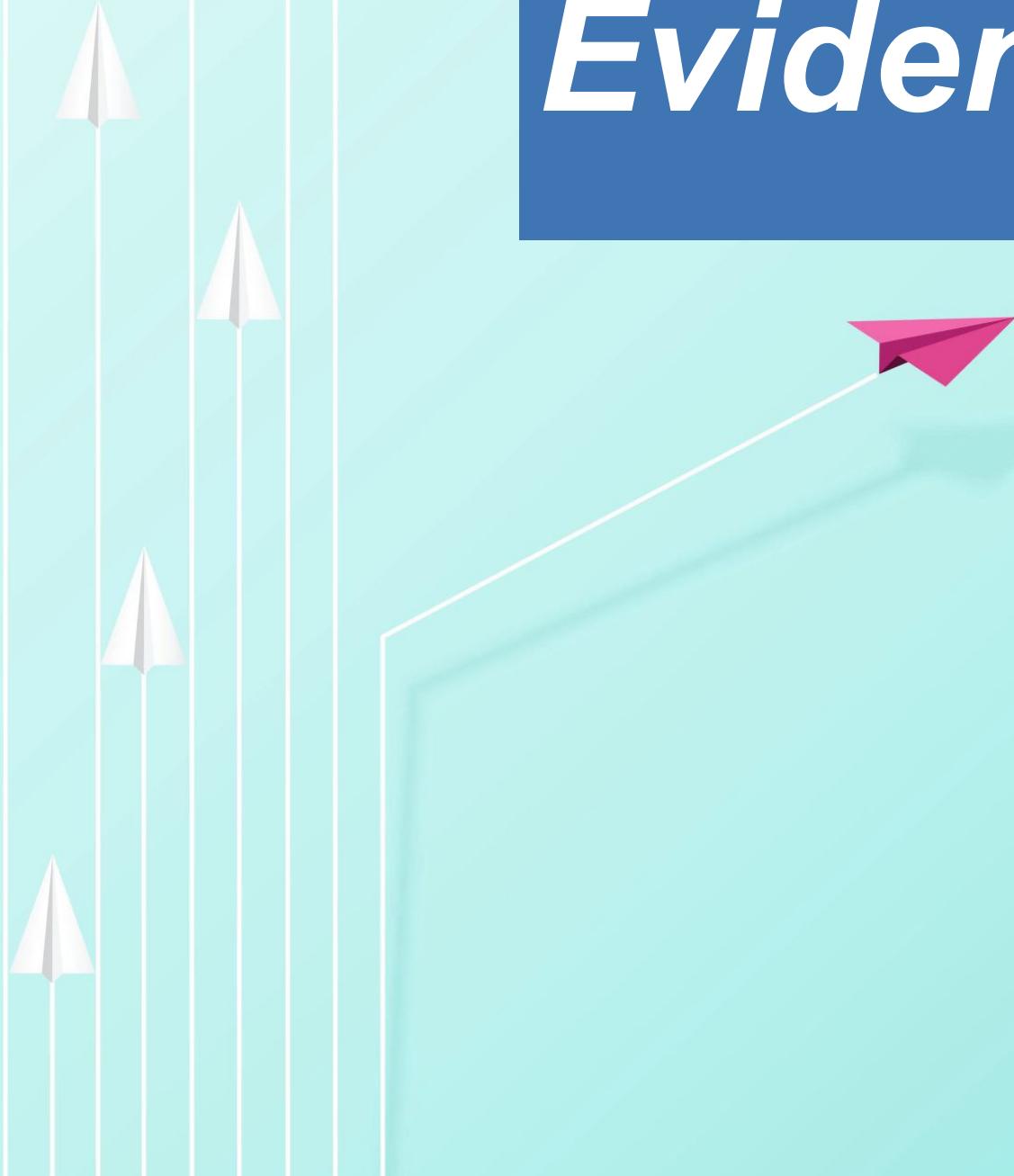


# AI supporting science

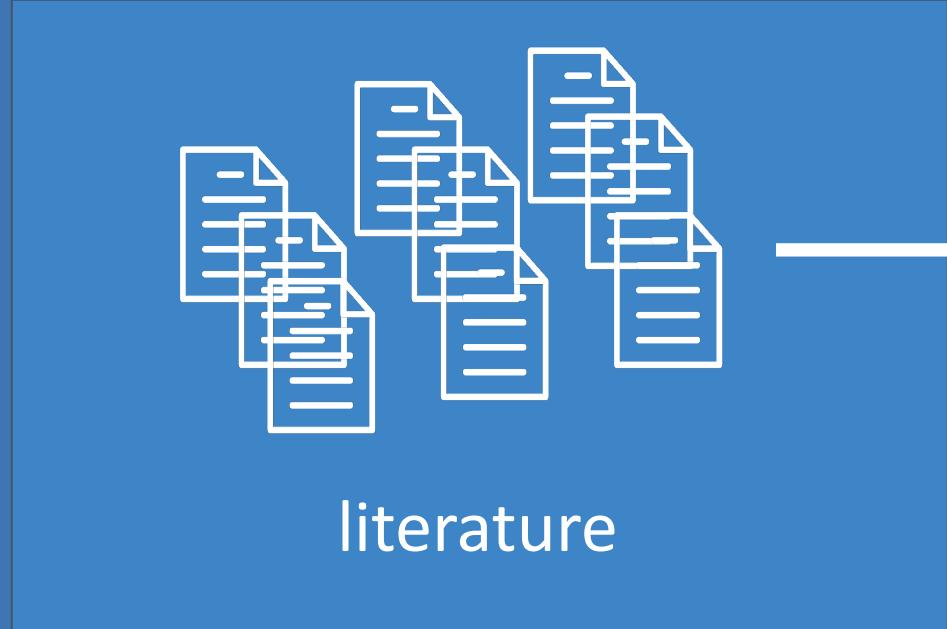
- **Evidence detection** enabling *concept* search
- **Evidence exploration** tools allowing more open-ended literature navigation
- **Evidence summarization and synthesis**
- **Evidence discovery**



# *Evidence Detection*



# Organising knowledge



- Find key concepts, entities and events
- Map to standard identifiers and/or ontology terms
- Support indexing and retrieval

# Recognising biological ontology concepts

Previous in vitro experiments using renal

GO:0005623 – “cell”

CL:0000000 – “cell”

PR:000004182 – “aquaporin-2”

EG:359 – “Aqp2”

cell lines suggest recessive Aqp2

SO:0001059 – “sequence\_alteration”

GO:0006810 – “transport”

mutations result in improper trafficking

SO:0001059 – “sequence\_alteration”

GO:0015250 – “water channel activity”

of the mutant water pore.

CHEBI:15377 – “water”

# Concept Recognition ≈ Named Entity Recognition

Previous in vitro experiments using renal cell lines  
suggest recessive Aqp2 mutations result in  
improper trafficking of the mutant water pore.

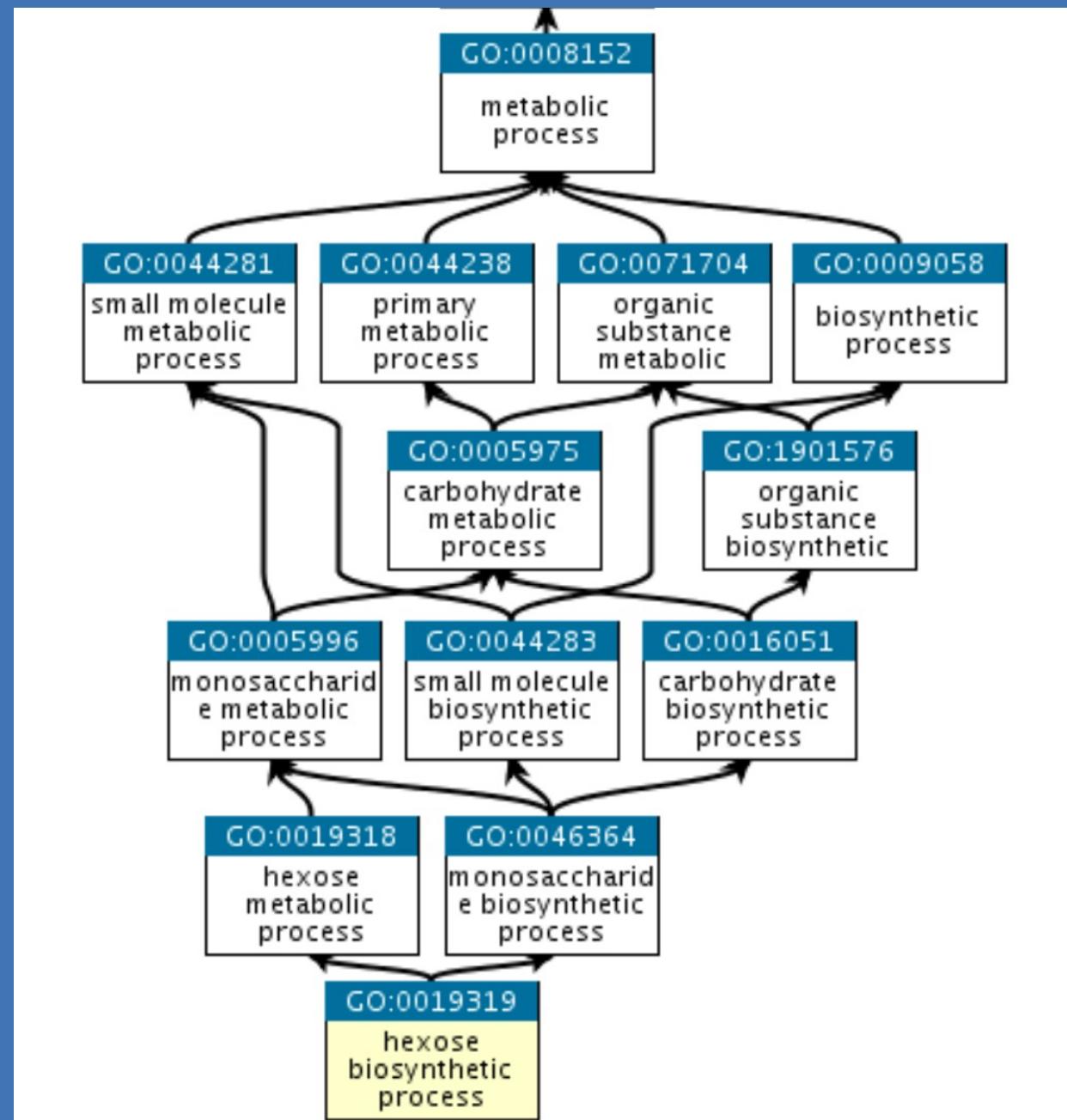
The diagram illustrates concept recognition annotations. The text "Previous in vitro experiments using renal cell lines" is followed by "suggest recessive Aqp2 mutations result in". Below this, "improper trafficking of the mutant water pore." is annotated with several brackets:

- A bracket labeled "protein" covers the word "Aqp2".
- A bracket labeled "mutation" covers the words "mutations result in".
- A bracket labeled "GO\_biological\_process" covers the word "trafficking".
- A bracket labeled "mutation" covers the word "water".
- A bracket labeled "GO\_cellular\_component" covers the word "pore".
- A bracket labeled "chemical" covers the word "pore".

- NER: recognising terms of specific general *types*
- Concept recognition: NER + normalize term to ontology ID

# Ontologies

- Comprehensive
  - Gene Ontology: 42k terms
  - SNOMED CT “Disease”: 49k terms
  - ICD 11: 17k codes;  
120k terms (5+ languages)
- Systematic (cf. natural)
- Hierarchical



# Gene Ontology vs Natural Language

- Variation in PMID: 12925238

[Term]

id: GO:0006900

**name:** membrane budding

...

def: "The evagination of a membrane, resulting  
in formation of a vesicle."

...

**synonym:** "membrane evagination"

**synonym:** "nonselective vesicle assembly"

**synonym:** "vesicle biosynthesis"

**synonym:** "**vesicle formation**"

...



- Lipid rafts play a key role in **membrane budding**...
- ...involvement of annexin A7 in **budding of vesicles**...
- ...Ca<sup>2+</sup>-mediated **vesiculation process** was not impaired.
- Red blood cells which lack the ability to **vesiculate** cause...
- Having excluded a direct role in **vesicle formation**...

# Machine learning for concept recognition?

## NER

- a handful of target classes
- annotated training data with many examples of each class

→ Leverage annotated data  
→ Supervised Learning

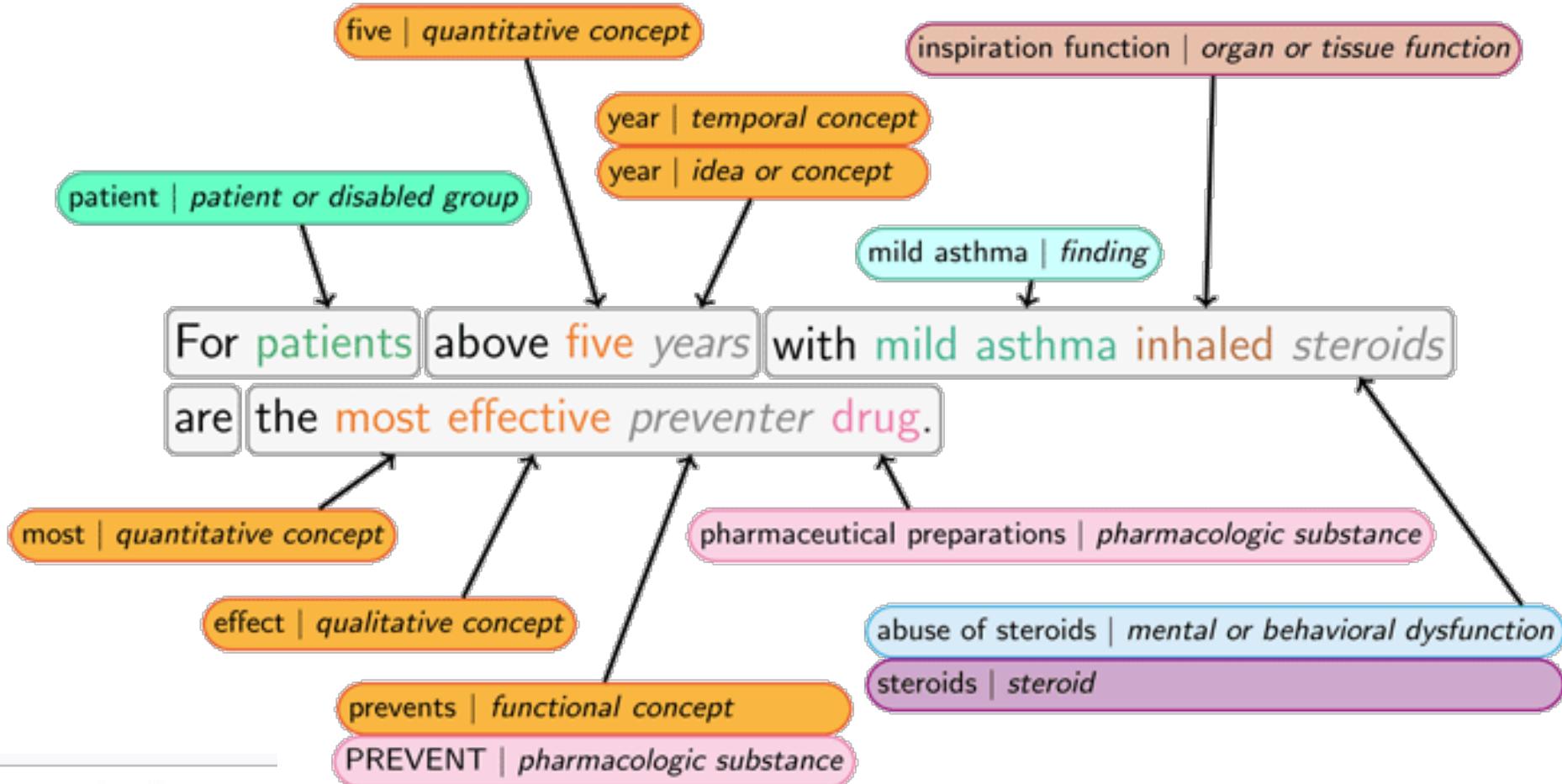
## Concept Recognition

- 10s of thousands of target ‘labels’
- difficult to produce enough training data to enable supervision

→ Leverage Ontology itself  
→ Match terms (synonyms, etc.)

*New opportunities with LLMs?*

# Recognising clinical concepts: UMLS

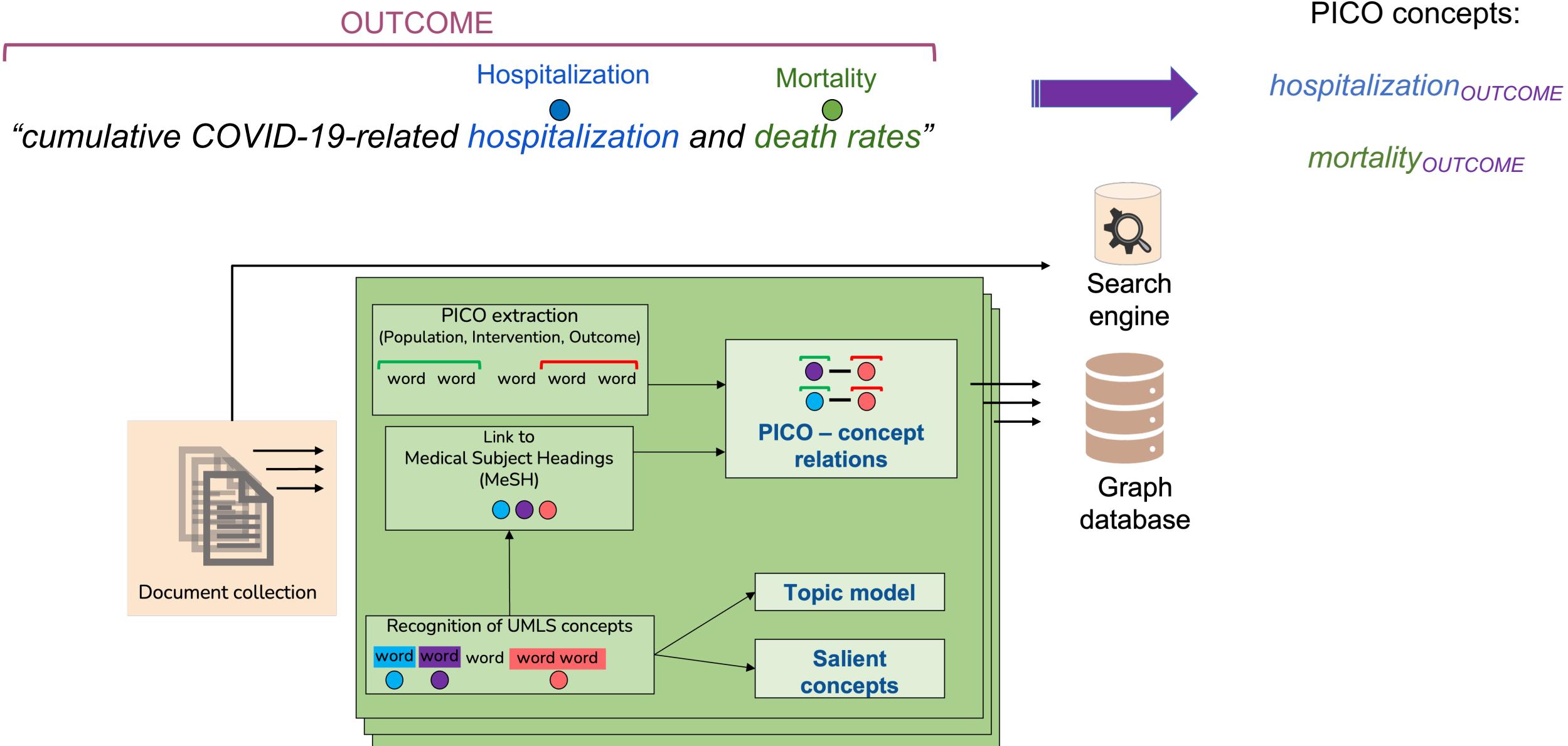


# PICO spans

1	Randomized controlled study of chemoimmunotherapy with bestatin of acute nonlymphocytic leukemia in adults.	<b>Intervention</b>	<b>Participants</b>
3	A new immunomodulating agent, bestatin (INN: Ubenimex has low toxicity even after long-term oral administration and has significant modifications in immunological response.	<b>Intervention</b>	
4	A cooperative randomized controlled study of bestatin immunotherapy in combination with remission maintenance chemotherapy for adult acute nonlymphocytic leukemia (ANLL) was performed.	<b>Intervention</b>	<b>Participants</b>
5	After induction of complete remission, patients were randomized to the bestatin group (30 mg/bw per os (po) daily) and the control group.	<b>Intervention</b>	
6	The 101 eligible cases (bestatin: 48, control: 53) were analyzed; the bestatin group achieved longer remission than the control group and a statistically significant longer survival.	<b>Participants</b>	<b>Intervention</b>
7	Though this prolongation of remission was not significant in the bestatin group compared to the control group in the 15-49 yr age group, in the 50-65 yr age group it was significantly longer.	<b>Outcomes</b>	<b>Intervention</b>
8	Bestatin is shown to be a clinically useful drug for immunotherapy of adult ANLL, since it has prolonged survival and remission especially in elderly patients, with few side-effects.	<b>Intervention</b>	<b>Outcomes</b>

- Evidence Based Medicine (EBM-NLP) corpus
- BiLSTM-CRF model trained to recognise PICO elements

# PICO + clinical concepts (MeSH/UMLS)



# Structuring relations

- Capturing entities and relations
  - “PROTEIN interacts with PROTEIN”
  - “CHEMICAL treats DISEASE”
  - “MUTATION causes DISEASE”
- Incorporating knowledge
  - cf. “ACE inhibitor treats hypertension”
  - + benazepril –isa- ACE inhibitor

Cyclin E2 interacts with Cdk2 in a functional kinase complex.



protein protein interaction:  
interactor1: cyclin E2  
interactor2: cdk2

id: GO:0009358  
name: polyphosphate kinase complex

# Chemical-induced disease

Title	<b>Propylthiouracil-induced hepatic damage</b>
Abstract	Two cases of <b>propylthiouracil-induced liver damage</b> have been observed. The first case is of an acute type of damage, proven by rechallenge; the second presents a clinical and histologic picture resembling <b>chronic active hepatitis</b> , with spontaneous remission.
Entity	D011441, Chemical, "Propylthiouracil", 0-16
Entity	D011441, Chemical, "propylthiouracil", 54-70
Entity	D056486, Disease, "hepatic damage", 25-39
Entity	D056486, Disease, "liver damage", 79-91
Entity	D006521, Disease, "chronic active hepatitis", 246-270
Relation	D011441-D056486
Relation	D011441-D006521

# Information Extraction from Chemical Patents

## 2-Phenyl-2H-imidazo[1,5-a]pyridinium tetrafluoroborate (1)

The general synthesis starts with the slow addition of **excess concentrated hydrochloric acid** to **aniline** (4.66 g, 4.6 mL, 50.0 mmol) dissolved in a small amount of **methylene chloride** under rigorous stirring. A solid immediately formed, which was collected, washed with diethyl ether and dried at 40 °C at <10 mbar for two hours. Then the **hydrochloride salt** was dissolved in 100 mL **ethanol**, and 37 wt% aqueous **formaldehyde** solution (2.25 g, 2.1 mL, 75.0 mmol) as well as **2-pyridinecarboxyaldehyde** (5.36 g, 4.8 mL, 50.0 mmol) were added.

## 2-(4-Methoxyphenyl)-2H-imidazo[1,5-a]pyridinium chloride monohydrate (3)

The synthesis followed *the general procedure as given for 1* but without salt metathesis to *the corresponding tetrafluoroborate salt*. **4-Methoxyaniline** (6.16 g, 50.0 mmol) was used as *amine*.



## Product 1: 2-Phenyl-2H-imidazo[1,5-a]pyridinium tetrafluoroborate

### Stage 1:

**Reactant 1:** hydrochloric acid

**Reactant 2:** aniline

**Solvent 3:** methylene chloride

**Product:** hydrochloride salt<sup>1</sup>

Stage 2: collected, washed with diethyl ether

### Stage 3:

**Reactant 4:** hydrochloride salt<sup>1</sup>

**Solvent 5:** ethanol

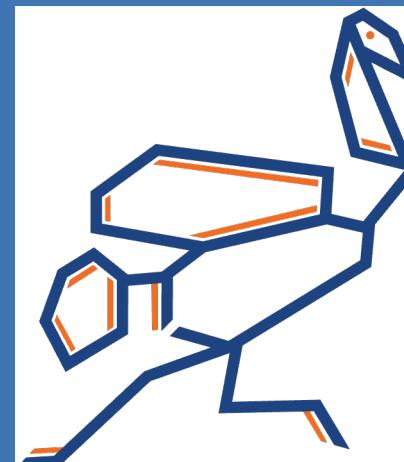
**Solvent 6:** aqueous formaldehyde solution

**Reactant 7:** 2-pyridinecarboxyaldehyde

**Product 3:** 2-(4-Methoxyphenyl)-2H-imidazo[1,5-a]pyridinium chloride monohydrate

- Pull out key entities and events
- Identify roles of entities
- Resolve references and analogous reactions
- Structure chemical information

- ▶ Search
- ▶ Compare
- ▶ Synthesise
- ▶ Connect
- ▶ Discover
- ▶ Characterise



**ChEMU**  
Cheminformatics Elsevier  
Melbourne Universities

# A Chemical Reaction Snippet

10.0 g (35.0 mmol) of **2-tert-butyl 4-ethyl 5-amino-3-methylthiophene-2,4-dicarboxylate** (Example 1A) were dissolved in 500 ml of **dichloromethane** and 11.4 g (70.1 mmol) of **N,N'-carbonyldiimidazole** (CDI) and 19.6 ml (140 mmol) of **triethylamine** were added

ID	Type	Text span
T1	Starting _material	2-tert-butyl 4-ethyl 5-amino-3-methylthiophene-2, 4-dicarboxylate
T2	Solvent	dichloromethane
T3	Starting _material	N,N'-carbonyldiimidazole
T4	Reagent	triethylamine
T5	Trigger	dissolved
T6	Trigger	added

ID	Event type	Event trigger	Argument _1	Argument _2	Argument _3
E1	Reaction _step	T5	Theme:T1	Theme:T2	
E2	Reaction _step	T6	Theme:E1	Theme:T3	Theme:T4

Task 1 – NER – in Red

Task 2 – Event extraction – in Purple

# Quick aside on anaphora: Rich anaphora phenomena in procedural texts

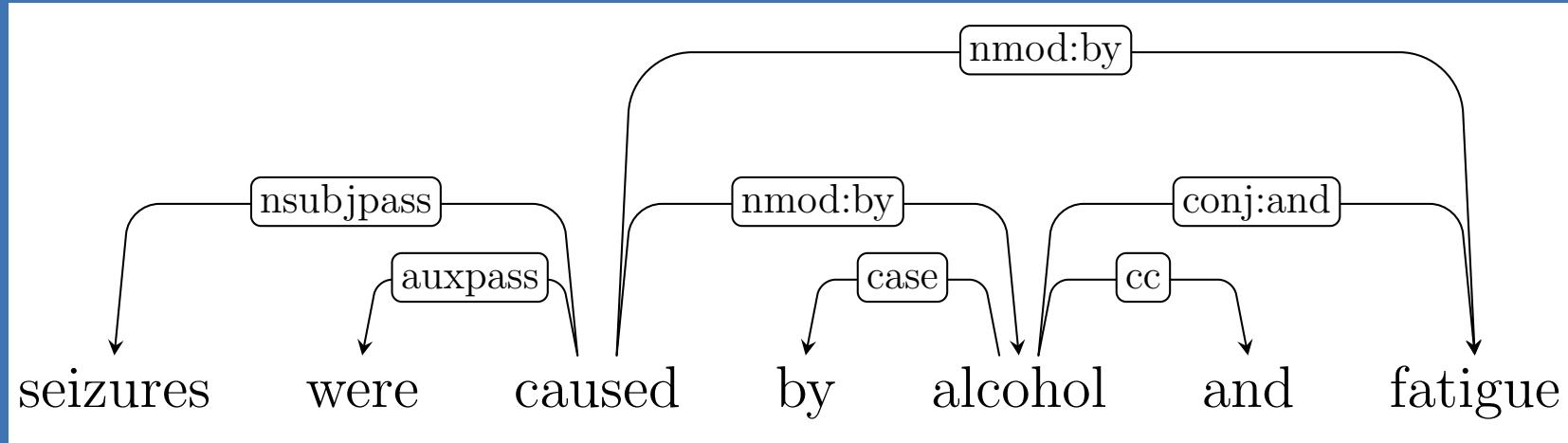
1. To the solution of Compound (4) (0.815 g, 1.30 mmol) in THF (4.9 ml) in a flask were added acetic acid (9.8 ml) and water (4.9 ml).
2. The mixture was stirred for 3 hrs at 50°C and then cooled to 0°C.
3. 2N-sodium hydroxide aqueous solution was added to the mixture until the pH of the mixture became 9.
4. The mixture was extracted with ethyl acetate for 3 times.
5. The combined organic layer was washed with water and saturated aqueous sodium chloride.
6. The organic layer was dried over anhydrous magnesium sulfate and evaporated.

An example from chemical patents

1. Preheat the oven to 400F.
2. Lightly grease a baking sheet.
3. Place the biscuits on the prepared baking sheet and use the palm of your hand to flatten the dough to 1/4 inch in thickness.
4. Divide the sauce evenly among the biscuits, top with a pinch of the oregano, then layer the mozzarella, pepperoni (if using), and Parmesan cheese.
5. Make sure the cheese is covering and bake until the biscuits are golden, about 15 minutes.
6. Allow the biscuits to cool slightly and serve warm.

An example from recipes

# Machine learning of entity relations with Approximate Subgraph Matching



Shortest path between *seizures* and *fatigue* is through *caused*

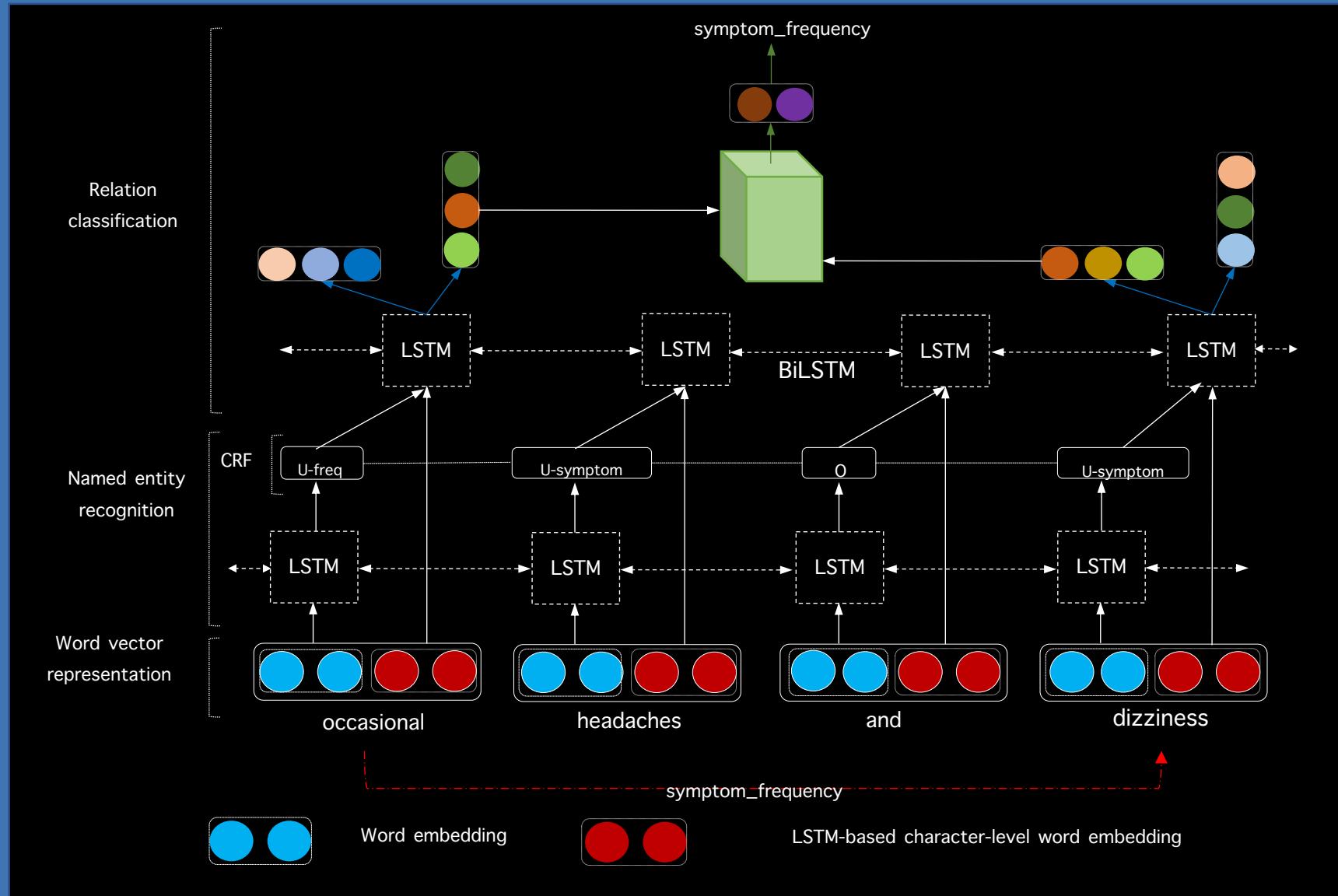
$$\phi_{\text{dist}} = (0.9)^2 \quad \phi_{\text{forward}} = 0.9 \quad \phi_{\text{backward}} = 0.9 \quad \phi_{\text{nsubjpass}} = 0.9 \quad \phi_{\text{nmod:by}} = 0.9$$

Consider shortest path between vertices x and y in Graph G

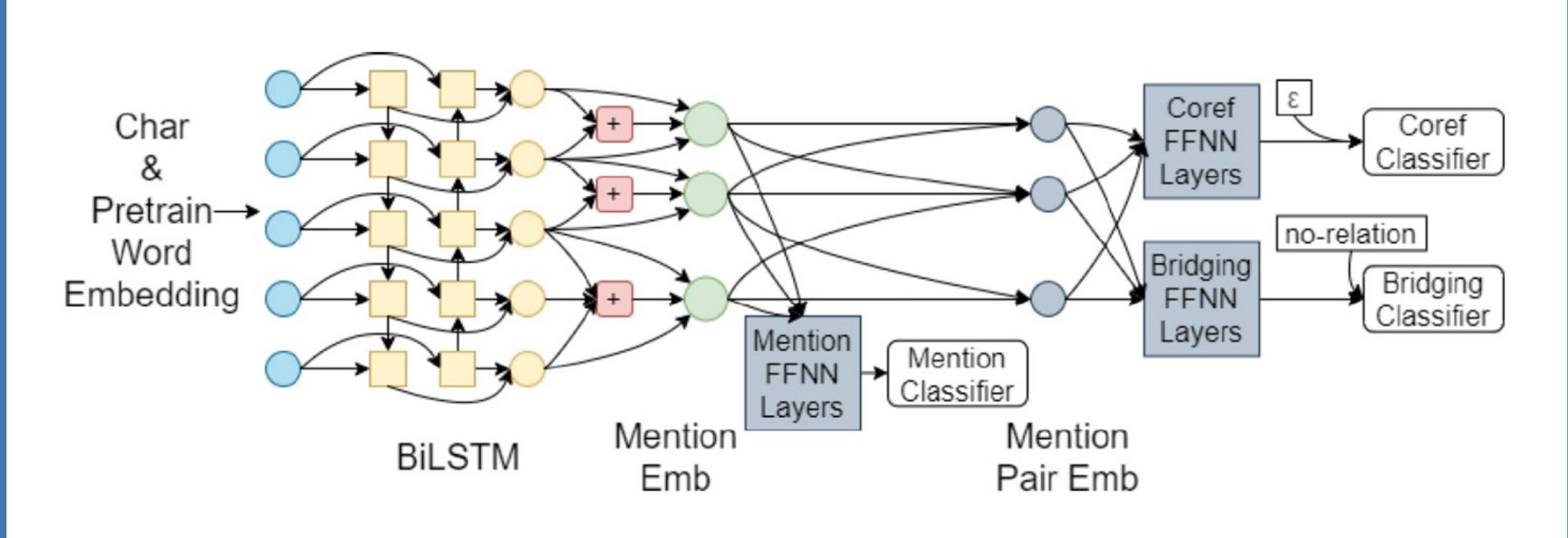
Approximate subgraph matching:

Feature map  $\phi$  concatenation of features for similarity of graph along structural, directional, edge dimensions.

# Methods for Information Extraction



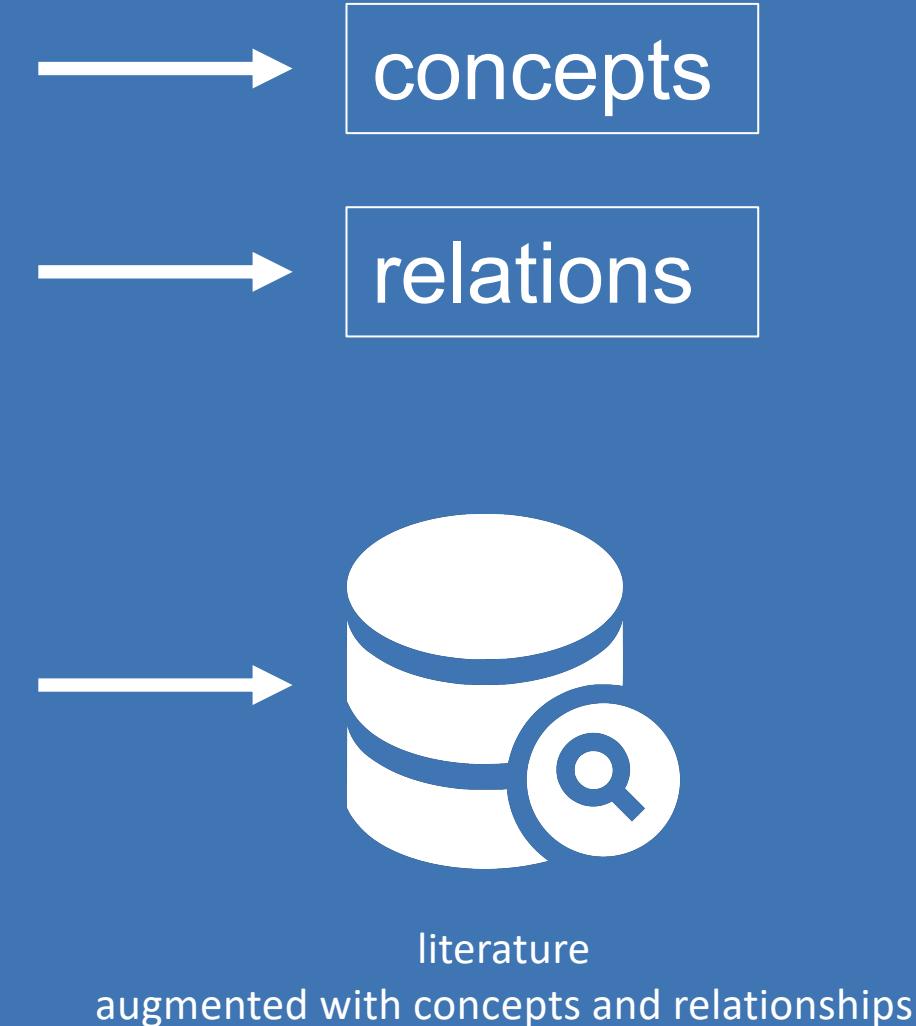
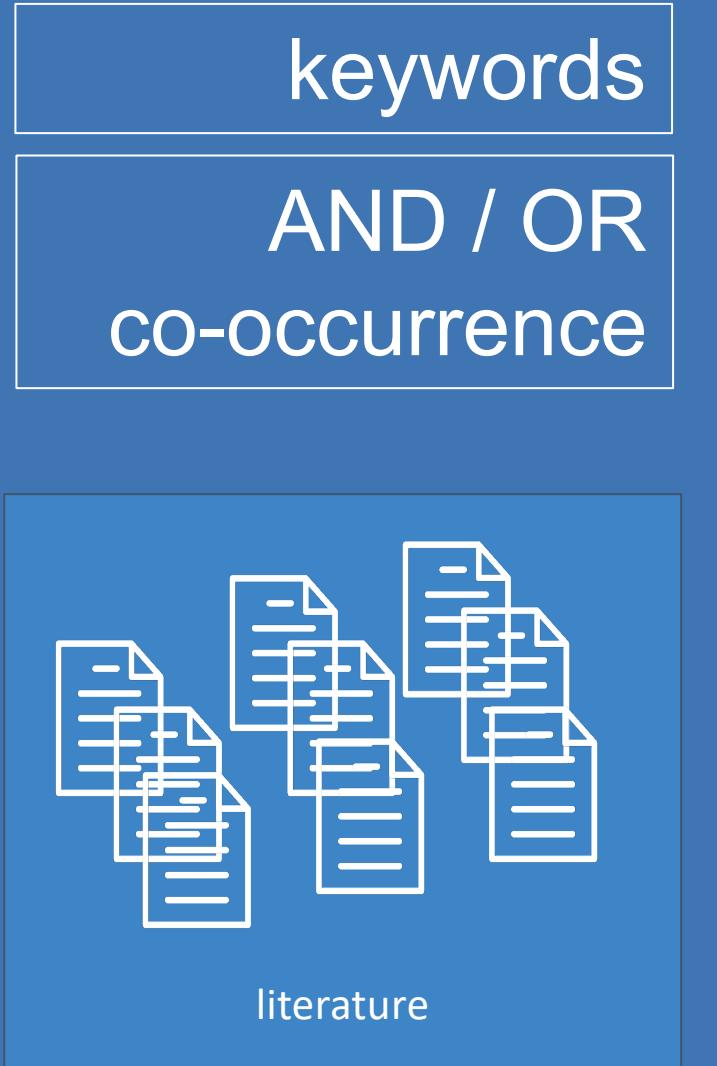
# Methods for Information Extraction



Pipeline

Entity detection using pre-trained word embeddings → Relation classification

# Organising knowledge enables semantic search



Find papers on

[bariatric surgery]  
[type 2 diabetes]  
[remission]

[Flurbiprofen]  
[metabolized-by]  
[CYP2C9]

# *Evidence Exploration*



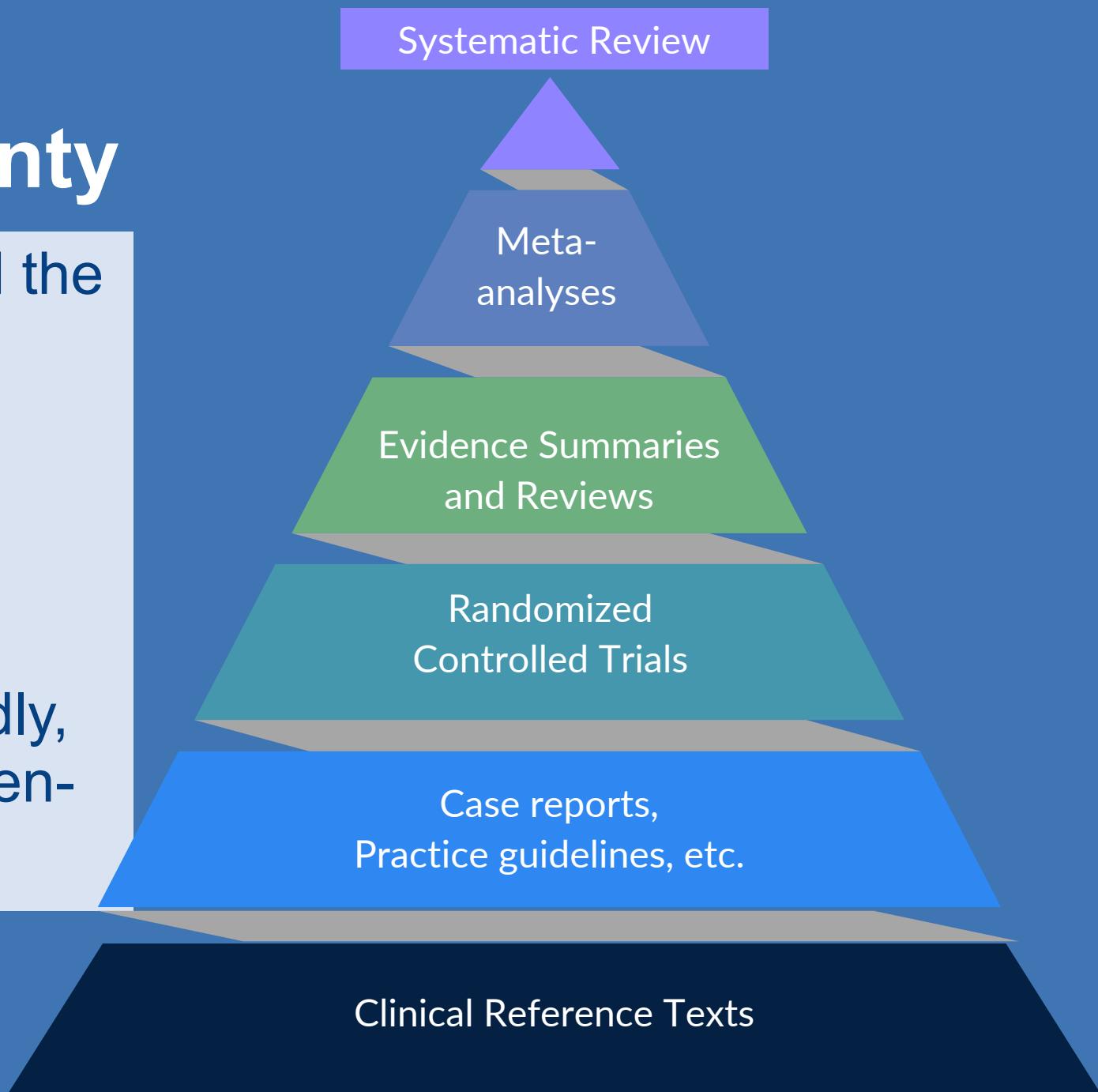
# Evidence – in times of uncertainty

Research is (typically) slow, and the need for rapid accumulation of information is sometimes great

– such as during the COVID-19 pandemic.

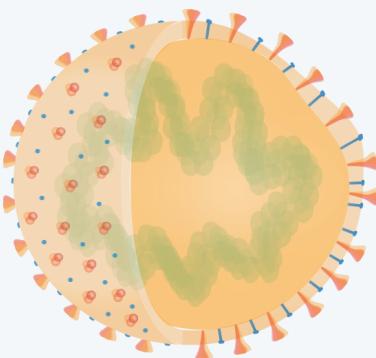
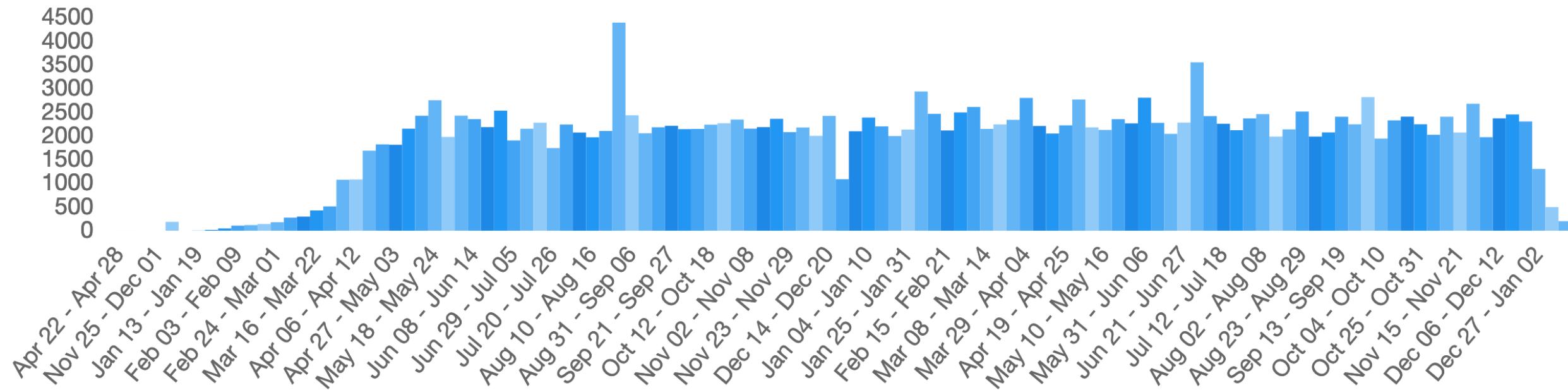
We needed to get answers rapidly, and our questions were very open-ended.

Systematic Review





## WEEKLY PUBLICATIONS



LitCovid is a curated literature hub for tracking up-to-date scientific information about the 2019 novel Coronavirus. It is the most comprehensive resource on the subject, providing a central access to [209561](#) (and [growing](#)) relevant articles in PubMed. The articles are updated daily and are further categorized by different research topics (e.g. transmission) and geographic locations.

[CITE](#)[FAQ](#)[DOWNLOAD](#)[LONG COVID](#)



SARA GIRONI CARNEVALE

## Scientists are drowning in COVID-19 papers. Can new tools keep them afloat?

By [Jeffrey Brainard](#) | May. 13, 2020 , 12:15 PM

Another challenge is making the tools more user friendly. Although data scientists have spent more than 20 years building tools to mine other topics in scientific literature, they have lagged in fine-tuning ways to help users explore the content of research articles, says Karin Verspoor, a computational linguist at the University of Melbourne. At the same time, “People on the user side haven’t quite realized that they need [these tools], until now,” she says. And that could promote greater attention to building helpful interfaces for COVID-19 and, eventually, other research topics.

Standard search tools aren't good enough ...

Science discovers text mining!

# WHO: “Find new insights”

**What has been published about medical care?**

**What do we know about vaccines and therapeutics?**

**What do we know about COVID-19 risk factors?**

**What do we know about non-pharmaceutical interventions?**

**What do we know about diagnostics and surveillance?**

# Supporting access to information: Search

targeted queries

well-defined  
information need

keyword snippet  
previews

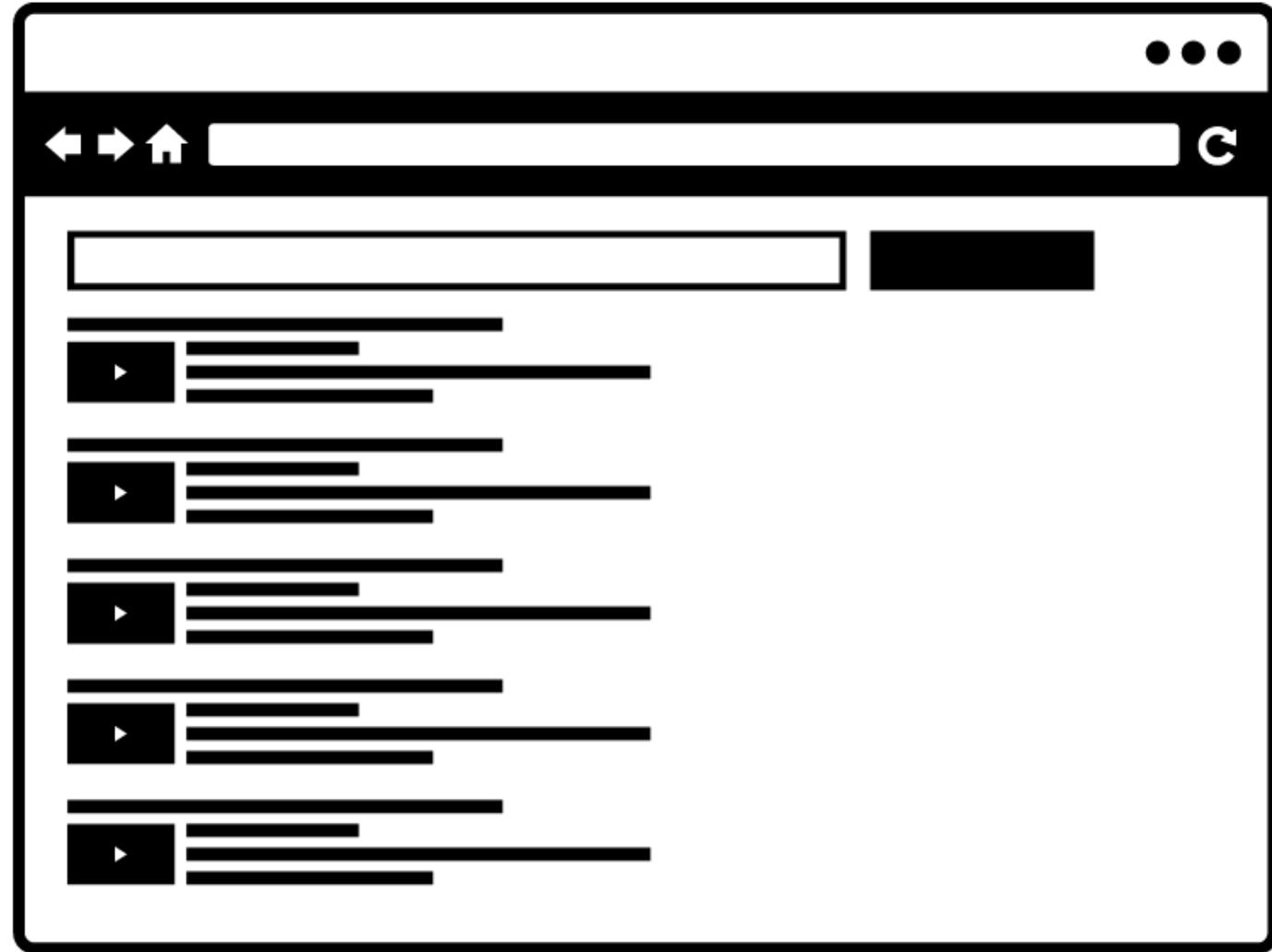
intelligent ranking

user formulates  
query

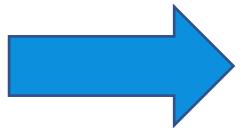
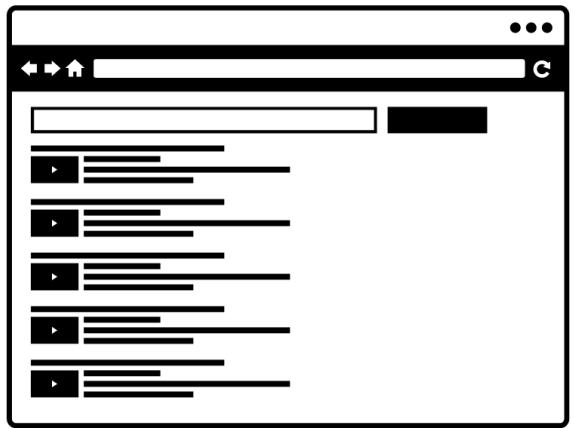
user scans results

limited depth in  
search

results opened  
individually



# What's Beyond Search?



document retrieval

information analysis  
and synthesis

Transforming documents into information (automatically) requires **AI/NLP**

categories

concepts

relationships

summaries

synthesis

# Introducing COVID-SEE

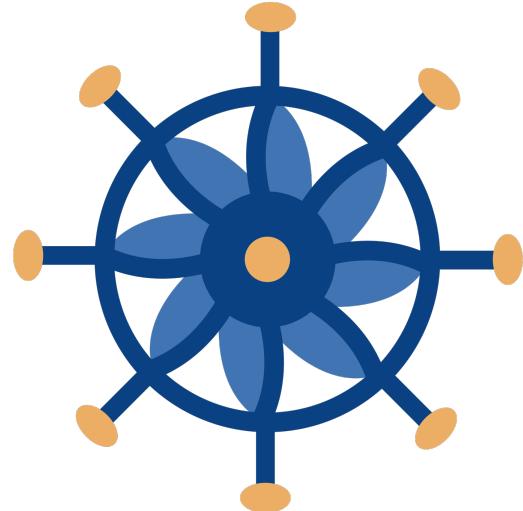
<http://covid-see.com>

search

exploration

concepts

relations



**COVID-SEE**  
Scientific Evidence Explorer

collection-level  
overview

visual summaries

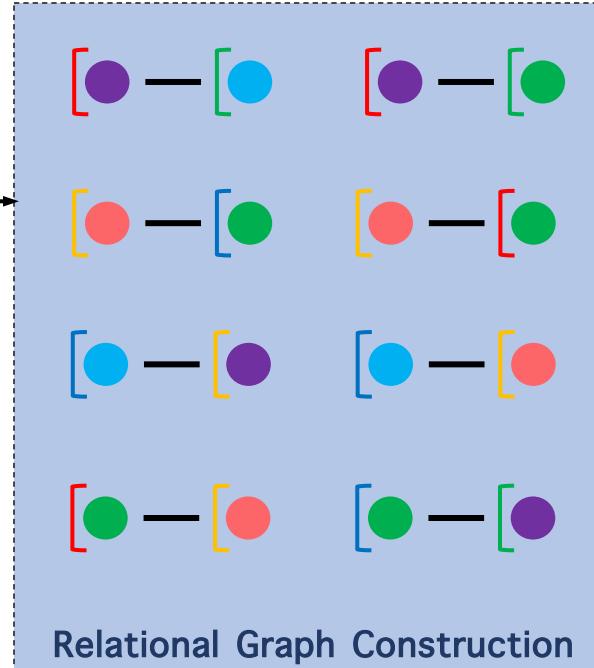
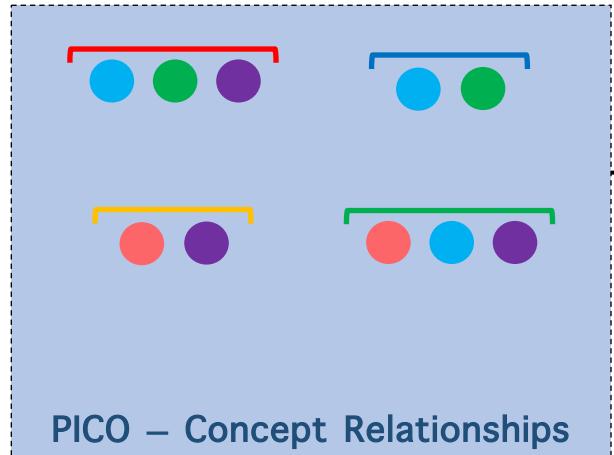
thematic  
generalisation

user “briefcase”

co-occurrence of  
PICO concepts:

*child*<sub>POPULATION</sub>

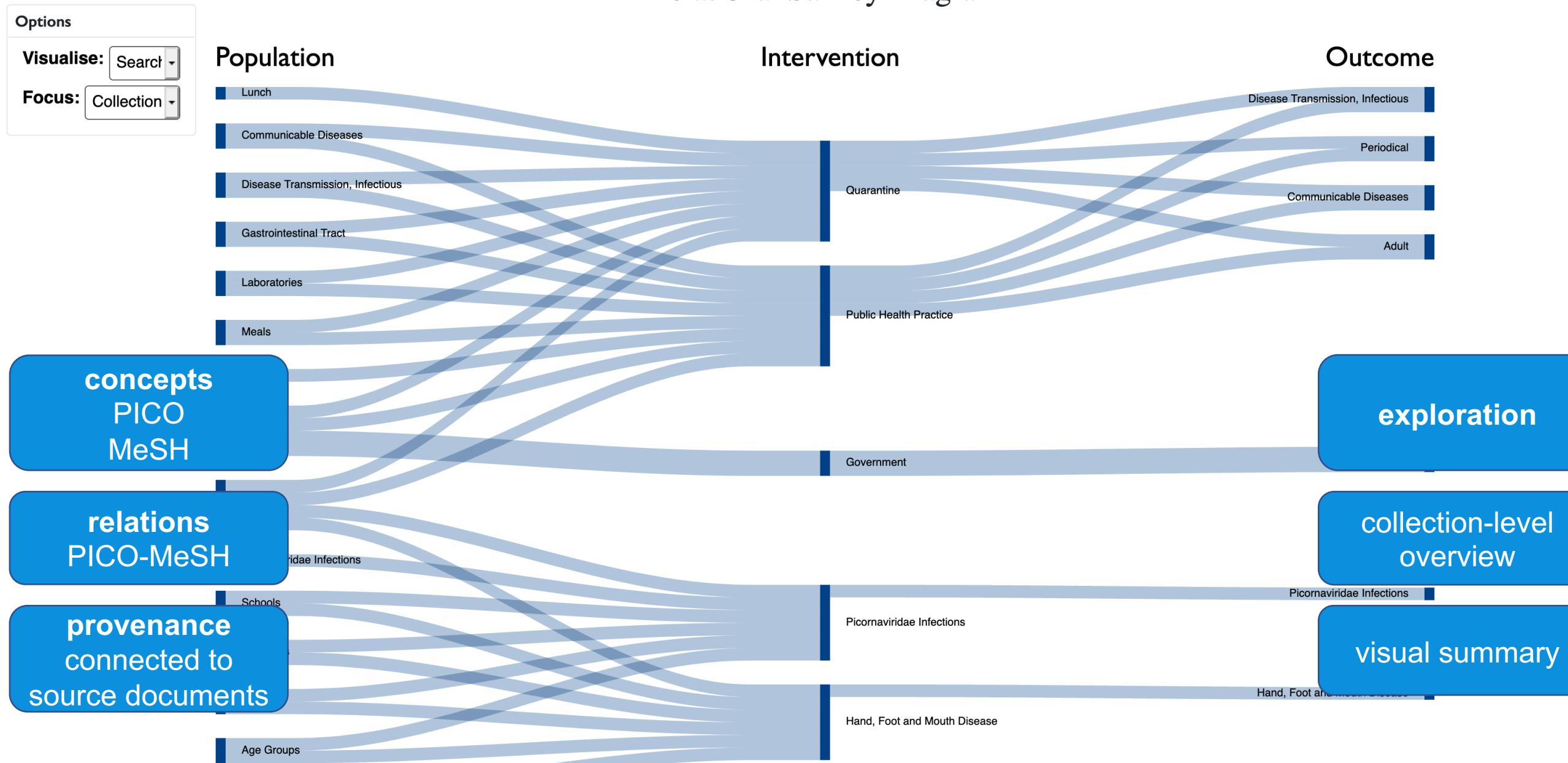
*quarantine*<sub>INTERVENTION</sub>



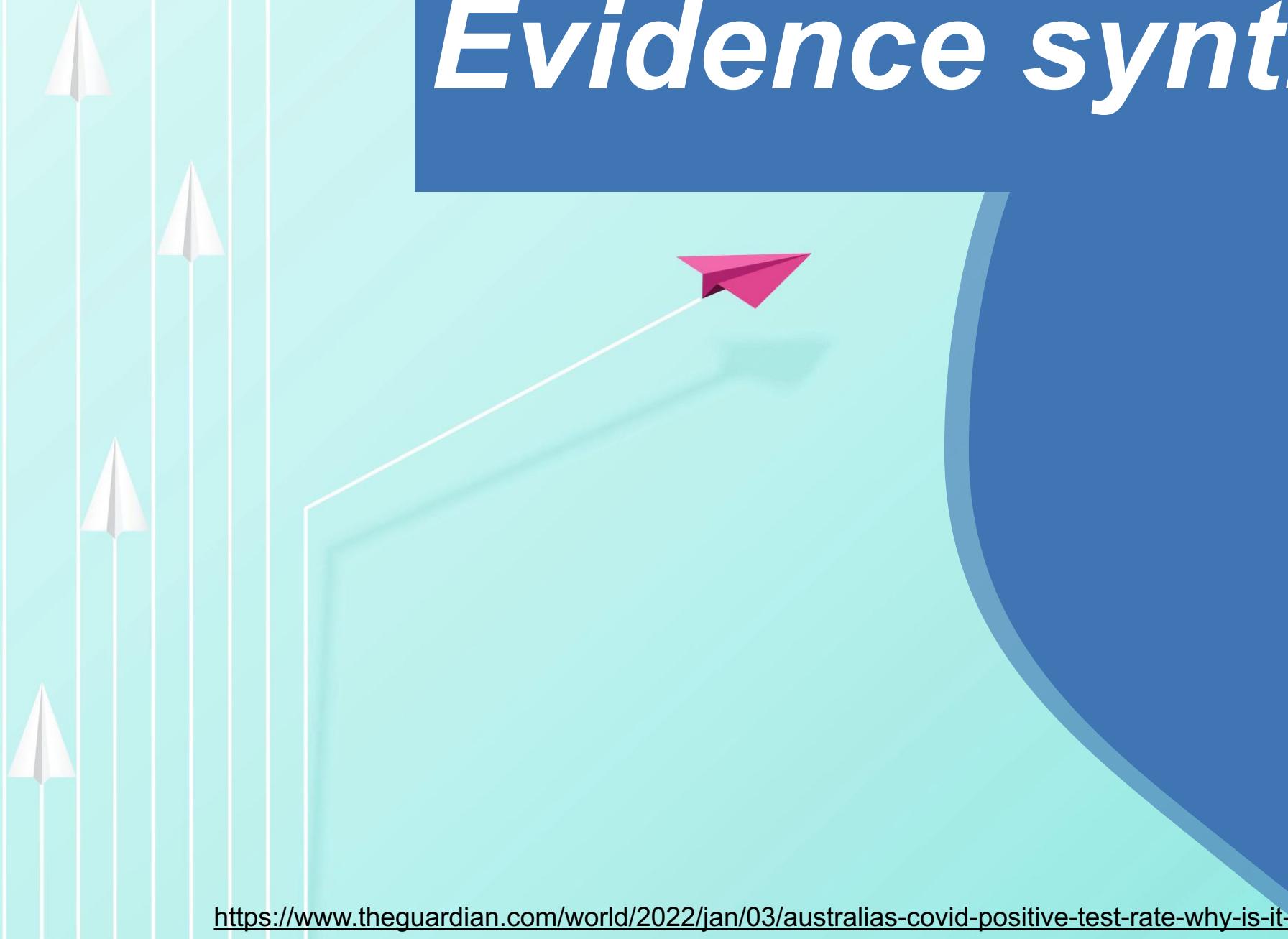
Population concept – Intervention concept  
respiratory tract infection – vaccines  
child – quarantine  
students – health education

Intervention concept – Outcome concept  
vaccines – recovery  
antiviral agents – cd8+ T-lymphocytes  
health education – attitudes

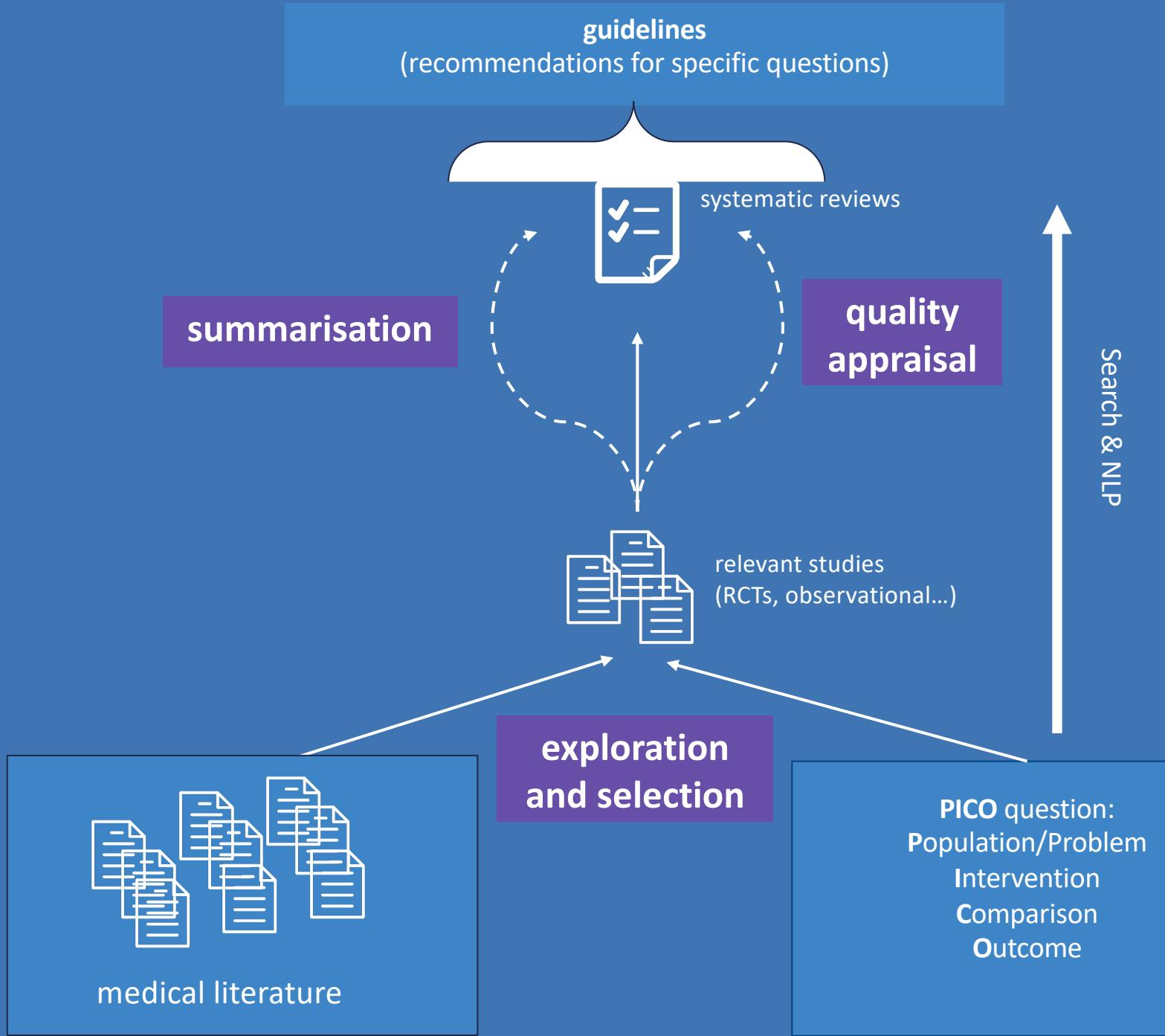
# Relational Sankey Diagram



# *Evidence synthesis*



# Systematic reviewing





# Summarisation requires synthesis

[Aliskiren]

[blood pressure]

[lower]

- A. Aliskiren lowers blood pressure
- B. It appears that Aliskiren may lower blood pressure
- C. Aliskiren does not lower blood pressure
- D. There is not enough evidence to confirm if Aliskiren lowers blood pressure
- F. Thus it is important to establish if Aliskiren lowers blood pressure

# Building blocks of a claim

[Aliskiren, blood pressure]

[Aliskiren, blood pressure] + [lower]

[Aliskiren, blood pressure] + [lower] + [may]

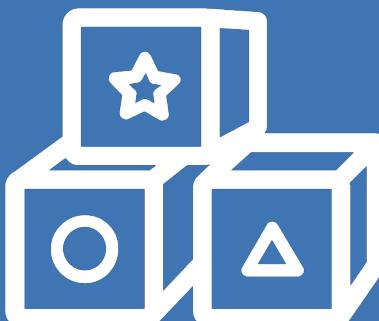
PICO = **clinical question**

PICO + direction = **proposition**

PICO + direction + modality = **claim**

No modality, no claim!

F. Thus it is important to establish if Aliskiren lowers blood pressure



# PICO-level aggregation

Do **robotic companions** help elderly patients?

This pilot study, which compared the benefits of a **robotic cat** and a plush toy cat as interventions for elderly persons with dementia....

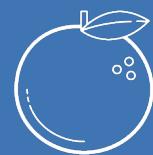
Findings on usability and user experience illustrate that the **robot** has considerable potential to be accepted to support daily living at home.

**Socially assistive robot (SAR)** technology could assume new roles in health and social care to meet this higher demand.

... impact of such low-cost **robotic pets** based on perceptions and experiences of its use with older adults...

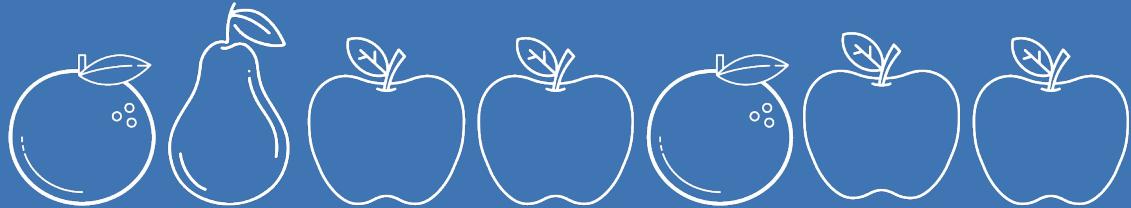
The easiest (but still hard).

# Aggregating direction



(e.g. increases, decreases, no effect)

Direction from input documents:



Bad strategies:

**Listing:**



**Majority:**



Good strategies:

**Contrasting:**

Some say that while others and some

**Synthesis:**

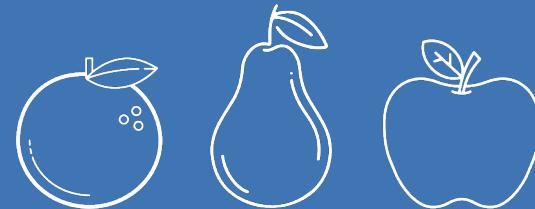


(or something else, it depends)

# Aggregating modality

When do we say  
there is  
**no evidence?**

**Too much conflict?**

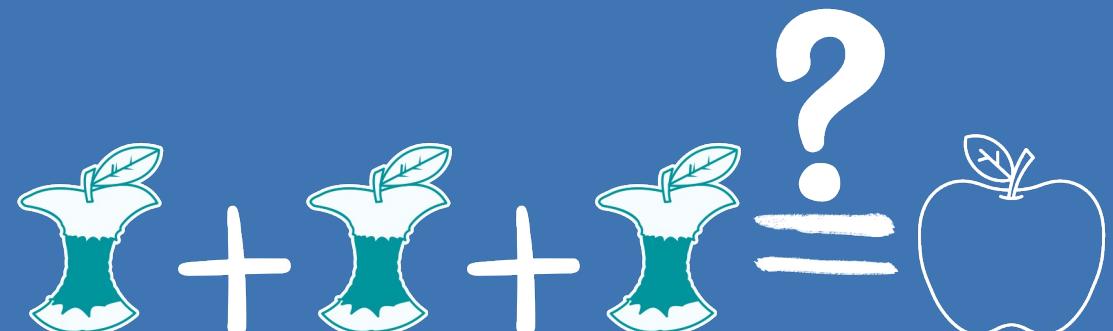


**Weak evidence?**

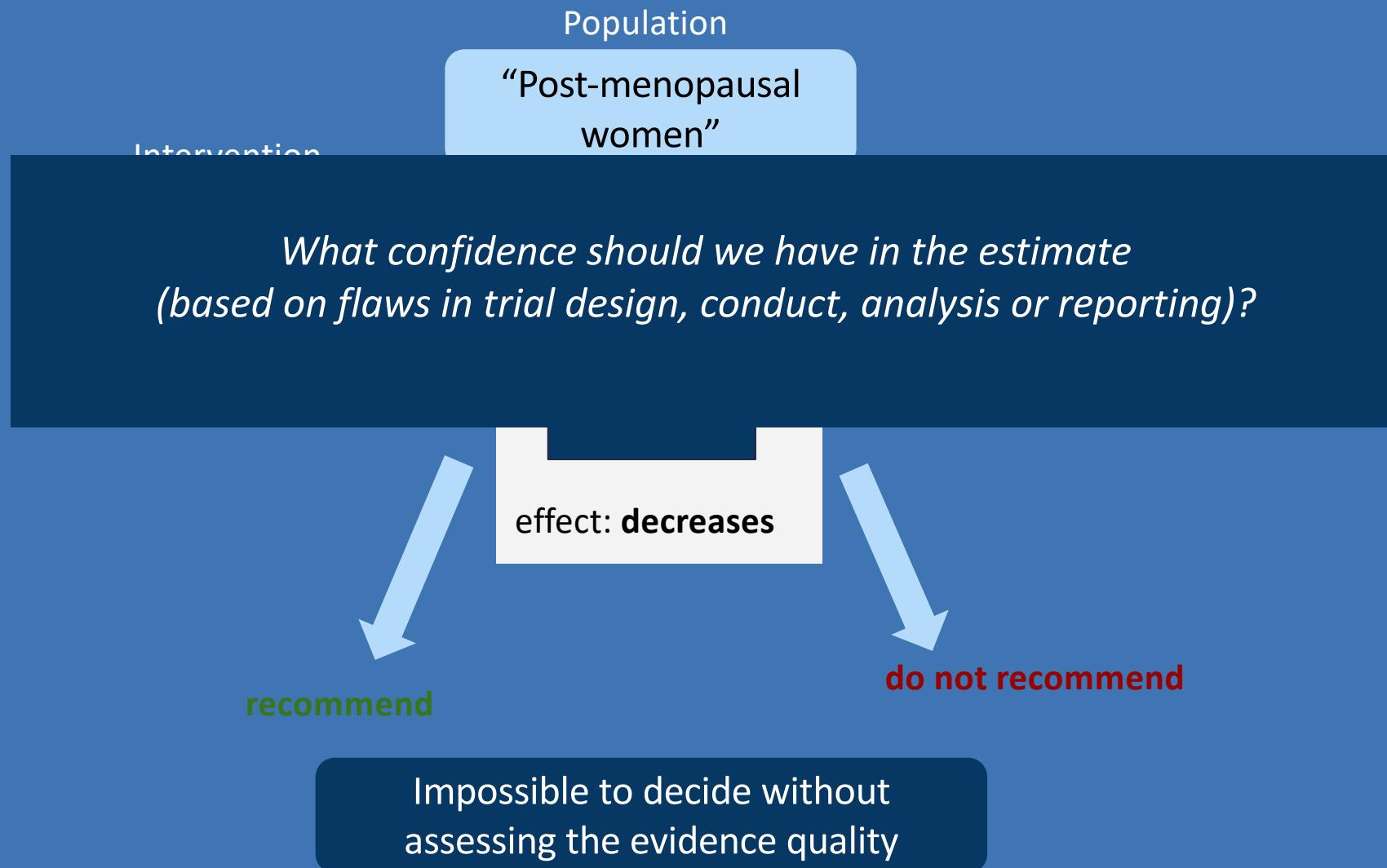


**No evidence at all?**

How do we  
aggregate weak to  
moderate to strong?

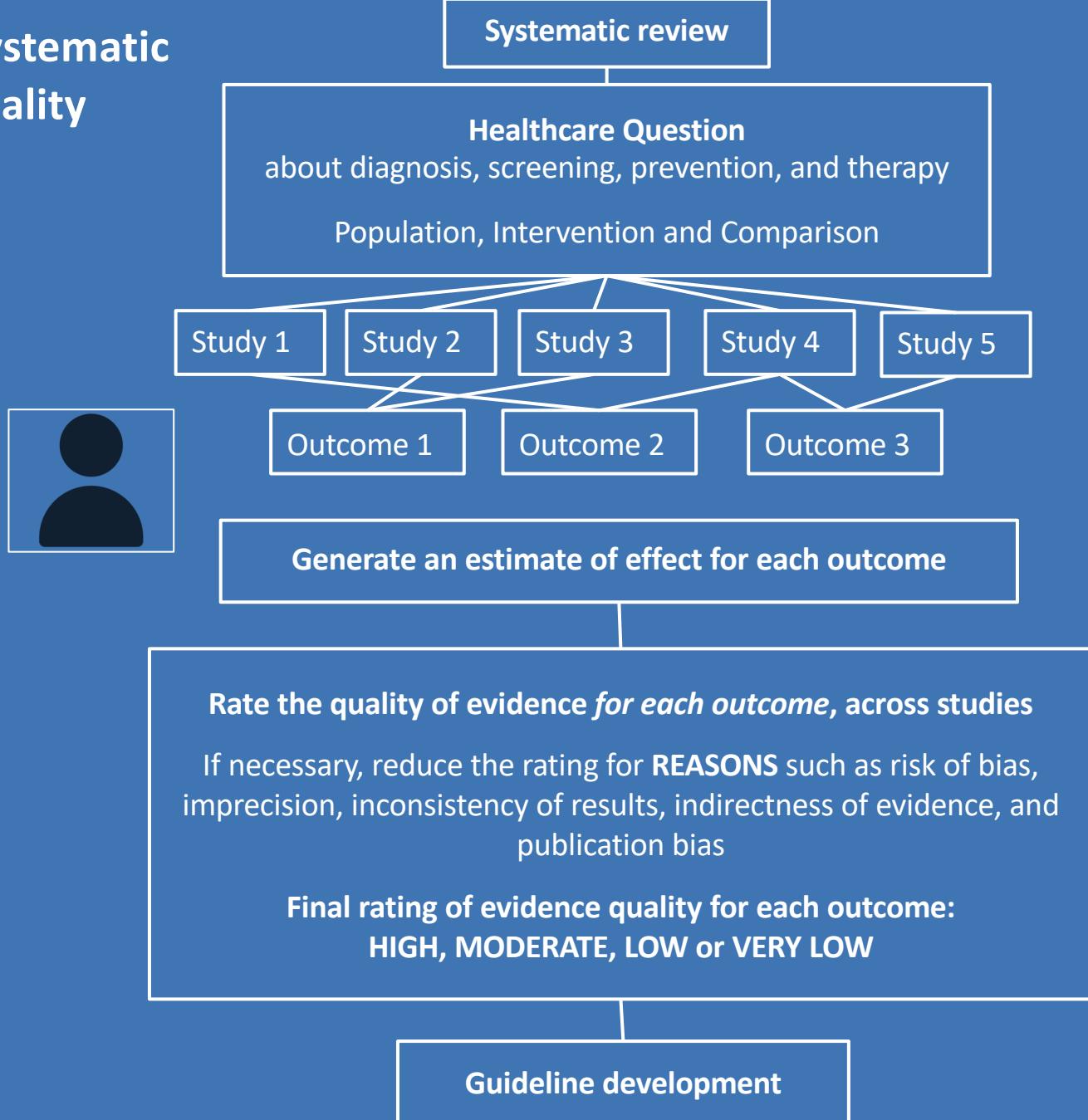


# Quality assessment in evidence synthesis



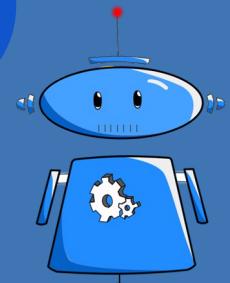
# Constructing systematic reviews and quality assessment

## Systematic review



Our goal:

Assume we're given a piece of evidence from a systematic review, predict its quality



Dataset + Tasks + Models with heterogeneous inputs (structured and non-structured)

# Grading of Recommendations Assessment, Development and Evaluation (GRADE) framework

Randomised  
controlled  
trials: HIGH

Downgrade for:

- Risk of bias
- Inconsistency
- Indirectness
- Imprecision
- Publication bias

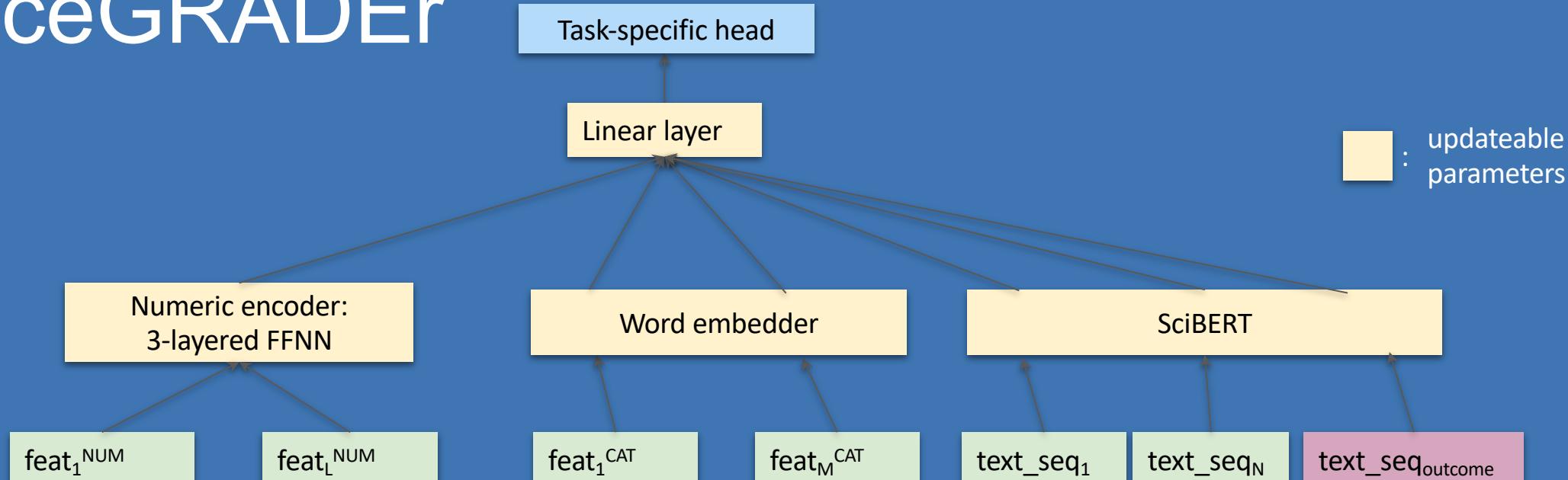
Final grade:  
High  
Moderate  
Low  
Very low

Consider other  
factors affecting  
recommendation

Make  
recommendation

# EvidenceGRADEr

## Base model



example inputs:

number of  
participants

...

topic

...

full abstract

...

## Task-specific heads

Multi-label classification with  
sigmoids  
(Binary cross-entropy loss  
with class weightings)

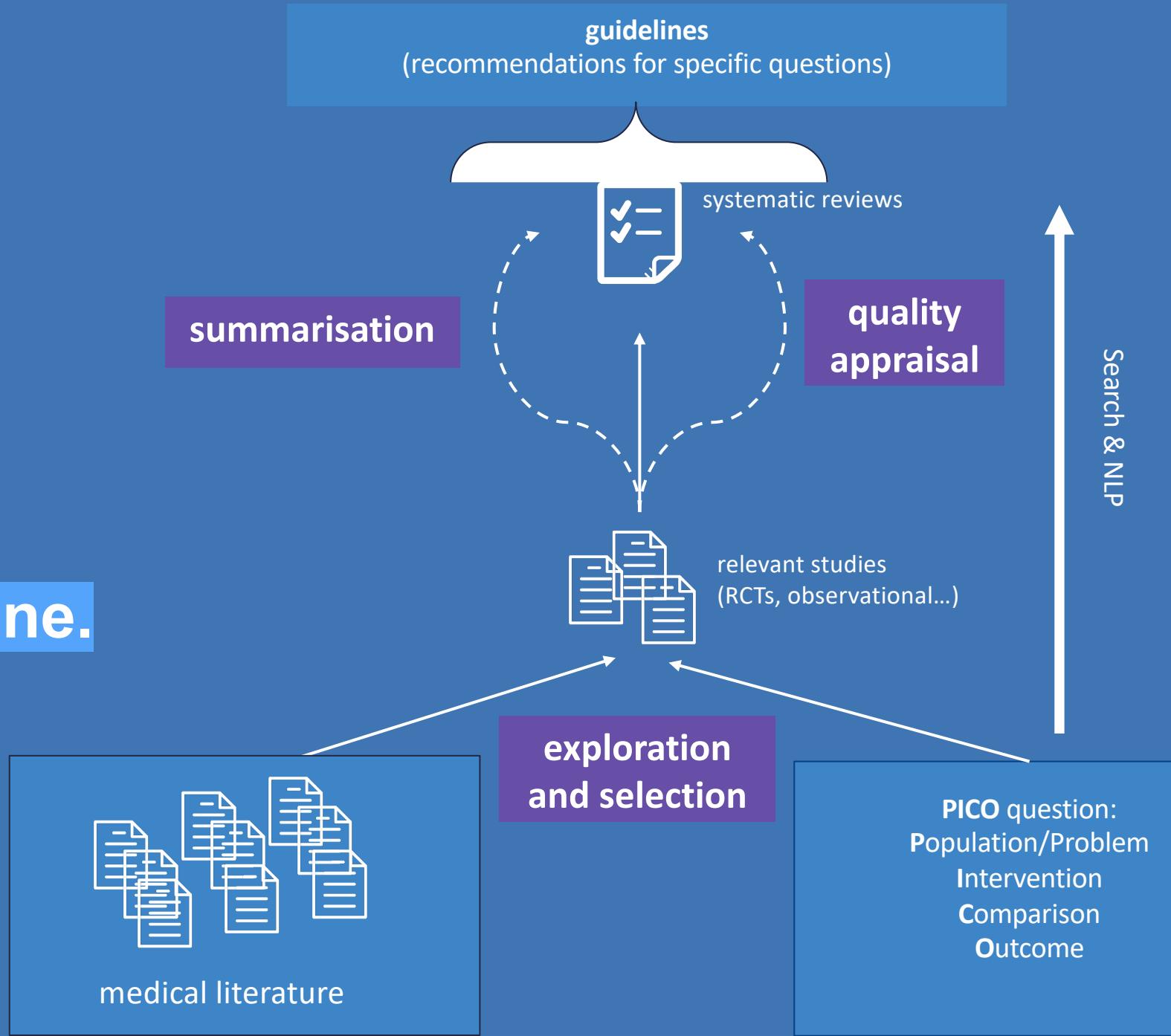
Classification with softmax  
(Cross-entropy)

Regression: quality  
scalar in the range 0-3  
(MSE loss)

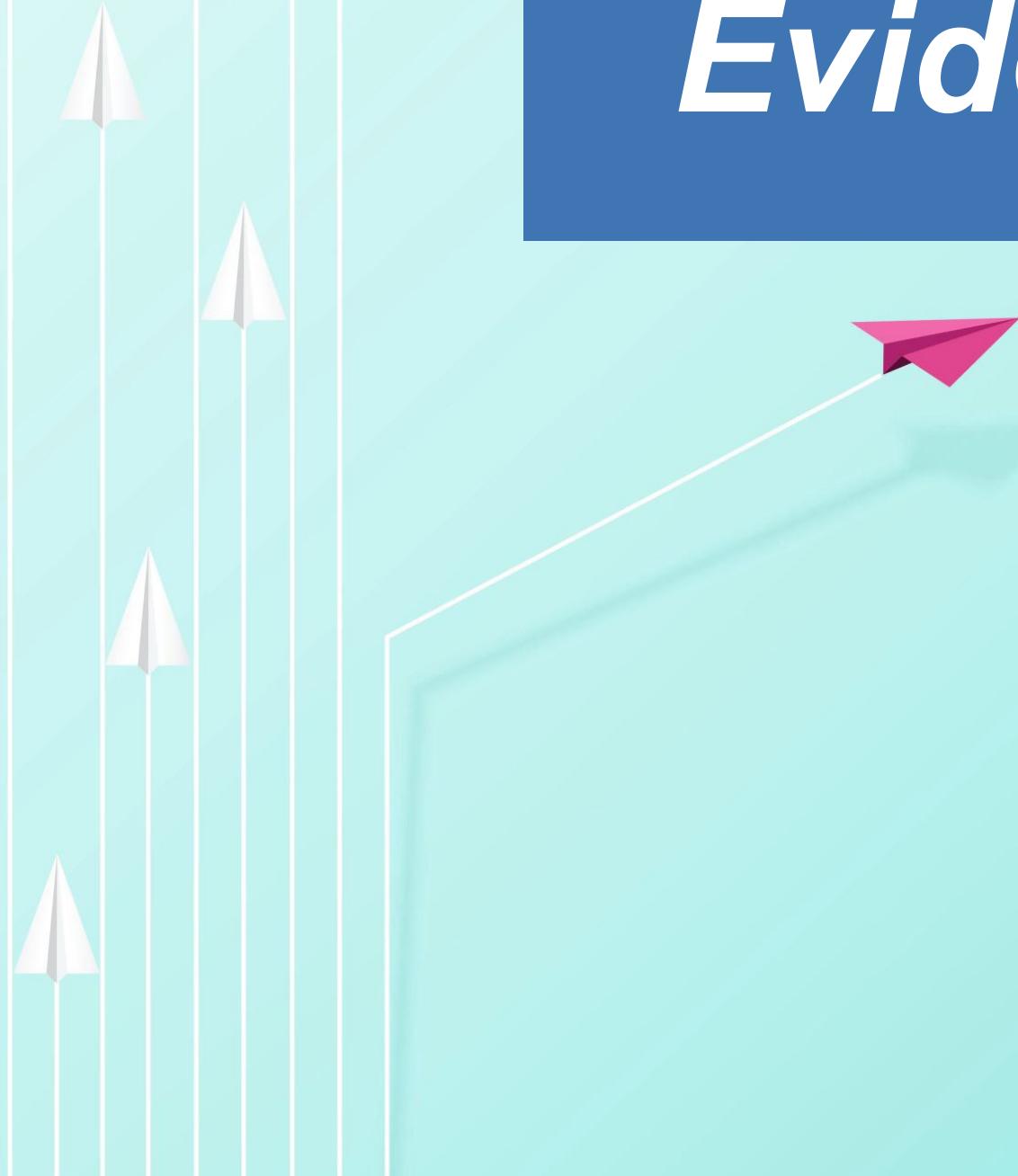
# Systematic Review Automation

Making progress.

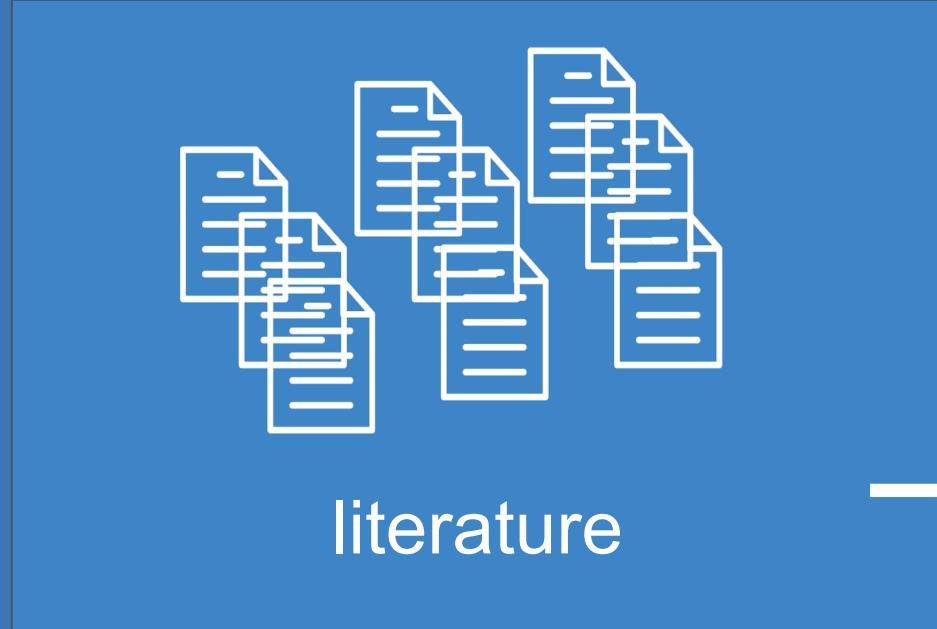
More work to be done.



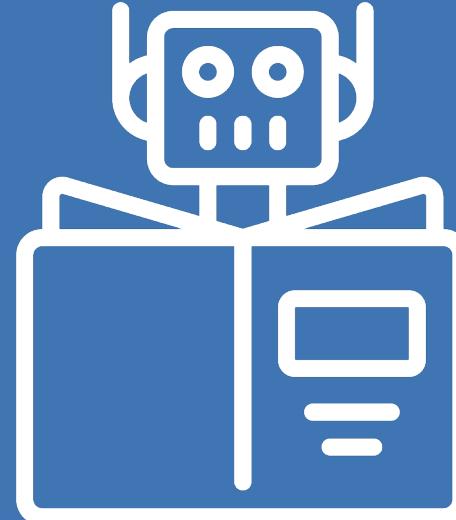
# *Evidence discovery*



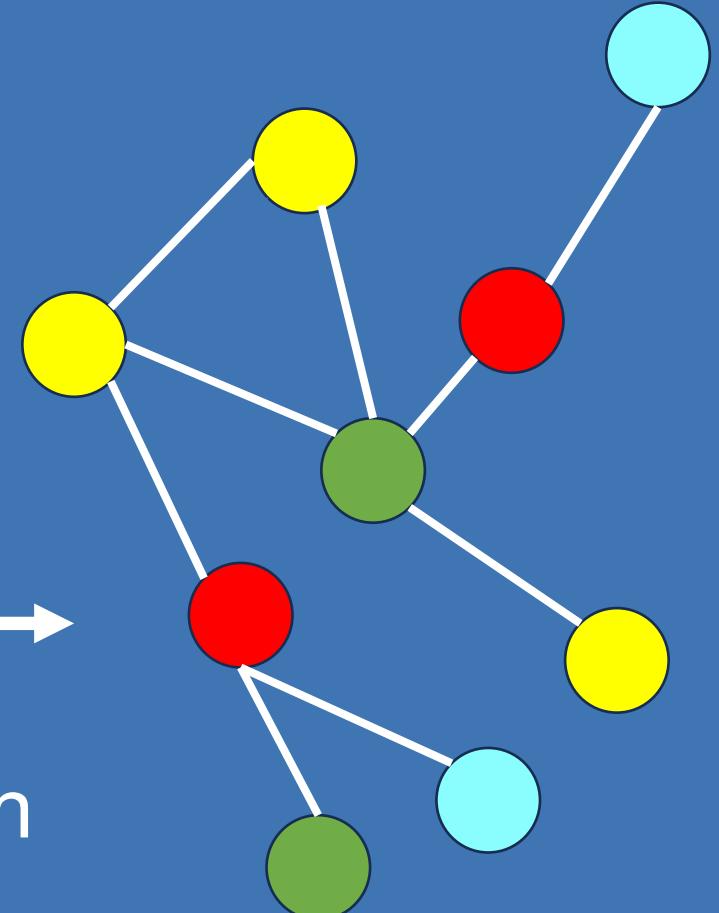
# Analysing knowledge graphs



literature

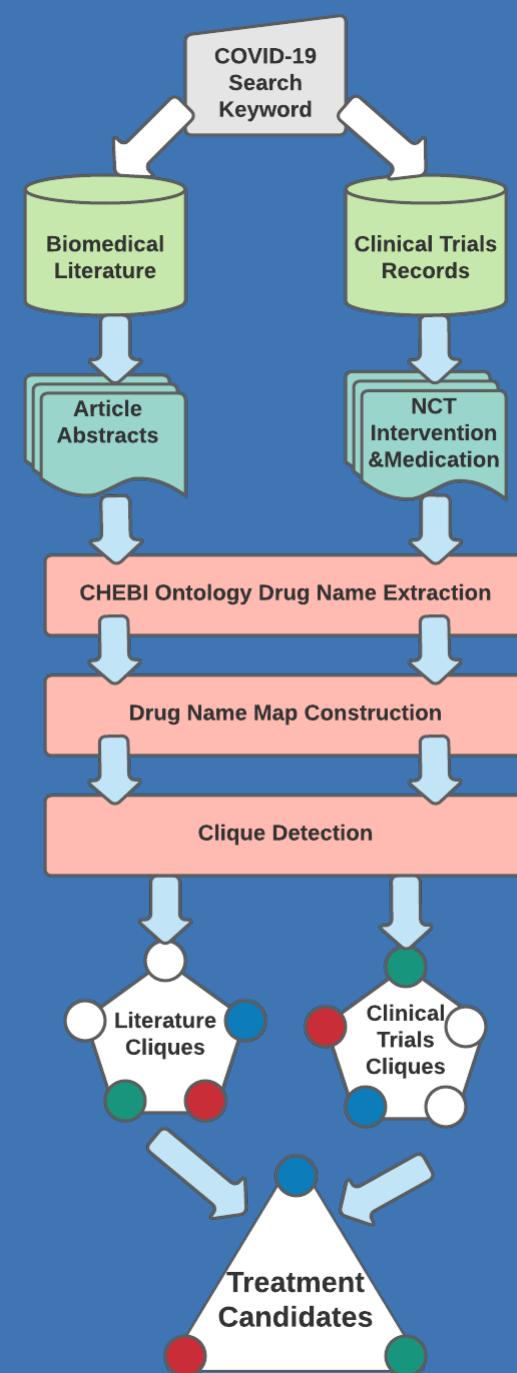


concept, entity,  
relation extraction



# Hypothesis generation from literature

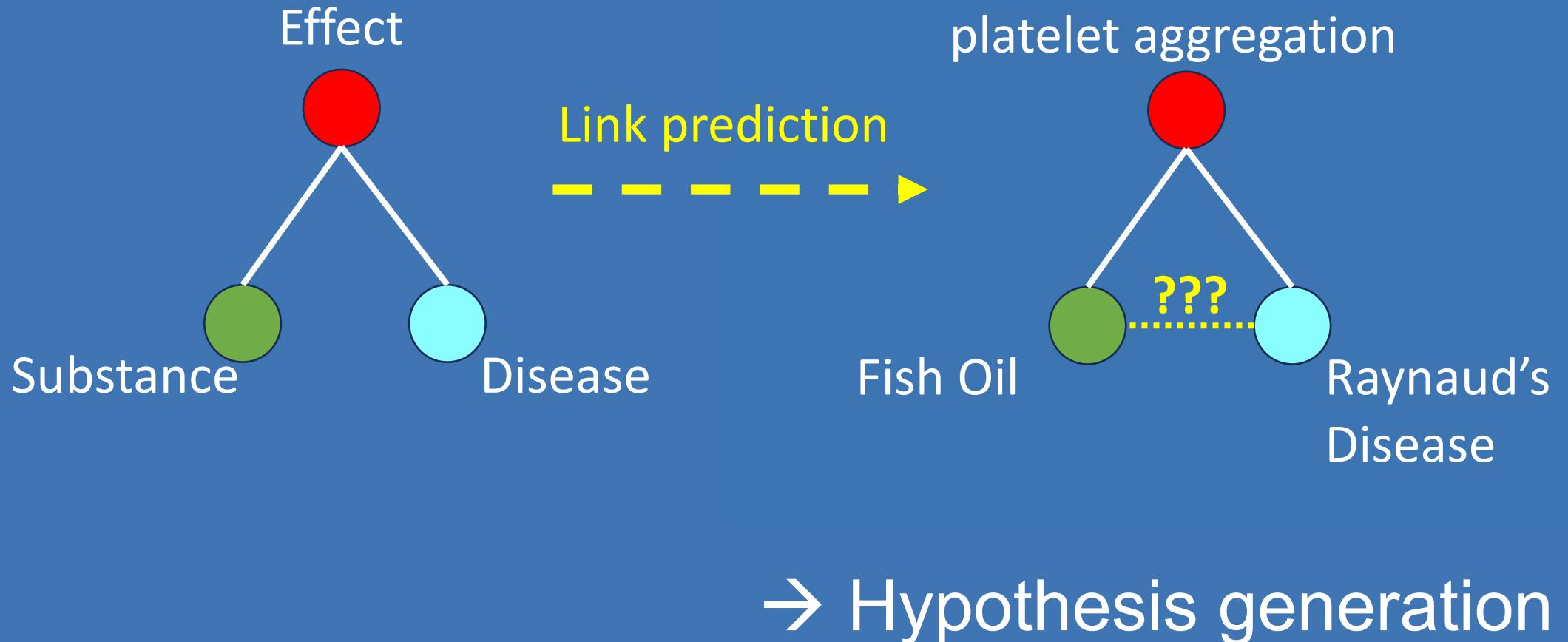
- Information Extraction from Literature + Clinical Trials
- Network construction
  - co-occurrences
  - filtered using Association Analysis
- Network analysis
  - clique detection



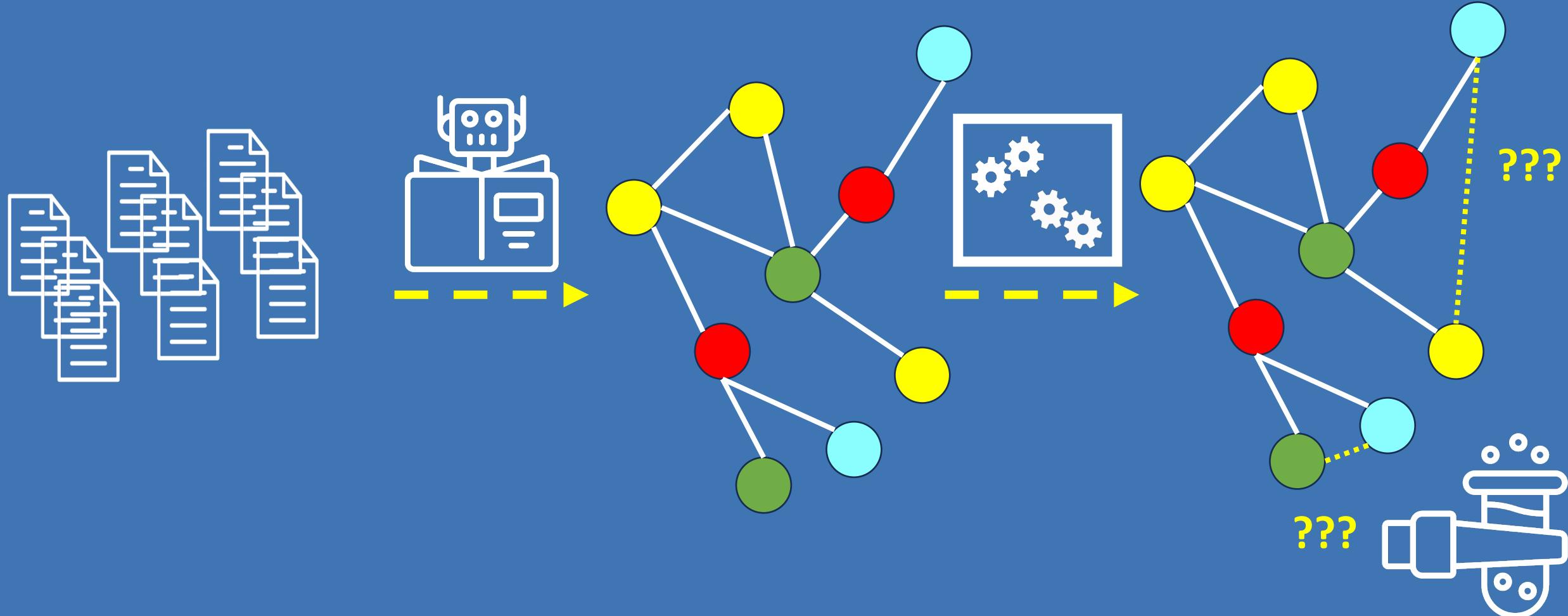
**Table 5.** Two-drug combinations of COVID-19 treatment candidates identified for further investigation.

Drug 1	Drug 2	Combineability
Estrogen (ChEBI:50114)	Estradiol (ChEBI:23965)	No
Hydroxyethylidene(ChEBI:5801)	Azithromycin (ChEBI:2955)	Possible
Lopinavir (ChEBI:31781)	Ritonavir (ChEBI:45409)	Yes
Ruxolitinib(ChEBI:66919)	Colchicine (ChEBI:23359)	Possible
Hydroxychloroquine (ChEBI:5801)	Favipiravir ChEBI:134722	Possible
Hydroxychloroquine (ChEBI:5801)	Chloroquine ChEBI:3638	No
Azithromycin (ChEBI:2955)	Ivermectin ChEBI:6078	Possible
Hydroxychloroquine (ChEBI:5801)	Lopinavir(ChEBI:31781)	Probably not
Hydroxychloroquine (ChEBI:5801)	Doxycycline(ChEBI:50845)	Possible
Daclatasvir (ChEBI:82977)	Sofosbuvir(ChEBI:85083)	Yes

# Literature-based Discovery



# Literature-based discovery at scale



graph with thousands of nodes,  
representing 20 years of research

→ lots of new hypotheses

# Conclusions

We need AI to enable learning from the scientific literature, to support evidence detection, exploration, synthesis, and discovery.

AI helps us to find, infer, and utilise knowledge to support ever-improving scientific understanding.



# Thank you!



@karinv



Special thanks to:

*RMIT University*

Vlada Rozova

Estrid He



*U. Melbourne*

Simon Suster

Yulia Otmakhova

Gracie Pu

Jey Han Lau

Zenan Zhai (Oracle)

Biaoyan Fang (CSIRO)

Trevor Cohn (Google)

Jinghui Liu (CSIRO)

Timothy Baldwin (MBZUAI)



*Elsevier*

Saber Akhondi

Christian Druckenbrodt

Camilo Thorne