

Bios:

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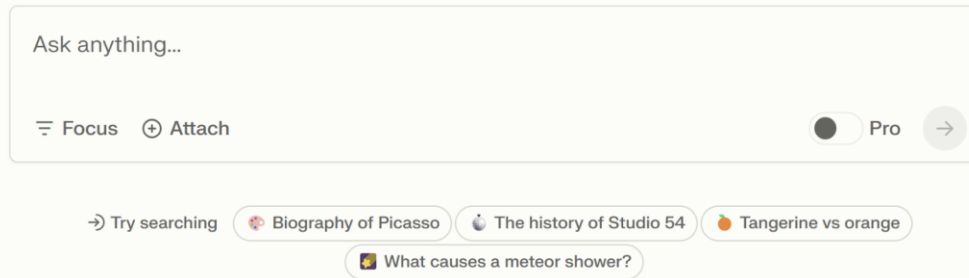
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Abstract: This essay explores the rise of generative AI and LLM tools for internet search and their potential impact on student information seeking behavior. Reviewing what is known about best search practices, the essay identifies a schism between AI companies’ vision of search and information science’s understanding of robust search environments. It argues that generative search tools fail to create ethical spaces for search, leading to dangerous territories for knowledge production. Specifically, the essay discusses “friction” as a critical concept where the field of information science and AI development philosophies diverge. Whereas information science views friction as a valuable and often necessary component to search, AI companies view friction as a problem to eliminate. It is this mismatch between corporate AI philosophies and known best practices for search that, this essay argues, renders current LLM and generative AI search tools fundamentally incompatible with ethical processes of knowledge production.

Keywords: AI, LLMs, generative search, information literacy, information seeking behavior, friction, information systems

Where Knowledge Begins? Generative Search, Information Literacy, and the Problem of Friction

Where knowledge begins



Introduction: The Future of Search

Will generative AI and large language model tools replace search engines? Some tech leaders are betting on it. In January 2024, venture capitalists including Jeff Bezos invested over \$70 million in the generative search startup Perplexity (Kruppa, 2024). Perplexity describes their internet search tool, Perplexity AI, as an “answer engine” and “an alternative to traditional search engines” (“What is Perplexity?”). Instead of supplying users with a list of web links, Perplexity AI generates text responses to user prompts in a conversational chatbot format. The Perplexity AI web interface is minimalist: a mostly blank white page. Hovering over the prompt box at its center, in large lettering, is the product tagline: “Where knowledge begins” (Fig. 1).

The aim of Perplexity, and of the investors who have contributed to the company’s nearly \$1 billion valuation, is to unseat the Google Search monolith (Kruppa & Jin, 2024). “Google is going to be viewed as something that’s legacy and old,” Perplexity’s CEO has declared; “If you can directly answer somebody’s question, nobody needs those 10 blue links” (Hu and Biswas, 2024; Kruppa, 2024). Google, for what it’s worth, seems to agree. In May 2023, they debuted their own “Search Generative Experience,” or SGE, which positions LLM text responses to user queries at the top of the Google Search results page. Currently in testing mode, the SGE interface pushes “those 10 blue links” practically off the screen (Peters, 2023). And in February 2024, Google released Gemini AI, a chatbot interface that functions similarly to Perplexity AI, generating text in response to user prompts, supplemented by select links to “similar content” found in Google Search.¹

¹ The Gemini AI platform, formerly known as Bard, originally featured image as well text generation. However, by the end of February, Google was mired in controversy regarding Gemini’s generation of historically inaccurate images, and the image generation tool was paused shortly after launching. See De Vynck and Tiku, 2024.

In the current profit-driven GenAI arms race, these products are likely to have evolved by the time this commentary goes to print. No matter what product is trending, however, the use of generative AI tools for internet search warrants interrogation. When it comes to search, what are the broader implications of losing “those 10 blue links?” What happens when internet search, as a practice, is streamlined—or flattened—into one interface and a single prompt-and-response process?

We approach these questions through the lens of writing and research pedagogy. As academic writing instructors, we have spent much of our professional lives focused on strengthening college students’ research skills. We have come to recognize students’ understanding of search infrastructure—including concepts like SEO, algorithmic bias, and PageRank—as foundational to their educational development. In higher ed conversations, we note that little attention has been paid to how generative AI and LLM tools might impact students’ research habits. Pedagogical discussions about large language models have mostly revolved around their utility as writing machines: countless articles have explored how students might use LLMs for various composition processes, including brainstorming, drafting, feedback, editing, and assessment. This inattention to the pedagogical implications of LLMs for internet search might be attributed to a lack of familiarity with the technical differences between LLMs, retrieval augmented generative search tools, and traditional search engines—and, consequently, a lack of awareness for how these differences drastically impact students’ ability to access and glean information. It also speaks to a tendency to conflate “research” with “writing,” which, despite being intertwined practices, require very different modes of human-computer interaction.

Scholars Chirag Shah and Emily Bender have done important work to critically assess contemporary information access systems, including contemporary search engines and the new class of generative search systems.² In two recent papers, they unpack the implications of LLMs being positioned as tools for information retrieval and access, and they persuasively demonstrate that how individuals seek, access, and retrieve information is not inconsequential: the design of information access systems has incredibly high civil and epistemological stakes (Shah & Bender 2022, 2024). As Shah and Bender emphasize, information access is an important dimension of knowledge production, and when users have access to humane and healthy systems, information seeking is an important avenue of empowerment. We concur with their declaration that “we should be looking to build tools that help users find and make sense of information rather than tools that purport to do it all for them” (Shah & Bender 2022, 230).

² Following Shah and Bender, we use the descriptor “generative” to refer to search systems which “create new content based on the underlying LLM trained on large corpora.” These are distinguished from traditional “discriminative” search systems, such as Google Search, which “class or rank existing content” (2024, 7). Liu et al. refer to LLM-driven search tools as “generative search engines”, which they define as tools that “fulfill user information needs by directly generating responses to input queries, along with in-line citations” (2024, 7001).

For the remainder of this essay, we will review what is known about best search practices, and we will underscore the schism between AI companies' vision of search and information science's understanding of humane search environments. We will then show how contemporary generative AI search tools fail to create ethical spaces for search, leading to dangerous territories for knowledge production. Specifically, we identify "friction" as a critical concept where the field of information science and AI development philosophies diverge. Whereas information science views friction as a valuable and often necessary component to search, AI companies view friction as a problem to eliminate. It is this mismatch between corporate AI philosophies and known best practices for search that, we argue, renders current generative search tools fundamentally incompatible with ethical processes of knowledge production.

What Information Seeking Practices Are Best for Advancing Knowledge?

Before considering generative search tools' role in student research, we should first ask what information seeking practices we want students to develop. Librarians and other information science experts have explored this question for over a century, and there are many theories and models of information seeking. Today, the Association of College and Research Libraries outlines its philosophy of information seeking in the "Framework for Information Literacy for Higher Education." Its sixth frame, "Searching as Strategic Exploration," defines search as "inquiry, discovery, and serendipity." It is "a contextualized, complex experience that affects, and is affected by, the cognitive, affective, and social dimensions of the searcher." Importantly, the ACRL claims that what distinguishes the novice researcher from the expert is the novice's inclination to depend on a limited set of sources, while expert researchers "search more broadly and deeply to determine the most appropriate information within the project scope" (2015, 22). In other words, effective information seeking behavior requires awareness of social context, recognition of complex affective experiences, avenues for serendipity, and persistence in the face of undesired results.

In their 2022 article "Situating Search," Shah and Bender consider whether current search engines advance these fundamental tenets of research. Like the ACRL, they advocate for search systems that "help users find and make sense of information rather than tools that purport to do it all for them" (230). One recommendation they make includes increasing transparency around sources and ranking (230). Enacting this change involves considering the concept of "friction," which we define as any process that results in the deliberate slowing of information or user action. It's clear that information science values a degree of friction in search; feelings of frustration and doubt, slow processes, and experiences of indeterminacy are important in knowledge production.

It is important to note, however, that not all friction is desirable. While some kinds of friction foster ethical, humane search experiences, others can prevent it. In his comprehensive overview

of the concept of friction in information technology, Marcus Tomalin distinguishes between different types of technological friction, including “protective,” “elective,” and “reflexive,” with non-elective friction often being the most ethically dubious (2023). Elective friction is friction that users willingly consent to, such as a plugin that turns off social media after a certain amount of time has passed. Protective friction is friction that prevents the user from either being harmed or causing harm, such as “are you sure you want to send?” reminders in online bank transfers. These types of friction can go a long way in creating ethical digital environments. Conversely, “non-elective” friction -- that is, friction that inhibits user access without the user’s knowledge or consent – prevents information seeking. Paywalls on news sites, pop-up advertisements, dead links, and throttled internet traffic are all examples of non-elective friction. An ideal search system would therefore seek to enhance “elective” and “protective” friction while minimizing non-elective friction.

Indeed, Google Search’s deteriorating reputation could be viewed as a response to the increasing amount of non-elective friction required to navigate information. Thanks to Google’s search optimization features, corporations now regularly exploit ranking metrics, monetizing poor quality, often meaningless, and often AI generated content (Warzel, 2022; Brereton, 2022; Bevendorff et al. 2024). Ads currently comprise 80% of Google’s revenue, mostly from simple text-based ads (Langley and O’Reilly, 2024). To sidestep the inundation of ads and SEO driven content that crowds the top of a Google search, users have begun looking for search alternatives, with many turning to Reddit and TikTok as default starting points for their information seeking (Huang, 2022; Warzel, 2023). Google, for its part, has continued to modify its algorithm and develop generative AI components to supplement the search experience. Faced with paywalls, algorithms that deprioritize news, limited filtering tools, and a chaotic and uncured jumble of sources, students using Google Search for academic research have been shown to engage in “satisficing,” or “mak[ing] do with results that are less than ideal”; they choose sources that will meet basic assignment expectations instead of endeavoring to find the most useful and trustworthy perspectives and information (Komissarov & Murray, 2016; Warwick et al., 2009; Dahlen & Hanson, 2023). They have been told that Google will quickly and easily give them what they want, and when they don’t find it, are left with “making do.”

Generative Search: A Dangerous Promise

Considering the toxic state of search, it is reasonable to consider how educators might view AI as a welcome alternative for their students. Even before generative AI products explicitly marketed for internet search came on the market, students were eager to use ChatGPT as a search engine, a conflation OpenAI arguably encouraged.³ According to a 2024 online survey of 217 college

³ In an article called “Open AI isn’t doing enough to make ChatGPT’s limitations clear,” *The Verge* reporter James Vincent argued that OpenAI (and the journalists who cover them) is not doing enough to properly educate users on the differences between ChatGPT and search, making the case that the company benefited from downplaying the distinction (2023).

students conducted by Intelligent.com, “research” was the second most cited reason for using ChatGPT, at 67% (“4 in 10 College Students Are Using ChatGPT,” 2024). A 2023 Pew Research Poll found that 69% of teenagers believed that using ChatGPT to “research new topics” was an acceptable use of the platform (Sidoti and Gottfried, 2023). Students clearly believe that ChatGPT has the potential to eliminate non-elective friction, offering them the exact information they are seeking in a fraction of a second.

Of course, ChatGPT’s ability to retrieve information is not like Google Search, as it is not an information retrieval system, nor is it “connected” to the internet.⁴ But that messaging was neither widely received nor broadly understood, and examples of professionals mistaking ChatGPT for a search engine quickly began piling up.⁵ These examples publicly exposed LLMs’ problem with *provenance*, the ability to attribute information to an original source. Without provenance, LLMs become black boxes, leaving it impossible to trust the accuracy of the information provided.⁶

Generative AI search tools have vowed to fix the provenance problem by integrating web search within the LLM, though *how* web search is integrated into the search process is often unclear. Tools like Perplexity AI, Microsoft Copilot (formerly Bing), and Google SGE supplement LLM technology with retrieval-augmented generation, or RAG (Smith, 2024; Microsoft, 2024; Venkatachary, 2024). RAG adds external document retrieval to the pretrained large language model, so the LLM can process additional text outside of its original training data. With RAG, text from current, live web pages can be input into an LLM. For example, Perplexity uses its own web crawler to index websites, creating a continually updating vector database from current, ranked web pages. Text retrieved from those web pages is used to augment user prompts in Perplexity AI, which are fed into the LLM to generate new text (Smith, 2024). Google Gemini similarly supplements its LLM with website content indexed in Google Search. These generative AI search tools also produce web links for users that ostensibly correspond to the generated text.

Generative search tools, then, tell users they can have the best of both worlds: tailored, synthesized responses to questions, with a trail of websites to trace their sources. But do these search tools fulfill this promise? The answer is a resounding no. As will be demonstrated in a series of examples below, the relationship between the generated text and the supplied internet links produced by an LLM search tool in response to a prompt is consistently opaque, presenting only the illusion of provenance.

⁴ ChatGPT’s relationship to the internet is very confusing to the average user. While the foundation model remains trained only up to 2021, ChatGPT 4, available as a subscription, has access to a browsing feature. Those who can only access ChatGPT 3.5 have no access to the internet.

⁵ Perhaps the most notorious example was Steven A. Schwartz, a New York attorney who, upon the advice of his college-aged children, used ChatGPT to create a legal brief filled with fabricated cases and judicial opinions. When pressed by a federal judge to explain his actions, Schwartz stated that “I heard about this new site, which I falsely assumed was, like, a super search engine” (Weiser and Schweber, 2023).

⁶ For more information on the problems of provenance and AI, see Tiku, 2023.

Consider the following search query. In Gemini and Perplexity AI, we entered an informational search query for “recipe for slow cooker chicken fajitas.” This query is a standard informational search, hardly involving the nuance of an academic research query. Gemini, however, struggles. As shown in Figure 1, rather than providing a recipe with clear sources, it participates in confusing practices of synthesis and citation practices. At first glance, it seems like Gemini largely delivers what we asked for. Gemini displays recipe directions, complete with ingredients and cooking steps. At the bottom, under the heading “Sources,” Gemini lists a single source, a recipe from Allrecipes. Yet, upon further investigation, the source citation only serves to confuse and confound. For instance, Gemini’s ingredient list includes one can of diced tomatoes, and suggests an optional $\frac{3}{4}$ cup of salsa. However, the Allrecipes recipe Gemini listed as its source does not mention diced tomatoes, and does not list the salsa as an optional ingredient. Furthermore, Gemini’s recipe includes olive oil, which Allrecipes does not. When we clicked “double check response,” Gemini then highlighted multiple sentences and included *additional* websites. Under the instruction to “coat the inside of the slow cooker with olive oil,” Gemini stated it found “similar content” on TheKitchn’s website. The link titled, “Do You Need to Use Nonstick Spray in a Slow Cooker?” does not provide a chicken fajita recipe involving olive oil, but instead debates the general merits of greasing a slow cooker (Prakash, 2019). Contrary to Gemini’s recommendations that the user grease the slow cooker with olive oil, TheKitchn recommends greasing the slow cooker only in the case of starchy recipes, like mashed potatoes. This experience leaves the user unable to determine what websites directly align with the generated text, and what websites might only serve as “ballast” to support a particular generated claim.

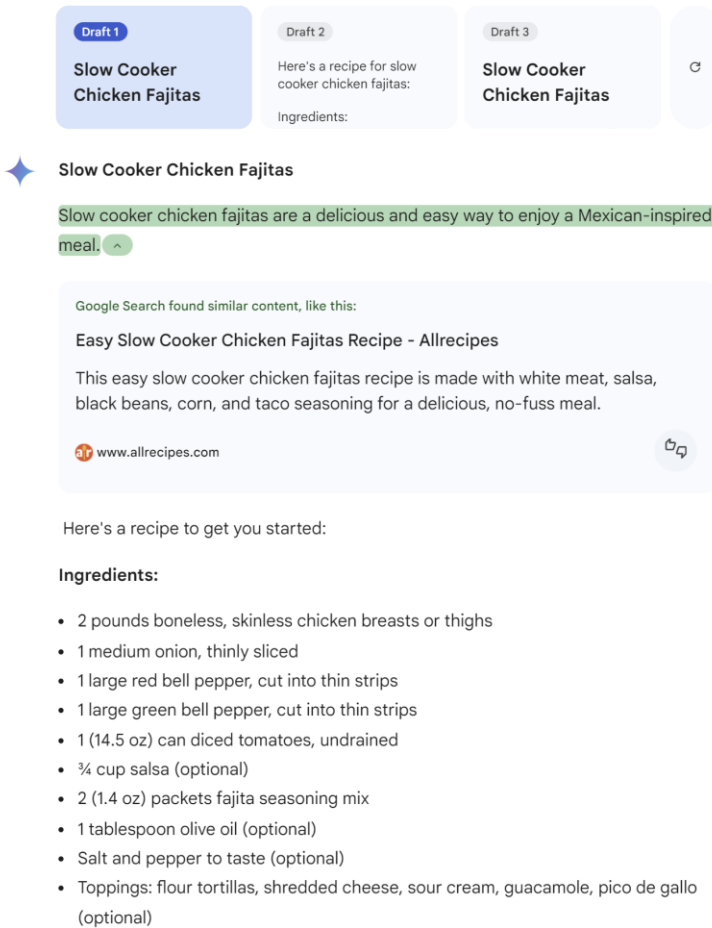


Figure 1. A sample search response using Gemini (2024).

Perplexity AI contains even more problems. At the top of its display, it lists five “sources” which largely match the first five sources of a standard Google Search (Fig. 2). Its recipe contains “citations” that resemble footnotes, which link back to the five “sources” presented. Yet, like Gemini, it does not synthesize or trace these sources in any real way. Rather, it fabricates a response based on its predictive infrastructure and gives the appearance of valid source material. For instance, it tells the user to “cook until done,” without specifying a cook time. All five websites, however, recommend a cook time of 6-8 hours. Only one website, Cooking Classy, optionally recommends honey, while the others do not. Yet Perplexity does not provide a citation specifying which website recommended honey. All five citations are clumped together at the end, with no real distinction as to what website references what information.

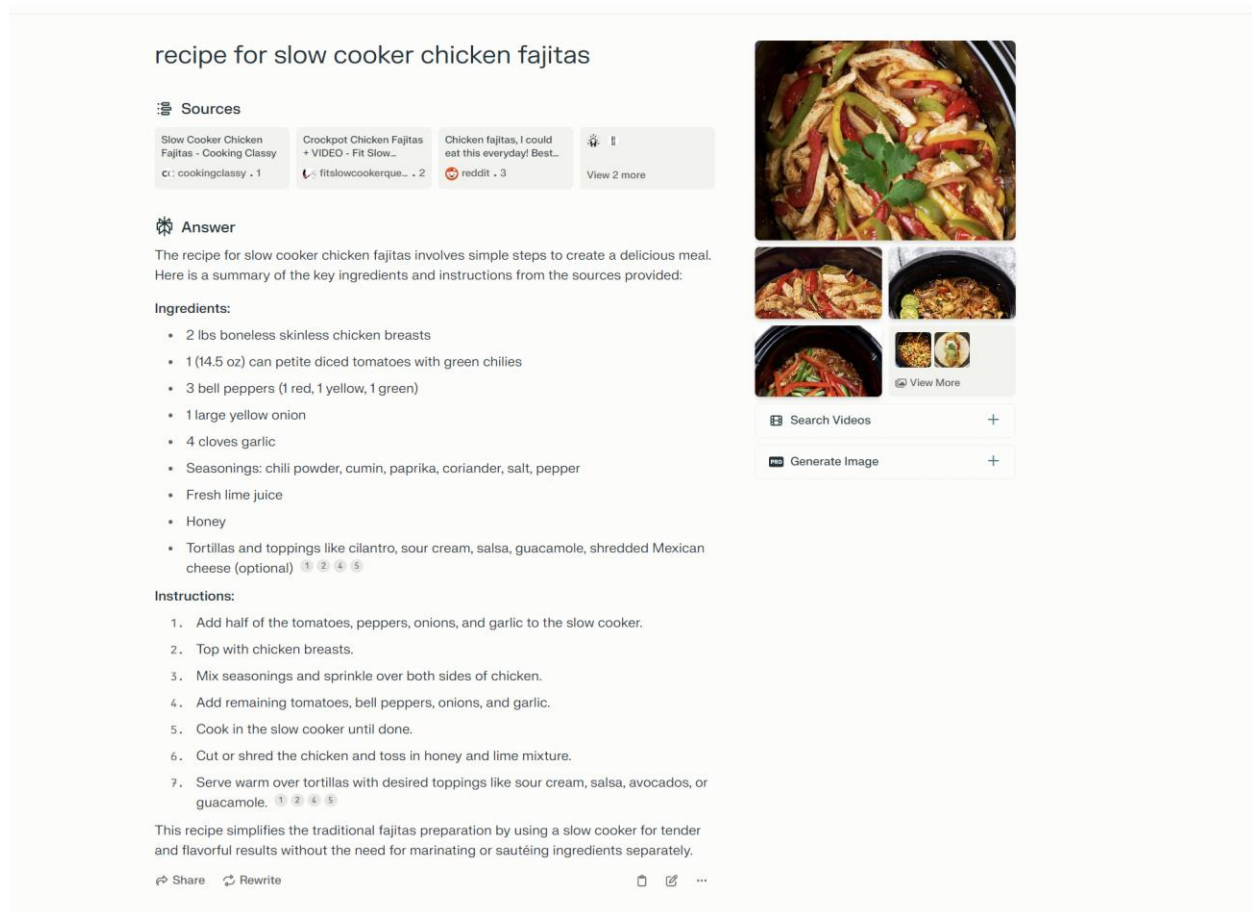


Figure 2. A sample search response using Perplexity AI (2024).

The issue at play here isn't whether Gemini or Perplexity produced valid fajitas recipes; presumably, the user could cook the recipe as presented and get an edible result. Rather, the problem is that both generative search tools participate in deceptive citation and synthesis practices. Neither Gemini nor Perplexity can directly trace their output to sources with any fidelity, because they are not legitimately performing the necessary steps of authentic information seeking. In Gemini's case, it appears that "double checking" its response invokes a behavior similar to that of a novice student researcher rushed for time -- haphazardly paraphrasing a single source and then *retroactively* attempting to verify its output with multiple sources. Similarly, Perplexity's search results and generated output rarely match, and at times directly contradict its "source" material.

These problems are not unique to Gemini or Perplexity, nor are they a "bug" of generative search tools that will soon be remedied. Instead, they are a feature, inherent to the operations of generative search. In an examination of the verifiability of generative search tools, Liu, Zhang, and Liang (2023) found that only 51.5% of generated sentences contained any citations, of which only 74.5% directly supported the statements. Even more concerning, they found citation precision to be *inversely* correlated with perceived utility, meaning that the more helpful the

responses *seemed* to be, the more likely they were to contain inaccurate citations. This inverse correlation reveals today's generative search products to be tools that actually increase non-elective friction (by actively preventing the user from accessing quality, relevant sources) under the *guise* of a simple, frictionless experience. Shah and Bender, as well, express their concern with generative search, claiming that the field "is rushing ahead with a technology without sufficient study of the uses it is meant to serve, how it would be used, and what its use would mean" (2024, 1). As they declare, "information access is not merely an application to be solved by the so-called 'AI' techniques du jour. Rather, it is a key human activity, with impacts on both individuals and society" (1). They worry that generative search systems stand to disrupt relationships of information providers and information accessors, making it harder for people to not only find trustworthy sources, but also to *know* that they've found trustworthy sources (13).

Conclusion

From our standpoint as writing instructors, we share this worry. Without appropriate levels of friction in our search systems, students will face an information landscape that presents the illusion of straightforward answers while preventing students from successfully accessing the means by which those answers were derived. Generative AI search tools narrow the amount of sources available for browsing, a key action necessary to knowledge production. Furthermore, as scholars who take genuine pleasure in moments of serendipity and discovery associated with meaningful research, we worry that students stand to lose rich experiences of falling down rabbit holes, chasing down dogged questions, and discovering little known texts. Information seeking is not merely an academic exercise; as Gary Marchioni noted nearly thirty years ago, it is a "fundamental human process" in which "humans engage in to change their knowledge" (1998, 5-6). We must insist on the role that students, teachers, and the public should play in deciding how these tools are designed, deployed, and implemented. In a world that presents the illusion of frictionless search, we may need to become the friction ourselves.

References

- “4 in 10 College Students Are Using ChatGPT On Assignments.” 2024. Intelligent. February 27, 2024. <https://www.intelligent.com/4-in-10-college-students-are-using-chatgpt-on-assignments/>.
- Asher, Andrew D., Lynda M. Duke, and Suzanne Wilson. 2013. “Paths of Discovery: Comparing the Search Effectiveness of EBSCO Discovery Service, Summon, Google Scholar, and Conventional Library Resources.” *College & Research Libraries*, 74 (5): 464-488. <https://doi.org/10.5860/crl-374>.
- Association of College and Research Libraries. 2015. “Framework for Information Literacy for Higher Education.” American Library Association. <https://www.ala.org/acrl/standards/ilframework>.
- Bevendorff, Janek, Matti Wiegman, Martin Potthast, and Benno Stein. 2024. “Is Google Getting Worse? A Longitudinal Investigation of SEO Spam in Search Engines.” *Advances in Information Retrieval*. Dresden/Leipzig: Center for Scalable Data Analytics and Artificial Intelligence. https://downloads.webis.de/publications/papers/bevendorff_2024a.pdf.
- Brereton, Dmitri. 2022. “Google Search Is Dying.” *DKB Blog* (blog). February 14, 2022. <https://dkb.blog/p/google-search-is-dying>.
- Dahlen, Sarah P. C., and Kathlene Hanson. 2023. “In Their Words: Student Reflections on Information-Seeking Behaviors.” *The Journal of Academic Librarianship* 49 (4): 102713. <https://doi.org/10.1016/j.acalib.2023.102713>.
- De Vynck, Gerrit, and Nitasha Tiku. 2024. “Google Takes down Gemini AI Image Generator. Here’s What You Need to Know.” *Washington Post*, February 23, 2024. <https://www.washingtonpost.com/technology/2024/02/22/google-gemini-ai-image-generation-pause/>.
- Gemini, response to “Recipe for slow cooker chicken fajitas,” Google, March 15, 2024. <https://gemini.google.com/app/d61aff511eb69c9e>.

- Hu, Krystal, and Pritam Biswas. 2024. "Search Startup Perplexity AI Valued at \$520 Mln in Funding from Bezos, Nvidia." *Reuters*, January 4, 2024.
<https://www.reuters.com/technology/perplexity-ai-valued-520-mln-funding-bezos-nvidia-2024-01-04/>.
- Huang, Kalley. 2022. "For Gen Z, TikTok Is the New Search Engine." *The New York Times*, September 16, 2022, sec. Technology.
<https://www.nytimes.com/2022/09/16/technology/gen-z-tiktok-search-engine.html>.
- Komissarov, Sloan, and James Murray. 2016. "Factors That Influence Undergraduate Information-Seeking Behavior and Opportunities for Student Success." *The Journal of Academic Librarianship* 42 (4): 423–29. <https://doi.org/10.1016/j.acalib.2016.04.007>.
- Kruppa, Miles. 2024. "Jeff Bezos Bets on a Google Challenger Using AI to Try to Upend Internet Search." *Wall Street Journal*, January 4, 2024, sec. Tech.
<https://www.wsj.com/tech/ai/jeff-bezos-bets-on-a-google-challenger-using-ai-to-try-to-upend-internet-search-0859bda6>.
- Kruppa, Miles, and Berber Jin. 2024. "AI Search Startup Perplexity Set to Double Valuation to \$1 Billion - WSJ." *The Wall Street Journal*, March 5, 2024. <https://www.wsj.com/tech/ai/ai-search-startup-perplexity-set-to-double-valuation-to-1-billion-b84be204>.
- Kuhlthau, Carol C. 1991. "Inside the Search Process: Information Seeking from the User's Perspective." *Journal of the American Society for Information Science* 42 (5): 361–71.
[https://doi.org/10.1002/\(SICI\)1097-4571\(199106\)42:5<361::AID-ASI6>3.0.CO;2-#](https://doi.org/10.1002/(SICI)1097-4571(199106)42:5<361::AID-ASI6>3.0.CO;2-#).
- Langley, Hugh, and Lara O'Reilly. 2024. "How Google lost its way." *Business Insider*, February 29, 2024.
<https://www.businessinsider.com/google-gemini-ai-layoffs-innovation-boring-2024-2>.
- Liu, Nelson F., Zhang, Tianyi., and Percy Liang. (2023). "Evaluating Verifiability in Generative Search Engines." *Findings of the Association for Computational Linguistics: EMNLP 2023*: 7001-7025.
<https://arxiv.org/abs/2304.09848>.

Marchioni, Gary. *Information Seeking in Electronic Environments*, Cambridge: Cambridge University Press, 1995. <https://doi.org/10.1017/CBO9780511626388>.

Microsoft. 2024. “Microsoft Copilot for Microsoft 365 Overview.” Microsoft Learn. February 2, 2024. <https://learn.microsoft.com/en-us/microsoft-365-copilot/microsoft-365-copilot-overview>.

O’Reilly, Hugh, and Lara Langley. 2024. “Google Is Shaking up Its Sales Strategy to Push Its Most Important AI-Powered Product to More Advertisers.” *Business Insider*, October 24, 2023. <https://www.businessinsider.com/google-sales-team-focus-mid-size-advertisers-performance-max-ai-2023-10>.

Perplexity.ai, response to “Recipe for slow cooker chicken fajitas,” Perplexity, March 15, 2024. https://www.perplexity.ai/search/recipe-for-slow-T_twPgAIQraOWRqS8sCU6Q.

Peters, Jay. 2023. “Google Wants You to Forget the 10 Blue Links.” *The Verge*, May 12, 2023. <https://www.theverge.com/2023/5/12/23720396/google-search-generative-experience-blue-links>.

Prakash, Sheela. 2019. “Do You Need to Use Nonstick Cooking Spray in the Slow Cooker?” *The Kitchn*, May 1, 2019. <https://www.thekitchn.com/do-you-need-to-use-nonstick-cooking-spray-in-the-slow-cooker-228490>

Shah, Chirag, and Emily M Bender. 2022. “Situating Search.” In *Proceedings of the 2022 Conference on Human Information Interaction and Retrieval*, 221–32. CHIIR ’22. New York, NY, USA: Association for Computing Machinery. <https://doi.org/10.1145/3498366.3505816>.

Shah, Chirag, and Emily M. Bender. 2024. “Envisioning Information Access Systems: What Makes for Good Tools and a Healthy Web?” *ACM Transactions on the Web*. <https://doi.org/10.1145/3649468>.

Sidoti, Olivia, and Jeffrey Gottfried. 2023. “About 1 in 5 U.S. Teens Who’ve Heard of ChatGPT Have Used It for Schoolwork.” *Pew Research Center*, November 16, 2023.

<https://www.pewresearch.org/short-reads/2023/11/16/about-1-in-5-us-teens-whove-heard-of-chatgpt-have-used-it-for-schoolwork/>.

Smith, Matthew S. “Perplexity.ai Revamps Google SEO Model for LLM Era.” *IEEE Spectrum*, February 24, 2024. <https://spectrum.ieee.org/perplexity-ai>.

Tiku, Nitasha. 2023. “AI Researchers Uncover Ethical, Legal Risks to Using Popular Data Sets.” *The Washington Post*, October 25, 2023. <https://www.washingtonpost.com/technology/2023/10/25/data-provenance/>.

Tomalin, Marcus. 2023. “Rethinking Online Friction in the Information Society.” *Journal of Information Technology* 38 (1): 2-15. <https://doi.org/10.1177/02683962211067812>.

Venkatachary, Srinivasan. 2024. “A New Way to Search with Generative AI: An Overview of SGE.” Google. <https://static.googleusercontent.com/media/www.google.com/en//search/howsearchworks/google-about-SGE.pdf>.

Vincent, James. 2023. “OpenAI Isn’t Doing Enough to Make ChatGPT’s Limitations Clear.” *The Verge*, May 30, 2023. <https://www.theverge.com/2023/5/30/23741996/openai-chatgpt-false-information-misinformation-responsibility>.

Warwick, Claire, Jon Rimmer, Ann Blandford, Jeremy Gow, and George Buchanan. 2009. “Cognitive Economy and Satisficing in Information Seeking: A Longitudinal Study of Undergraduate Information Behavior.” *Journal of the American Society for Information Science and Technology* 60 (12): 2402–15. <https://doi.org/10.1002/asi.21179>.

Warzel, Charlie. 2022. “The Open Secret of Google Search.” *The Atlantic*, June 20, 2022. <https://www.theatlantic.com/ideas/archive/2022/06/google-search-algorithm-internet/661325/>.

Warzel, Charlie. 2023. “The Tragedy of Google Search.” *The Atlantic*, September 22, 2023. <https://www.theatlantic.com/technology/archive/2023/09/google-search-size-usefulness-decline/675409/>.

Weiser, Benjamin, and Nate Schweber. 2023. "The ChatGPT Lawyer Explains Himself." *The New York Times*, June 8, 2023, sec. New York.
<https://www.nytimes.com/2023/06/08/nyregion/lawyer-chatgpt-sanctions.html>.

"What Is Perplexity?" n.d. *Perplexity: Frequently Asked Questions* (blog). Accessed January 24, 2024. <https://blog.perplexity.ai/faq/what-is-perplexity>.