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Of models and monocultures: epistemic risks of artificial intelligence in medical research

De modelos y monocultivos: riesgos epistémicos de la inteligencia artificial en la investigación médica

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"The real danger is not that computers will begin to think like humans, but that humans will begin to think like computers."
—*Sydney J. Harris*

Artificial intelligence (AI) is transforming medical research. From automating literature reviews to detecting patterns in large datasets, AI promises efficiency and access at unprecedented scale (1). Language models and writing assistants also support researchers in low- and middle-income countries (LMICs) by improving clarity and translation, potentially broadening participation in global publishing (2,3). Yet beneath this promise lies a quieter danger: AI may reinforce long-standing inequities in who produces, validates, and disseminates medical knowledge.

Epistemic inequity in medicine

Epistemic inequity refers to the uneven recognition of whose knowledge is treated as authoritative. In medicine, this matters because perspectives excluded from dominant systems—often those from underrepresented regions, languages, or traditions—carry vital insights into patient care, cultural practices, and health system realities that global standards alone cannot capture. Ignoring such diversity narrows evidence and limits innovation (4).

The risk of monocultures of knowledge

At the core is the risk of monocultures of knowledge: the dominance of a single epistemic framework that elevates computational precision as the ultimate arbiter of truth (5). This shift privileges what is measurable over what is meaningful, marginalizing tacit clinical wisdom and context-specific understanding of disease (6).

Large language models (LLMs) illustrate this risk. Bender et al. have shown that LLMs trained on corpora such as Wikipedia or Common Crawl amplify cultural and linguistic hegemonies embedded in their data, entrenching dominant worldviews (7). Alvero and colleagues, analyzing over 25,000 AI-generated essays, found that outputs most closely resembled the writing of socially privileged groups (8). If AI homogenizes expression toward dominant norms, it may also homogenize how research questions are framed and problems are approached. For medical research, this means alternative perspectives may be silenced before they are even considered (9).

Manifestations of monocultures

Monocultures manifest in at least three domains:

Clinical data. Models trained predominantly on high-income country datasets are exported as global defaults, despite dramatic differences in disease burdens and care pathways elsewhere (10–12).

Scientific literature. AI-driven discovery tools such as Elicit, Connected Papers, and Litmaps rely on corpora like Semantic Scholar and CrossRef. Studies show that over 90% of indexed documents in Web of Science and Scopus are in English, while Spanish and Portuguese account for barely 1% combined (13). Elicit itself acknowledges exclusive reliance on Semantic Scholar, structurally omitting non-English studies (14). When integrated into AI pipelines, these biases become automated and scaled.

Everyday information environments. Social media algorithms deliver content aligned with user preferences, creating "filter bubbles."Similarly, medical AI tools may prioritize highly cited or English-language studies, reinforcing dominant perspectives and filtering out regionally relevant alternatives.

What makes AI different

Skeptics may argue that these inequities already exist. What distinguishes AI is how it transforms their scale and operation. First, AI accelerates exclusion by automating it: biases that once appeared sporadically in editorial or funding decisions now operate continuously and invisibly. Second, AI increases opacity: while human decisions can be scrutinized, algorithmic filters act as black boxes. Third, AI universalizes patterns from dominant datasets, transforming local norms into global defaults. Together, these features magnify inequities, institutionalizing them in ways that are faster, harder to detect, and more difficult to contest.

Toward epistemic plurality

If left unchecked, AI risks narrowing rather than diversifying medical knowledge. To counter this, three principles are essential:

Plurality. Tools must incorporate non-English databases (e.g., SciELO, LILACS, AJOL), grey literature, and regionally grounded journals. Including multiple traditions of evidence ensures that research questions are not framed exclusively by dominant systems.

Transparency. Developers should disclose sources, ranking criteria, and exclusions, akin to nutritional labels for food. Without this, users cannot know what evidence has been silently removed.

Humility in interpretation. Beyond transparency and diversity, humility is crucial. Models should display not only included but also excluded studies; clinical systems should clarify the scope of their training data; editors should treat AI-derived outputs as provisional, not definitive. Humility reminds researchers that AI is a complement, not a substitute, for human judgment. Such humility could serve as a counterweight to the monocultures of knowledge described earlier, ensuring that automation does not harden into unquestioned authority.

CONCLUSION

Artificial intelligence does not simply mirror existing inequities; it transforms them. By embedding biases into algorithmic infrastructures that operate at scale, AI risks creating monocultures of knowledge that privilege the universal over the particular, the measurable over the meaningful. The novelty lies not in the existence of inequity, but in how AI changes its operation, reach, and detectability.

Harnessed responsibly, AI could expand epistemic diversity in medicine. But this requires conscious design choices guided by plurality, transparency, and humility. Otherwise, the tools meant to illuminate complexity may end up obscuring the very knowledge we most need.

Use of generative artificial intelligence

The author used ChatGPT (OpenAI, GPT-5, September 2025 version) to improve the fluency and readability of the English text.

Conflicts of interest

JIAS is the Editor in Chief for the Colombian Journal of Anesthesiology.

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