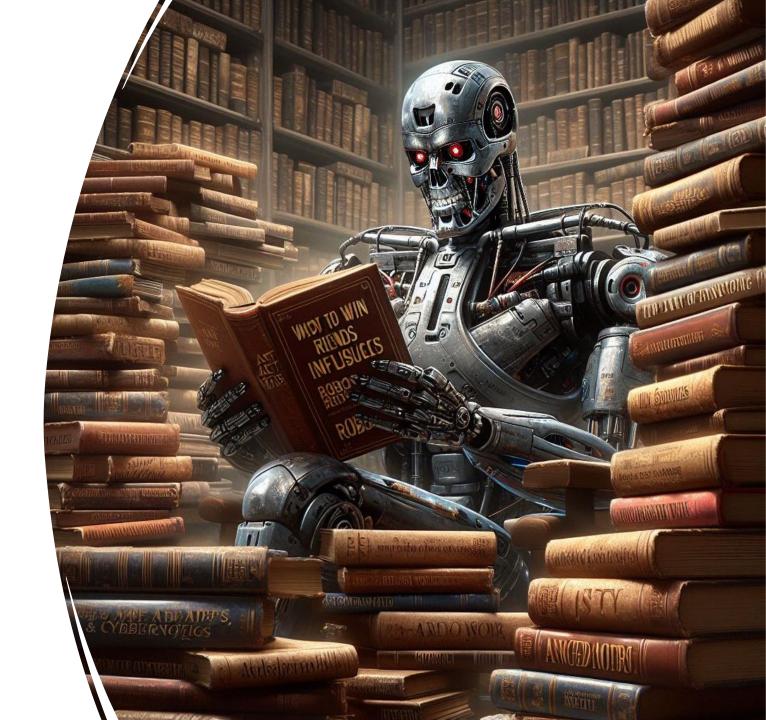
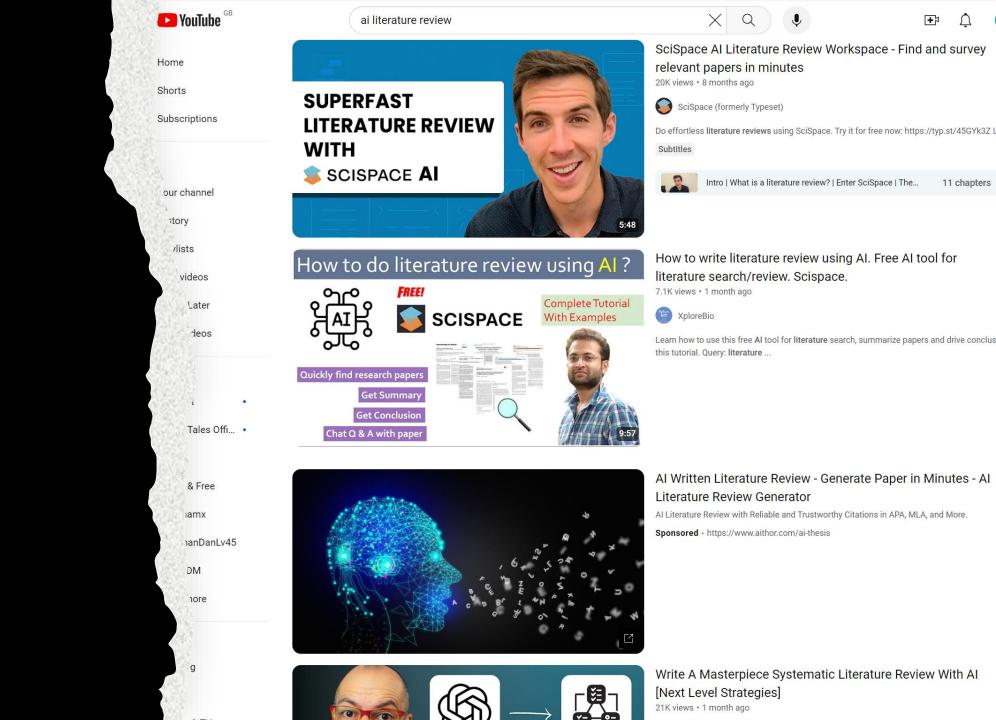


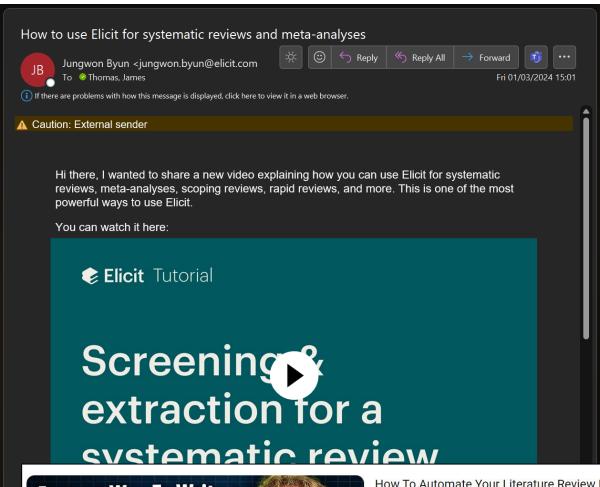


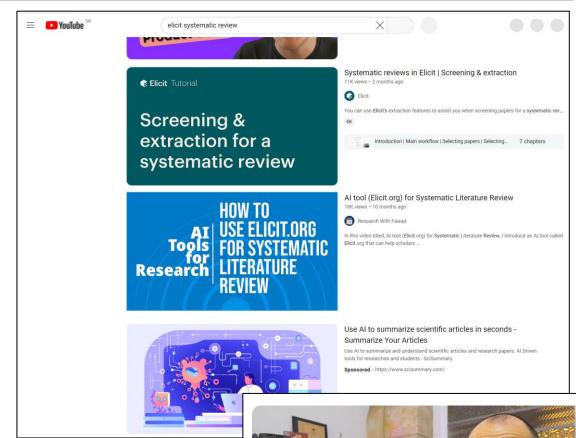
Outline

- The robots are coming here
- We need to be ready to benefit
- We need to maintain standards
- Guidance development







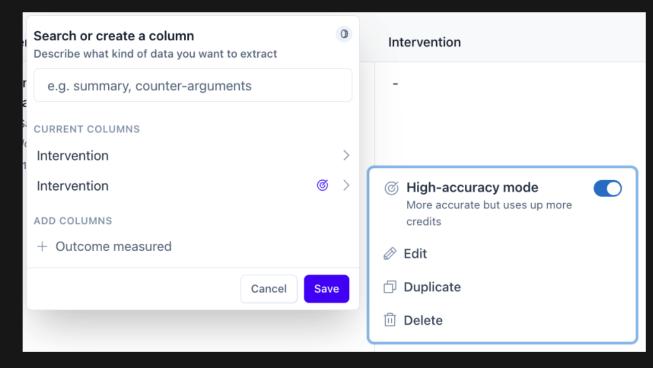


Lit Review



What is high-accuracy mode?

High-accuracy mode gives better results when adding columns and extracting data. In our testing, high-accuracy mode had about 1/2 the error rate of standard columns. High-accuracy mode is particularly useful for conducting systematic reviews and meta-analyses.



High-accuracy mode is only available to Elicit Plus subscribers, and costs about 250 credits per answer.

Learn more about high-accuracy mode <u>here</u>.

Improvements

As of today, we're using a new technique for high-accuracy mode. Our testing found that our new technique reduces the error rate by about 8% compared to our old technique.



- Elicit can be used in 'high accuracy mode' for systematic reviews and meta-analyses
- Apparently the error rate is reduced by 8% compared with... something else

 Published evaluations by developers of new tools are poor to non-existent

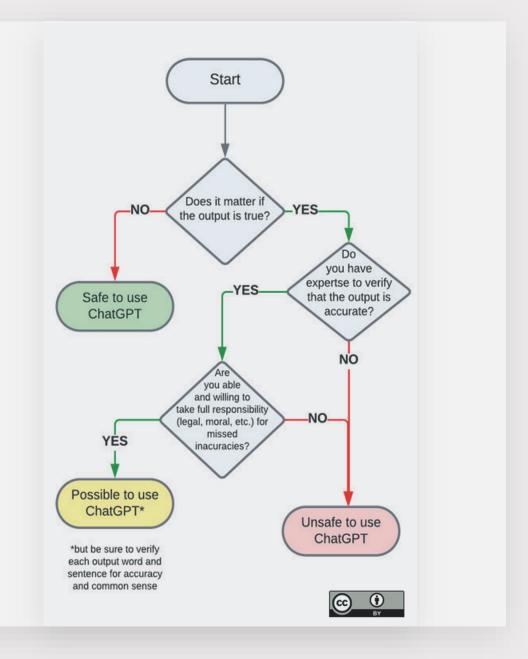
What does this mean for the systematic review field?

- Automation in systematic reviewing is coming fast
- It may be hugely disruptive possibly akin to the impact of systematic reviews on EBM / evidence informed policy
- There is a danger that established standards for evidence synthesis are compromised / left behind
 - Either because we fail to adapt
 - Or because we allow good evidence synthesis to be displaced by less rigorous (but cheaper) approaches



When can we use this new technology?

Guidance and standards are emerging



Process for developing guidance and recommendations for responsible use of AI in systematic reviews

- ICASR, Cochrane, Campbell, JBI + others involved
- If you want to get involved please register here
 - https://forms.office.com/e/Dg2vwD8agf
- Draft timeline
 - July draft open for feedback and input
 - September special session at Global Evidence Summit
 - September December further rounds of feedback & revision
 - December version 1.0 available online
 - Mid-2025 update (if necessary)

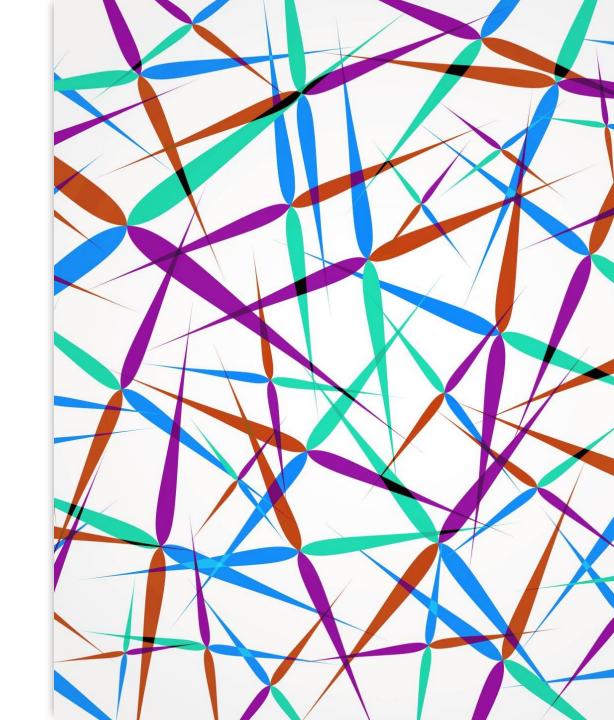


Research integrity

- Considering how accepted principles of research integrity apply can be helpful
 - Rigour
 - Honesty
 - Transparency and open communication
 - Care and respect
 - Accountability

Rigour

- The use of an AI tool in a systematic review must be clearly justified by good evidence
- Rigorous and valid evaluation is key
- Are findings replicable?
- Prevent contamination between training and testing datasets is vital
- We need to build a cumulative evidence base – hence, Studies Within a Review (SWAR)





Development pipeline to justify the use of the Cochrane RCT Classifier









Conventional machine learning model trained on 280,000 records from Cochrane Crowd

Model was calibrated to achieve 99% recall on a second ('Hedges') dataset (~50,000 records)

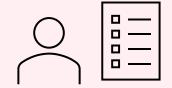
Model was validated on 92,000 studies included in Cochrane intervention reviews

Model was deployed for live use in Cochrane review workflows



Being rigorous in development and testing

Development and evaluation of a classification task using a language model



Prompt development with development dataset



Prompt testing with a *different* dataset

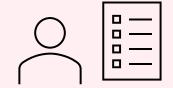


The language model can then apply the prompts to the remaining data



Being rigorous in development and testing

Development and evaluation of a classification task using a language model



Prompt development with development dataset



Prompt testing with a *different* dataset

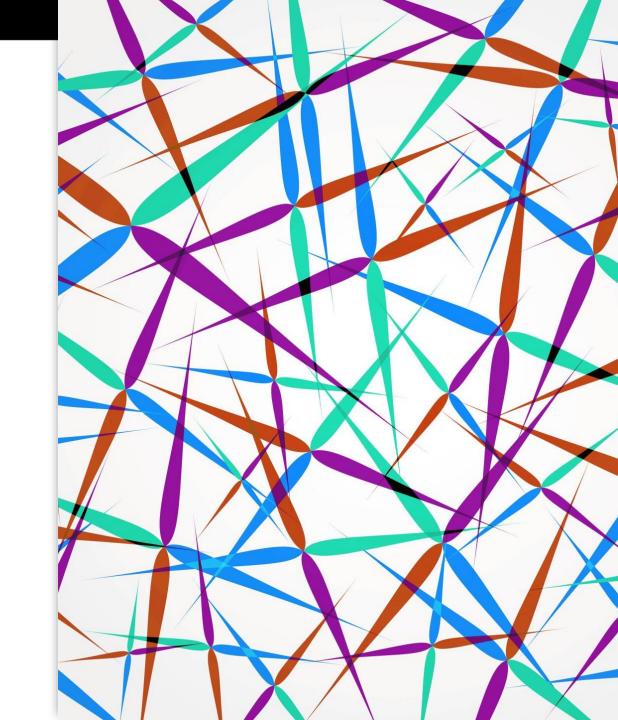


The language model can then apply the prompts to the remaining data

Critical to avoid contamination between development and testing!

Rigour

- The use of an AI tool in a systematic review must be clearly justified by good evidence
- Rigorous and valid evaluation is key
- Are findings replicable?
 - Deterministic vs non-deterministic / probabilistic algorithms
- Avoiding contamination between training and testing datasets is vital
- We need to build a cumulative evidence base – hence, Studies Within a Review (SWAR)



(+++) "Marketing PASSION Thanks for BOOM! 9 a.M NEVER helping me! "WORK" 8.30 focus on MORE concepts! Toal 11:00 TALK. LESS PROJEC DON'T FORGE forget to quate 10 PAY TAX system with design team Table POSITIVE THINKING WHAT 11! operb VOY NEW CALL To do list What's PAM @ 6 PM DAILY IDEA REPORTI NEXT? Before 10 AM !! Double check! INTERN Schedulei STUDENTS VDO CONFERENCE 70% a Few

Honesty

- Honesty about tool performance
- Honesty about making claims in advance of using a tool (e.g. when bidding for work)
- Honesty about evaluation no sneaky tests of language model prompts outside a proper evaluation framework © (or at least, no contamination of data)

Care and respect

- Language models are known to be biased
- Some development processes remove the most obvious and objectionable output (usually)
 - But biases remain
- We need to be very careful before trusting that it will not generate bias even in a systematic review context

Assessing the potential of GPT-4 to perpetuate racial and gender biases in health care: a model evaluation study

Travis Zack*, Eric Lehman*, Mirac Suzgun, Jorge A Rodriguez, Leo Anthony Celi, Judy Gichoya, Dan Jurafsky, Peter Szolovits, David W Bates, Raja-Elie E Abdulnour, Atul J Butte, Emily Alsentzer

Summary

Background Large language models (LLMs) such as GPT-4 hold great promise as transformative tools in health care, ranging from automating administrative tasks to augmenting clinical decision making. However, these models also pose a danger of perpetuating biases and delivering incorrect medical diagnoses, which can have a direct, harmful impact on medical care. We aimed to assess whether GPT-4 encodes racial and gender biases that impact its use in health care.

Methods Using the Azure OpenAI application interface, this model evaluation study tested whether GPT-4 encodes racial and gender biases and examined the impact of such biases on four potential applications of LLMs in the clinical domain—namely, medical education, diagnostic reasoning, clinical plan generation, and subjective patient assessment. We conducted experiments with prompts designed to resemble typical use of GPT-4 within clinical and medical education applications. We used clinical vignettes from NEJM Healer and from published research on implicit bias in health care. GPT-4 estimates of the demographic distribution of medical conditions were compared with true US prevalence estimates. Differential diagnosis and treatment planning were evaluated across demographic groups using standard statistical tests for significance between groups.

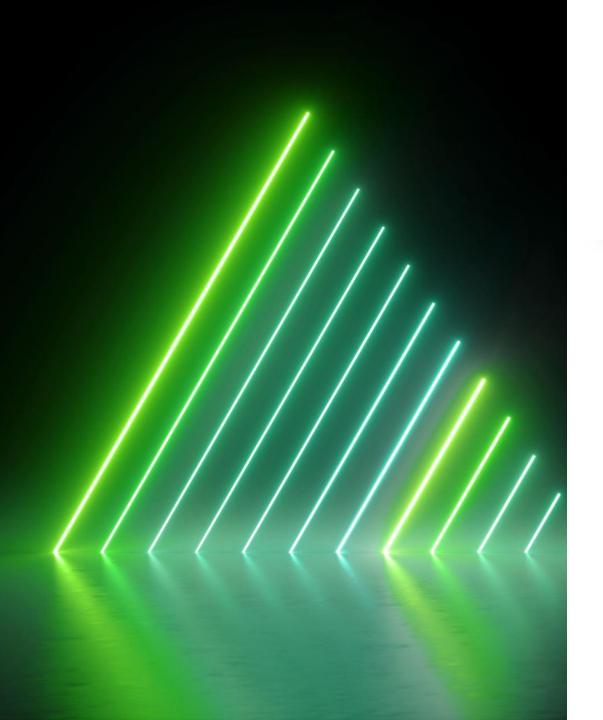
Findings We found that GPT-4 did not appropriately model the demographic diversity of medical conditions, consistently producing clinical vignettes that stereotype demographic presentations. The differential diagnoses created by GPT-4 for standardised clinical vignettes were more likely to include diagnoses that stereotype certain races, ethnicities, and genders. Assessment and plans created by the model showed significant association between demographic attributes and recommendations for more expensive procedures as well as differences in patient perception.

Interpretation Our findings highlight the urgent need for comprehensive and transparent bias assessments of LLM tools such as GPT-4 for intended use cases before they are integrated into clinical care. We discuss the potential sources of these biases and potential mitigation strategies before clinical implementation.

Transparency and open communication

- How does the tool work?
- How can I replicate / confirm your results?
- Honesty about conflicts of interest
- In evaluation methods





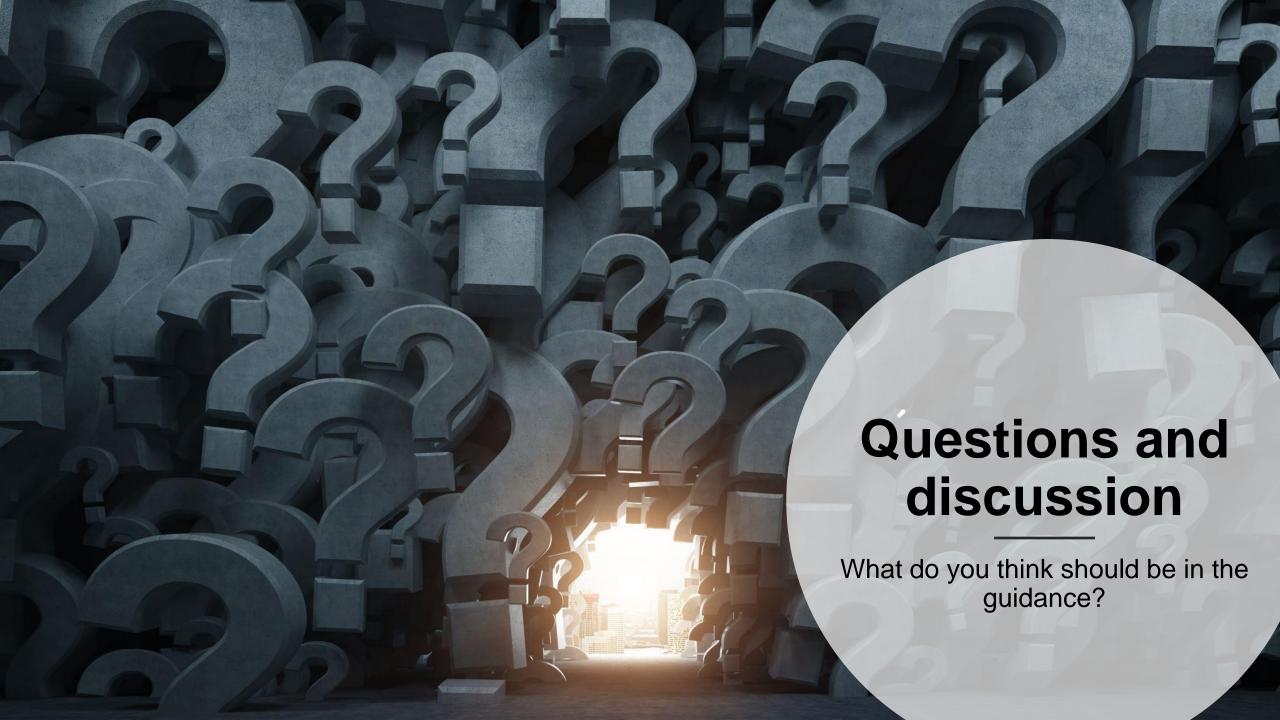
Accountability

- Review authors are responsible for the selection and use of an AI tool (it cannot be accountable for anything)
- We shouldn't take on trust marketing materials that promote specific tools
- Important reviewers understand (at least up to a point) how a tool works, so they can gauge its risk in their review



Recommendations for

- Systematic reviewers
- Tool developers
- Systematic review organisations



Research integrity

- What would you like guidance on in terms of using AI in systematic reviews?
 - Rigour
 - Honesty
 - Transparency and open communication
 - Care and respect
 - Accountability