

The Matthew Effect in AI Summary

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IN THE LAST YEAR, the giant AI companies have released tools with indistinguishable names: Deep Research (Google), Research (Anthropic), deep research (OpenAI), Researcher (Microsoft), and—yes—Deep Research (Perplexity).¹ In the highly profitable world of scholarly publishing, meanwhile, some of the biggest players have launched their own products, based on their proprietary databases of the academic literature: Scopus AI (Elsevier), Web of Science Research Assistant (Clarivate), and Dimensions AI Assistant (Digital Science).²

The AI companies and publishers draw on overlapping bodies of knowledge. The products from Elsevier and company leverage the peer-reviewed literature, while the various Deep Researches cite not just academic work but reports, Wikipedia, and posts on the open web. But the tools arrive at a similar place: summary and citations.

Even the marketing is hard to distinguish. Google pitches its Gemini-based tool as “your personal research assistant.” OpenAI touts its model’s ability to produce reports at the “level of a research analyst,” with “clear citations.” Anthropic’s Research promises “high-quality, comprehensive answers in minutes” and “easy-to-check citations.” All of that is echoed in the scholarly publishers’ marketing boasts. Elsevier’s Scopus AI generates “reliable and digestible research summarization.” The offering from Clarivate, the Web of Science Research Assistant, lets you “synthesize the literature more efficiently.” The Dimensions AI Assistant, from Springer Nature’s corporate sibling Digital Science, will return “immediate and more relevant summary results.”³ Silicon Valley and big publishing are even converging on product language: Elsevier’s Scopus AI recently released its own “Deep Research”-branded feature.⁴

At the core of all these tools is a series of verbs: to surface, to rank, to summarize, and to recommend. In this sense the AI products are already acting as knowledge arbitrators, by picking winners and losers according to what they make visible. There are two big and interlocking problems with this role: the models are trained on the scholarly past, and their filtering logic is inscrutable. As a result, they may smuggle in the many biases that mark the history of scholarship, around gender, geography, and other lines of difference.

In this context it’s useful to revive an old concept in the sociology of science. According to the Matthew effect—named by Robert Mer-

¹ “Gemini Deep Research,” Gemini, accessed November 9, 2025, <https://gemini.google/overview/deep-research>; “Claude Takes Research to New Places,” Claude Blog, April 15, 2025, <https://www.claude.com/blog/research>; “Introducing Deep Research,” OpenAI Release, February 2, 2025, <https://openai.com/index/introducing-deep-research>; Jared Spataro, “Introducing Researcher and Analyst in Microsoft 365 Copilot,” Microsoft 365 Blog, March 25, 2025, <https://www.microsoft.com/en-us/microsoft-365/blog/2025/03/25/introducing-researcher-and-analyst-in-microsoft-365-copilot>; Perplexity Team, “Introducing Perplexity Deep Research,” Perplexity Blog, February 14, 2025, <https://www.perplexity.ai/hub/blog/introducing-perplexity-deep-research>.

² “Scopus AI: Think Bigger. Move Faster. Act with Confidence,” Elsevier, accessed November 9, 2025, <https://www.elsevier.com/products/scopus/scopus-ai>; “Web of Science Research Assistant,” Clarivate, accessed November 9, 2025, <https://clarivate.com/academia-government/scientific-and-academic-research/research-discovery-and-referencing/web-of-science/web-of-science-research-assistant>; “A New Way of Exploring Dimensions Data,” Dimensions: A Digital Science Solution, accessed November 9, 2025, <https://www.dimensions.ai/discover-dimensions-ai-assistant>. I invoke the term “scholarly publishing” loosely, to include database and analytics companies like Clarivate and Digital Science (which is owned by Springer Nature’s corporate parent, Holtzbrinck). A more precise term for these three is “scholarly communication service providers,” for the sheer range of scholarly workflow products they

ton decades ago—prominent and well-cited scholars tend to receive still more prominence and citations. The flip side is that less-cited scholars tend to slip into further obscurity over time. These dynamics of cumulative advantage have, in practice, served to amplify the knowledge system's patterned inequalities—with, for example, diminished citations for female scientists, a development aptly labeled the Matilda effect by Margaret Rossiter.⁵

The deployment of AI tools in scholarship, as their use picks up, may produce a Matthew effect on the scale of Scopus, and with no paper trail. The problem is analogous to the well-documented bias-smuggling with existing generative models; image tools trained on, for example, mostly white and male photos reproduce the skew in their prompt-generated outputs. With our bias-laden scholarship as training data (“120 years of research,” in Web of Science’s boast), the research models may spit out results that, in effect, double-down on inequality.⁶

What’s worse is that we won’t really know, due to the models’s black-boxed character. Thus the tools may act as laundering machines—context-erasing abstractions that disguise their probabilistic “reasoning.” Existing biases, like male academics’ propensity for self-citation, may win a fresh coat of algorithmic legitimacy. Or consider center-periphery dynamics along North-South and native-English-speaking lines: Gaps traceable to geopolitical history, including the legacy of European colonialism, may be buried still deeper. The models, in short, could serve as privilege multipliers. Early evidence suggests that’s exactly what’s happening.⁷

The Matthew Effect in (Human) Scholarship

The Columbia sociologist Robert Merton named the Matthew effect in 1968. Merton sourced the idea—that the already well-known accrue still-more reputational lucre—to the New Testament: “For to every one who has will more be given, and he will have abundance; but from him who has not, even what he has will be taken away” (Matthew 25:29). The reason that the scholarly rich get richer, according to Merton, is familiarity. The eminent scientist is already lodged in other scholars’ memories; when it comes time to cite or reference or read, these are the names that are ready at hand. The subsequent spread of the famous name leads to still-stickier impressions, seeding even more mentions. The result is a visibility cascade.⁸

Merton framed the dynamic as a “misallocation” of recognition—an injustice to those (often junior) scientists whose credit is diverted to the undeserving few. He invoked what he called the “class structure” of science, which the Matthew effect helps underwrite. Akin to

offer. Lorcan Dempsey, “Libraries, AI and Training Collections,” *Against the Grain*, July 5, 2024, <https://www.charleston-hub.com/2024/07/libraries-ai-and-training-collections>.

³ “Gemini Deep Research”; “Introducing Deep Research”; “Claude Takes Research to New Places”; “Scopus AI: Think Bigger”; “Web of Science Research Assistant”; “A New Way of Exploring.” Elsevier’s Scopus AI has a sibling product, ScienceDirect AI, that summarizes full-text items (mainly from Elsevier journals) hosted on its ScienceDirect platform. “Elsevier Lunches ScienceDirect AI to Transform Research With Rapid Mission-Critical Insights From Trusted Content,” Elsevier, March 12, 2025, <https://www.elsevier.com/about/press-releases/elsevier-launches-sciencedirect-ai-to-transform-research-with-rapid-mission>.

⁴ “Latest release: Deep Research (August 2025),” Elsevier, accessed November 9, 2025, <https://www.elsevier.com/products/scopus/scopus-ai/product-release-notes>. A related (and fascinating) dynamic around the embrace of the word “research” is a notable conflation the scholarly sense of the term with the idea of “research” invoked in corporate and everyday-life contexts, especially notable in the AI companies’ marketing materials. To the extent that the Deep Research tools are widely adopted, the very meaning of “research” could—through its elastic application—get flattened. My gratitude to the participants of the Price Lab for Digital Humanities at the University of Pennsylvania, who raised this point in a September 2025 presentation of an earlier version of this paper.

⁵ Robert K. Merton, “The Matthew Effect in Science,” *Science* 159, no. 3810 (1968); Margaret W. Rossiter, “The Matilda Effect in Science,” *Social Studies of Science* 23, no. 2 (1993). For good summaries of the enormous Matthew effect literature, see Harriet E. Zuckerman, “The Matthew Effect Writ Large and Larger: A Study in Sociological Semantics,” in *Concepts and the Social Order: Robert K. Merton and the Future of Sociology*, ed. Yehuda Elkana, György Lissauer, and András Szígeti (Central European Press, 2011); Thomas A. DiPrete and Gregory M. Eirich, “Cumulative Advantage as a

the broader society's stratification system, the academic class structure distributes life-chances unevenly. The already famous don't just win honor and esteem; they also secure "access to the means of scientific production"—and thus the chance for still more prestige and more resources.⁹

Merton heavily qualified his critique, however. Yes, the Matthew effect may be unfair to individual scientists, but it serves a healthy, system-wide purpose. Given the crushing volume of research (even in 1968), the rich-get-richer dynamic acts to tame the literature, by "focalizing" attention on important findings. This "communication function" helps to clear the field—to concentrate attention—and thereby "accelerate" the march of science.¹⁰ He also downplayed his core point—cumulative advantage—by singling out the unique "character structure" of renowned scientists. These luminaries really are different from their peers: They're more confident and "self-directed," and they're better at recognizing, and then framing, key findings. So perhaps it's a good thing, after all, that they've won the spotlight.¹¹

The takeaway from Merton's famous paper is that, whatever the injustice to individuals, the overall *system* of science benefits. Merton's upbeat functionalism was soon challenged, within a broader 1970s critique of his sociology-of-science program. The problem wasn't with the Matthew effect thesis itself; indeed, most subsequent studies furnished empirical support for the claim. The issue was with Merton's claim that the system benefits, even if individuals suffer.¹²

It's not just isolated individuals who suffer, after all. The Matthew effect helps mete out the rewards of recognition in *patterned* ways—along lines of difference already inscribed in the postwar U.S. (and world) academic system. Consider gender: The Matthew effect helped to sideline already marginal female scientists. Dynamics of cumulative *dis*-advantage worsened, and thereby perpetuated, the patterned exclusion of academic women. This was Margaret Rossiter's charge in her 1993 "The Matilda Effect," named for Matilda Gage, a late nineteenth-century U.S. suffragist who both described and experienced the spiraling of silence. Rossiter, the late historian of science, cited the history of male-colleague credit accrual. The Matilda effect names a process of erasure that, in traceable ways, adds insult to reputational injury.¹³

One of these Matildas, arguably, was Merton's graduate student and future wife, Harriet Zuckerman. Merton's 1968 paper (cited over 12,000 times) was largely based on Zuckerman's 1965 dissertation on Nobel laureates. In a self-exemplifying irony, Zuckerman's 1967 journal-article writeup, like her subsequent book, have attracted far less attention—and she is almost never credited as the concept's co-

Mechanism for Inequality: A Review of Theoretical and Empirical Developments," *Annual Review of Sociology* 32, no. 1 (2006); Rudolf Fares and Tobias Wolbring, "Matthew Effects in Science and the Serial Diffusion of Ideas: Testing Old Ideas with New Methods," *Quantitative Science Studies* 2, no. 2 (2021): 507–9; Tony Ross-Hellauer et al., "Dynamics of Cumulative Advantage and Threats to Equity in Open Science: A Scoping Review," *Royal Society Open Science* 9, no. 1 (2022). For a book-length overview of the Matthew effect in a number of domains, including scholarship, see Daniel Rigney, *The Matthew Effect: How Advantage Begets Further Advantage* (Columbia University Press, 2010).

⁶ "Web of Science Research Assistant."

⁷ A nascent preprint literature, not yet peer-reviewed, has found suggestive initial support for Matthew effect-style biases in large-language model recommendation systems similar to the tools discussed here. See Daniele Barlo et al., "Whose Name Comes Up? Auditing LLM-Based Scholar Recommendations," arXiv preprint, September 10, 2025, <https://doi.org/10.48550/arXiv.2506.00074>; Jiange He, "Who Gets Cited? Gender- and Majority-Bias in LLM-Driven Reference Selection," arXiv preprint, August 2, 2025, <https://doi.org/10.48550/arXiv.2508.02740>; and Anthony Howell et al., "Prestige over Merit: An Adapted Audit of LLM Bias in Peer Review," arXiv preprint, September 18, 2025, <https://doi.org/10.48550/arXiv.2509.15122>; and Yifan Tian et al., "Who Gets Recommended? Investigating Gender, Race, and Country Disparities in Paper Recommendations from Large Language Models," arXiv preprint, December 31, 2024, <https://doi.org/10.48550/arXiv.2501.00367>. All four studies report significant dynamics of cumulative advantage, especially around existing prestige; some of the papers also found disparities around gender and geography.

⁸ Merton, "The Matthew Effect," 57–58.

⁹ Merton, "The Matthew Effect," 57–59.

¹⁰ Referencing this communication function alongside the injustice to individual scientists, Merton added: "This is not the first instance of of a social pattern's being functional for certain aspects of a social system and dysfunctional for certain individuals within that system. That, indeed, is a principal theme of classical tragedy." Merton, "The Matthew Effect," 58.

author. Hence Rossiter's half-serious suggestion to call it the "Harriet Effect" in honor of Merton's "invisible collaborator."¹⁴

Rossiter's point about doubling-down on patterned exclusion has been extended to other "have-nots," who, like women, have been "ignored, denied credit or otherwise dropped from sight."¹⁵

Too Much to Know

One of Merton's claims for the upsides of the Matthew effect was that it helped the scientific community cope with the publication on-rush. In conditions of published abundance and attention scarcity, we can't help but sift and summarize. As Ann Blair has brilliantly shown, there was always too much to know—leading, in the early modern European case she studies, to various filtering and synopsis devices like the index and the reference work. The more recent emergence of the journal-article abstract is another concession to information overload.¹⁶

The scholarly citation is also a summary device. On the textbook construal, references are the linchpin of the collective enterprise of science; when we cite, we stand on the shoulders of select and worthy predecessors. But the humble citation is much more than this; in-text and footnoted references to the "literature" are flexible, indeed baggy, symbols, doing all kinds of diverse work for citing authors. Citations can signal allegiance, call out a rival, establish precedence, and spread the peacock feathers. They are legitimacy set in type. And they serve to summarize and direct—to offload the burdens of evidence and support.¹⁷

In the last half-century, we have come to collate and count citations—to distill them into lean and precise-seeming metrics. The bibliographic labor of scholars is, of course, the raw material from which tallies and indexes are made. In this second layer of abstraction—by which symbols are fashioned from symbols—a single integer stands in for each of us. A journal's citations are counted too, and rendered with ordinal clarity to encourage citation-seeking submissions that—in an autopoietic coupling—run up both scores in addition to publisher margins. All to answer the legibility demands of rushed administrators.¹⁸

The metric tide has, among many other things, added *another* recursive layer to the Matthew effect. Circa 1968, the effect hinged on scholars' memories—on what amounted to an availability heuristic repeated across the academic system. The quantified proxies of the h-index and Journal Impact Factor focalize—to borrow Merton's verb—visibility and attention. The scores themselves act as direct signals to fellow scholars. And they're also fed into ranking algorithms that

¹¹ Merton, "The Matthew Effect," 59–60, 61–62.

¹² An excellent overview of criticism of the Mertonian program is Sal Restivo, "The Theory Landscape in Science Studies: Sociological Traditions," in *Handbook of Science and Technology Studies* (rev. ed.), ed. Sheila Jasanoff et al. (Sage, 1995).

¹³ Rossiter, "The Matilda Effect in Science," 335–37.

¹⁴ Rossiter, "The Matilda Effect in Science," 335–37. Merton later admitted that, given the paper's debts to Zuckerman, "clearly, the paper should have appeared under joint authorship." Robert K. Merton, "The Matthew Effect in Science, II: Cumulative Advantage and the Symbolism of Intellectual Property," *Isis* 79, no. 4 (1973): 607. Even had that happened, however, the core dynamic identified by the pair would have resulted in far more recognition for the far more famous Merton. See Harriet Zuckerman, "Nobel Laureates in the United States: A Sociological Study of Scientific Collaboration" (PhD diss., Columbia University, 1965); Zuckerman, "Nobel Laureates in Science: Patterns of Productivity, Collaboration, and Authorship," *American Sociological Review* 32, no. 3 (1967); and Zuckerman, *Scientific Elite: Nobel Laureates in the United States* (Transaction Publishers, 1977).

¹⁵ Rossiter, "The Matilda Effect in Science," 325. Here again, the literature is enormous. See, for a small sampling, Hannah Rubin and Cailin O'Connor, "Discrimination and Collaboration in Science," *Philosophy of Science* 85, no. 3 (2018); Márton Demeter, *Academic Knowledge Production and the Global South: Questioning Inequality and Under-Representation* (Palgrave Macmillan, 2020); Molly M. King et al., "Men Set Their Own Cites High: Gender and Self-Citation Across Fields and Over Time," *Socius* 3 (2017); Diego Kozlowski et al., "The Howard-Harvard Effect: Institutional Reproduction of Intersectional Inequalities," *Journal of the Association for Information Science and Technology* 75, no. 8 (2024); and Andrea Rajköf et al., "The Matilda Effect in Communication Research: The Effects of Gender and Geography on Usage and Citations Across 11 Countries," *Communication Research* 52, no. 2 (2025).

¹⁶ Ann M. Blair, *Too Much to Know: Managing Scholarly Information before the Modern Age* (Yale University Press, 2010); and Aileen Fyfe, "The Surprising History of Abstracts," *Nature Reviews Physics* 6, no. 8 (2024).

power, for example, first-page Google Scholar results.¹⁹ Thus to every one who has will more be given.

The Handoff to Computational Probability

The example of Google Scholar is half the way to Deep Research-style AI summary. The algorithmic logic that generates the ten blue citations is a closely guarded secret. Even the Google engineers who manage the complex recommendation engine are unlikely, as individuals, to have a full grasp on how it works. Old-school Matthew effects, by contrast, could be traced and measured; the task was to follow the bibliographic paper trail left by humans.

The AI-driven summary-and-cite products are flat-out inscrutable. They're all using foundation models to power their reference-studded summaries—even the scholarly publishers, who use the big AI models to mine their proprietary databases.²⁰ Anthropic and Google and OpenAI aren't inviting outsiders to audit their LLMs, of course, but it wouldn't much matter if they did. At the level of any particular output, it is near-impossible to look under the hood—to scrutinize the matrix of probabilistic calculations that result in well-ordered text. Nor is it possible to glean a model's actual "sources"—a word that, within the vast oceans of training data and retrieved information, has no human-legible analogue.

All AI models, one way or another, use the past to make probabilistic predictions about the future. In the deep research case, the tools—when they turn to the academic literature—inherit the whole sordid legacy of patterned exclusion. With each probabilistic bet on *which* literature to surface, they are likely to re-inscribe those legacies. Yet we won't have any easy way to know.

The pre-digital Matthew effect helped to stratify science and scholarship—to reproduce an academic "class structure" through visibility and all its attendant rewards. The system's structural inequalities—around race and gender, the English language, and global center-periphery dynamics—have their own roots and causes. But they're all propped up by dynamics of cumulative advantage.

Silicon Valley and the big commercial publishers are likely, in the coming years, to fight over who has rights to mine the scholarly record. The publishers are re-fashioning themselves as data-analytics companies, and they think they're sitting on a copyrighted gold mine. There will be drama, including lawsuits, licensing deals, and (perhaps) acquisitions.²¹

In some ways all the deck-shuffling to come is a side show. The bigger story is the embrace of foundation models as knowledge distillers by both industries, the one chasing profit and the other ap-

¹⁷ There is a large literature on the idea of citations as symbols. Two important contributions include Henry G. Small, "Cited Documents as Concept Symbols," *Social Studies of Science* 8, no. 3 (1978); and Charles Bazerman, *Shaping Written Knowledge: The Genre and Activity of the Experimental Article in Science* (University of Wisconsin Press, 1988), chap. 9.

¹⁸ There is another huge literature on citations, metrics, scholarly knowledge, and inequality. See, e.g., Juan Pablo Pardo-Guerra, *The Quantified Scholar: How Research Evaluations Transformed the British Social Sciences* (Columbia University Press, 2022). On the proprietary databases themselves, see Simon van Bellen, Juan Pablo Alperin, and Vincent Larivière, "Scholarly Publishing's Hidden Diversity: How Exclusive Databases Sustain the Oligopoly of Academic Publishers," *PLoS One* 20, no. 6 (2025).

¹⁹ See, e.g., Lai Ma, "Information, Platformized," *Journal of the Association for Information Science and Technology* 74, no. 2 (2023): 279.

²⁰ See "Scopus AI: Think Bigger"; and "Web of Science Research Assistant."

²¹ See Jefferson Pooley, "Large Language Publishing: The Scholarly Publishing Oligopoly's Bet on AI," *KULA* 7, no. 1 (2024). See also Lai Ma, "Generative AI for Academic Publishing? Some Thoughts About Epistemic Diversity and the Pursuit of Truth," *KULA* 7, no. 1 (2024). On the broader transformation of scholarly publishers into data analytics companies, see Jefferson Pooley, "Surveillance Publishing," *Journal of Electronic Publishing* 25, no. 1 (2022).

pallingly lucrative. Of all the hyped promises of AI, LLMs' knack for summary is disarmingly impressive. The summaries are pretty good, they're easy to generate, and they come with citations. Yes, the models hallucinate, and that's a problem in itself. But the Matthew effect dynamics traced here depend, ironically, on *real* references—and there are lots of them.

The key point is that summary-and-cite AI tools are performative. Since visibility begets visibility, they help enact the world they purport to merely describe. It's true, as OpenAI puts it, that the "ability to synthesize knowledge is a prerequisite for creating new knowledge."²² This task was a vexed one already, when humans were doing the summarizing. If we hand off the work to computational probability and the profit motive, we may reproduce, or perhaps worsen, an academic "class structure" with all of its accumulated—and now hidden—injustices.

²² "Introducing Deep Research."

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