

AI for Literature Reviews



Digital Integration Teaching Initiative

Discussion

- Has anyone ever used ChatGPT or another generative AI?
- What do you think it did well or poorly?
- Were there any aspects of the responses you found odd or misleading?

Workshop Agenda

- Generative AI: Bias, Confabulation/Hallucination, and Ethics
- Counteracting Bias
- Claude and ChatGPT for Literature Reviews
- Other AI-Powered Literature Review Tools: Elicit and Litmaps
- Conclusion

Generative AI

Important questions

- How do human biases impact generative AI model outputs?
- How can we counter the weaknesses of current AI models?
- How can we integrate generative AI with other tools and practices?

Vocabulary (1/2)

- Artificial Intelligence (AI) System: “[A]n engineered or machine-based system or functionality that is designed, for a given set of objectives, to generate outputs such as text, images, predictions, or to make recommendations or decisions influencing human action, or real or virtual environments” (Northeastern Policy on the Use of Artificial Intelligence Systems).
- Large Language Model (LLM): “A large language model (LLM) is a language model trained with self-supervised machine learning on a vast amount of text, designed for natural language processing tasks, especially language generation” (Wikipedia).

Vocabulary (2/2)

- Generative AI: “Generative Artificial Intelligence (AI) refers to large learning models (LLMs) that can generate high-quality text, images, and other content based on the data they were trained on, (including user-submitted text) and are designed to predict the most relevant sequence of words in response to a prompt” ([Standards for the Use of Artificial Intelligence in Research](#))
- Bias in AI: “[A] systematic error in decision-making processes that results in unfair outcomes... [AI] bias can arise from various sources, including data collection, algorithm design, and human interpretation” ([Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies](#))

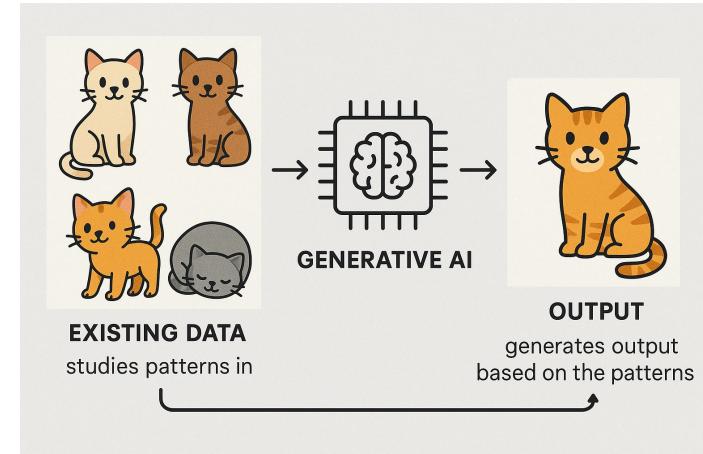
Generative AI: Introduction

AIs like ChatGPT and Claude 3.7 Sonnet (which generate text) and DALL-E and Midjourney (which generate images) work by training on very large datasets of information and then mimicking that training data to produce “new” outputs.

Generative AI: How it Works

- Generative AIs are fundamentally based on statistics. A text-generation AI like ChatGPT generates words according to patterns learned from the training data.
- Similarly, an image-generation AI learns patterns from existing data and generates images that “looks right” but do not exist in the data. For example, AI might generate an image of a cat based on several sample images.

Generated by GPT4o
Aug 15th 2025



Example Prompt and Response

Prompt: Explain in two sentences why someone might be afraid of public speaking, in the style of Sigmund Freud. Model: Claude, Haiku 4.5,
Prompted on 12/16/25.

From a Freudian perspective, the fear of public speaking stems from deep-seated anxieties rooted in childhood experiences—perhaps a fear of paternal judgment or rejection that becomes displaced onto the audience, triggering unconscious defense mechanisms. The speaker's ego struggles to manage the conflict between the id's desire for recognition and the superego's internalized critical voices, manifesting as performance anxiety when forced to expose oneself to the gaze and potential judgment of others.

How the Freud Paragraph Was Generated

- A large language model analyzed Freud's existing writings and identified patterns
- These patterns are recreated in the generated text
 - Mimicking his psychoanalytic vocabulary (e.g., ego, superego, regression, unconscious)
 - Using Freudian logic (e.g., adult anxiety linked to childhood experiences)
 - Emulating his style of argumentation, often abstract and speculative.

Confabulation/ Hallucination in AI

Confabulation/Hallucination

- Confabulation refers to the phenomenon where large language models (LLMs) generate incorrect, nonsensical, or fabricated information, even when presented with seemingly clear and accurate prompts.
- AI confabulation is also referred to as hallucination or, more colorfully, as BS-ing.

Generative AI and “Truth”

- Text-generation AI’s aim to produce text that is grammatically correct and linguistically probable.
 - They do not understand “facts,” only patterns of word use.
- They can generate truthful text, but also frequently create confabulations/hallucinations.
 - When asked to generate citations, they can generate plausible-looking but fake sources.
 - They may link real but irrelevant sites as sources for made-up facts. They may also invent URLs that do not work and have never worked.

News: Lawyer Cited AI Fake Cases (1/2)

- In 2023, “Colombia-based Avianca Airlines sought to dismiss a federal court case in which a man, Roberto Mata, alleged he was “struck by a metal serving cart” onboard a 2019 flight and suffered personal injuries.”

Lawyer Used ChatGPT In Court—And Cited Fake Cases. A Judge Is Considering Sanctions

By [Molly Bohannon](#), Former Staff. Molly Bohannon has been a Forbes news reporter since 2023.

Published Jun 08, 2023, 02:06pm EDT, Updated Jun 08, 2023, 03:42pm EDT

News: Lawyer Cited AI Fake Cases (2/2)

- “When filing a response, Mata’s lawyers cited at least six other cases to show precedent, including Varghese v. China Southern Airlines and Shaboon v. Egypt Air—but the court found that the cases didn’t exist and had “bogus judicial decisions with bogus quotes and bogus internal citations,” leading a federal judge to consider sanctions.”
- “A member of Mata’s law team then revealed he had used ChatGPT to conduct legal research for the court filing that referenced the cases and that the artificial intelligence tool assured him the cases were real.”

(Bohannon, 203)

Lawyer Used ChatGPT In Court—And Cited Fake Cases. A Judge Is Considering Sanctions

By [Molly Bohannon](#), Former Staff. Molly Bohannon has been a Forbes news reporter since 2023.

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Hallucination: Generative AI summary of literature

- AI may inaccurately attribute concepts to individuals or omit co-contributors and earlier influences.
- It may lack citations or invent fake references.
- It may change parts of references

Hallucination Example

Prompt: Provide a bibliography of 10 academic sources on the United Nations.

Model: Claude, Haiku 4.5, Prompted on 11/25/25. Excerpt of Sources:

- Weiss, T. G., Forsythe, D. P., & Coate, R. A. (2014). *The United Nations and changing world politics* (7th ed.). Westview Press. Excluded author
- Hurd, I. (2007). *After anarchy: America's role in a world of fragmented authority*. Princeton University Press. Wrong subtitle (correct: *Legitimacy and Power in the United Nations Security Council*)
- Bellamy, A. J. (2009). *Responsibility to protect: The global effort to end mass atrocities*. Polity Press. Hallucinated subtitle

Ethics in AI

Ethics: Generative AI “Originality”

- Some argue that all AI-generated output constitutes plagiarism and copyright infringement, since it is remixing training data that was scraped from the internet without permission from the original creators.
- Many AI companies are facing lawsuits from people whose content was used as training data without their consent.
- Some publication venues, like the *Science* journals, have made it an official policy that AI does not meet the standard for authorship and require authors to disclose use of AI.

Ethics: Generative AI Training

- AI training data is sometimes supplemented by labels (annotations) added by people (Amironesei and Díaz, [Social and Ethical Norms in Annotation Task Design](#), 2024). These labels can worsen bias in training datasets.
- People from middle and low income countries often labor in poor working conditions to annotate data for clients in high income countries. Fieldwork by Muldoon et al ([The poverty of ethical AI: impact sourcing and AI supply chains](#), 2023) revealed that workers faced traumatizing content, in addition to experiencing discrimination in the workplace and receiving low wages.

Ethics: Environment

- Training and using AI requires processing very large amounts of data, which is done in data centers
- These data centers can have a negative impact on the environment and communities
- Given their intensive energy and water demands, data centers can worsen local water scarcity and increase electricity prices
- To explore how the energy use of AI compares to other digital tasks, check out Jon Ippolito's "What Uses More" app

Ethics: AI Plagiarism Checkers

- AI plagiarism checkers, which claim to identify whether text is human or AI generated, have the potential for false positives (identifying human texts as AI).
- False positives are especially likely for texts by writers for whom English is not their first language or for writers who have autism, ADHD, dyslexia, or related neurodivergence.
- To make things worse, writers can often reduce their “AI score” by using an AI to reword their essays.

What You Can Do

- By using smaller models, where possible, and running fewer prompts you may be able to reduce your contribution to AI's environmental impact.
 - To learn more about energy consumption by AI and machine learning, check out the ML Energy Initiative, a collaboration among computer scientists at multiple universities, and the AI Energy Score.
- Public awareness can help pressure companies to adopt good practices. For more information on fair labor in AI, see the report AI for Fair Work: From principles to practices by Fairwork

Bias in AI

What is AI bias?

- Training data for AI often contains biases that are then reproduced in AI responses, potentially exacerbating harmful and unjust outcomes. Here, we refer to this as ‘AI bias’. However, there is not a single authoritative definition of AI bias.
 - For example, when AI was used to summarize medical notes, “Google’s AI tool Gemma described men’s health issues with terms like ‘disabled,’ ‘unable,’ and ‘complex’ significantly more often than women’s, who were often framed as more independent despite similar needs, an alarming gender bias trend.” (Source: crescendo.ai)
- What is the ideal “unbiased” scenario? Is an “unbiased” scenario possible?

Bias in AI Overview

- AI training data reflects the injustices and biases of the society that produced it.
- These biases can be amplified when they are input as training data into an AI, because they seem to be the “right” answers (Dwivedi et al, [Breaking the Bias: Gender Fairness in LLMs Using Prompt Engineering and In-Context Learning](#), 2023).

Bias in Source Summarization

Prompt: Write two sentences about the greatest discoveries in the social sciences and humanities and who made those discoveries. Model: Claude, Haiku 4.5, Prompted on 11/25/25.

The discovery of the unconscious mind by Sigmund Freud fundamentally transformed psychology and our understanding of human behavior, revealing that much of what drives us operates outside our conscious awareness. Max Weber's analysis of the relationship between Protestant ethics and capitalism reshaped sociology by demonstrating how cultural and religious values shape economic systems and social structures in ways that transcend simple material determinism.

Why do you think these discoveries were chosen by the model?

Bias in Source Collection (1/3)

Prompt: Provide a bibliography of 10 academic sources on the United Nations. Model: Claude, Haiku 4.5, Prompted on 11/25/25. Sources:

- Weiss, T. G., Forsythe, D. P., & Coate, R. A. (2014). *The United Nations and changing world politics* (7th ed.). Westview Press. Excluded author
- Fasulo, L. M. (2004). *An insider's guide to the UN* (2nd ed.). Yale University Press. Wrong date
- Kennedy, P. (2006). *The parliament of man: The past, present, and future of the United Nations*. Random House.

Bias in Source Collection (2/3)

Prompt: Provide a bibliography of 10 academic sources on the United Nations. Model: Claude, Haiku 4.5, Prompted on 11/25/25. Sources:

- Malone, D. M. (Ed.). (2004). *The UN Security Council: From the Cold War to the 21st century*. Lynne Rienner Publishers.
- Luck, E. C. (2006). *UN Security Council: Practice and promise*. Routledge.
- Thakur, R., & Weiss, T. G. (Eds.). (2009). *The UN and global governance: An idea and its prospects*. Indiana University Press. Wrong date
- Hurd, I. (2007). *After anarchy: America's role in a world of fragmented authority*. Princeton University Press. Wrong subtitle (correct: *Legitimacy and Power in the United Nations Security Council*)

Bias in Source Collection (3/3)

Prompt: Provide a bibliography of 10 academic sources on the United Nations. Model: Claude, Haiku 4.5, Prompted on 11/25/25. Sources:

- Bellamy, A. J. (2009). *Responsibility to protect: The global effort to end mass atrocities*. Polity Press. Hallucinated subtitle
- Barnett, M. N. (2002). *Eyewitness to a genocide: The United Nations and Rwanda*. Cornell University Press. Wrong date
- Mingst, K. A., & Karns, M. P. (2011). *The United Nations in the 21st century* (4th ed.). Westview Press.

Types of Bias (1/2)

| Bias Type | How It Shows Up in the Example | Why It Happens |
|--|---|--|
| Geographic/ language bias | Of the 13 authors cited, 11 had institutional affiliations in the US, Canada, or UK. Also changed reference subtitle to be more US-centric. | Training data may over-represent English-language and American-centric scholarship |
| Longevity bias | The most recent source is from 2014, over 10 years ago. | Older sources may appear more often in training data, leading to their overrepresentation in results |

Types of Bias (2/2)

| Bias Type | How It Shows Up in the Example | Why It Happens |
|--------------------|--|---|
| Gender bias | <p>Out of 13 cited authors, only 2 are women. Also erroneously excluded the only female author (Kelly-Kate Pease) from the citation for <i>The United Nations and changing world politics</i>.</p> | <p>Historical exclusion of women from scholarship may influence disparities in training data, leading to biased results</p> |

Counteracting Bias

Women Scholars (1/2)

Prompt: Write two sentences about the greatest discoveries in the social sciences and humanities made by women. Model: Claude, Haiku 4.5, Prompted on 11/25/25.

Women have made transformative contributions to the social sciences and humanities, from Ruth Benedict's groundbreaking work in cultural anthropology that challenged ethnocentric views of society, to Simone de Beauvoir's existentialist philosophy that fundamentally reshaped how we understand gender and identity. Their discoveries—spanning fields like psychology (Carol Dweck's growth mindset theory), ...

Women Scholars (2/2)

Prompt: Write two sentences about the greatest discoveries in the social sciences and humanities made by women. Model: Claude, Haiku 4.5, Prompted on 11/25/25.

...linguistics (Noam Chomsky's contemporary, though he overshadowed many women in the field), history, and literature—have not only expanded human knowledge but have often required challenging the male-dominated institutions that initially excluded them from full participation in these disciplines.

Why do you think these scholars were chosen by the model? What do you think of the reference to Noam Chomsky?

Global South Scholars (1/2)

Prompt: Write two sentences about the greatest discoveries in the social sciences and humanities made by scholars in the Global South.

Model: Claude, Haiku 4.5, Prompted on 11/25/25.

Scholars from the Global South have fundamentally reshaped our understanding of colonialism, postcolonialism, and knowledge production itself—figures like Edward Said challenged Western intellectual dominance by revealing how power structures shape what we consider "truth," while scholars like Gayatri Spivak interrogated whose voices are heard in academic discourse. Beyond these critical theories, researchers across Latin America, Africa, and Asia...

Global South Scholars (2/2)

Prompt: Write two sentences about the greatest discoveries in the social sciences and humanities made by scholars in the Global South.

Model: Claude, Haiku 4.5, Prompted on 11/25/25.

...have made groundbreaking contributions to development economics, anthropology, and history, such as Raúl Prebisch's center-periphery analysis of global economic inequality and the work of scholars documenting indigenous knowledge systems that challenge Western epistemologies and demonstrate alternative ways of understanding the natural and social worlds.

Why do you think these scholars were chosen by the model?
Why do you think the response focuses on these topics?

Counteracting Bias: Prompts and Feedback

- Bias can be partly countered through careful prompt design and feedback (Dwivedi et al, [Breaking the Bias: Gender Fairness in LLMs Using Prompt Engineering and In-Context Learning](#), 2023). However, these methods do not remove bias intrinsic in the model (Shin et al, [Can Prompt Modifiers Control Bias? A Comparative Analysis of Text-to-Image Generative Models](#), 2024)
- Practices for counteracting bias
 - Identify gaps or inconsistencies in generative AI responses.
 - Use additional inquiry and prompt revision to help fill in gaps.
 - Double check responses with other sources.

Counteracting Bias: Discussion

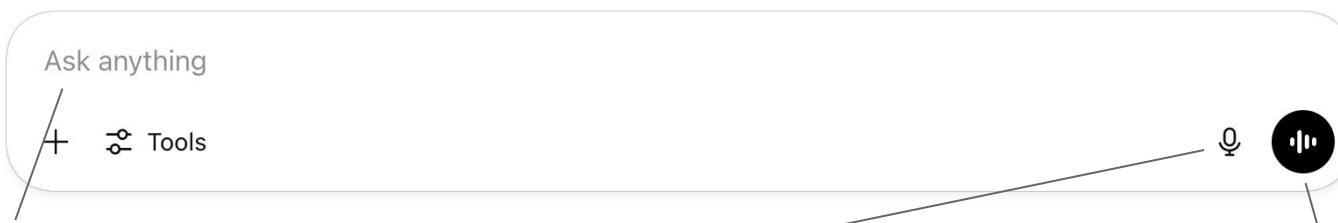
- What groups of scholars are still excluded from these summaries of the greatest discoveries in the social sciences and humanities?
- What other biases may they contain?
- What are biases that we cannot counter by changing prompts?

How to use ChatGPT and Claude for literature reviews

Prompting ChatGPT (1/2)

Go to: <https://chatgpt.com/>

What's on your mind today?



Enter prompt
in text format

Enter prompt as speech
(transcribed automatically)

Use voice mode

Prompting ChatGPT (2/2)

Upload files

What's on your mind today?

Ask anything

+



Create image

Thinking

Deep research

Shopping research

Study and learn

Web search

Canvas



Other tools

Follow publisher policies if uploading copyright material to an AI system. See [Northeastern recommendations](#) for more details.

ChatGPT Results

Can you provide a list of common biases in AI-generated literature reviews?

Initial prompt

Here's a clear, research-informed list of **common biases in AI-generated literature reviews**, especially those produced by large language models (LLMs). These appear across disciplines and are well-documented in recent meta-evaluations of LLM-assisted academic writing.

Response

Enter subsequent prompts as text or speech

Common Biases in AI-Generated Literature Reviews

1. Hallucinated Citations and Findings

- Fabricating articles, authors, publication years, or study results.
- Misattributing findings to real papers that never reported them.
- Citing plausible-sounding but nonexistent jourr ↓ or conferences.

Use voice mode

2. Over-Reliance on Highly Popular or High-Visibility Sources

Ask anything

+ Tools



ChatGPT can make mistakes. Check important info.



Accessing Claude at Northeastern

- Northeastern has partnered with Anthropic to provide students, faculty, and staff with access to Claude
- To access Claude using your Northeastern account go to <https://claude.northeastern.edu/>
- Select **Log in with SSO**
- Login in with your Northeastern email

Prompting Claude

Enter prompt
in text format

Follow publisher policies if uploading
copyright material to an AI system.
See [Northeastern recommendations](#)
for more details.

How can I help you today?



Upload files, take
screenshot, or use project

Enable extended
thinking

Haiku 4.5 ▾



Select model

Prompting Claude (1/2)



How can I help you today?

+ ⌂ ⏲

Set up

- Search menu
- Use style
- Extended thinking
- Research
- Web search
- + Add connectors
- Manage connectors

for your

Normal

Learning

Concise

Explanatory

Formal

+ Create & edit styles

Allow Claude to think out loud for longer for trickier questions and challenges.

Research
Analyze and organize research

Open menu

Prompting Claude (2/2)

SM Can you provide a list of common biases in AI-generated literature reviews?

I'd be happy to walk through the main biases that tend to show up in AI-generated literature reviews.

Selection bias is probably the most significant. AI models are trained on text available in digital form, which means they tend to over-represent published, English-language research from well-funded institutions and underrepresent work from smaller publishers, non-English sources, and scholars from less affluent regions. This skews what gets included in the review.

Methodological bias occurs because AI tends to gravitate toward studies with clear, quantifiable results and robust methodologies—which sounds good in theory, but can actually exclude valuable qualitative research, newer methodologies, or emerging areas where rigorous standards are still being established. The AI essentially privileges a particular epistemic approach.

Recency bias appears when AI overweights recent publications simply because they're more prominent in training data or appear frequently in search results. This can make older, foundational work seem less relevant than it actually is.

Social desirability bias is particularly interesting in literature reviews—the AI tends to emphasize research that reaches conclusions aligned with current academic or social

Reply...



Haiku 4.5



Initial prompt

Initial response

Enter subsequent prompts as text

What other issues do you think might arise?

Your turn

- Go to chatgpt.com or claude.ai
- Enter a literature search related prompt for a subject you are familiar with
- Identify issues in the response
 - Are any groups excluded?
 - Are the facts correct?
 - If you ask for citations, does it provide real sources?
- Revise the prompt to address the issues and generate a new response
- Evaluate the strengths and limitations of the new response

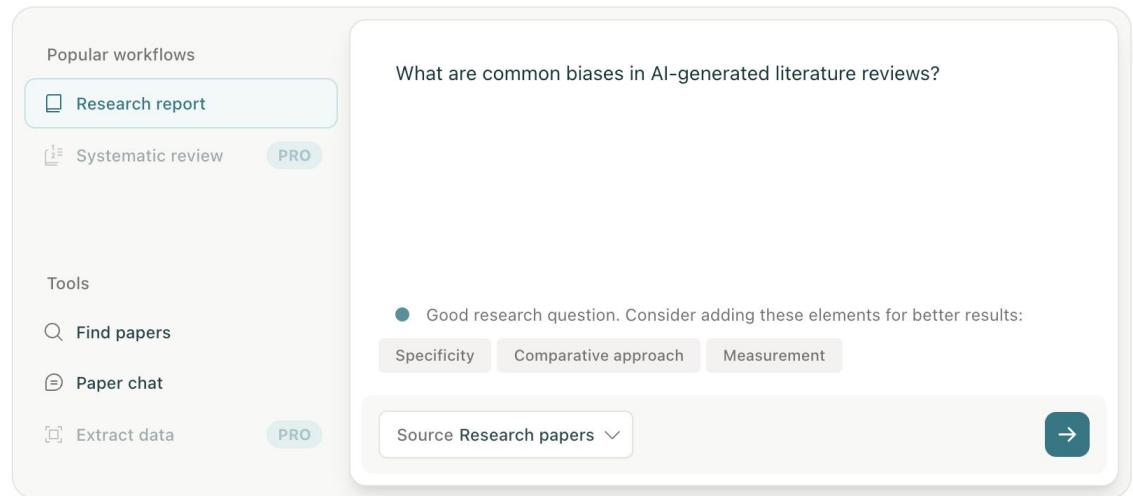
Discussion: Further Inquiry

- Was anything surprising about the responses?
- What are other ways ChatGPT and Claude could be used to counter biases in academic literature searches?
- What other types of sources could be useful for checking ChatGPT's and Claude's responses?

Other AI-Powered Literature Review Tools

Elicit

- Elicit uses AI to generate literature reports
- Provides feedback on research question



Elicit: Results (Research Report)

DECEMBER 5, 2025

What are common biases in AI-generated literature reviews?

Common biases in AI-generated literature reviews include citation bias favoring highly-cited papers, hallucination of non-existent information, reference inaccuracies, and comprehensiveness limitations that result in systematically missing relevant studies despite reasonable precision in identifying individual papers.

ABSTRACT

This review of 2 sources identified four primary types of bias in AI-generated literature reviews: citation bias, where AI systems preferentially select highly-cited studies (AI-selected papers averaged 202 citations versus 64.4 for manually-selected papers) * ; hallucination bias, involving generation of information not grounded in actual sources * ; reference inaccuracies * ; and depth/comprehensiveness bias, reflecting limited critical analysis capabilities *. These biases affect multiple stages of the systematic review process, including search and retrieval, study selection, data extraction, and synthesis.

The screenshot shows the 'Report' section of the Elicit interface. It displays four status items: 'Gather sources' (50 sources found), 'Screen sources' (2 sources included), 'Extract data' (16 data points extracted), and 'Generate report'. A 'Save PDF' button is located at the bottom right of this section. Below the report section is a 'Chat' section with a placeholder 'Ask anything about the results'.

| Status | Description | Details |
|-----------------|--------------------------|-----------|
| Gather sources | 50 sources found | Details ↗ |
| Screen sources | 2 sources included | Details ↗ |
| Extract data | 16 data points extracted | Details ↗ |
| Generate report | | Save PDF |

Elicit: Results (Find Papers)

What are common biases in AI-generated literature reviews?

Sort: Most relevant + Column Export

Save to library

| Paper | Summary |
|--|--|
| <input type="checkbox"/> Quantitative Measurement of Bias in AI-Generated Content: A Comprehensive Narrative Literature Review Ashish K. Saxena International Symposium on Technology and Society, 2024, 1 citation, DOI | Not mentioned (the abstract discusses bias in AI-generated content but does not specify common biases in literature reviews) * |
| <input type="checkbox"/> Unveiling bias in artificial intelligence: Exploring causes and strategies for mitigation Yuhan Liu Applied and Computational Engineering, 2024, 2 citations, DOI | Biases in AI systems include gender and race biases * ; underrepresentation of women in AI development is a confirmed bias *. Strategies for mitigation include fair datasets and increased female participation. * (Methodology: Comprehensive literature review) |

Chat with papers Edit columns

Answer

AI-generated literature reviews exhibit significant biases, particularly around gender, race, and representation, with research showing systematic limitations in bias detection and mitigation.

The evidence reveals striking patterns: [Sourojit Ghosh et al., 2025](#) found that 82% of bias research papers did not establish a clear definition of bias, and 79.9% narrowly focused on gender bias. Specifically, bias research concentrated on:

- Gender bias: 79.9% of papers
- Race/ethnicity bias: 30.2%
- Age bias: 20.6%
- Religious bias: 19.1%

[Emilio Ferrara et al., 2023](#) further emphasizes that these biases can "reproduce and amplify societal stereotypes" in generative AI content. Critically, only 10.6% of studies included recommendations for implementing bias mitigation in real-world systems, indicating a significant gap between academic research and practical application.

Litmaps

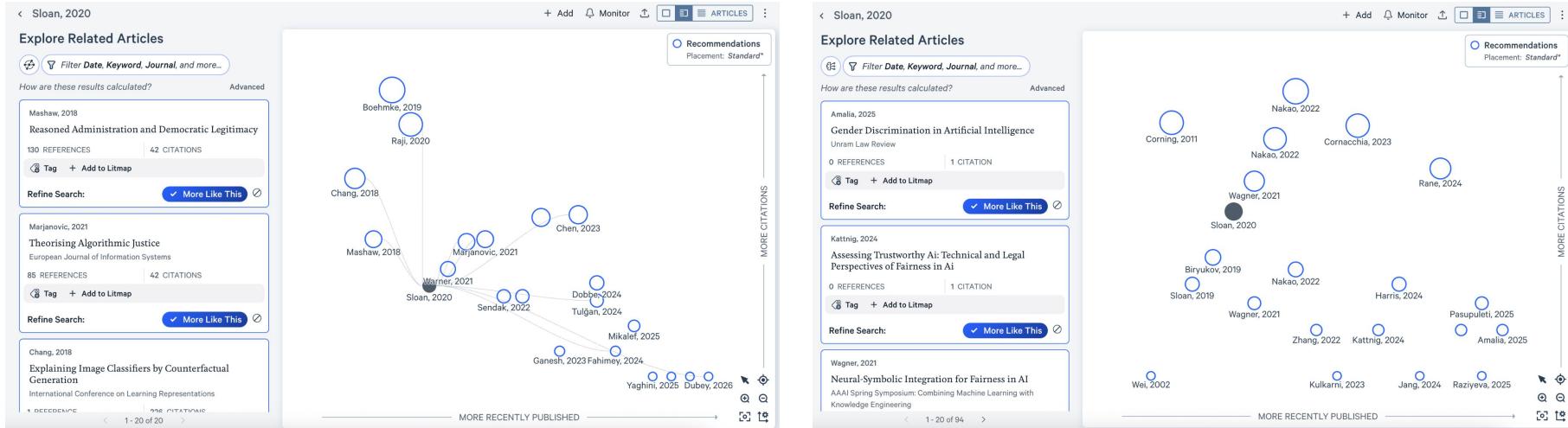
- Litmaps maps relevant literature based on citations, authors, or textual similarity
- Uses AI to find articles with similar text
- Enter search information then select seed article

Discover the world of Scientific Literature

The screenshot shows a search interface for scientific literature. At the top is a search bar with the placeholder "Search by keyword, author, DOI, Pubmed ID or arXiv ID". Below it is a blurred background image of a network graph. In the center, a search result card is displayed with the query "Bias, Artificial Intelligence". Below the card, three article titles are listed:

- Eric J. Topol, 2019 High-performance medicine: the convergence of human and artificial intelligence
- R. Sloan, 2020 Beyond Bias: Artificial Intelligence and Social Justice
- Burak Koçak, 2024 Bias in artificial intelligence for medical imaging: fundamentals, detection, avoidance, mitigation, challenges, ethics, and

Litmaps: Results



Mapping by shared references and citations (does not use AI)

Mapping by textual similarity (uses AI and requires account)

Other tools

- [Scite.ai](#), finding and summarizing papers (subscribed to by Northeastern University).
- [docAnalyzer.ai](#), document analysis.
- [Consensus](#), finding papers and evaluating the extent to which their results agree.
- [Research Rabbit](#), finding and organizing papers.
- Additional [AI tools for your research](#) from Northeastern Library

Conclusion

How to use AI responsibly **EVERY** time

- “Evaluate the initial output to see if it meets the intended purpose and your needs.”
- “Verify facts, figures, quotes, and data using reliable sources to ensure there are no hallucinations [or confabulations] or bias.”
- “Engage in every conversation with the GenAI chatbot, providing critical feedback and oversight to improve the AI’s output.”
- “Revise the results to reflect your unique needs, style, and/or tone. AI output is a great starting point, but shouldn’t be a final product.”
- “You are ultimately responsible for everything you create with AI. Always be transparent about if and how you used AI.”
- Source from [AI for Education](#)

Main Points

- AIs, and the data used to train them, are biased
- You can design inputs to help counteract biases
- Always double check AI output
- There are multiple AI tools that may be useful at different points in your work

For Further Exploration: DITI Resources

Handouts

- [Copyright and fair use handout](#)
- [Data Ethics handout](#)
- [Data Privacy handout](#)
- [Scite handout](#)

For Further Exploration: NU Resources

Northeastern University Policy

- [Northeastern Policy on the Use of AI](#)
- [Standards for the Use of Artificial Intelligence in Research](#)
- [Generative AI in Teaching and Learning](#)

Northeastern Library

- [Research Tutorials: Generative AI](#)

Center for Advancing Teaching and Learning Through Research (CATLR)

- [AI in Teaching & Learning Across the Network](#)

Information Technology Services

- [AI at Northeastern University](#)

For Further Exploration: External (1/3)

- [Generative AI Product Tracker](#), Ithaka S+R
- [Generative AI Tools for Literature Researching](#), Oregon State University
- [Generative Artificial Intelligence \(AI\), What tools can I use for my literature review?](#), George Mason University
- [Teaching Literature Reviews in the Age of Generative Artificial Intelligence \(AI\)](#), Ozlem Tuncel, APSA Educate

For Further Exploration: External (2/3)

- [Resisting GenAI and Big Tech in Higher Education](#), Just Sustainability Design
- [Modern Day Oracles or Bullshit Machines?](#), Bergstrom and West (2025)
- [On Being A GenAI Killjoy](#), Fernandes (2025)
- [Nothing About AI is Inevitable](#), Auslander (2025)
- [Where Cloud Meets Cement \(Data Center Report\)](#), Barakat et al (2025)
- [We are lecturers in Trinity College Dublin. We see it as our responsibility to resist AI](#), Kelly et al (2025)

For Further Exploration: External (3/3)

- [Ridicule as praxis, darling! Alex Hanna on busting “AI” hype and building the world we want](#), Shadel (2025)
- [The Cloud is Material: On the Environmental Impacts of Computing and Storage](#), Monserrate (2022)
- [Digital Revolutionary Infrastructures \(Very Encrypted\)](#), Scientist Rebellion

NULab Faculty Research (1/2)

- “[John Wihbey and Christo Wilson on Tiktok Data Espionage Concerns](#)”
- “[Alan Mislove Co-Authors Research on Discriminatory Ad Algorithms](#)”
- “[John Wihbey Weighs In On AI's Potential to Impact the 2024 Presidential Election](#)”
- “[Tina Eliassi-Rad Co-Creates New AI Model that Predicts Human Lifespan](#)”
- “[Nabeel Gillani Interviewed by Tech Talk Podcast on AI and Education](#)”

NULab Faculty Research (2/2)

- “[John Wihbey Participates in a Panel on Content Moderation](#)”
- “[John Wihbey Comments on Google’s New ‘AI Overview’](#)”
- “[John Wihbey on the Politics of AI](#)”
- “[John Wihbey Interviewed on AI and Epistemic Risk](#)”
- “[Malik Haddad on the Regulation of AI](#)”

Thank you!

—Developed by: Zhen Guo, Sara Morrell, Sean Rogers, Ayah Aboelela, and Johan Arango-Quiroga

- For more information on DITI, please see: <https://bit.ly/diti-about>
- Schedule an appointment with us! <https://bit.ly/diti-meeting>
- If you have any questions, contact us at: nulab.info@gmail.com