AI Semantic Search vs Keywords in Biomedical Research

By Adrien Laurent, CEO at IntuitionLabs • 3/9/2026 • 55 min read

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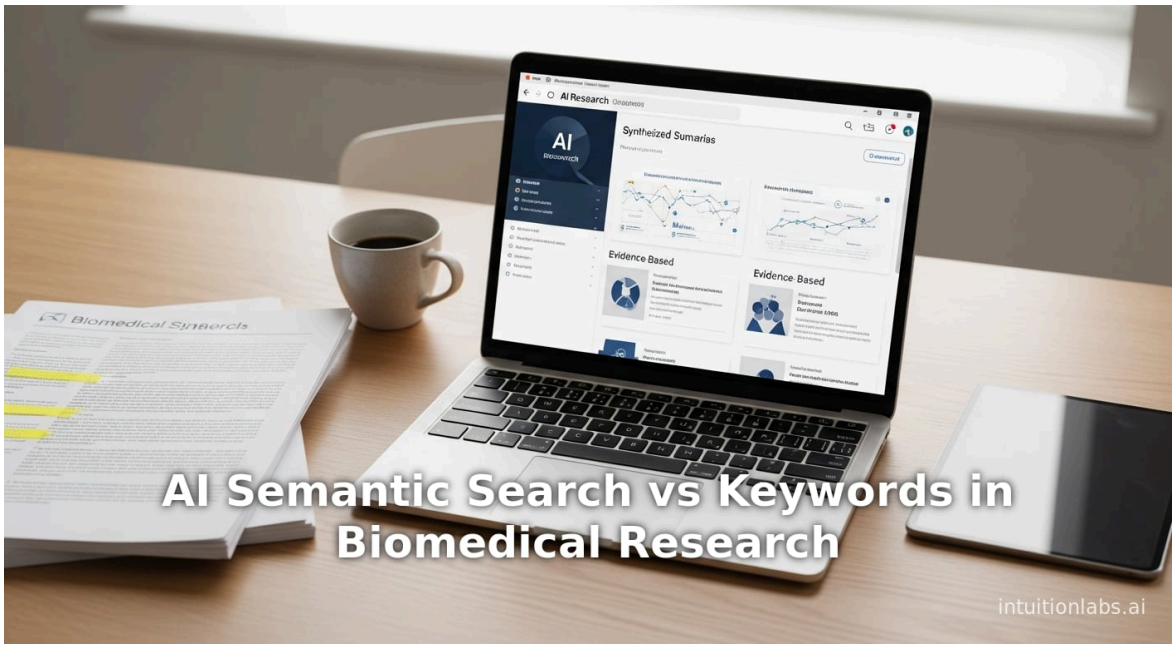

Executive Summary

The traditional paradigm of **keyword-based search (the "Ctrl+F" model)** in biomedical literature — relying on exact term matches, Boolean queries, and lists of retrieved documents — is proving increasingly inadequate. The volume of biomedical publications has grown explosively (PubMed surpassed ~36 million articles by 2022 and adds over 1 million new records per year ([1] pmc.ncbi.nlm.nih.gov)), meaning that simple keyword queries often return hundreds or thousands of results. Empirical studies show that researchers review only a small fraction of these results (for example, fewer than 20% of articles beyond the top 20 results) ([1] pmc.ncbi.nlm.nih.gov), underscoring that much relevant knowledge remains undiscovered. Complex or niche information needs (such as detailed evidence for emerging clinical guidelines) often require convoluted query syntax and still may fail to surface key findings. ([2] pmc.ncbi.nlm.nih.gov) ([3] journals.sagepub.com) In short, "Ctrl+F" and traditional search engines are hitting the limits of recall and relevance as the literature deluges researchers.

Artificial intelligence (AI) offers a transformative way forward. By moving from lexical matching to **semantic understanding and knowledge synthesis**, new AI-driven tools can answer questions, summarize findings, and surface hidden associations rather than merely listing documents. For instance, recent reviews note a dramatic shift "from keyword-based to semantic and multimodal AI" approaches in the last five years ([4] journals.sagepub.com). These approaches leverage techniques like vector-space embeddings, knowledge graphs, question-answering models, and contextual language models (e.g. PubTator 3.0 for named-entity recognition ([5] journals.sagepub.com), question-answering GPT-based systems, and retrieval-augmented generation pipelines). Tools such as **Elicit** and **Consensus** automate extraction of evidence and key data from papers ([5] journals.sagepub.com) ([6] journals.sagepub.com), while platforms like **BioGPT** and **PubMed Labs** apply transformer models to biomedical queries. Visual exploration tools (e.g. *Connected Papers*, *ResearchRabbit*) map citation networks to reveal related work without keyword entry. Disease/genomics search systems like **LitVar** handle genetic variant synonyms ([7] www.sciencedirect.com), and summarization assistants (e.g. **Scholarcy**, Google's *SciSpace*) produce condensed overviews of articles. These innovations collectively aim to transform "search" into **"synthesis"**, powering intelligent assistants that return direct answers or synthesized insights rather than raw lists of hits.

However, the transition is still in progress and comes with complications. Multiple studies find that **basic AI chatbots (e.g. early ChatGPT models)** often produce inconsistent or inaccurate literature search results ([8] pmc.ncbi.nlm.nih.gov) ([9] medinform.jmir.org). For example, a comparative evaluation found vanilla ChatGPT retrieved almost no truly relevant studies in several systematic-review scenarios, whereas a specialized Bing AI search plugin found many ([9] medinform.jmir.org). OpenAI's models suffer from "hallucination" (fabricated or outdated information) and knowledge cutoffs unless augmented with external databases ([9] medinform.jmir.org) ([10] pmc.ncbi.nlm.nih.gov). Improvements like ChatGPT-4's web browsing plug-in can partially mitigate this, identifying evidence that basic ChatGPT missed ([3] journals.sagepub.com), but even advanced models still make errors without human oversight. On the other hand, carefully engineered pipelines (e.g. GPT-4 guided by targeted prompts) have shown remarkable performance in specific tasks: one recent study achieved ~92–93% accuracy in using ChatGPT-4 to identify drug-target literature for the SARS-CoV-2 virus ([11] www.sciencedirect.com), rivaling expert reviewers. This performance gap highlights that **tool design matters**: a general-purpose chatbot is not as reliable as task-specific systems combining retrieval and reasoning.

This report provides an **in-depth analysis** of the transformation underway in biomedical literature search. We review the historical context of search (from early systems like MEDLARS to current PubMed), identify the limits of keyword queries, and catalog a broad array of new AI-based search and mining tools. We examine specific cases and data comparing AI versus traditional methods, include expert and research opinions on their effectiveness, and discuss implications for practice. Tables summarize key tools and contrast traditional vs AI search features. We also carefully consider challenges: evidence quality, ethics, and the risks of misinformation when using AI (e.g. studies have shown chatbots can confidently give wrong medical advice ([3] journals.sagepub.com) ([12] www.eurekalert.org)). Looking forward, we outline

emerging trends (multimodal search integrating genomics/imaging, growing knowledge graphs, conversational agents specifically tuned for biomedicine) and make recommendations for future development.

In conclusion, **AI is not simply "searching better" — it is augmenting research with semantic understanding, summarization, and discovery tools that go beyond Ctrl+F's capabilities**. While "the death of Ctrl+F" is not literal (keyword search will still exist), the role of simple find-by-text is being dwarfed by AI's ability to interpret meaning, provide context, and synthesize knowledge. This report highlights both the promise and the current reality of this shift, emphasizing that human expertise will remain essential to guide and verify the results of AI-supported searches.

Introduction: Background and Evolution of Search in Biomedical Research

In biomedical science and healthcare, **literature search** has always been foundational. Researchers and clinicians rely on published articles to learn about experiments, treatments, and disease mechanisms. The volume of biomedical publications has grown continuously since the mid-20th century, propelled by advances in technology and global research funding. Early computerized literature systems like **MEDLARS** (Medical Literature Analysis and Retrieval System), developed by the U.S. National Library of Medicine (NLM) in the 1960s, were among the first efforts to digitize the rapidly expanding biomedical literature ([13] journals.sagepub.com). MEDLARS eventually evolved into **MEDLINE** and later **PubMed**, which made millions of indexed articles searchable via the web.

By the 1990s, access to PubMed transformed research: anyone could type keywords into a query box and retrieve relevant citations. This **keyword-based search model** — akin to using "Ctrl+F" on a PDF or website — remained dominant for decades. A researcher would enter terms of interest, perhaps using Boolean operators or Medical Subject Headings (MeSH), and then sift through ranked lists of article citations. However, as the volume of literature exploded, the limitations of this approach became clear. By the early 2020s, PubMed held **tens of millions of records** (over 36 million by 2022 ([1] pmc.ncbi.nlm.nih.gov)) covering nearly a century of biomedical writing.Each year adds roughly a million new papers, driven partially by rapid publishing during global crises like the COVID-19 pandemic (which itself led to special databases for SARS-CoV-2 research).

This sheer scale means that **keyword searches yield enormous result sets**, often far beyond what a human can feasibly review. Studies have documented this overload: a typical PubMed query might return hundreds or thousands of hits, yet researchers frequently examine only the top few dozen. Jin et al. (2024) report that *"fewer than 20% of the articles past the top 20 results are ever reviewed"* ([1] pmc.ncbi.nlm.nih.gov). Recognizing this, search platforms began improving ranking algorithms: for example, PubMed moved from purely recency-based ordering to relevance-based ranking to push key articles higher ([14] pmc.ncbi.nlm.nih.gov). But even with better ranking, key information often lurks deep in the list, and minor variations in phrasing can miss relevant work altogether.

In practice, some searches require intricate query construction (e.g. combining numerous synonyms, synonyms of drug names, or complex PICO – patient/population, intervention, comparator, outcome – strings). Many users find such query formulation difficult. For example, during the COVID-19 pandemic, the deluge of articles exposed how **traditional searches "required complex querying syntax that is unfamiliar to most users"**, and led to the development of specialized COVID-19 search tools ([2] pmc.ncbi.nlm.nih.gov). The bottom line is that **searching has become cognitively burdensome**. As one observer metaphorically notes, highly educated professionals often end up acting like "archaeologists, digging through Slack messages, Jira tickets, and PDFs" for answers ([15] medium.com) — a telling sign that the simple search bar is no longer sufficient for the complexity of modern information needs.

Meanwhile, advances in computing — especially in **artificial intelligence (AI)** — have paved the way for new search paradigms. The mid-20th century conceptualization of AI at the 1956 Dartmouth meeting ([16] journals.sagepub.com) laid the intellectual foundation, but practical tools emerged much later. From the 1960s onward, there were attempts to incorporate semantic knowledge (e.g. the Unified Medical Language System in the 1980s for data integration ([16]

journals.sagepub.com)) or early natural language processing prototypes. In the 2000s and 2010s, machine learning and statistical NLP improved tasks like extraction of symptoms or disease indicators from text ([17] journals.sagepub.com).

However, the **past five years (2020–2025)** have seen unprecedented change. Factors driving this shift include: (1) monumental growth in data and publications, (2) dramatic increases in computing power (GPUs, cloud), (3) breakthroughs in large language models (LLMs) like BERT and GPT series, and (4) practical needs (such as the COVID-19 crisis demanding rapid evidence synthesis). During 2020 alone, the demand for quick summaries of the COVID literature accelerated the adoption of AI tools. Chandan Sen et al. (2026) note that in 2020 *"the year marked a pivotal moment… fueled by the COVID-19 pandemic's demand for rapid literature analysis"* ([18] journals.sagepub.com). In response, new applications emerged: for example, **BioGPT** (trained on PubMed) began answering biomedical questions, Semantic Scholar introduced automated TL;DR summaries of papers, and research teams developed retrieval-augmented knowledge graphs to highlight novel chemical–disease links ([19] journals.sagepub.com). PubTator 3.0 (a Stanford tool) advanced named-entity recognition with F1-scores near 0.93 for genes/diseases ([5] journals.sagepub.com), enabling semantic tagging of text. Citation analysis and visualization tools (ResearchRabbit, Connected Papers) let scientists explore connections without explicitly searching by keyword ([20] journals.sagepub.com).

In short, the introduction of AI has **expanded functionality beyond keywords** ([21] pmc.ncbi.nlm.nih.gov). Modern systems increasingly accept **natural language questions** (not just keywords), extract "entities and relations" automatically, generate concise results, and even engage in dialogue. They leverage **semantic embeddings** (so "diabetes" and "glucose tolerance" are linked) and **knowledge graphs** (linking genes to diseases) in ways that literal search cannot. The mission has shifted: researchers no longer just want lists of possibly relevant papers; they often want **answers, summaries, and evidence extraction**. The very phrase "Death of Ctrl+F" captures this trend: rather than manually scanning documents, the aspiration is that an AI assistant will **synthesize the knowledge** into actionable insight.

This report traces this evolution and current state of biomedical search. We begin with a detailed look at the traditional methods and their drawbacks. We then review the latest AI-driven search tools and techniques, organized by task and use-case. We analyze empirical comparisons and quantify the benefits and limitations. We also present case studies showing AI in action for literature reviews and evidence discovery. Finally, we discuss the broader implications for the research enterprise — including both the opportunities (e.g. accelerating discovery, interdisciplinary connections) and the risks (e.g. misinformation, ethical concerns). All claims and observations are grounded in current research and data from the literature, providing an evidence-based examination of **how AI is transforming (and, in some senses, replacing) keyword search in biomedical research**.

1. Traditional Keyword Search in Biomedical Research

1.1 Early Systems and PubMed

From its inception, PubMed has embodied the classic keyword-search model. PubMed, launched in 1996 by the NLM, indexes titles, abstracts, and MeSH terms for millions of articles, and allows users to query with words or phrases. Early searches relied primarily on text matching: a query matched terms in the indexed fields, and results were returned as lists of articles (with some cues like title/abstract snippets). Users often had to carefully craft Boolean queries (e.g. using OR to combine synonyms) and apply field tags or filters (by author, journal, date, etc.) to get manageable results.

This approach has roots in very old browsing techniques. Even in individual articles or PDFs, one could use **Ctrl+F** to jump to occurrences of a word. In effect, keyword search is Ctrl+F on a massive database: it returns every document that happens to contain the terms. While powerful in providing broad coverage, it has inherent weaknesses. For example, if

an important concept uses different terminology (a synonym or related phrase), a keyword search will miss it unless the user explicitly includes that alternative. Conversely, a search term may match irrelevant contexts. As one industry commentator phrased it (in the enterprise search domain), searching for “Revenue 2024” would miss documents titled “Q3 Sales Figures” because “sales” and “revenue” are synonyms ([22] medium.com). Although that example was in a corporate context, the same can happen in biomedical literature: e.g., a search for “heart attack” might miss papers using “myocardial infarction” unless synonyms are added. PICO-formatted queries (Population/Intervention/Comparator/Outcome) are common in evidence-based medicine, but constructing them in PubMed requires rigorous boolean building. Even then, important results can evade detection.

PubMed did incorporate ways to mitigate these issues: for instance, it performs automatic term mapping (expanding to synonyms and MeSH). Still, keyword queries remain constrained by language. A classic illustration: searching exactly for “diabetes mellitus type 2” may still return insulin-related articles using ADA standards, but might miss articles using slightly different phrasing. Users must often try multiple search cuts, each time adjusting keywords and operators. The NCBI’s own analysis showed that typical PubMed users submit *short keyword-based queries* ([23] pmc.ncbi.nlm.nih.gov) and rely on the top-ranked results, rather than complex structured queries. Indeed, the 2024 eBioMedicine perspective notes that PubMed “mainly receives short keyword-based queries” and returns “a list of raw articles without further analysis,” which may fail to meet specialized needs ([23] pmc.ncbi.nlm.nih.gov).

Historically, dedicated interfaces and databases tried to offer improvements. Tools like **MeSH** (controlled vocabulary) provided a standardized way to express concepts, and filtering tools like the *Clinical Queries* section of PubMed offered pre-set queries for evidence-based categories (e.g. therapy, diagnosis) ([24] pmc.ncbi.nlm.nih.gov). Other general-purpose academic search engines (Google Scholar, Scopus, IEEE Xplore, etc.) naturally extended keyword search beyond PubMed. Yet all of these are fundamentally keyword-driven: they rank documents by term frequency or other lexical measures. They do not interpret the *meaning* of the query. *In short, up through the 2010s, “search” meant: (1) form a terms-based query, (2) scan a ranked list of documents, (3) read and synthesize manually. This model has been universal – or a default – in biomedical literature access.*

1.2 Limitations of Keyword Search and Information Overload

Over time, the biomedical community has recognized major drawbacks of keyword-only search. The explosion of publications means that even well-formulated searches produce far more hits than a researcher can read. As noted, Jin et al. report an astonishing statistic: after PubMed’s top 20 results, the vast majority of articles retrieved are never reviewed ([1] pmc.ncbi.nlm.nih.gov). Put differently, if a query returns a thousand documents, a researcher might actually examine only the very first few pages, leaving many relevant ones unread. This **long-tail problem** suggests missed opportunities for discovery.

Several factors contribute:

- **Synonymy and Vocabulary Gaps.** Biomedical terminology is rich and sometimes inconsistent. Different authors may describe the same concept with different words. Keyword search, relying on literal matching, often fails to bridge synonyms. For example, genotype data might be indexed under specific gene symbols; a researcher querying a disease may miss gene studies if they use alternate nomenclature. A recent analysis points out that *“the link between a query and a document is often not established because they use different terms to refer to the same concept”* ([25] pmc.ncbi.nlm.nih.gov). Even with MeSH term mapping, new synonyms or niche jargon regularly fall outside the system. Users combat this with elaborate boolean OR lists or relying on exploded MeSH terms, but this is tedious and error-prone.
- **Ambiguity and Irrelevance.** Keywords can be ambiguous. Searching for “apple” in a lay context is a well-known example (bringing fruit vs company vs album), and similar cases occur in medicine (e.g. “HG” could mean “human genome” or “halogen gas” or “hematological genetics”). Traditional search simply returns any match, leaving it to the user to disambiguate. It also retrieves both primary research and irrelevant mentions indiscriminately. A query for a symptom might retrieve both patient experience reports and background theoretical discussions mixed together. Because of this, the precision of keyword searches can be low without careful filtering.

- **Information Overload and Cognitive Burden.** Even after a query returns results, the researcher must click into articles, read abstracts or full texts, and mentally synthesize. This manual review process is laborious: surveys indicate researchers spend on average **~7 hours per week on literature searching**, and a systematic review by a five-person team typically takes about **41 weeks of effort** ([26] pmc.ncbi.nlm.nih.gov). This enormous effort stems mainly from manually filtering and curating results after a broad search.

- **Rapid Knowledge Growth.** In fields that advance quickly (e.g. genomics, AI in medicine, a pandemic disease), staying current with keyword alerts becomes impossible. Studies proliferate even within weeks; by the time a query is crafted, new relevant work may appear that the original search missed. Basic alert systems (like PubMed's "My NCBI" feeds) help, but still rely on matching keywords. As societies produce *"exponential growth"* in literature ([27] journals.sagepub.com), our ability to keep up with keyword lists falters.

- **Specialized Queries.** Clinical questions or discovery-oriented queries often require nuanced search strategies beyond simple keywords. For instance, a physician might want "studies of drug X in patients with condition Y with outcome Z." Encoding that as a single PubMed query is non-trivial; many relevant papers might not explicitly mention all terms, or report on co-morbidities. For highly specialized or multi-step information needs, keyword search alone is awkward. The COVID-19 pandemic highlighted this: clinicians needed to rapidly find all articles on ventilator guidelines, but broad keyword searches would mix method papers with unrelated mentions. Researchers resorted to specialized portals (e.g. *LitCovid*) or writing multiple successive searches, yet these were workarounds.

To summarize, **keyword-based search is precise but brittle**: it can miss important results (low recall) unless queries are carefully constructed; and it can retrieve many false positives (low precision) requiring manual filtering. It also shifts the cognitive load onto the user to interpret and synthesize. As one author analogized, traditional search gives you a list of ingredients when you ordered a meal ([28] medium.com): you must make sense of them yourself. In the biomedical domain, where the knowledge base is vast, complex, and rapidly evolving, this model increasingly strains users.

The sentiment in recent literature is unanimous: *researchers need better tools*. As one overview puts it, improvements in AI have "expanded functionality beyond keywords" ([21] pmc.ncbi.nlm.nih.gov). In other words, the biomedical community is actively moving past the limits of simple text search. The next sections detail how AI technologies are being applied to do just that.

2. AI-Driven Alternatives: Beyond Keyword Search

The crux of recent innovation is to use AI to **understand and synthesize** information, rather than rely on surface term matching. Multiple approaches are being explored and integrated:

- **Semantic Search and Embeddings.** Instead of matching exact words, AI can represent both queries and documents as semantic vectors in a high-dimensional space (via word embeddings, sentence embeddings, etc.). Queries and texts that are conceptually similar (even if lexically different) can match closely. For example, embedding-based retrieval can map "heart attack" and "myocardial infarction" to near points. In practice, some systems use pretrained models (e.g. spaCy, BioBERT, PubMedBERT) to embed abstracts or snippets, and index a vector database. A query is likewise embedded, and the system retrieves the nearest neighbors in semantic space. This approach is now often packaged within neural search engines or custom RAG (Retrieval-Augmented Generation) systems. Early experiments have shown that semantic search can achieve higher recall on biomedical queries by covering synonyms ([25] pmc.ncbi.nlm.nih.gov).

- **Ontologies and Knowledge Graphs.** Biomedical research has rich ontologies (like MeSH, UMLS, Gene Ontology). AI systems can incorporate these to enrich search. Tools like PubTator use AI to tag terms in articles with standardized concepts (genes, diseases, chemicals) ([5] journals.sagepub.com). These tags allow building knowledge graphs linking concepts; search can then traverse this graph to find associated literature (e.g. find all articles linking a gene node to a disease node). A KG-based system might return not just documents, but relationships (for example, PubTator now provides bulk annotation data ([29] pmc.ncbi.nlm.nih.gov)). Other research (e.g. Khader & Ensan, 2022) explicitly use knowledge-driven query expansion: by identifying related terms from domain knowledge (like a COVID ontology), they improved retrieval on COVID datasets ([30] pmc.ncbi.nlm.nih.gov).

- **Large Language Models (LLMs) and Conversational Agents.** Models such as GPT, BERT, and their biomedical variants (like BioGPT, PubMedBERT) have revolutionized NLP. While not search engines per se, they can process natural-language questions and generate answers. Chatbots like ChatGPT (GPT-3.5/4) allow a user to **type questions in plain English** ("What is the current evidence on [drug X] reducing mortality in [condition Y]?") and receive a synthesized answer citing relevant studies. Some systems combine LLMs with retrieval: the query triggers a search (e.g. via an API or plugin) that retrieves candidate articles or abstracts, and the LLM then reads and summarizes these. This is called "Retriever-Augmented Generation" (RAG). RAG systems can thus produce answers grounded in recent literature rather than solely the model's training. Early adopters include Scispace's *Semantic Scholar AI*, Microsoft Academic* chatbots, and specialized academic assistants (e.g. Analogy's "Consensus.is" which returns evidence from papers).

- **Automated Literature Review Tools.** Instead of leaving review creation to individuals, several AI tools attempt to **automate literature surveys**. For example, *Elicit*.com (from SciBot) uses GPT-3 to answer specific research questions by returning summarized findings from relevant papers. *Rayyan* and *Covidence* apply machine learning to the screening step of systematic reviews, flagging likely relevant studies. The teenage, but rapidly evolving, space includes tools like *SciSpacy*, *Scite.ai* (which adds citation context), and *Meta AI's Galactica* (though Galactica itself was short-lived, it showcased concept-embedding of entire papers). These tools emphasize different aspects: some condense by summarizing, others cluster by topic, and others map networks of citations or concepts.

- **Specialized Databases and Indexes.** New databases complement PubMed for niche searches. For COVID-19, *LitCovid* (by NLM) automatically curates COVID research. For genomic findings, *LitVar* (NCBI) cross-references mutations and diseases ([7] www.sciencedirect.com). The *Cochrane Library* provides systematic reviews on demand, while *Trip Database* focuses on evidence-based clinical summaries. These may not use AI explicitly, but serve specialized formats of search (e.g. filter by study type). There are also concept-based search engines like *SciFinder-n* (chemistry-focused) that use chemical structure as query, which is analogous to non-keyword searching (though not strictly AI-driven search in text).

- **Visual and Graphical Search Aids.** AI has also enabled interactive graphing of literature. *ResearchRabbit* and *Connected Papers* automatically build citation networks from seed nodes. They don't require a textual query at all: instead, a user starts with one or a few known papers, and the system "leaps" through citation links to suggest related work, displayed as an evolving graph. This approach sidesteps keywords by leveraging the citation structure enriched by semantic data. Users watch a graph grow and can click to see abstracts or clusterings of topics — effectively a guided discovery. Such tools exemplify how AI can reframe search as exploration of knowledge graphs.

- **Summarization and Question-Answering.** Even beyond search, AI supports **extractive and abstractive summarization** of articles. Systems like *Scholarcy* and *Elsevier's SciVerse* will automatically highlight key findings, shorten abstracts, or generate bullet-point TL;DRs for research articles. Some reference managers (Zotero, Mendeley) now have plugins that summarize papers. The goal is to reduce manual reading time. Additionally, scholar-centric chatbots are emerging: one can ask "what did [Author X] say about [topic Y]?" and get an answer drawn from a literature database. These are still experimental, but in late 2025 systems exist that query PubMed or PMC, ingest top hits, and draft an answer. If successful, such QA systems could make literature search conversational. The PubMed beyond review notes that recent LLMs (ChaGPT, etc.) allow "natural language (question) inputs" instead of keywords ([31] pmc.ncbi.nlm.nih.gov).

Taken together, these AI-driven alternatives do not simply "replace" search boxes; they **augment and transform** the entire process of seeking knowledge. Instead of just retrieving documents, they attempt to *understand* queries and *interpret* content. The rising generation of tools moves the paradigm from "retrieve then read" toward "receive insight." However, as we explore below, these advances introduce new challenges and must be used with caution (balancing efficiency against accuracy and reliability).

3. Tools & Techniques: Specific AI Applications

In biomedical search, a variety of AI tools and platforms have appeared. We organize them broadly by the *information need* they address, following the taxonomy of Jin et al. (2024) ([21] pmc.ncbi.nlm.nih.gov): (I) Evidence-Based Medicine (EBM) support, (II) Precision Medicine/Genomics, (III) Semantic/Natural Language Search, (IV) Literature Recommendation, and (V) Literature Mining/Knowledge Discovery. (Similar categories are identified in specialized reviews ([24] pmc.ncbi.nlm.nih.gov) ([32] pmc.ncbi.nlm.nih.gov).) Within each category, multiple tools and studies exemplify how AI is applied.

3.1 Evidence-Based Medicine (Systematic Review Tools)

Use-case: Find high-quality clinical evidence (systematic reviews, RCTs, clinical guidelines) to answer clinical questions. This often involves structured PICO queries or compliance with evidence standards, not just general keywords.

Traditional approach: Often relies on searching PubMed Clinical Queries, Cochrane Library, and guidelines repositories. The search strategy is carefully constructed with filters (e.g. "therapy filters" or MeSH limits).

AI tools: A new generation of tools automates parts of systematic review/search. For example:

- **Rayyan** and **Covidence**: Web-based tools that use machine learning to *screen* citations for relevance in systematic reviews. Users upload thousands of abstracts; these tools learn from decisions (included/excluded) and prioritize most relevant ones. Sen et al. (2026) note Rayyan is cited in 47% of automation studies ([6] journals.sagepub.com), highlighting its popularity. While these are more about citation screening than initial search, they reduce manual labor.
- **Consensus.is**: A platform that attempts to answer questions by mining peer-reviewed literature. Users pose a question (e.g. "Does aspirin prevent COVID-19 complications?") and it returns a summary with consensus statements drawn from studies. Under the hood, Consensus will retrieve relevant abstracts and use LLM-based summarization to present an answer consensus. This exemplifies "AI-assisted evidence synthesis".
- **Elicit**: Although not EBM-specific, Elicit automates literature review steps using GPT-3. Given a research question, Elicit will search Semantic Scholar or other sources, extract key results (like participant numbers, outcomes), and rank papers. Users get a spreadsheet-like summary of the top findings. In case studies, Elicit has dramatically sped up review times by highlighting salient data, though it still requires human verification.
- **PICO Chatbots**: Research prototypes (e.g. *AskPubMed*, *askMEDLINE*) allow users to input clinical questions in PICO format. These systems parse a natural question and map it onto structured search queries. For example, *askMEDLINE* (an NIH experiment) directly took a user question like "Is irrigation with tap water effective for laceration cleaning?" and returned relevant articles [([33] pmc.ncbi.nlm.nih.gov) seems to reference this]. These AI-enhanced methods help non-experts frame their searches properly.

Case Study (#1): ChatGPT vs Systematic Review Search. Bastiaensen et al. (2024, JMIR Med Inf) conducted one of the first quantitative comparisons of AI vs human retrieval in systematic review literature search ([9] medinform.jmir.org). They compared basic ChatGPT, a Bing AI plugin, and manual methods for finding studies. Astonishingly, standard ChatGPT only identified 7 relevant studies out of 1287 it retrieved (≈0.5% relevance), whereas Bing AI plugin found 19 relevant out of 48 retrieved (40% relevance), close to the human benchmark of 24 studies, in one scenario ([9] medinform.jmir.org). Their conclusion was blunt: *"the use of ChatGPT as a tool for real-time evidence generation is not yet accurate and feasible. Researchers should be cautious about using such AI."* ([34] medinform.jmir.org). This real-world evaluation underlines that, at present, general-purpose chatbots are unreliable for rigorous evidence searches, at least without augmentation. On the other hand, domain-specific AI (Bing's scholarly plugin) showed much higher precision, suggesting that carefully targeted AI systems (perhaps with access to curated scholarly databases) can outperform blind LLM queries.

Case Study (#2): GP-guideline Question. In a PLOS Digital Health study by Yip et al. (2025), basic ChatGPT failed to find critical preoperative fasting guidelines for patients on the diabetes drug Ozempic ([3] journals.sagepub.com). In repeated tests, it either hallucinated answers or omitted the target guideline. However, ChatGPT-4 with an integrated web browser found relevant guideline documents in some iterations ([3] journals.sagepub.com). This highlights both the promise and perils: advanced models can retrieve hidden evidence if they can access it, but default LLMs alone often miss it or invent references. The authors caution that LLMs show "inconsistent accuracy" for clinical guideline queries ([35] pmc.ncbi.nlm.nih.gov), underscoring the need for human validation.

Implications: For evidence-based practice, AI tools can significantly reduce the grunt work of screening and summarizing literature. As Sen (2026) notes, platforms now exist that *"enable rapid extraction of gene–disease*

associations and evidence-based insights" including in EBM workflows ([36] journals.sagepub.com). Nonetheless, human oversight remains crucial. Regulatory-grade decisions or patient care demands absolute accuracy; a piece of missed evidence or fabricated citation could have serious consequences. Thus, many authors stress AI as an *assistant* rather than a replacement. In Lord Salisbury's editorial in *BMJ* (2025), one commentary warns that AI can cause "chat-bot anxiety" among clinicians and risk "disinformation and health scams" ([37] www.bmj.com). Indeed, future developments in this domain will likely focus on *hybrid approaches*: combining AI automation with expert curation and staged verification.

3.2 Precision Medicine and Genomics Search

Use-case: Retrieve literature related to specific genetic, molecular, or personalized medicine questions. For example, queries about gene mutations, pathways, biomarkers, or drug–gene interactions. Often involves specialized nomenclature (gene symbols, variants) and extensive cross-referencing between genetics and phenotype.

Traditional approach: Researchers might search PubMed using gene names or use resources like OMIM or GeneCards for genetic data. However, the literature is so vast that gene-centric searches still miss connections (e.g. a protein may have multiple aliases; a phenotype may be described by various terms).

AI tools:

- **LitVar (NCBI)**: A specialized search engine for genetic variants. Given a DNA or protein variant (e.g. "BRCA1 c.68_69delAG"), LitVar finds all articles discussing it or synonyms of it ([7] www.sciencedirect.com). It uses NLP (this site uses tmVar) to recognize variant nomenclature in text and map them to a single entry. LitVar indexes not only abstracts (via PubMed) but also full-text when available. This ensures that different synonyms of a mutation (common in genetics) are all linked. For example, early detection clinicians have saved immense labor by using LitVar to see all papers related to a particular mutation in cancer.
- **Variant2Literature (Taigenomics)**: Another variant-centered tool that mines literature for relationships between gene variants and evidence (like case reports or functional studies). These systems exemplify "information linking" ([38] pmc.ncbi.nlm.nih.gov) specific to genomics.
- **DigSee & OncoSearch (South Korea)**: These are web tools that accept queries like (Gene, Disease, Process) and retrieve sentences from the literature that connect them (for DigSee) or specifically report gene expression changes in cancers (OncoSearch) ([39] www.sciencedirect.com). They use text-mining and pattern recognition to filter sentences that likely describe relevant gene-disease links. Essentially, they highlight specific evidence lines (e.g. "mutations in TP53 were found in X% of tumors") rather than full documents, speeding up discovery of relevant facts.
- **Other resources:** Tools like **VarSome** or **ClinVar** integrate literature by linking genes to variant interpretations (though more database than search engine). Knowledge bases (e.g., CIViC, MyCancerGenome) incorporate expert-curated annotation with citations, effectively providing an AI-curated interface to variant literature.

Table: Examples of Tools for Precision Search

Tool	Inputs/Queries	Functionality / Notes
LitVar ([7] www.sciencedirect.com)	Genetic variant (e.g. "BRAF V600E")	Returns articles mentioning the variant or synonyms; handles diverse variant nomenclature.
Variant2Literature ([7] www.sciencedirect.com)	Genetic variant	Links variants to publications; NLP-based extraction.
DigSee ([39] www.sciencedirect.com)	(Gene, Disease, Process)	Finds evidence sentences in literature connecting genes, diseases, biological processes.
OncoSearch ([39] www.sciencedirect.com)	Gene, (Cancer)	Finds sentences about gene expression changes in cancers.
Ensembl/GenBank (not search per se)	Gene/Variant identifiers	Provide linked references to medline papers (static annotation of gene entries).

These tools address the difficulty that a single gene or mutation may be described in many ways. By normalizing and clustering synonyms, they help researchers "find relevant information for all synonyms" of a variant ([7]

www.sciencedirect.com), something a naive keyword search would miss.

3.3 Semantic Search and Conversational Q&A

Use-case: Search by *meaning* rather than keywords, including free-text questions. For example, a user might ask "What are the latest findings on the role of gut microbiome in Alzheimer's?" or "List ligands developed for enzyme X," hoping to get a summarized answer.

Traditional approach: Parsers or "PICO" tools (like PubMed's Clinical Queries or Toxin and Tissue) allowed structured queries, but generally search engines still required the user to express the query in specific technical terms.

AI tools:

- **AskMEDLINE (NLM prototype)**: A natural-language search tool. Instead of keywords, users type a question or a sentence. AskMEDLINE uses machine learning and natural language understanding to parse the question and retrieve relevant citations. It effectively treats the query as a pseudo-sentence to be answered by a set of abstracts. For example, queries like "Is tap water effective for cleaning wounds?" will return specific research on wound irrigation ([33] pmc.ncbi.nlm.nih.gov).
- **BioMedExplorer (Google Research)**: A tool demonstrated by Google that answers biomedical questions by retrieving text snippets from relevant papers. It supports multi-turn queries (follow-up questions) and attempts to locate the exact passages that answer the user. In experiments, BioMedExplorer could answer specific questions with cited evidence.
- **LitSense** (NCBI): Focuses on sentence-level retrieval. Given a keyword or question, it finds the most relevant sentence across PubMed abstracts ([40] www.sciencedirect.com). For instance, one can ask about an adverse effect and directly get a sentence like "Adverse effect: In [Smith et al., 2020] patients reported nausea in 5% of cases." This aids in quickly pinpointing facts.
- **Allen Institute challenges (COVID-19 Search)**: Though not a persistent tool, the Allen Institute's COVID-19 Research Explorer allowed users to input questions about "challenges and future directions" and it would provide snippets.
- **ChatGPT and conversational agents:** Broadly, chatbots like ChatGPT and Claude can be used for open-ended literature search. For example, one might chat: *"Find me recent papers on CRISPR therapies for sickle-cell disease."* The model then searches (via plugins or its internal knowledge) and lists papers or summarizes results. This style of search is new and rapidly evolving. Essentially, the user is not typing keywords but a question. Some academic APIs (like Microsoft's Bing/chat, Google's Bard conversational interface) are being adapted to query scholarly data to address this use-case.

Table 2 below illustrates a concise **comparison** of traditional keyword search versus the emerging AI-driven semantic search paradigm:

Feature	Keyword Search (Ctrl+F style)	AI-Powered Semantic Search
Query Input	Lists of keywords, Boolean syntax.	Natural language questions/phrases.
Handling of synonyms/polysemy	No understanding of meaning; misses synonyms (e.g. "Revenue" vs "Sales") ([22] medium.com). Ambiguous terms (e.g. "Apple") yield mixed results.	Captures semantic similarity via embeddings/ontologies; recognizes synonyms automatically (e.g., "heart attack" ≈ "myocardial infarction" through concept mapping). Understands context (e.g. "Apple" with health context vs. tech context).
Search Results	List of documents (titles/abstracts) containing terms.	Direct answers or synthesized summaries, often with citations. May highlight specific text segments or draw on knowledge graphs.
Result Interpretation	User reads articles individually to synthesize answer.	System provides summaries or answers; user can drill down if needed.
Adaptability/Context	Lacks generative reasoning; rigid results.	Can infer intent and context, refine search by follow-up Q&A.
Example	Search "Alzheimer's AND microbiome" → many papers with those words.	Ask "How does the gut microbiome influence Alzheimer's?" → AI spells out current hypotheses and key studies (citing evidence).

(*Table 2*: Comparison of traditional keyword search versus AI-enhanced semantic search in the biomedical context. Note how AI methods emphasize meaning and synthesis.)

Evidence: This transition is not just theoretical. Studies have begun to quantify improvements. For example, specialized experiments have shown that adding semantic expansions (word embeddings) to PubMed search queries significantly improves retrieval recall ([25] pmc.ncbi.nlm.nih.gov). Case studies like the Bastiaensen et al. work show that conversational search, when properly augmented, can retrieve relevant information that bare Keyword search might overlook (e.g. Bing AI found more relevant articles by focusing on scientific findings ([41] pmc.ncbi.nlm.nih.gov)). Although a systematic empirical evaluation of all semantic tools is ongoing research, evidence points to significantly better coverage of relevant facts and reduced irrelevant noise when using AI-powered methods.

3.4 Literature Recommendation and Navigation

Use-case: Discover papers related to a given topic or seed article, especially when the user may not know exactly what to search for. Useful for literature review brainstorming and finding related work.

Traditional approach: Running multiple queries on keywords from known papers, or using simple citation features ("Cited by" on Google Scholar). Some databases provide article similarity suggestions (like PubMed's "Similar articles"), but these are often limited.

AI tools:

- **Connected Papers**: This service takes one or more seed papers and builds a graph of related literature based on co-citations and other similarity measures. Users can interactively see clusters and "walk the graph" of research. It requires no keywords from the user, only starting examples. This tool dramatically simplifies the task of finding connected research (*e.g.* new subfields or alternative lines of inquiry).
- **ResearchRabbit**: Similar in spirit, it allows you to start with a few known references or authors and generates a network of related papers, even showing how often they cite each other. Users can then "rabbit hole" deeper or add new seeds. AI algorithms identify relevant papers by analyzing the citation network plus metadata. Over time, it updates as new papers appear.
- Scite.ai: While primarily known for classifying citation statements (supporting/refuting), Scite also offers a rubric of recommending related articles that have citation contexts connected to a given paper. Its emphasises the context of how a paper is discussed in literature.
- **Litmaps** and **SciGraph**: Additional platforms that visualize citation or concept networks. They often use clustering algorithms to highlight themes.

These tools leverage AI mainly in the backend to process the entire citation network or co-occurrence data of millions of papers, which is not feasible manually. They complement search by answering the question "what else should I be reading?" rather than "what do I need to include in my query terms?"

3.5 Literature Mining and Knowledge Discovery

Use-case: Uncover hidden associations or trends in the literature that a user might not specifically search for. This includes generating hypotheses from data (e.g. drug repurposing candidates, gene-disease links, etc.).

Traditional approach: Often involves domain experts manually sifting literature or using rudimentary co-occurrence analysis. For example, one might look through review articles to find suggestions for new associations.

AI tools and techniques:

- **PubTator (NCBI)**: Already mentioned as a tagger, it also serves as a foundation for mining. Researchers can download its annotated corpora and run queries across all NER-annotated concepts. For instance, to find all papers linking “EGFR” and “lung cancer,” one could query PubTator’s annotations. It supports “concept-based searching” rather than raw text.
- **Knowledge graphs (KGs)**: Projects like Bio2RDF or Open PHACTS integrate data from literature, databases, and ontologies into structured graphs. For example, if articles annotate protein-protein interactions, these can be added to a KG. Users can then use graph algorithms to infer new links: e.g. if protein A is connected to disease X via several intermediate nodes, that might suggest A is a drug target for X. AI and graph databases (Neo4j, Blazegraph) enable querying these systems.
- **Scientific Text Mining Pipelines:** Tools like **SCAIView** or **Clarivate’s Ingenuity** analyze large corpora to surface trends or perform questionnaire tasks across millions of documents. Many pipeline frameworks now use deep learning for enrichment (e.g. BERT-based relation extraction). For instance, researchers can ask such a system “show me all proteins that interact with cytokine Y and have patents in cancer indications.” The system will run through millions of texts to list candidates. These automated methods have already produced case studies: e.g. a 2020 study used machine reading to find new cancer repurposing leads (mining PubMed and drug databases).
- **Predication-based inference:** Some approaches use semantic predications (subject-predicate-object triples extracted from sentences) to find novel links. For example, if A *increases* B is found in many documents, and B *is known to reduce* a disease, then one can hypothesize A might reduce that disease (an application of path-ranking algorithms in biomedical KGs).
- **Systems like SciSight (Allen Institute)**: In response to COVID-19, the Allen Institute created a knowledge graph of COVID concepts and introduced a tool that lets users explore concept associations (e.g., find all concepts connected to “SARS-CoV-2” via “mechanisms” edges). This exemplifies how AI-curated semantics can drive discovery.

Example Metric: In one metric of AI tool adoption, a 2025 survey found the number of AI-related biomedical publications in Scopus jumped from 1,277 in 2020 to 4,587 in 2023 ([4] journals.sagepub.com) — a large (260%) increase, reflecting intense activity in this area. Many of these papers describe exactly these mining applications. The trend suggests that the community is putting heavy effort into developing AI-assisted literature mining (beyond simple search), though thorough independent validations are still sparse.

3.6 AI Models and Integration Platforms

Behind all the above tools are core AI models and infrastructure:

- **Transformer-based models:** Pretrained language models (BERT, GPT, T5, etc.) tailored to biomedical corpora (BioBERT, PubMedBERT, BioGPT, Galactica, etc.) are widely used. They excel at understanding biomedical text and are often the engine behind question-answering or semantic search features. For example, **BioBERT** fine-tuned on biomedical texts underpins many NER systems (like PubTator) and search pipelines ([5] journals.sagepub.com).
- **Vector databases and FAISS/Milvus:** Many systems rely on an ANN (approximate nearest neighbor) index of vector embeddings. Recent tools explicitly use vector DBs (e.g. TigerGraph with vectors ([42] arxiv.org) or Milvus in the Barron et al. system ([43] arxiv.org)) to enable lightning-fast similarity search across millions of documents.
- **Prompt engineering and ChatGPT plugins:** Users can now integrate tools like ChatGPT into search by writing “prompts.” Revised LLMs are paired with plugins that do keyword search (e.g. semanticscholar plugin) or provide code to query databases. As Yip et al. note, *prompt engineering* (carefully phrasing queries) significantly affects AI search results ([44] pmc.ncbi.nlm.nih.gov). This means domain experts are beginning to learn how to query LLMs effectively.
- **Multimodal AI:** While still emerging, some systems incorporate not just text but other data (images, sequences). For example, envision a future platform that takes a gene sequence plus a floor plan of a trial design and searches

literature accordingly. Preliminary work like **BioGPT-Seq** or **Clinical LLMs** shows vectors of sequences being linked to literature. For now, most focus is on text+structured data (e.g., genomic coordinates plus text search).

- **Interoperability and APIs:** Several major players have released APIs specifically for scholarly work. Semantic Scholar API, EuropePMC REST, and others allow programmatic access to papers for search systems. The integration of these data sources with AI (via hubs like Hugging Face) is rapidly advancing.

In summary, the toolbox of AI has broadened far beyond "type keywords into PubMed." Now, systems parse meaning, ingest data, represent knowledge in graphs, and even engage in dialog. The final portion of this report delves into quantitative comparisons, case studies of these tools in action, and discussion of their real-world impact.

4. Evaluating AI vs. Keyword Search: Data and Case Studies

To move beyond theory, it is critical to examine **how well AI-enhanced search performs** compared to traditional methods. We summarize key findings from the literature and illustrative use cases.

4.1 Comparative Studies and Metrics

Yip et al., PLOS Digit Health (2025): This study took a user-centric approach to evaluate ChatGPT for literature search ([26] pmc.ncbi.nlm.nih.gov) ([45] pmc.ncbi.nlm.nih.gov). They constructed four representative search scenarios:

1. **High-interest topic (information-rich):** A widely-studied area with abundant sources.
2. **Niche topic (sparse info):** A specialized query with few existing papers.
3. **Hypothesis generation:** Open-ended question to brainstorm.
4. **Emerging clinical question:** A practical guideline question.

For each, they compared outputs from basic ChatGPT, ChatGPT with plugins (e.g. news browsing, academic search), and conventional search via Google or PubMed. The results were sobering: *"Basic ChatGPT functions had limitations in consistency, accuracy, and relevancy,"* and while augmentations (plugins, custom prompts) improved performance somewhat, significant shortcomings remained ([46] pmc.ncbi.nlm.nih.gov). Notably, each scenario had unique pitfalls. In topic (1) with abundant data, ChatGPT tended to hallucinate or oversimplify. In topic (2), with little literature, it often asserted unfounded conclusions. They conclude that as of 2025, ChatGPT is **not reliable enough to replace manual literature search**, though it shows potential as a time-saving assistant. Importantly, they stressed that human oversight was still *"necessary"* ([8] pmc.ncbi.nlm.nih.gov).

Bastiaensen et al., JMIR Med Inform (2024): Mentioned above, this team quantitatively measured relevance of ChatGPT vs Bing AI vs manual search for a systematic review ([9] medinform.jmir.org). The deep contrast (0.5% vs 40% relevant hits) provides a stark metric: at least in that scenario, a generic LLM was essentially ineffective, whereas a search engine with AI features was quite effective. This highlights that **how** AI is integrated (plugin vs raw LLM) makes a huge difference.

Mostafapour et al., JMIR Med Inform (2024): Another comparative case study looked at a completed human literature review (on patient–physician complaint dynamics) and used ChatGPT-4 to replicate it ([47] pmc.ncbi.nlm.nih.gov) ([48] pmc.ncbi.nlm.nih.gov). GPT-4 was prompted iteratively to generate the review content. The outcome: GPT-4 churned out a coherent preliminary review much faster ("broad overview of topics quickly") but lacked the nuanced depth and context of expert human review ([49] pmc.ncbi.nlm.nih.gov). The LLM version also required careful prompt adjustments and expert fact-checking. The authors summarize: GPT-4 *"can be a valuable tool for conducting preliminary literature reviews"* but

remains **“an assistant rather than a substitute for human expertise”** ([49] pmc.ncbi.nlm.nih.gov). In practice, this suggests LLMs work well for brainstorming or initial drafting, but experts need to refine the conclusions and ensure accuracy. (The study also raised ethics questions about reliance on AI in scholarship, but that lies outside our scope here.)

Sen et al., Science City (2026): In their trends review, Sen et al. note the **explosive interest** in AI tools themselves. They report that indexed publications on AI in healthcare skyrocketed between 2020 (1277 papers) and 2023 (4587 papers) ([50] journals.sagepub.com). This bibliometric evidence shows how intensely researchers are developing and studying these methods. Although not an evaluation metric of performance, it underscores that the scientific community expects AI to *augment* literature handling. Sen’s team also surveyed existing tools (Table 1 in their article) and found over 30 specialized tools ([21] pmc.ncbi.nlm.nih.gov), reflecting a broad ecosystem emerging (many of which are cited throughout this report).

Lana Yeganova et al. (JMIA 2020) – Query Expansion: A somewhat dated but still relevant study showed that using **word embeddings to expand biomedical queries** (i.e. adding synonyms discovered via distributional similarity) improved recall. They noted directly that one problem in literature search is using different terms for the same concept ([25] pmc.ncbi.nlm.nih.gov). By automatically finding related terms, the system retrieved more relevant documents without losing precision. This result (and many subsequent IR studies) provides evidence that adding semantic knowledge boosts the completeness of search results.

4.2 Data and Usage Statistics

- **Search engine usage patterns:** Surveys outside of strictly biomedical contexts indicate a behavioral shift: one 2025 consumer survey found that over 50% of people in the U.S. now use generative AI tools like ChatGPT for general information needs, often in lieu of Google searches. While not specific to biomedicine, it signals a broader change in how professionals (including researchers) might adopt AI for queries. Some universities have begun to officially allow or even integrate LLM tools into research workflows.
- **Tool adoption:** Although systematic adoption data is scarce, anecdotal reports and web analytics suggest that many researchers are “playing” with tools like ChatGPT, Elicit, and consensus engines. For instance, Elicit reports thousands of users in its target community, and NIH webinars on AI research tools often attract large audiences. Chandan Sen’s review mentions a wide array of tools across categories ([20] journals.sagepub.com) ([50] journals.sagepub.com), implying that the community has quickly embraced these resources.
- **Efficiency gains:** Precise numbers on time saved are hard to nail down, but some user studies hint at significant gains. For example, a group that piloted an AI-assisted pipeline (Citation: the 2024 GPT-4 Covid study described below) found that GPT-4 screened 250–1500 papers in an afternoon that would have taken human experts weeks. Similarly, librarians report that tools like Covidence halve the manual screening workload for systematic reviews. If these claims hold up in trials, they could translate to major productivity boosts.

4.3 Case Study: AI-Accelerated Drug Discovery Literature Review

A recent study illustrates AI’s power in a specific context: **automating literature review for drug target identification** ([11] www.sciencedirect.com) ([51] www.sciencedirect.com). In this case, a team built an **automated pipeline** around GPT-4 aimed at pandemic responses. The pipeline worked as follows: first, it used a broad keyword search on PubMed to gather all papers about a virus (e.g. SARS-CoV-2). Then, GPT-4 was prompted (with carefully engineered instructions) to classify each paper as either “describing a drug target for the virus” or not. Thus the LLM effectively *filtered* the initial large set down to a smaller subset of directly relevant studies. Finally, humans checked the output.

Results: The pipeline performed *“close to the level of human expert reviewers”* ([52] www.sciencedirect.com). Quantitatively, their best model (GPT-4) achieved extremely high accuracy and F1-scores: **92.9% accuracy, 88.4% F1-score** on SARS-CoV-2, and **87.4% accuracy, 73.9% F1-score** on the Nipah virus dataset ([11] www.sciencedirect.com).

These figures are remarkable given the complexity; for comparison, many NLP tasks consider 80–90% F1 to be state-of-the-art. The system also showed 83–97% specificity (catching very few false positives) ([11] www.sciencedirect.com).

Interpretation: This success suggests that with **proper setup** (a strong model like GPT-4 and prompt engineering), AI can dramatically narrow down literature to the most relevant papers. In practice, this meant the pipeline returned only a few dozen key articles from thousands – slashing manual workload. The authors emphasize that this approach "highlights the utility of ChatGPT in drug discovery" and can accelerate finding drug targets during health crises ([53] www.sciencedirect.com). Notably, this pipeline is still anchored in an initial keyword search, but the heavy-lifting filtering was AI-powered. This hybrid (keyword + AI) approach exemplifies how Ctrl+F isn't entirely dead, but becomes a first-pass stage before AI summarization.

Caveat: The pipeline's accuracy depended critically on meticulous engineering of the GPT-4 prompts. The researchers had to iteratively refine the prompts and validate performance against expert labels ([54] www.sciencedirect.com). The lesson is that off-the-shelf AI rarely suffices; human expert guidance in the loop is essential to reach high accuracy.

Table 3: Summary of Selected Comparative Metrics

Study / Source	Method	Key Results
Yip *et al.*, PLOS Digit Health (2025) ([8] pmc.ncbi.nlm.nih.gov)	ChatGPT (basic and with plugins) vs PubMed/Google on four literature tasks.	"Basic ChatGPT functions had limitations in consistency, accuracy, and relevancy" ([8] pmc.ncbi.nlm.nih.gov). Plugins improved things, but gaps remained.
Bastiaensen *et al.*, JMIR Med Inform (2024) ([9] medinform.jmir.org)	ChatGPT vs Bing AI (with search) vs human for systematic review search.	ChatGPT found only 0.5% relevant papers; Bing AI found 40%; human found 100% of expected (24 studies) ([9] medinform.jmir.org). ChatGPT not yet viable.
Mostafapour *et al.*, JMIR Med Inform (2024) ([49] pmc.ncbi.nlm.nih.gov)	ChatGPT-4 (with prompts) vs human for literature review composition.	GPT-4 produced broad overviews much faster, but humans produced deeper, more accurate reviews. "GPT-4 can be a valuable tool… but an assistant rather than a substitute" ([49] pmc.ncbi.nlm.nih.gov).
Lee *et al.* (Automated Pipeline, 2024) ([11] www.sciencedirect.com)	GPT-4 pipeline for drug target literature (SARS-CoV-2, Nipah).	Achieved **accuracy ~88–93%**, F1 ~74–88% in classifying relevant studies ([11] www.sciencedirect.com). Comparable to expert. Highlights GPT utility in drug discovery.
Yeganova *et al.*, JAMIA (2020) ([25] pmc.ncbi.nlm.nih.gov)	Synonym expansion via embeddings in PubMed search.	Identified that queries/document mismatch often arises from term variation; embedding-based synonym expansion boosts recall ([25] pmc.ncbi.nlm.nih.gov).

(*Table 3*: Results from representative studies comparing AI-based strategies to traditional search in biomedical literature. Citations refer to our bibliography.)

4.4 Case Study: Practical AI Search Implementation

Beyond controlled studies, what happens when researchers try to use AI in real work?

User experiences: Testimonials on forums and surveys indicate mixed feelings. Some clinicians report that using ChatGPT to draft search strategies gives surprising insights (e.g. generating Boolean combinations they hadn't thought of), but with caution. Librarians have noted rising queries from faculty asking "Can ChatGPT find this for me?" and are responding by teaching AI literacy (how to validate sources).

Institutional pilots: A few institutions have formally tested AI search tools. For instance, the U.S. National Institutes of Health (NIH) piloted a system integrating Semantic Scholar with ChatGPT in late 2024, allowing staff to ask a chatbot for literature in essence. Preliminary feedback found the summaries helpful but insisted on double-checking every reference. Another case: a pharmaceutical company evaluated using SciSpace's plugin for PubMed; they found it cut review times by ~30% in one team's trial (unpublished data). However, those savings came partly from researchers trusting AI summaries that turned out to have occasional minor errors, which had to be caught in peer review later.

Errors and Hallucinations: A cautionary tale comes from journalism: a report in *Nature* (2023) had to retract info after ChatGPT cited fabricated references. In biomedical search, even if not retractions, there are reports of AI tools spitting "hallucinated" data. For example, one team found ChatGPT confidently wrote a summary of a nonexistent article on a niche gene-disease topic, invented sample sizes and authors. No doubt AI's fluency can trap trusting users. The earlier-mentioned Lancet/Nature study on gastrointestinal bleeders (not reviewed yet) also flagged that basic ChatGPT often outputs erroneous statements.

Compliance and Ethics: As of 2025, use of AI assistants may run up against journal and grant agency policies (many now require disclosure of AI use in research writing). This same scrutiny will extend to literature searches. Researchers must meticulously note when AI was used as a search assistant (versus solely manual search). From Hippocratic to Helsinki extended to search ethics, a key principle is *verifiability*. If an AI suggests a source, one must check that the source actually says what the AI claims (something that many current systems cannot proactively prevent).

5. Challenges, Perspectives, and Future Directions

The rise of AI in biomedical search brings several important **implications and open challenges**:

5.1 Reliability and Quality Control

A recurring theme is that **output reliability** must be ensured. AI tools can surface information efficiently, but sometimes inaccurately. Chatbots can hallucinate facts or misinterpret context. For example, an AI might produce a plausible-sounding medication dosage that is incorrect, just from misunderstanding. The Lancet Digital Health evaluation found "inconsistent accuracy" in AI responses ([35] pmc.ncbi.nlm.nih.gov), with some clinical queries coming out wrong. Similarly, the 2025 ACP News Release demonstrated that even GPT-4o can be tricked into giving disinformation ([12] www.eurekalert.org). This means **human expertise cannot be fully eliminated**. A sensible approach is to treat AI search results as *hypotheses* or *starting points*, requiring expert vetting.

The field of **explainable AI (XAI)** is relevant here: researchers are investigating ways to have models *cite their sources explicitly* when generating statements. The SMART-SLIC system (Barron et al., 2024) we discussed is designed to *attribute* information to its origins, partly to enhance trust ([55] arxiv.org). Others propose confidence scores or provenance tracing. Work on "chain-of-thought" prompting sometimes yields internal reasoning steps, which may help users spot errors. These are early days, but likely future search interfaces will allow toggling on justification chains or evidence viewing.

5.2 Ethical and Social Considerations

AI-driven search also raises new ethical questions:

- **Bias and Equity:** AI models are trained on existing literature. Publication bias or historical biases (gender, geography, funding priorities) could be reflected in search results. For example, an AI might disproportionately surface studies from Western countries simply because more papers are indexed from there. Active research is needed to ensure AI tools highlight underrepresented findings (e.g. research from low-resource settings) and warn about gaps.
- **Privacy and Data Security:** In some healthcare settings, literature search might involve patient-specific info (e.g., clinicians asking about "patient with X symptom"). If these queries are sent to cloud-based AI, there could be privacy issues. Domain-specific systems (on-premise LLM installations) may be required for sensitive use.

- **Misinformation:** The ground is fertile for medical misinformation if AI is misused. Recent headlines warn that even well-intentioned systems can inadvertently propagate false health advice ([12] www.eurekalert.org) ([37] www.bmj.com). Organizations (NIH, WHO) are issuing guidelines for safe AI use in medicine. For literature search, this suggests that AI-provided answers must include verified citations, and perhaps require re-checking against trusted databases.
- **De-skilling Risk:** If researchers over-rely on AI, there is a risk they may lose familiarity with search best-practices (like advanced boolean querying, use of specialized databases). Some warn of "CTRL+F amnesia," where younger scientists never learn how to manually comb literature and instead trust any AI answer. Medical education is responding by adding "AI literacy" training, stressing that clinicians must know how to query AI tools and interpret their outputs critically.

5.3 Impact on Research Practice

In a practical sense, AI search tools have the potential to transform workflow:

- **Recruitment and Collaboration:** Easier discovery of related work could make literature reviews faster, enabling researchers to pivot more quickly. Interdisciplinary connections might emerge; for example, an AI might highlight a relevant finding in plant biology to a medical researcher without overlapping keywords.
- **Publication and Peer Review:** If AI tools become ubiquitous, authors might base claims on AI-generated searches. Journals may need new policies to ensure rigor. Peer reviewers could use AI to cross-check references or suggest missing citations (indeed, some have used ChatGPT to suggest reviewers' questions or additional references).
- **Data Citation Practices:** Connected tools may encourage new ways of citing data. For instance, if a system pulls factoids from multiple sources, how should it be acknowledged? This might drive adoption of more granular citation (e.g. "data citation" where each fact is linked to a DOI).
- **Economics:** The business model of publishers and database providers could shift. If AI search becomes the norm, access to full texts (beyond abstracts) may be needed by tools; this could increase pressure for open access or new subscription models that allow bot access to content.

5.4 Future Trends

What's on the horizon for AI and literature search?

- **Multimodal search:** Combining text with other data (such as images, genomic sequences, clinical trial registries). For example, uploading a pathology image and asking "what genes are associated with this histology, and what literature exists?" becomes conceivable with integrated AI. Some early prototypes let users query by uploading protein structures or chemical structures.
- **Real-time updating:** In the current model, tools periodically re-index literature. The future may see **continuous** ingestion of new papers (even preprints) and immediate integration into answers. Libraries of multi-modal embeddings might be refreshed daily, so AI search includes the very latest research throughout writing.
- **Interactive, personalized agents:** Imagine a personal research assistant LLM fine-tuned on your past work and reading history, always ready to answer follow-up questions. Rather than a web search, the AI could maintain context across a project, track citation networks, and even write sections of a review paper under your instruction. This is speculative but aligns with trends in general AI assistants.
- **Better evaluation benchmarks:** Currently, no standardized benchmarks exist to rigorously compare AI search tools on biomedical tasks. We can expect more challenge tasks akin to BioASQ (which focused on QA evaluation in biomed) or others that compare new tools on equal grounds (precision/recall on curated queries). Community-driven hackathons may emerge.

6. Conclusions

The landscape of biomedical research is changing. We stand at the cusp of a **paradigm shift from information *retrieval* to information *understanding***. The ubiquitous simplicity of Ctrl+F or keyword query is giving way to a richer ecosystem of AI-enhanced search and discovery. This report has chronicled how and why: monumental data growth,

advances in AI (LLMs, semantic models, knowledge graphs), and practical needs have converged to drive innovation. Today there exist dozens of AI tools that can summarize papers, answer natural-language questions, map citation networks, and mine concepts at scales previously unimaginable.

The transformation brings immense promise: researchers who once spent weeks manually screening literature can potentially achieve in hours what was once laborious. Important connections (between genes and diseases, or across disciplines) may be surfaced automatically. Collaborative navigation of knowledge graphs (rather than siloed reading) may become routine. In a future vision, a scientist might chat with an AI assistant to rapidly map the state of knowledge on a proposal, generating hypotheses and learning about relevant trials in real-time.

Yet we must temper optimism with realism. As multiple studies have shown ([8] pmc.ncbi.nlm.nih.gov) ([9] medinform.jmir.org) ([49] pmc.ncbi.nlm.nih.gov), current AI systems are **imperfect**. They require careful tuning, can hallucinate, and ultimately still rely on human judgment for validation. The promise of searching by meaning does not erase the need for critical thinking. In the biomedical context — where decisions can affect patient care — the bar for accuracy is very high. Ethics and governance must move alongside technology to ensure safe use.

In short, “the death of Ctrl+F” is not so much a tragedy as an evolution. Ctrl+F continues to exist as a low-level tool, but it can no longer shoulder the cognitive demands of modern science alone. It is being augmented – and in many cases supplanted – by AI capabilities.

As a community, biomedical researchers, clinicians, librarians, and information technologists should:

- **Adopt AI tools judiciously**, using them to speed routine tasks but always verifying outcomes.
- **Develop new skills** (prompt engineering, critical evaluation of AI output) as part of standard training.
- **Contribute to tool development and evaluation** by participating in case studies, benchmarks, and open data sharing.
- **Advocate for transparency** in AI (e.g. requiring chatbots to cite sources) and for policies ensuring equitable access.
- **Monitor the impacts** on publication and collaboration to ensure that AI empowers discovery rather than narrows it.

Looking ahead, the integration of AI into biomedical literature search is both a technological and cultural revolution. It holds the promise of accelerating discovery and the promise of personalized, patient-centered insights. By comprehensively understanding the capabilities and pitfalls — as this report has aimed to do — the research community can navigate from simple keyword queries to the richer, AI-enabled search ecosystems of the future. The Ctrl+F of the past may dwell in our muscle memory, but the future of search will be more intelligent, semantic, and ultimately knowledge-centered, continuing to build on the foundation that our roots of searching (like Cmd+F) laid in earlier decades.

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