

AI, libraries, and literacy: revisiting the *Journal of the Medical Library Association's* policy on the use of generative artificial intelligence in submissions

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In the fall of 2023, the *Journal of the Medical Library Association (JMLA)* introduced its policy on generative artificial intelligence (AI) submissions, predicting that these tools would become embedded within the workflows of clinicians, educators, researchers, and students. Those predictions dramatically underestimated AI's impact. On the three-year anniversary of that editorial, we revisit the issue in light of AI's unprecedentedly rapid adoption across knowledge work. We examine the educational challenges AI poses, arguing that excessive cognitive offloading threatens the deep thinking on which learning depends. We then consider the challenges AI creates for researchers, from hallucinated citations to fabricated diseases. We suggest that health sciences librarians, who offer expertise in approaching information systems with discernment, are well suited to be leaders in this space. To help prospective *JMLA* authors weigh whether and when to use AI, we propose the Compliance, Verifiability, and Disclosure (CVD) Framework. Throughout, we reaffirm our conviction that education and research must remain human-centered endeavors.

Keywords: Artificial Intelligence; information literacy; AI in Libraries; AI literacy; literacy skills; lifelong learning; scholarly communication; scholarly publishing; scholarly writing

INTRODUCTION

In the fall of 2023, the *Journal of the Medical Library Association* introduced its policy on generative artificial intelligence (AI) submissions. In our editorial introducing this policy, we predicted that AI applications would become embedded into the workflows of clinicians, educators, researchers, and students, which would in turn affect health sciences librarianship [1]. Although our policy advocated against unrestricted use of AI tools during manuscript preparation, we recognized the transformative potential of these tools and encouraged the *JMLA* community to explore using them.

Our predictions dramatically underestimated AI's impact [2, 3]. The speed of these tools adoption is unprecedented [4]; by December 2024, ChatGPT users sent more than one billion messages each day, just over two years after its public release [5]. By comparison, it took Google nearly eight years to reach this same one billion daily uses benchmark [6]. In July 2025, over 750 million accounts were using ChatGPT each week, which represents nearly 10% of the global adult population [7]. Rogers' diffusion of innovation theory suggests that AI usage would be concentrated among a handful of early adopters [8], yet these tools are now being used widely among different demographic groups across the world [9]. This widespread integration of AI tools runs contra to early forecasts of how AI adoption would manifest among workers generally and librarians in particular [10, 11].

However, adoption of AI tools in the workplace is not only a reflection of individual workers' preferences. Businesses across many industries, including healthcare, are partnering with vendors to embed AI within their own networks. Firms investing in AI infrastructure are increasingly expecting their workers to demonstrate how they are using AI, with some technology firms evaluating individual worker productivity based on their quantity of AI tool usage. For those of us familiar with Goodhart's Law, this has led to the predictable result of workers performatively using AI in order to appear more productive [12, 13]. Although affirmative adoption of AI remains contested within librarianship [14, 15], AI applications have become so thoroughly integrated into enterprise software that refusal to use AI is no longer tenable for many information professionals [16]. These tools' rapid ascension has prompted us to revisit generative AI on the three-year anniversary of our previous editorial on AI.

EDUCATIONAL CHALLENGES CREATED BY AI TOOLS

The most advanced AI models appear superintelligent, responding accurately and rapidly to complex questions designed to assess clinician reasoning skills [17]. Although the most robust models often require subscription fees to access, even free versions of AI tools can interpret and answer quantitative and qualitative questions alike [18].

Yet the ubiquity of AI has proven double-edged: AI's presence within workplaces and classrooms invites workers and students to become overly reliant upon it [19]. Early evidence on the integration of AI into workplaces and educational settings suggests that using these tools does not facilitate permanent skill development [20], and in fact may inhibit learning new skills [21].

That AI tools could inhibit learning follows from our understanding of how humans learn: deep thinking is essential for learning new things [22]. Repeated exposure to concepts and intentional practice applying skills improves retention and transfer [23], which are essential for promoting lifelong learning [24]. However, thinking is a cognitively intensive task that can be psychologically unpleasant in the short term, so learners often seek to avoid cognitively challenging tasks when possible. Educators account for this by designing "desirable difficulties," assignments that push students to persevere past these difficult thresholds and to achieve real learning [25]. AI tools can disrupt this model of learning, as they present a ready means for students to solve assignments that instructors use to create desirable difficulty.

AI tools' capacity to trivialize major assignments has led to concerns that AI will promote maladaptive, excessive cognitive offloading behaviors among students. Excessive use of these tools within classroom environments may limit students' ability to internalize knowledge and to think critically [26]. Excessive cognitive offloading is most likely to occur when novices are allowed to use AI tools without guardrails. Large language models have a handful of critical limitations baked into their probabilistic design that ensure that they can never be unfailingly correct in all instances [27]. However, novices learning about a new topic lack the prior knowledge needed to recognize when an AI is offering mistakes in facts or interpretations [28]. This portends a vicious cycle: students who become reliant upon AI will fail to gain the lasting, broad-based knowledge of the world needed for critical thinking, which will in turn push the learners to use AI for even more tasks.

Yet cognitive offloading is not inherently maladaptive [29]. Because the human's brain capacity to store information within long-term, short-term, and working memory is limited [30], without cognitive offloading, humans' ability to perform analytical reasoning is limited by the knowledge they can store in their mind at one time [31]. The development of literacy enabled humans to write down and physically store knowledge elsewhere until it was needed, leading to the creation of libraries and librarianship [32]. The human brain's ability to use literacy to offload and onramp knowledge is why libraries eventually became essential infrastructure for modern health care and the scientific research enterprise [27]. As curators of cognitively offloaded knowledge, librarians have a clear role to play in guiding novices' use of AI tools.

RESEARCH CHALLENGES CREATED BY AI TOOLS

While the term "novices" often connotes students, researchers publishing outside of their narrow band of expertise can cognitively behave like novices. The downstream effects of researchers using AI tools to publish outside their areas of expertise are no longer hypothetical. Hallucinated citations to non-existent papers are now a common occurrence within published papers [33]. AI tools have been linked to a massive increase in low-quality manuscripts [34], a trend so intense within computer science that the preprint server arXiv suspended accepting review article submissions in early 2026 [35]. Perhaps most concerning for health information professionals, intentionally fake diseases loaded into large language model's training data are now cited as true conditions [36]. Because AI tools are correct in most instances, students and researchers alike can become accustomed to trusting the validity of their outputs, even if they know that these tools can facilitate fraud and make mistakes that are obvious to a human expert.

Yet despite these negative externalities, the scientific research community remains split on the role AI should have within research workflows. These opinions range from viewing AI as antithetical to the humanistic enterprise of genuine scientific inquiry [37], believing AI will transform every aspect of research [38], and everywhere in between [39]. Given these deltas, consensus among researchers on the appropriate roles for AI in research is unlikely. This creates another opportunity librarians and information scientists to take a leading role in guiding ethical adoption of AI.

IMPLICATIONS FOR HEALTH SCIENCES LIBRARIANS

As domain experts in information systems, librarians and information professionals are poised to become leaders in how AI is implemented into research workflows. But to earn a space at the leadership table, librarians must be able to articulate clear guidance on AI use that is grounded in our broad conceptual knowledge about information architectures, our deep expertise in navigating information systems, and our own professional ethics. We suggest three criteria for information professionals to foreground during discussions over whether to use AI tools in research workflows: compliance, verifiability, and disclosure. Though not comprehensive of all ethical considerations, the Compliance, Verifiability, and Disclosure (CVD) Framework provides pragmatic, domain-agnostic guidance for weighing whether and when to use AI tools within research. These criteria are summarized in Table 1.

Compliance recognizes that practical or legal constraints limit tasks that AI can be used for. Local institutional review boards, and journal editorial staffs, have wide ranging policies that span from extremely restrictive to very permissive. Prior to using AI, researchers should

ascertain whether their data or other materials are permitted to be uploaded into a large language model in the first place.

Table 1		
The Compliance, Verifiability, and Disclosure (CVD) Framework for AI use in research workflows		
Criteria	Guiding Question	Professional Implication
Compliance	Are you allowed to use AI for this task?	Rely on forward guidance from relevant ethics groups (e.g., Institutional Review Board) or prospective publication outlets (e.g., journal policies).
Verifiability	Are you capable of confirming the validity of an AI's output for this task?	Do not use AI tools to perform tasks that you do not know how to do yourself. And have verified the veracity of the output.
Disclosure	Are you prepared to describe (in detail) how you used AI during your research?	Only use AI for tasks that you would be willing to disclose to a counterparty (e.g., stakeholder, supervisor, journal editorial staff), and be prepared to describe exactly how AI was used.

Verifiability recognizes that a researcher's prior knowledge and existing expertise should dictate what tasks an AI performs within a research process. This consideration suggests that researchers should only use AI tools to complete tasks they already know how to do. If a researcher cannot perform a given task using other means, then they cannot be confident in the validity of the AI's output. Moreover, verifiability requires researchers to critically evaluate AI outputs against trusted, gold standard sources of evidence in addition to relying upon their own expertise [40].

Disclosure recognizes that researchers have an intuitive, personal sense of what tasks an AI should or should not perform on their behalf. If a researcher feels hesitant to acknowledge their use of AI to perform a task, it indicates their own recognition that they ought not to have used AI to do it.

GUIDANCE FOR PROSPECTIVE JMLA AUTHORS

We remain skeptical of unrestricted use of AI tools within research. The *JMLA* editorial team wants its authors to grow and learn through process of conducting practitioner-based research. We see every task offloaded to an AI as a lost opportunity to potentially learn

something new. To that end, we view writing as a unique and valuable form of thinking [41], through which a researcher decides which information to share with readers and how best to communicate it. Engaging deeply in the writing process is an essential step for understanding your own findings and for identifying which components of your work are worth highlighting. Authors who elect not to use AI when writing their manuscripts will likely have a richer understanding of their own work and may be better equipped to respond to reviewers' comments and critiques.

For authors who wish to use AI tools as part of their workflows, we encourage *JMLA* authors to carefully consider the CVD Framework described in Table 1. Consult your local institutional review board prior to instigating a study. Be careful about offloading tasks to an AI that you do not already know yourself. Be prepared to proactively disclose, in detail, the full extent of how AI was used during your study planning, data collection, data analysis, and manuscript preparation.

Authors that elect to use AI must ensure that, as the human authors assuming responsibility for the content of their manuscript, they retain authorial control of their research outputs. Table 2 offers a comparison of Not Recommend Practices and Recommended Practices. While opinions on these specific examples will vary, we believe these are emblematic of our broader belief that research within health information science is a human-centered process: performed by humans for the benefit of humans.

Table 2		
Possible approaches to using AI within manuscript preparation. Not Recommended Practices depict an author ceding excessive authorial control to an AI, while the Recommended Practices depict authors remaining in control of the writing process.		
Manuscript Section	Not Recommended Practices	Recommended Practices
Abstract	"I have attached my draft manuscript. Please write me a structured abstract that is fewer than 250 words."	"My draft abstract is below. I am currently at 260 words and need to get down to 250 words. Can you identify any words I could remove without altering the meaning of the section?"
Introduction	"I have attached a draft Methods and Results section for my paper. Please find me relevant citations from the literature and then use those citations to craft a five-paragraph Introduction section that justifies my study."	"Below is a draft of my Introduction section. Does each paragraph have a comprehensive topic sentence that explains what the remainder of the paragraph will discuss?"

Methods	"I have uploaded a copy of my IRB application. Use the protocol within the document to write several paragraphs of prose for my Methods section."	"Below is a draft of my Methods section. I have attempted to write the section chronologically. Are there any sections that appear out of order, or that may be unclear to a reader?"
Results	"Run some inferential statistics on these data and report any significant findings."	"I am planning to visualize these data using a vertical bar chart. Are there any other chart types that I could consider using?"
Discussion	"What is interesting about my data?"	"What are some of the limitations of my research design that could be improved upon in future work?"

For *JMLA* authors who plan to use AI tools as their research assistants, copyeditors, and internal reviewers, we close with one final note to consider: large language models lack an analytic, human mind [42]. While AI tools invite anthropomorphism through their use of natural language and their impressive capabilities across domains [42], large language models cannot read [44]. Their ability to use word sequences to detect patterns within text is remarkable, but it is categorically a different process than how humans learn to read [45]. Likewise, although large language models can rapidly produce volumes of text, the language model has no understanding of what these words mean; the text they create is best described as what Shakespeare's King Claudius called "words without thoughts" [46]. Though AI can produce literary text rich with simile and metaphor [47], the *sui generis* figures of speech created by AI lack the grounded human meaning that made The Bard's dialogue so inimitable [48].

Conducting original research is an opportunity for librarians to make their mark on the research record, and to make the case that humans are central to the work of information and data. Researchers who offload their brainstorming, hypothesizing, and interpreting onto a large language model are taking ideas from a machine that cannot think; authors who offload their editing process onto a large language model are taking advice from a machine that can neither read nor write. We urge caution against removing ourselves out of these processes entirely.

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Causal inference methods for systematic reviews

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Systematic reviews are frequently used to ask and answer causal questions, and decisions made throughout the review process can introduce bias because of the causal relationships between variables of interest, even when the question being asked is not itself causal. However, current systematic review best practices do not consider most of these impacts.

The author presents an introduction to the basic principles and terminology of causal inference as apply to systematic reviews and discusses how some simple causal inference concepts can be used to create clearer and less biased research questions, search strategies, eligibility criteria, and data analysis. By taking into account confounder and collider bias, and by paying careful attention to the differences in assumptions made in intervention- and non-intervention-based reviews, health science librarians can aid systematic review teams in minimizing the risk of bias, and in appropriately analyzing and assessing that risk.

Keywords: Systematic review; causal inference; methodology; confounder bias; collider bias

INTRODUCTION

Systematic reviews, like many evidence-based practice (EBP) tools, are often used to ask and answer causal questions. The PICO framework, frequently used and recommended to guide question formation in reviews, is focused on the outcomes of interventions. Researchers want to learn the effect of interventions on the patient, to better inform the practices of clinicians.

But the causal element of systematic reviews is not limited to question formation. Just as in a primary study, nearly every step in the systematic review process can have a profound impact on the reliability of the information procured, even when the question being asked is itself not causal. Decisions made about exclusion criteria, search strategy, and data analysis can introduce not just selection bias, but other subtler inaccuracies, because of the causal relationships between the factors being measured and studied. In particular, any review of non-intervention studies, such as cohort and case-control studies, is at risk for introducing bias both through the individual studies collected and through the process used to collect them. However, many current EBP best practices for systematic review do not take into account most of those impacts [1].

Librarians are often included on systematic review teams in order to help write and run the search strategy. However, that is not the only role that librarians can or do take in systematic reviews; librarians are often called on to advise or assist with question formation, protocol development, database selection, and other elements of a review that can be profoundly impacted by causal considerations [2]. Outside of reviews proper, health

sciences librarians often have a significant role in teaching researchers and clinicians the EBP tools that form part of the systematic review process, including research question formation, critical appraisal, and some basic statistics and outcomes reporting needed for evidence evaluation [3]. As both practitioners and teachers of systematic review methods, it is therefore vital that health sciences librarians understand the ways that causal relationships affect the input and output of these tools.

Causal inference is an approach to statistics and data analysis that is concerned with determining whether associations within data are due to causal relationships. This paper presents some basic causal inference principles that are applicable to the systematic review process and discusses how health sciences librarians can use them to create and teach clearer and less biased research questions, search strategies, eligibility criteria, and data analysis.

DIRECTED ACYCLIC GRAPHS

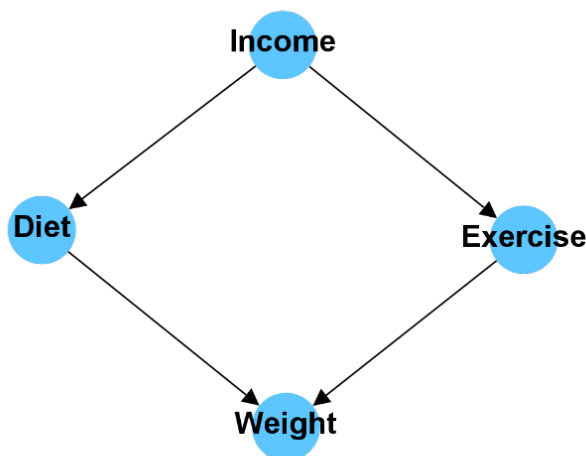
One of the foundational tools in the causal inference toolbox is the *causal graph*. A causal graph represents the causal relationship between variables; each variable is a node in the graph, and arrows (*directed edges*) between the nodes represent the direction of causality [6]. A *directed acyclic graph* (DAG) is one in which none of the arrows form a cycle.

Causal graphs are best understood as a visual depiction of the *data-generating process*: the story of how the variables in question came to take on the values we see in the data. Because of that, a causal graph implies consistent and testable independence relationships between variables in

the data. Two variables are dependent in a data set if values of one variable are associated with, or predictable from, changes in the other. Two variables are independent if their values are not related. Based on a causal graph, we can predict whether two variables will be dependent or independent of each other. We can also predict whether they will be independent *conditional on* a third variable, that is, after controlling for or stratifying on values of another variable in the graph. These relationships are called *conditional independence relationships*.

Conversely, if we know the causal graph underlying a data set, we can use the graph to rigorously make decisions about how to interpret the data. Or, in the case of systematic reviews, how to seek out data while minimizing the risk of certain kinds of bias. This paper will discuss the inferences we can make based on two different kinds of graph structures: *confounders* and *colliders*.

Figure 1 A directed acyclic graph (DAG). In this graph, Income is a confounder of Diet and Exercise, and Weight is a collider of Diet and Exercise. Income is a parent of Diet and Exercise, and an ancestor of Weight. Weight is a child of Diet and Exercise, and a descendant of Income.



Confounders occur when one variable is the *parent* (direct cause) of two other variables; the parent variable *confounds* the relationship between the children [5]. The child variables are dependent in general, but are independent conditional on the confounder. For instance, income level has a significant impact on both diet and exercise [7, 8]. It therefore confounds the relationship between those two variables. People with sedentary lifestyles might be more likely to eat less healthy food, not because either diet or exercise is cause of the other, but because both are effects

of lower income. *Confounder bias* occurs when researchers fail to control for a confounder, causing two unrelated variables to appear related.

Colliders occur when one variable is the *child* (direct effect) of two other variables [4]. When that happens, arrows from the two parent variables “collide” at the child variable. For example, diet and exercise are both factors that influence body weight. In a causal graph, weight is a child of both variables, and thus a collider. Colliders occur often in health care, and can create serious bias, but they are less widely understood than many other sources of bias [9].

QUESTION FORMATION

As part of the process of developing a search strategy and advising researchers on methodological concerns, librarians are frequently called upon to participate in and comment on the development of the research question itself [2]. This often takes the form of helping to define the scope of the review: what populations, subpopulations, specific treatments, article types, and so on will be included. Decisions made in shaping the research question have major impacts on the outcome of the review, including the amount of bias—because the research question is one significant place where confounder bias might make its way into a review.

The PICO framework (patient/problem/population, intervention, comparison/control, outcome) is the most widely used system for constructing a research question for systematic reviews, recommended in authoritative resources such as The Cochrane Handbook [10]. Although the PICO framework appears simple, constructing a question using it can be deceptively complex. The elements of a PICO question, particularly population, can be multifaceted. When constructing a research question about the relationship between brain rest (intervention) and recovery time (outcome) from concussion (population), for instance, should our population be all people with concussion? Should it be people with minor concussions or major concussions only? Should we limit our population to *athletes* with concussion, or children with concussion, or people with pre-existing migraine and concussion? In causal inference terms, when we’re determining whether “brain rest” and “concussion recovery time” are dependent, should we condition on concussion severity, age, or comorbidity?

Logic models, or theories of change, are often cited as a tool for making these “lumping” vs. “splitting” decisions in literature reviews [10, 11]. Logic models are similar to a causal graph in that they provide a visual organization of the flow of causation. But there is little practical advice on how to construct or interpret a logic model causally, or how to use one to identify confounders. And yet, because of confounders, lumping and splitting decisions can have

a profound impact on the results that a systematic review produces.

Consider, for example, that you are consulting on a systematic review of the effectiveness of a new kidney stone treatment. Together, you construct a question using the PICO framework: “Does New Treatment have a higher single-treatment clearance rate than Old Treatment for kidney stones larger than 2 cm?” The researchers’ justification for limiting the population is that stone size can have an impact on treatment success, and therefore it is sensible to examine the new treatment’s impact on the most severe disease. But after an initial pilot search returns a relatively small number of results, the researchers want to consider expanding the population to stones of all sizes: “Does New Treatment have a higher single-treatment clearance rate than Old Treatment for kidney stones?” How would you advise them? What tools would you use to do so?

Causal inference provides a rigorous method for deciding lumping and splitting questions. This method, called the *backdoor criterion*, is used to decide whether or not we should condition on a variable when determining the relationship between a treatment and an outcome (12). The backdoor criterion tells us that we should only condition on that variable if it lies on a “backdoor” path between the two—that is, if in the DAG representing the causal relationships, the variable lies on a path between treatment and outcome where the arrows point *towards* the treatment and *out of* the outcome.

The first step in using the backdoor criterion to decide on the kidney stone problem would be to advise the researchers to construct a formal causal graph, using their own subject matter expertise and a background review of the subject. In doing so, they would hopefully come across a 1986 paper by Charig et al. that performed an observational comparison of three different types of kidney stone treatments [13], whose results are shown in Table 1.

Table 1

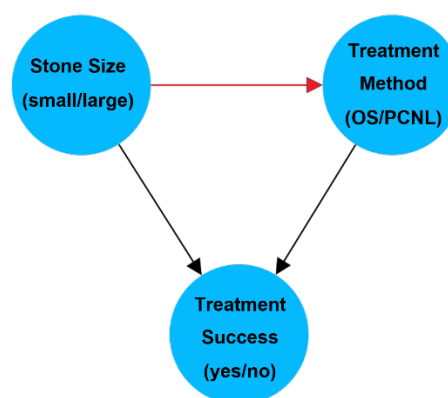
Success rate of open surgery vs. PCNL in removing kidney stones (13).

	Open Surgery success rate	PCNL success rate
Stone diameter < 2cm	81/87 (93.1%)	235/270 (86.7%)
Stone diameter ≥ 2cm	192/263 (73.0%)	55/80 (68.8%)
Total (all stones)	273/350 (78.0%)	289/350 (82.6%)

According to their data, open surgery was more effective at clearing kidney stones than percutaneous nephrolithotomy (PCNL) in patients with small stones (93.1% of stones were cleared with open surgery, vs. 86.7% of stones cleared with PCNL). And open surgery was more effective at clearing kidney stones than PCNL in patients with large stones (73% of stones cleared with open surgery, vs. 68.8% of stones cleared with PCNL). Conditional on stone size, open surgery was more effective than PCNL. But when the data of small stone and large stone patients were aggregated, the results were reversed: PCNL (82.6%) cleared stones more frequently than open surgery (78%). In this case, the question of whether to lump or split the population is critical to the outcome.

Charig et al.’s results are both illustrative of the importance of thinking critically about lumping vs. splitting questions and a helpful indicator of how the researchers’ causal graph should be constructed. It was eventually determined that the seemingly paradoxical results that Charig et al. found were because of a particular kind of confounder in the DAG, shown in Figure 2 [14].

Figure 2 A DAG representing the causal relationships between the variables in Charig et al.’s study. Stone Size is a confounder of Treatment Method and Treatment Success. The “backdoor” arrow into Treatment Method is highlighted in red.

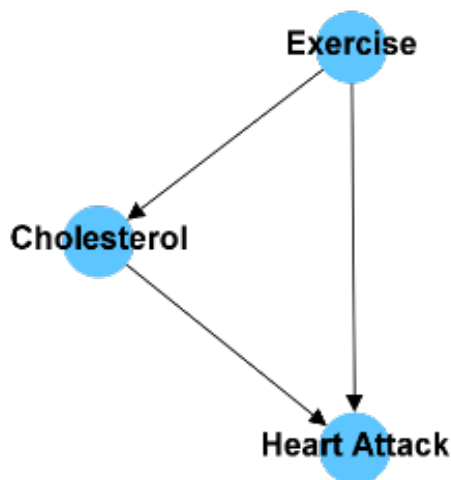


The confounding occurred because the stone size and treatment method were both a cause of treatment success, *and* stone size was a cause of treatment method. Doctors were more likely to prescribe the less aggressive, newer treatment to smaller, easier-to-treat stones, which biased PCNL in favor of a high stone clearance rate. Once we see the causal graph, we can see that Stone Size satisfies the backdoor criterion, because it is not caused by Treatment Method, and it blocks the only “backdoor” pathway (one in which there is an arrow into Treatment Method)

between Treatment Method and Treatment Success. In order to get the correct estimate of the efficacy of the treatment, we therefore need to condition on stone size—separate our analysis, our results, and crucially, our research question, into small-stone and large-stone categories. So for our hypothetical researchers, we would advise them to either use their original research question, or if they feel they need to broaden the scope, to include another limitation that addresses the problem of confounding, such as only considering randomized controlled trials.

In addition to confounder bias, the backdoor criterion can also help to avoid *overadjustment bias* in question formation. Overadjustment bias is the opposite of confounder bias; it occurs when controlling for a variable creates bias in data analysis. Not only is it not feasible to condition on every possible confounder in our population, controlling for the wrong variables can introduce bias in a number of ways. The most immediately obvious is that if a presumed confounder is instead a *mediator*—a variable that is part of the process by which a treatment affects an outcome—then by controlling for it, we can make the impact of the treatment on the outcome look smaller than it really is.

Figure 3 A DAG of the causal relationships between exercise, cholesterol, and heart attack risk. Cholesterol mediates the effect of exercise on heart attack. It does not lie on a path with a “backdoor” into Exercise.



For instance, regular exercise reduces heart attack risk. It does so in part by reducing cholesterol, which in turn reduces heart attack risk (15, 16). In a study of the effect of an exercise program on heart attack, controlling for cholesterol would reduce the effect size. Sometimes that's desirable; *mediation analysis* is a type of data analysis in which researchers use similar techniques to determine the amount that particular mediators contribute to overall effect. But if we treat cholesterol as a confounder, we will

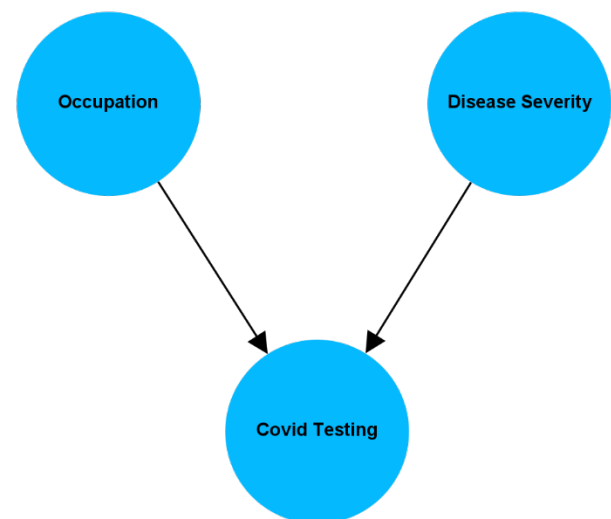
introduce bias that makes exercise look less effective than it truly is at reducing heart attack risk (See Figure 3). If we were consulting with researchers performing a review of the overall impact of exercise on heart attack risk, we could use the backdoor criterion to advise them not to include cholesterol as an element of the population in their research question.

COLLIDER BIAS

Another common form of overadjustment bias, and one which is frequently overlooked, is *collider bias*. When we condition on a collider, or on a child of a collider, we create an association between the two parent variables, even if none existed before. The parents are independent in general, but dependent conditional on the collider.

Collider bias often appears as a form of selection bias. For instance, collider bias appeared in early COVID-19 studies [17]. Early studies were performed using the available testing data, which at the time featured a significant oversampling of severe cases (who were more likely to be hospitalized and therefore tested) and healthcare workers (who were more likely to test frequently, due to their risk) [18].

Figure 4 A DAG representing the causal relationships between occupation, COVID severity, and COVID testing early in the COVID-19 pandemic.



The use of those studies created collider bias, in which it appeared that being a healthcare worker was protective against severe covid, because in that sample, healthcare workers were significantly less likely to have severe covid than non-healthcare workers.

Any situation in which we limit or stratify our sample has the potential to introduce collider bias, if decisions are not made in a careful and informed way. In PICO-based systematic reviews of experimental studies, collider bias is of most concern during data analysis, where teams that stratify their results based on study quality [19] or symptom or disease severity [20] can create a non-existent association between the variables they're interested in.

However, many systematic reviews include studies with non-experimental designs, like cohort and case-control studies. And not all systematic reviews are interested in the outcome of an intervention. Some are interested in the effects of an exposure (for instance, lead exposure, or diabetes) on an outcome (for instance developmental delays, or heart attack). Others are interested in the accuracy of a diagnostic test for a particular condition. These non-intervention reviews are at risk of collider bias at nearly every stage of the review.

Question Formation

In question formation, collider bias may arise if the population is causally linked to the outcome and the exposure. For instance, a review with the research question, "Does gallbladder inflammation exacerbate type II diabetes among hospitalized patients?" might induce collider bias by limiting the population to inpatients, because both the exposure (inflamed gallbladder) and the outcome (diabetes) are causes of being hospitalized [20]. This might make it appear that gallbladder inflammation is associated with less severe diabetes – because the sample would include a large number of people with severe diabetes but no gallbladder problems (who were hospitalized because of diabetes), a large number of people with mild diabetes and inflamed gallbladders (who were hospitalized because of gallbladder disease) and a very small number of people who just happened to have both gallbladder inflammation and severe diabetes. A better framing of this question might be setting-agnostic; that would capture the population of patients with mild diabetes and no gallbladder inflammation, who are unlikely to be hospitalized. This is particularly important to keep in mind when using alternative question frameworks such as SPICE (setting/population/intervention/comparison/evaluation) or PCC (population/concept/context) that more explicitly take setting into account.

Search Strategy

Collider bias may occur in the search strategy, if any database limits or search filters used are causally linked to elements of the research question. For instance, a team performing a review of the effect of kidney disease on heart attack risk might decide that they want to limit their search to clinically useful journals. But clinically useful journals are more likely to study and report on subjects in a clinical context, and health-care utilization is a collider

[9]. Both kidney disease and heart attack make people more likely to interact with physicians and other clinicians, so if search results are biased in favor of health care settings, we might again find a spurious association in which it looks like kidney disease is associated with a lower risk of heart attack, because we are missing out on the population of patients with low heart attack risk and no kidney disease.

Study Screening

In study screening, eligibility criteria might create a collider. For instance, study setting is a common eligibility criterion in systematic reviews, but excluding studies performed outside (or inside) a hospital can introduce collider bias. Before creating an exclusion criterion, review teams should assess whether it might be a downstream effect of the exposure, the outcome, or both.

Data Analysis

Most vitally, collider bias may occur in the data of the synthesized studies. Collider bias is a risk of any non-experimental study, even when the study draws from a very large sample, especially if that sample self-selects in any way. For instance, studies of the link between genetic variation and phenotypes (such as the expression of a genetic disease, or disease severity) often rely on gene banks for their data. But genes may influence factors that make people more or less likely to participate in a gene bank, making study participation itself a collider [21]. Most risk-of-bias assessment tools, however, do not ask about the possibility of collider bias in the study being assessed [1].

Collider bias is particularly troubling because it can create the appearance of associations that do not actually exist. Approaching a non-intervention systematic review with an understanding of causal inference can help reviewers to construct reviews that minimize the risk of creating those spurious correlations, and to appropriately analyze and report that risk. Although librarians are not always asked to collaborate on all of these stages of a review, when they are, they can help the teams they work with to minimize collider bias by encouraging the construction of a well-founded causal model before decisions are made about databases, exclusion criteria, and search filters. Librarians advising on risk-of-bias tools for non-intervention reviews can minimize collider bias by suggesting tools, such as ROBINS-I [22], that ask about the possibility of overadjustment.

DISCUSSION

Systematic reviewing, and evidence-based practice writ large, are a discrete set of practical tools for performing research and making clinical decisions. But they could equally be said to be a mindset: a way of viewing data, research, and literature search that aims to understand the

source of information, appraise its reliability, and minimize bias in its analysis and reporting.

Individual health sciences librarians can use causal inference to improve the evidence synthesis reviews that they participate in, and their instruction on the component EBP tools of reviews, by incorporating causal inference into that mindset:

- Encourage the development of a well-founded causal model before making decisions about the structure of a review, particularly in non-intervention reviews.
- When discussing question formation, in addition to considering the feasibility, relevance, and logic of the question, make sure that team members or students understand the potential causal implications of limiting or not limiting the population. In non-intervention reviews, consider whether the population might be a common effect of the exposure and outcome.
- When participating in non-intervention or non-experimental reviews, consider collider bias when deciding on and reporting on search strategies and eligibility criteria. During search, consider whether any filters or limits used might be a downstream effect of a collider such as healthcare utilization. During screening, pay attention to exclusion criteria that may be causally connected to the exposure and outcome. During data analysis, recommend risk of bias tools that ask about overadjustment and collider bias.

The specific EBP guidelines and tools used and recommended for systematic reviews could also benefit from incorporating causal inference methods. Critical appraisal and risk-of-bias tools of non-intervention studies might include questions appraising collider bias. Question formation frameworks might benefit from structured guidance on how to select elements in causally consistent ways. Better guidance could be developed for when logic models are and are not appropriate tools for assessing causation and justifying a theory of change, and for how to construct them in ways that clearly lay out their causal implications.

When a librarian's role in a systematic review grows outside the boundaries of designing the search, the role often becomes that of the custodian and record-keeper of the review's methodology—to understand and advise on how the decisions made in the design, implementation, and reporting of the review may impact its results, and to ensure that all of those decisions are documented so that others in the future can understand what happened. Librarians in these roles become keepers of the *how* and the *why*: How did this review come to be? Why did we use

these keywords? How did we find these studies? Why did we decide to keep some and discard others?

How and *why* are causal questions, and the best-prepared librarian will be the one who knows not just the answers, but what the answers mean. With the tools causal inference provides, we can prepare ourselves to give knowledgeable, evidence-based guidance to the researchers we work with, to help them get and understand the answers they're looking for.

DATA AVAILABILITY STATEMENT

There are no data associated with this article.

AUTHOR CONTRIBUTIONS

Madelyn Glymour: Conceptualization, investigation, visualization, writing – original draft, writing – review & editing.

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The *All of Us* dataset in scientific research: a bibliometric study of its utilization through 2024

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See end of article for authors' affiliations.

Objective: This study presents a comprehensive bibliometric analysis of research publications utilizing the *All of Us* Research Program dataset to characterize publication trends, collaboration networks, key research topics, and compliance with *All of Us* publication and presentation policies through December 2024.

Methods: A total of 561 publication titles were collected from the *All of Us* Publications Directory. Titles were then searched across Web of Science (WoS), Scopus, and PubMed, with WoS (475 publications identified) selected as the primary source for analysis. Productivity metrics, including publication growth, journal distribution, author productivity, and word frequency, were analyzed using Biblioshiny. Co-authorship and keyword co-occurrence networks were visualized in VOSviewer to reveal collaboration structures and emerging research themes.

Results: Among the 475 analyzed publications, 2,803 authors were identified across 211 journals. The annual number of *All of Us* publications increased by 82.45% from 2015 to 2024. Major research themes included epidemiology, chronic conditions, genomics, and health disparities, with dermatology emerging as a particularly active area. Network analysis revealed strong intra-institutional ties and some cross-institutional collaborations, primarily among R1 universities.

Conclusions: This bibliometric study demonstrates a rapid rise in scholarly activity leveraging the *All of Us* dataset, characterized by concentrated author and institutional engagement. These findings highlight both the growing impact of the *All of Us* dataset and opportunities to foster broader collaborations and diversify participation across the research community.

Keywords: *All of Us*; bibliometric analysis; publication trend; collaboration network; VOSviewer; Biblioshiny; dataset utilization; policy compliance



See end of article for supplemental content.

INTRODUCTION

The *All of Us* Research Program [1], led by the National Institutes of Health (NIH) and launched nationally in May 2018, represents a pioneering initiative aimed at accelerating biomedical research and improving health outcomes for all. The program seeks to build one of the largest, most comprehensive, and most broadly accessible biomedical datasets in history, with a goal of enrolling over one million participants from diverse backgrounds in the United States, including underrepresented communities. As of July 2025, over 865,000 individuals have enrolled, with 745,000+ completing initial steps [2].

With the generous contributions of participants, the *All of Us* program has achieved enormous scale and impressive diversity. The program curates a comprehensive dataset that encompasses various health-related dimensions, including health questionnaires, electronic health records (EHRs), physical measurements, wearable devices, and

genomics data [3]. Through the *All of Us* Research Hub (available at <https://www.researchallofus.org/>), researchers gain access to three tiers of data, ranging from aggregate data available to the public to individual-level data accessible via the Registered and Controlled Tiers [4]. The *All of Us* Researcher Workbench [5], launched in May 2020, is a collaborative platform that enables approved researchers in the Registered and Controlled Tiers to use cloud-based computing environments to analyze the *All of Us* data and pursue scientific inquiries.

Since the access to *All of Us* dataset expanded through the Researcher Workbench, scholarly output using the dataset has grown. Researchers are actively leveraging *All of Us* to explore a wide range of topics. As of July 2025, over 19,000 projects have been initiated through the Workbench [6] and hundreds of peer-reviewed articles have been produced [7]. This proliferation of research activity

presents an opportunity to systematically assess how *All of Us* is influencing the scientific landscape.

Bibliometric analysis offers a powerful method for exploring this question. As a branch of Library and Information Science, bibliometrics analysis uses quantitative methods to analyze patterns in publication data. Common methodological approaches include publication counts to measure productivity, co-authorship network analysis to map collaboration patterns, citation analysis to measure impact, and co-word analysis to identify emerging themes. Bibliometric analysis has been used to evaluate researchers (e.g., [8]), institutions (e.g., [9]), research topics (e.g., [10]), theories (e.g., [11]), articles (e.g., [12]), books (e.g., [13]), journals (e.g., [14]), conferences (e.g., [15]), and even entire fields (e.g., [16]). These works demonstrate the flexibility of bibliometric analysis across scales—from single artifacts to entire disciplines.

Bibliometrics has also been applied to examine the impact of specific datasets in a few studies. Su et al. [17] conducted a bibliometric analysis to characterize the published papers utilizing the National Cancer Database (NCDB) data, aiming to understand the influence of the US NCDB dataset. Fan et al. [18] utilized co-word network modularity analysis (CWNA), a specific bibliometric method, to analyze journal articles citing the National Longitudinal Study of Adolescent to Adult Health (Add-Health) dataset from the ICPSR repository. Their study investigated major research topics associated with this dataset and their evolution over a two-decade span. Outside of health, Belter [19] measured the impact of three oceanographic datasets on the scientific community through citation counts. These examples illustrate how bibliometric approaches can trace the scholarly footprint of datasets and evaluate their role in advancing research.

Although *All of Us* has been evaluated on programmatic aspects, such as participant recruitment [20,21], data infrastructure [22,23], policy frameworks [24,25], and annual publication reviews have been conducted on its genomics subset [26], no studies have yet examined its overall scholarly impact. While these prior studies provide valuable information about the program's design, goals and selected research outcomes, they do not examine how the broader research community is engaging with *All of Us* data or referencing the program in their scholarly work. A bibliometric perspective can fill this gap by mapping the evolution, pattern, and impact of *All of Us*-related publications.

This study presents the first bibliometric analysis of the *All of Us* Research Program's scholarly output. Our goal is to characterize research utilizing the *All of Us* dataset, addressing the following four sets of questions:

Publication Trends and Productivity

- What is the annual growth rate of publications?

- What are the predominant document types (e.g., journal articles, conference papers)?
- Which journals publish the most *All of Us*-related studies?
- Who are the most prolific authors contributing to this body of research?
- What institutions and countries are leading in research output?

Collaboration and Network Analysis

- What are the patterns of collaboration among authors and institutions conducting *All of Us*-related research?

Research Topics

- What are the primary research topics and themes emerging from studies utilizing the *All of Us* dataset?

Policy Compliance

- To what extent do *All of Us*-related publications comply with the *All of Us* publication and presentation policy [27]?

By answering these questions, we aim to provide a comprehensive overview of how *All of Us* is shaping current and future directions in biomedical research. As the dataset is relatively new, citation analysis was excluded, as publications require at least two years to accrue meaningful citation counts [28]. Instead, we focus on publication trends, collaborative patterns, thematic content, and publication policy compliance to assess the early scholarly footprint of the *All of Us* Research Program.

METHODS

Data Collection

The *All of Us* Publications Directory page (available at <https://www.researchallofus.org/publications/>), accessed in April 2025) serves as a central repository for studies using the *All of Us* data. Since researchers using the Controlled and Registered Tiers must submit their publications for indexing [27], this resource was selected for data collection. An initial search was conducted on the *All of Us* publications page on March 8, 2024, resulting in 229 publications. To ensure a comprehensive dataset for annual analysis, the *All of Us* Publications page was monitored regularly, and the final search was updated on April 27, 2025 to include all studies published through December 31, 2024, resulting in a total of 561 publications. The flow chart in Figure 1 shows our data collection and analysis process.

Please note that the *All of Us* publications page is a dynamic website. As of our final data collection on April

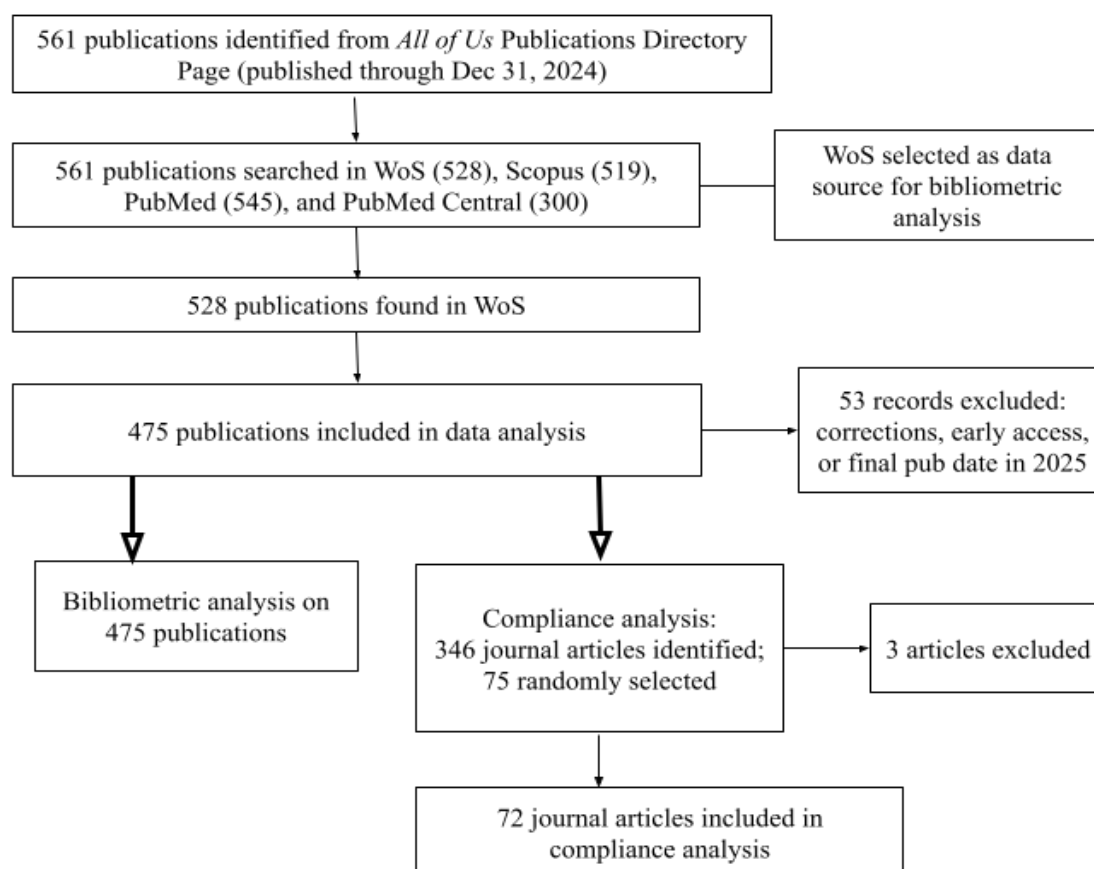
27, 2025, it listed publications that include various document types including journal articles, conference proceedings, letters and more. However, when we revisited the site on May 19, 2025, it had been updated to display only peer-reviewed journal articles, with other document types moved to an expanded catalog [29]. A subsequent revisit on April 6, 2026, revealed substantial changes: the site adopted a new interface, added filters, reverted to including multiple document types, changed its URL to <https://www.researchallofus.org/publication-directory/>, and introduced AI-generated summaries for each publication. All our data analysis was based on the dataset collected from the *All of Us* Publication Directory page on April 27, 2025. Any updates or changes made to the website after this date, including additions, removals, or reclassifications of publication types, are not reflected in our analysis or findings.

Publication titles collected from the website were then searched across Web of Science Core Collection (SCI-Expanded, SSCI, AHCI, and ESCI), Scopus, PubMed, and PubMed Central. If no exact match was found, partial title searches were performed. A Data Log (available at

<https://osf.io/sxe6k/>) created in Google Sheets was maintained to track searches across the four databases, documenting notes and search adjustments as needed. Of the 561 publications, 528 were found in Web of Science, 519 in Scopus, 545 in PubMed, and 300 in PubMed Central (see Figure 1). Given that Web of Science covers about 94% of the *All of Us* publications and is regarded as providing higher-quality bibliographic data than Scopus by the developers of our analysis tools, Biblioshiny and VOSviewer [30,31], it was selected as the primary data source for our bibliometric analysis.

To ensure to include only publications published through December 31, 2024, we applied additional filters in Web of Science, excluding document type: Correction and Early Access, and final publication year: 2025 before downloading the dataset. This filtering removed 53 records, resulting in a final dataset of 475 publications. To download the final dataset from Web of Science (WoS), the “Full Record” option was selected to include complete bibliographic information, and the dataset was saved as a plain text file.

Figure 1 Data collection and analysis flowchart



Data Analysis

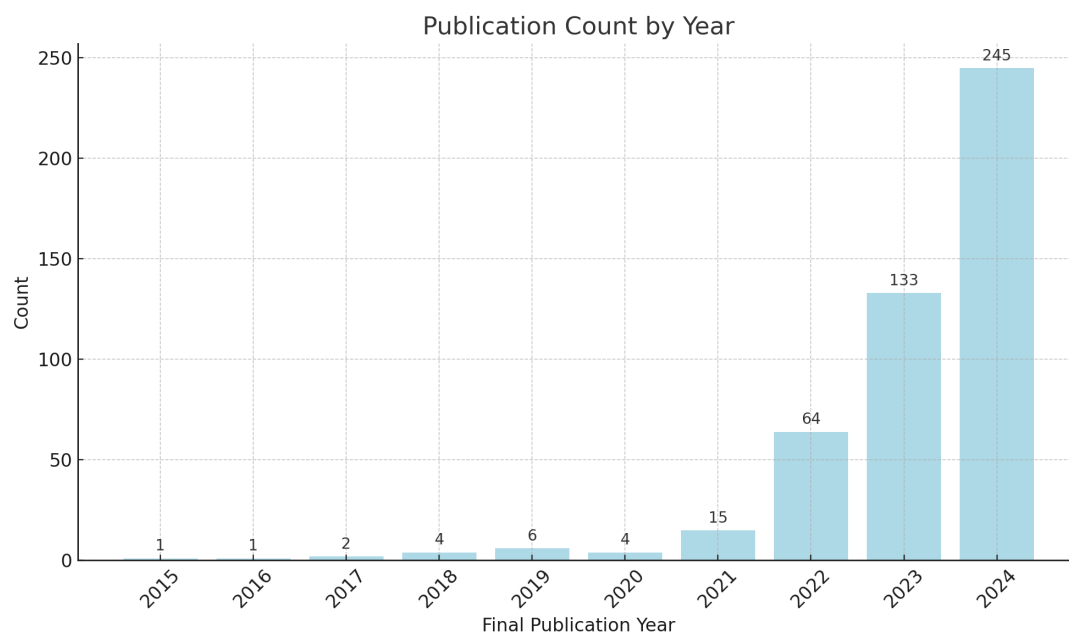
For data processing and analysis, Google Sheets was used to record the dataset, track publications, generate basic counts, and create simple charts. The plain text file containing 475 publication records downloaded from WoS was then imported into specialized bibliometric visualization tools for further analysis. Biblioshiny [32], a web application for the R package Bibliometrix version 4.3.2, was primarily employed to calculate and visualize key productivity metrics, including the number of publications per year, journal distribution, and author productivity, as well as word clouds. To analyze collaboration patterns and research themes, VOSviewer [33] software version 1.6.20 was used for co-authorship network analysis and word co-occurrence visualization, providing insights into author and institutional collaborations and emerging research topics. In addition, OpenRefine [34], a data cleaning tool, was used to clean affiliations and author names before conducting network visualizations in VOSviewer.

To examine how *All of Us* publications adhere to the *All of Us* publication and presentation policy [27], we conducted a compliance analysis on a random sample of 75 articles drawn from the 364 peer-reviewed journal articles (filtered by Document Type: Article) in our 475-records WoS dataset. A full-dataset compliance review was not feasible due to the labor-intensive and manual nature of assessing each article against multiple policy criteria. We limited our analysis to peer-reviewed journal articles only, as they typically have higher word limits that allow for more comprehensive reporting and the *All of Us* publication and

presentation policy [27] document outlines specific requirements applicable to this publication type. The *All of Us* policy has three key requirements. First, the policy mandates that authors submit the final, peer-reviewed manuscript to PubMed Central and make it publicly available immediately upon publication, without any embargo period. Second, it requires authors to acknowledge the contributions of *All of Us* participants and the program. Third, each article must include a statement on data availability or data access citing the Researcher Workbench and specifying the version of the *All of Us* dataset used.

Out of the 75 randomly selected journal articles, three were removed: one was an editorial letter, another was a journal article about program recruitment that did not use *All of Us* participant data, and one was a redacted journal article. This resulted in a final sample of 72 articles used for compliance analysis, approximately 20% of all peer-reviewed journal articles in our dataset. These 72 randomly-drawn articles provide a manageable yet representative sample for evaluating adherence to the *All of Us* publication and presentation policy. Full-texts of these 72 articles were then obtained. Author AS served as the primary coder for this compliance analysis. AS searched PubMed Central to verify article availability, reviewed each article's full text to evaluate the presence of appropriate acknowledgments and statements on data availability, and recorded the citation practices related to *All of Us* in the papers. Any articles marked as non-compliant in terms of acknowledgments or data statements were independently reviewed by author YH to validate the initial coding decisions. Discrepancies were resolved through discussion to reach consensus.

Figure 2 Publication count by year



RESULTS

Publication Trends and Productivity

The Number of Publications

Of the 475 publications examined in this study, the majority (245 publications, 52%) were published in 2024. From 2015 to 2024, there was an overall growth rate of 82.45% in the number of papers published annually, indicating a rapid increase in scholarly activity utilizing the *All of Us* dataset. This trend is illustrated in Figure 2. A small number of publications appeared prior to the program's national launch in 2018 and these early works primarily focused on the planning of the initiative. Beginning in 2021, the number of publications using *All of Us* data began to grow exponentially, continuing this upward trajectory through 2024. This is largely due to the launch of the Researcher Workbench in May 2020, enabling broad access to the *All of Us* dataset for the scientific community.

Document Types

Figure 3 shows the breakdown of document types across the 475 publications based on the WoS Core Collection document types categories. Journal articles (69.9%) make up the majority of published items, followed by Letters (19.5%), Editorial Materials (5.1%), Meeting Abstracts (2.5%), Review Articles (2.5%), and Proceeding Papers (0.6%).

Journals

From 2015 to 2024, a total of 211 journals published papers utilizing the *All of Us* dataset. Table 1 presents the top ten journals in terms of the number of *All of Us* related research published. The *Journal of the American Medical Informatics Association* (JAMIA) ranks first, reflecting its strong alignment with the informatics-driven nature of the *All of Us* initiative. Both the second- and third-ranked journals specialize in dermatology. In fact, five of the top ten journals are dermatology-focused, suggesting a particularly high level of engagement with the *All of Us* dataset within the dermatology research community.

Figure 3 Document types

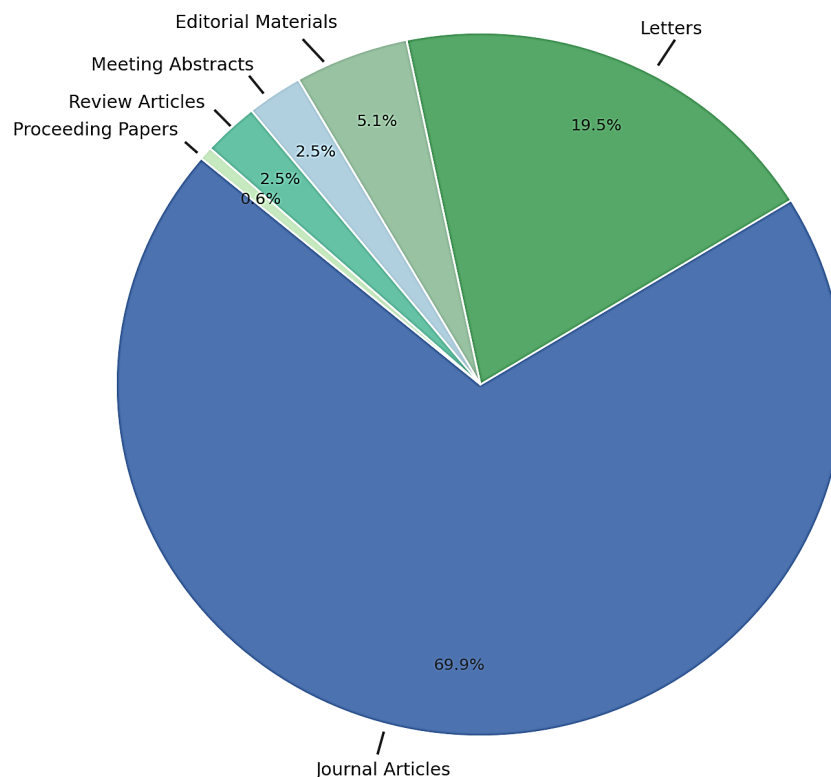


Table 1Top journals publishing *All of Us* research

Publication Titles	Record Count	% of 475
Journal of the American Medical Informatics Association	49	10.32%
Archives of Dermatological Research	34	7.16%
Journal of the American Academy of Dermatology (JAAD)	31	6.53%
Plos One	14	2.95%
Nature Communications	11	2.32%
International Journal of Dermatology	9	1.89%
Clinical and Experimental Dermatology	8	1.68%
JAMA Network Open	8	1.68%
Nature Genetics	7	1.47%
JAAD International	6	1.26%

Authors

A total of 2803 authors utilized the *All of Us* dataset. Figure 4 shows the most prolific authors, with Cohen JM leading with 42 publications, followed by Leasure AC

with 23 publications, and Baxter SL with 21 publications. In particular, the top two authors are from the same institutions and frequently co-author with each other, with a primary focus on dermatology. The third author Baxter SL's research focuses on ophthalmology, particularly glaucoma. When examining the publication timelines of the top 10 authors (see Figure 5), five began publishing in 2021, shortly after the Researcher Workbench became available in May 2020, suggesting they were early adopters of the *All of Us* dataset. All top 10 authors have consistently published *All of Us*-related research for at least three years after initially utilizing the dataset.

Institutions

Research utilizing the *All of Us* dataset has been conducted across 520 institutions, with 20% (99) of those institutions contributing at least three publications to the literature. Figure 6 highlights the top ten institutions based on publication count, all of which are located within the United States. The publication counts were calculated using author affiliations, with each institution receiving one count per article, regardless of the number of affiliated co-authors. Universities with a strong focus on medical research, such as Vanderbilt, UC San Diego, Johns Hopkins, are among the top users of this dataset. Major health institutions and hospitals, like the NIH and Massachusetts General Hospital, also play a leading role in utilizing the *All of Us* dataset.

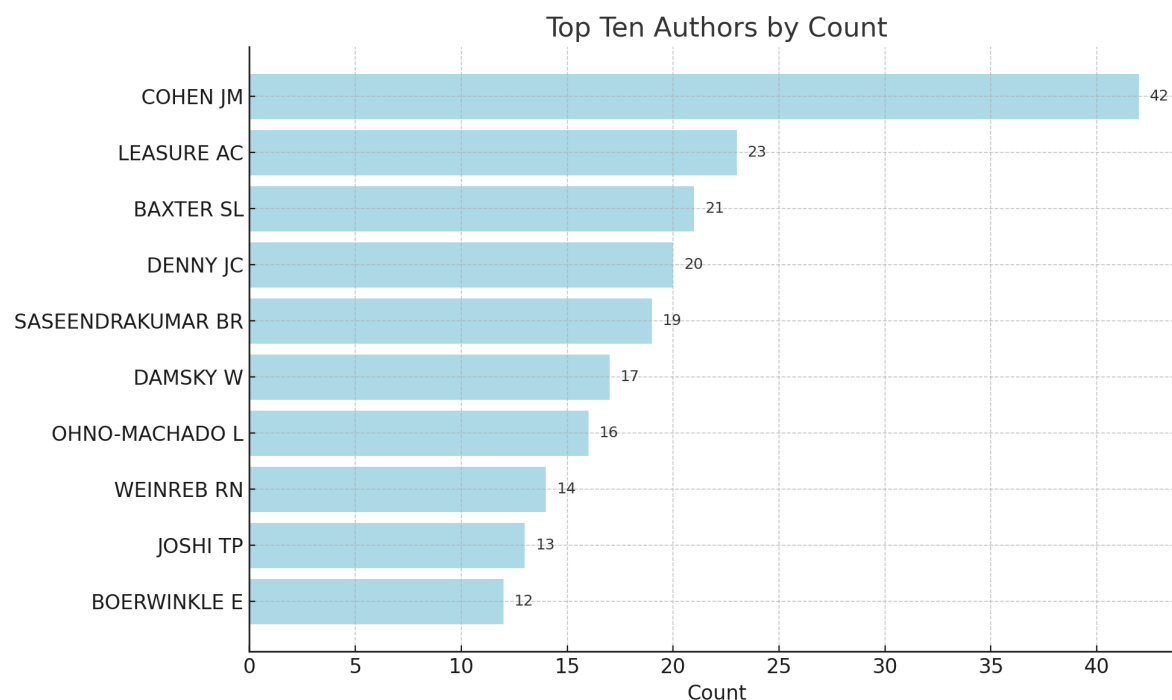
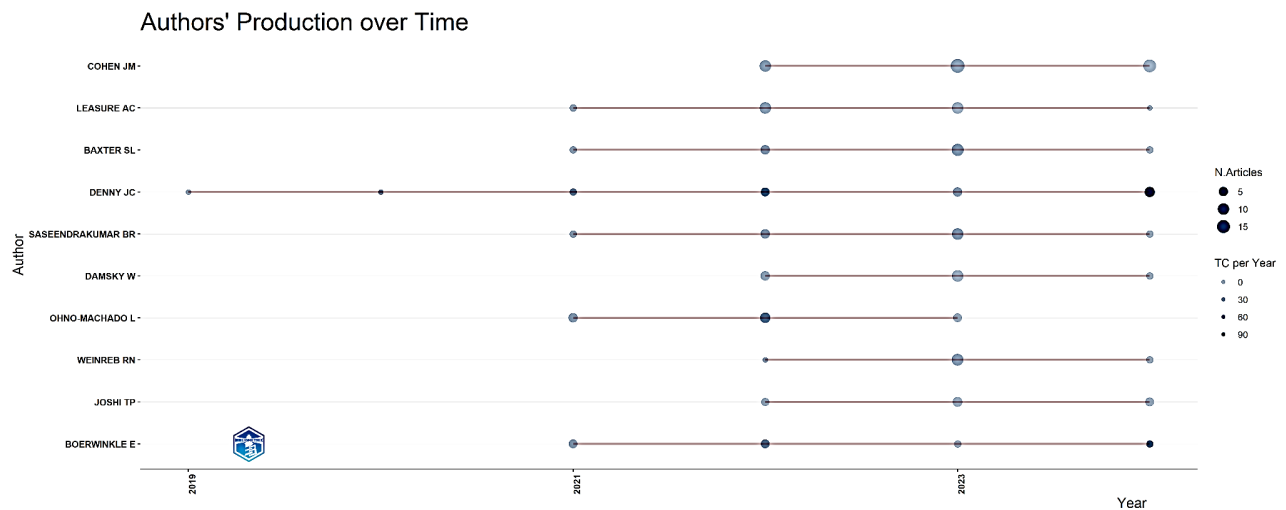
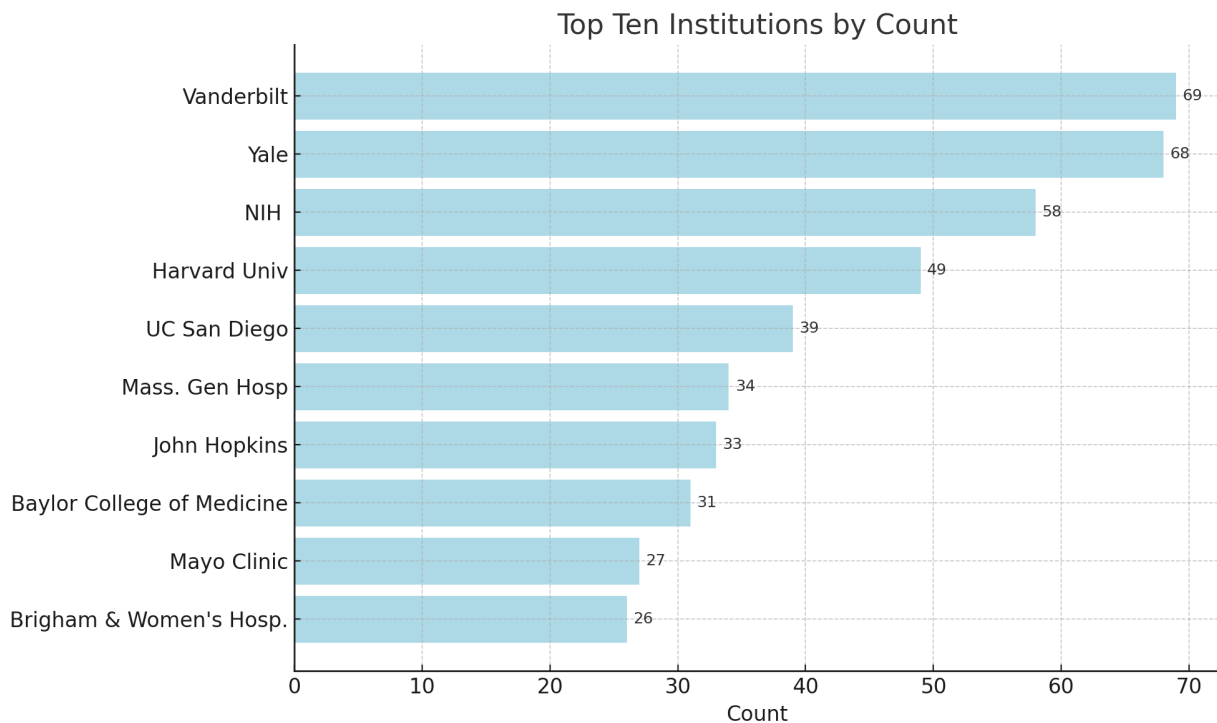
Figure 4 The most prolific authors

Figure 5 Top 10 authors' production over time**Figure 6** Top 10 institutions

Countries

Papers utilizing the *All of Us* dataset were published primarily by authors based in the United States, with a low international co-authorship of 12.87%. This limited global collaboration is not surprising, as the *All of Us* Research Program collects data exclusively from individuals living in the US, and institutions that have

signed the Data User and Registration Agreement (DURA) are predominantly US-based.

Collaboration and Network Analysis

Individual Co-authorship Map

The co-authorship collaboration map (see Figure 7) shows the names of authors who have published at least three

papers using the *All of Us* dataset. The size of each circle reflects the number of papers published by an author, while the lines connecting circles indicate co-authorship. Colors represent clusters of closely connected authors, who often belong to the same institution. The network map reveals that while many authors collaborate primarily within their institutions, cross-institutional collaboration is also common. A few authors have published independently without co-authors. In addition, authors with larger circles such as Cohen, Leasure, and Baxter stand out. This is consistent with Figure 4 on the top authors.

Institutional Co-authorship Map

The institutional co-authorship map (see Figure 8) displays institutions with at least five *All of Us* publications and at least one cross-institutional collaboration. A total of 57 institutions are represented in the graph. The network map shows collaborations among them. A thesaurus file was uploaded to VOSviewer to

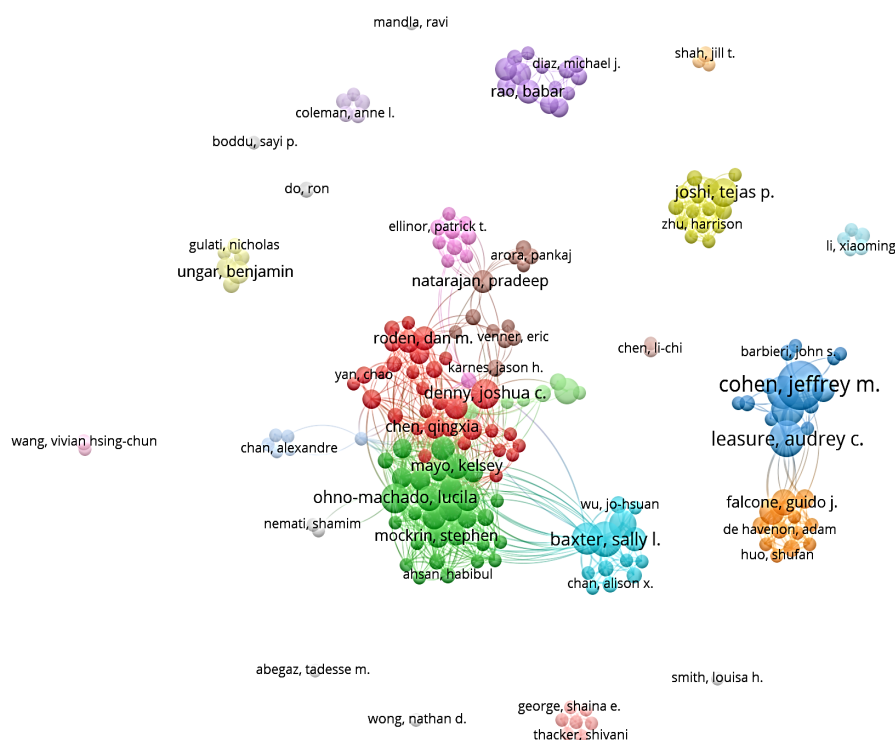
consolidate institution names, particularly those with medical campuses or specific departments cited. In the map, larger circles indicate higher publication counts. Leading institutions, such as Vanderbilt, Yale, the NIH, Harvard, and UC San Diego, stand out prominently. This is consistent with Figure 6 on the top institutions.

Research Topics

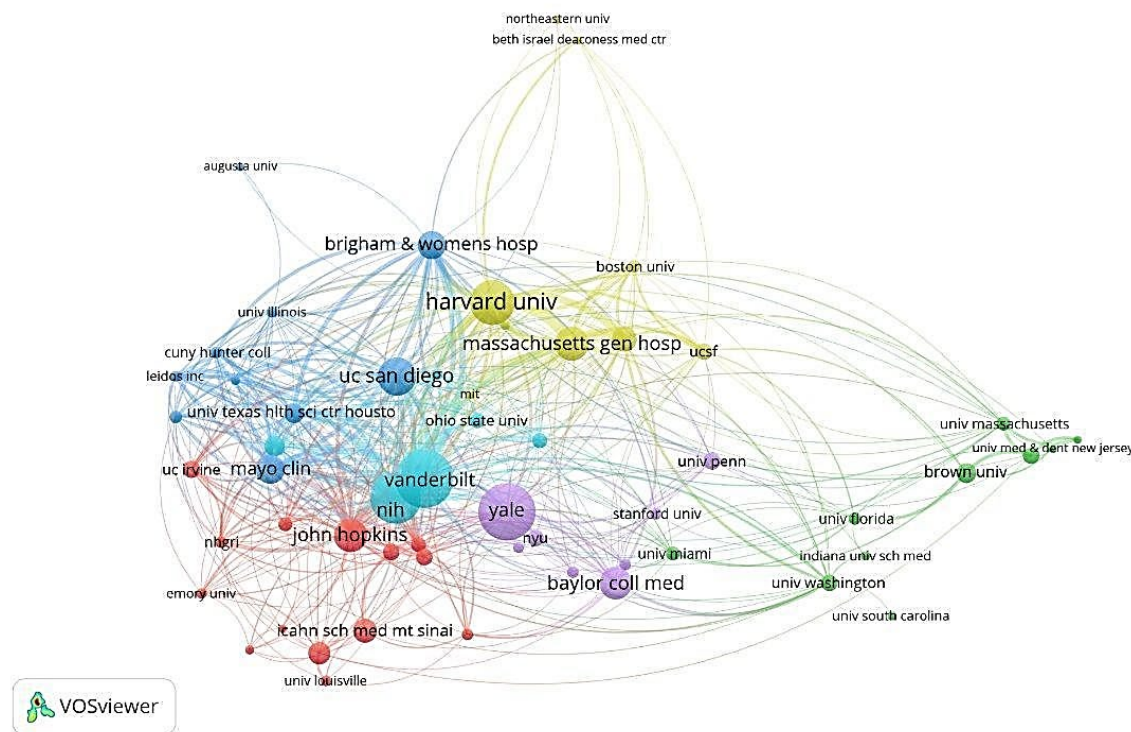
WOS Categories

Table 2 listed the top ten Web of Science categories for our dataset. These categories are assigned at the journal level and a single journal can be assigned to multiple WoS categories. Dermatology is the most prolific category listed at 115 records, which is nearly double the number of records of Health Care Sciences Services, the second largest category at 67 records.

Figure 7 Individual co-authorship network



VOSviewer parameters: full counting, a minimal of 3 publications, ignore papers with more than 25 authors, show all items. Interactive map: <https://tinyurl.com/27fzlbud>.

Figure 8 Institutional co-authorship network

VOSviewer parameters: full counting, a minimal of 5 publications, ignore papers with more than 25 authors, only show connected items. Interactive map: <https://tinyurl.com/23g35buf>.

Table 2

Web of Science categories

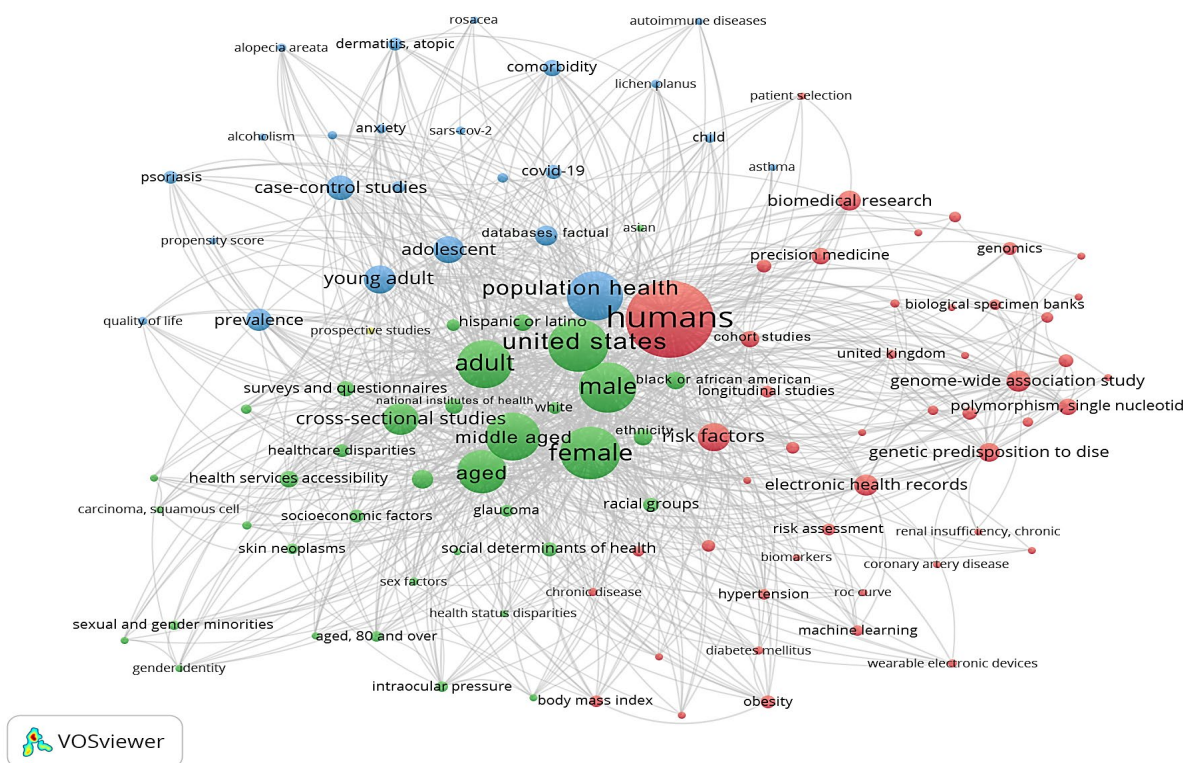
Web of Science Category	Record Count	% of 475
Dermatology	115	24.21%
Health Care Sciences Services	67	14.10%
Medical Informatics	64	13.47%
Computer Science	55	11.57%
Interdisciplinary Applications		
Computer Science Information Systems	51	10.74%
Information Science Library Science	49	10.32%
Medicine General Internal	40	8.42%
Multidisciplinary Sciences	37	7.79%
Genetics Heredity	34	7.16%
Ophthalmology	29	6.11%

Word Co-occurrence Maps

Keyword Map

The keyword map (see Figure 9) is based on the titles and abstracts of the publications in our dataset. Keywords were extracted using full counting, with a minimum threshold of eight occurrences per term, resulting in six clusters. This visualization highlights frequently mentioned terms with larger boxes, while terms that are spatially closer and share the same color indicate high levels of co-occurrence within the dataset. The blue cluster represents research centered on genomics and precision medicine. The red cluster focuses on chronic diseases (especially dermatological and metabolic) and their study within diverse or underrepresented populations. The bright greenish-blue cluster reflects studies of mental health conditions, especially depression and anxiety. The green cluster centers on barriers and facilitators in healthcare access, provider interactions, and health equity. The yellow cluster centers on the *All of Us* program, infrastructure and community. Finally, the small purple cluster reflects computational methods such as machine learning algorithms used to analyze the dataset.

Figure 10 MeSH Term Map



JMLA

MeSH Term Maps

The MeSH term map (see Figure 10), created using MeSH terms downloaded from PubMed, visualizes the co-occurrence patterns of MeSH terms assigned to *All of Us*-related research. Only terms with a minimum of five occurrences were included, and cluster analysis resulted in three main clusters. Unlike the box-style labeling used in Figure 9, Figure 10 employs the traditional circle label format, where the size of each circle reflects the frequency of term occurrence. Featured at the center of the map are terms such as “humans,” “adult,” “male,” “female,” “United States,” and “population health,” underscoring *All of Us*’ central focus on human subjects in the United States and population-based research. The thematic clusters revealed by MeSH term co-occurrence closely align with those observed in the title and abstract term maps. The red cluster highlights *All of Us*’ contributions to precision health and genomics research, often supported by electronic health records and advanced computational methods such as machine learning. The green cluster centers on population health, social determinants of health, and health equity, frequently investigated using survey data and sociodemographic variables provided by the *All of Us* dataset. Lastly, the blue cluster reflects disease-specific research and related methodological approaches, for example dermatology and mental health, and their study designs like case-control studies.

Word Clouds

To further explore the thematic focus of *All of Us*-related research, two word clouds were generated using Biblioshiny to visualize the most frequently used terms. These visualizations offer an alternative perspective on keyword usage patterns across the dataset. Figure 11 displays the top 50 terms from Keyword Plus on the WoS platform, which are algorithmically generated terms based on cited references and provide insight into broader contextual themes. Figure 12 presents the top 50 author keywords, which reflect the authors’ intentional framing of their research topics. Together, these word clouds highlight recurring research topic themes such as epidemiology, health disparities, chronic conditions (e.g., diabetes, hypertension, mental health), precision medicine, and the use of large-scale health data. While there is overlap between the two sets of keywords, differences also emerge: author keywords tend to be more specific, such as “*All of Us*” or “*All of Us* Research Program”, reflecting the absence of an established subject heading for this dataset, whereas Keyword Plus terms offer a broader thematic scope. These patterns reinforce findings from the abstract/title and MeSH term analyses, illustrating the multidisciplinary and data-driven nature of *All of Us* research.

Figure 11 Word cloud on Keyword Plus (50 words)



Figure 12 Word cloud on author’s keywords (50 words)



Compliance

Our compliance analysis evaluated how well *All of Us* journal articles adhere to three key requirements of the *All of Us* publication and presentation policy [27]: availability in PubMed Central, inclusion of an acknowledgment of *All of Us* program and participants, and inclusion of a statement on data availability or access

In our random sample of 72 journal articles, only 55% (40/72) found free full-text access in PubMed Central. Among the 32 articles not available in PubMed Central, 8 were under embargo at the time of analysis. Regarding acknowledgement, 73% (52/72) of the sampled articles included a statement recognizing *All of Us* participants and the program. A similar proportion, 71% (51/72) included a statement on data availability or data access. Overall, 58% of the publications included both an acknowledgment and a statement on data availability.

Among the 52 articles that included an acknowledgment of *All of Us* participants and the program, we also examined where these statements were located. The majority (79%, 41/52) placed the acknowledgment in a stand-alone Acknowledgments section, typically located at the end of the paper, just before the references. Seven articles included the acknowledgment within the funding section, while four placed it in other sections such as contributors/contributions, the appendix, or footnotes.

The location of the statement on data availability or data access was more varied. Approximately 47% (24/51) placed the statement in a dedicated Data Availability Statement section, while 39% (20/51) included it within the Methods section. The remaining seven articles included the statement in other locations, such as the Introduction.

We further analyzed how the *All of Us* program is cited in research publications by categorizing citations into three types:

- **Formal Citation:** The paper references at least one publication specifically about the *All of Us* program and includes it in the reference list.
- **Informal Citation:** The paper mentions and discusses the *All of Us* program but does not cite a specific publication in the reference list.

- **No Citation:** The paper does not mention or cite the *All of Us* program in any form.

In our 72-article dataset, most papers (61/72) included a formal citation, informal citations appeared occasionally (10/72), and only one paper lacked any citation. Table 3 lists the most frequently cited *All of Us* program publications (excluding citations to the Researcher workbench), noting that one article might cite multiple *All of Us* program publications.

DISCUSSION

All of Us Utilization

The findings from this bibliometric analysis reveal several early trends in how the *All of Us* dataset is being utilized in the research community. Our analysis demonstrates a rapid increase in scholarly activity following the launch of the Researcher Workbench in 2020, concentrated author and institutional contributions, and a strong but uneven thematic focus. These patterns suggest both areas of high engagement with the *All of Us* resource as well as notable gaps that merit attention.

The sharp increase in publication volume, particularly between 2022 and 2024, illustrates a growing adoption of the *All of Us* dataset. Over half of the 475 analyzed

Table 3

Most frequently cited publications about the *All of Us* Program

Full Citation	Number of Documents (n=61)
The <i>All of Us</i> Research Program Investigators. The “ <i>All of Us</i> ” Research Program. N Engl J Med. 2019 Aug 15;381(7):668–76.	57
Mapes BM, Foster CS, Kusnoor SV, Epelbaum MI, AuYoung M, Jenkins G, et al. Diversity and inclusion for the <i>All of Us</i> research program: A scoping review. PLOS ONE. 2020 July 1;15(7):e0234962.	10
Ramirez AH, Sulieman L, Schlueter DJ, Halvorson A, Qian J, Ratsimbazafy F, et al. The <i>All of Us</i> Research Program: Data quality, utility, and diversity. Patterns. 2022 Aug 12;3(8):100570.	7
Ramirez AH, Gebo KA, Harris PA. Progress With the <i>All of Us</i> Research Program: Opening Access for Researchers. JAMA. 2021 June 22;325(24):2441–2.	3
Sankar PL, Parker LS. The Precision Medicine Initiative’s <i>All of Us</i> Research Program: an agenda for research on its ethical, legal, and social issues. Genetics in Medicine. 2017 July 1;19(7):743–50.	2
Collins FS, Varmus H. A New Initiative on Precision Medicine. N Engl J Med. 2015 Feb 26;372(9):793–5.	2

publications were published in 2024 alone. This rapid growth underscores the success of the *All of Us* Research Workbench in enabling researcher access and reflects a rising interest in large-scale, diverse biomedical datasets in the research community. However, publication productivity is heavily concentrated among a small number of authors at a few elite research universities or health institutions: the top five authors contributed nearly 20% of all publications, and the top five institutions produced over half. While these contributors likely benefit from strong research infrastructure and support for health science in general, their outsized presence points to *All of Us*'s early adoption by a relatively narrow segment of the research community. The dominance of R1 universities with affiliated medical centers in both publication output and collaboration networks further emphasizes this concentration. In contrast, smaller institutions, teaching-focused universities and minority-serving institutions (MSIs) are largely absent from the top tier of contributors. This under-utilization may reflect barriers such as limited funding, lack of infrastructure, or insufficient awareness of *All of Us* resources. Addressing these gaps could broaden participation and enhance the diversity of perspectives in *All of Us*-based research.

Co-authorship and institutional network maps reveal moderately dense collaboration patterns, particularly among top authors and leading institutions. These patterns are characterized by strong intra-institutional ties and some cross-institutional collaboration. The collaboration maps further highlight that a small group of authors and institutions drive much of the early scholarly activity utilizing the *All of Us* dataset. It is also worth noting that when examining the top 10 authors' publication productivity over time (see Figure 5), a clear trend emerges: once researchers begin working with the *All of Us* dataset, they tend to continue publishing *All of Us*-related studies year after year. This sustained engagement suggests that *All of Us* serves not only as an initial research opportunity but also as an ongoing resource that supports long-term scholarly productivity. This is likely due to the dataset's longitudinal design, regularly updated data, and accessibility through the Workbench. This sustained engagement could serve as a compelling marketing point for attracting new researchers, highlighting the *All of Us* dataset not only as a valuable resource for initial studies but also as a platform that supports ongoing, long-term research agendas.

Word co-occurrence analysis of titles, abstracts, and MeSH terms reveals a strong focus on dermatology, genomics, and chronic conditions such as diabetes and mental health. Dermatology, in particular, appears to be an area of concentrated engagement, dominating both publication volume and author representation. Five of the top ten journals publishing *All of Us* research are dermatology-focused, and the most prolific authors share this research specialty. While this reflects a valuable application of the

dataset within specific health domains, it also suggests that *All of Us*'s broader multidisciplinary potential remains underutilized. The dataset holds substantial potential for a wide range of research areas, and as more researchers gain access and familiarity with its contents, new lines of inquiry are likely to emerge.

Compliance with *All of Us* policy

In addition to conducting a bibliometric analysis of publications utilizing the *All of Us* dataset, our research also investigates authors' degree of compliance with *All of Us* publishing policies. These policies require authors to submit a final, embargo-free manuscript of their peer-reviewed work to PubMed Central, acknowledge the *All of Us* program and participants, and include a statement on data availability or access.

In our sample of 72 journal articles, only about 55% of publications were available in PubMed Central, suggesting that many papers are inaccessible. After accounting for 8 articles that were under embargo and noting that *All of Us* has appended a note to their reporting form clarifying that the embargo-free clause is currently not enforced [35], 24 articles remain (33% of the sample) not accessible in PubMed Central. This suggests that these authors did not submit their manuscripts to PubMed Central as required. Based on our analysis, we estimate that approximately one-third of *All of Us* publications are not deposited in PubMed Central, raising concerns about overall compliance with *All of Us*'s public access policy.

58% of our sample papers provide both an acknowledgement statement and a data availability statement, which reveals a wide gap in policy compliance. Though authors are required to include these statements and self-report their own compliance to the *All of Us* program upon journal submission, our results show that many are not including the required information, or they include only one type of statement. Partial compliance, or lack thereof, implies that there is divergence from *All of Us* policy expectations and actual publishing practices.

Implications for Libraries

Based on these findings, there are a few implications for libraries. Libraries can play a role in promoting equitable access to and use of the *All of Us* dataset. The concentration of *All of Us*-related research at a small number of elite institutions points to potential gaps in awareness, capacity, or infrastructure at smaller, under-resourced institutions. This suggests an opportunity for libraries, particularly those at minority-serving institutions (MSIs) or teaching-focused universities, to participate in outreach and education efforts by raising awareness of the *All of Us* Researcher Workbench and its potential for inclusive health research on their campuses. Simple approaches might include adding *All of Us* into

relevant LibGuides or introducing the dataset to faculty and students as needs arise. Additionally, libraries with more developed data services can provide onboarding support, training, and sustained guidance for new users, helping researchers and students navigate the platform and integrate it into their work. Through these efforts, libraries can help broaden participation and support a more diverse range of voices and institutions represented in *All of Us*-related research.

Limitation

There are several limitations to this bibliometric study. First, bibliometric analyses are inherently dynamic, as publication trends and citation patterns evolve over time. The results of this study could change significantly if the utilization of the *All of Us* dataset were examined in the future. Second, since the publications included in this study are relatively recent, we did not analyze citation impact. Citation-based bibliometric indicators typically require articles to be at least two years old to accumulate a sufficient number of citations for reliable assessment [28]. Thus, our study does not evaluate citation impact of research utilizing the *All of Us* dataset, missing an important component in measuring its influence. Finally, our analysis only included publications that used the *All of Us* dataset through registered and controlled tier access. Studies utilizing data from the public tier, which does not require registration, were not captured in our data collection method. This limitation suggests that our findings may underestimate the overall impact of the dataset in the scientific community. Future research could employ alternative collection methods, such as tracking publications across broader sources or analyzing social media engagement, to provide a more comprehensive understanding of the dataset's utilization and influence.

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AUTHOR CONTRIBUTIONS STATEMENT

Yuqi He: Conceptualization; Formal analysis; Methodology; Project administration; Supervision; Validation; Visualization; Writing – original draft; Writing – review & editing. Abrielle Spaletta: Data curation; Formal analysis; Visualization; Writing – original draft; Writing – review & editing.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in the Open Science Framework at <https://osf.io/sxe6k/>.

ACKNOWLEDGEMENTS

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SUPPLEMENTAL FILES

Appendix A: Data Log

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Comparing AI chat tools and PubMed for medical literature searches

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See end of article for authors' affiliations.

Objective: This investigation compared six AI chat tools (ChatGPT, Claude, Copilot, Gemini, OpenEvidence, and Perplexity) to each other and to PubMed to assess their utility in medical literature searches.

Methods: Each tool was prompted with two standardized prompts simulating an academic and a clinical literature need. Prompts were repeated three times per tool, and results recorded for each prompt iteration.

Results: Main findings include the range in number of real and hallucinated articles for each AI tool, from no hallucinations in OpenEvidence to more than 80% hallucinated citations in ChatGPT. Across all tools, most real articles were assessed as relevant. Continued prompting of all tools produced duplicate results. Most tools showed very little consistency in citations provided to different researchers, suggesting low probability of replicating search results.

Conclusions: Though limited by small sample size, inconsistent data, and the rapid pace of change in LLM technology, this study suggests some advantages and drawbacks of using AI tools for literature searching compared with PubMed. AI tools with few or no hallucinations and high relevance, such as OpenEvidence and Perplexity, performed well in terms of simply supplying a few article citations on the topic, but small results sets and lack of consistency and transparency limit their value for thorough research. These results suggest that AI tools are not presently a viable replacement for PubMed or other academic databases for systematic reviews or other in-depth literature searches but may be adequate for limited information needs or as a complement to database or web searches.

Keywords: AI; literature searches; comparison

INTRODUCTION

Since the 2022 release of widely available large language model (LLM) chatbot tools, there has been interest in how this type of artificial intelligence (AI) might assist scientific research and writing. Numerous studies examine AI ability to formulate search queries, summarize data and articles, improve written work, and locate relevant literature citations [1–5]. Xu et al. found a majority of medical students reported using LLM tools in some way [6], showing this topic's relevance to medical libraries. Concerns with AI usage include 'hallucinations' (users relying on inaccurate information/citing nonexistent articles; frustration and lost time for library users and staff attempting to locate nonexistent articles in reference consultations or ILL requests), and opaque retrieval mechanisms that may provide inadequate or irrelevant results for literature search prompts. These tools have generally been found to perform better at summarizing and writing than at listing specific articles or information sources [7–13].

A literature search identified other studies investigating AI tools' provision of article citations. Several authors

noted that ChatGPT can hallucinate large numbers of citations [7,8,12–14]. Other studies compared citations produced by ChatGPT and Google Bard (now Gemini), concluding that both generated significant numbers of hallucinations [9,10,15]. Van der Werf [16], leading a workshop evaluating the citation-producing capabilities of Perplexity, Elicit, and SciSpace, reported participants found these tools fast and easy to use, but not transparent or reliable.

Previous studies clearly identify hallucination (both citations and information) as a concern with LLM tools, indicating that plausibly titled hallucinated works and the 'confidence' of tools presenting citations and summarized information makes it difficult for users to determine whether information is accurate [8,9]. Inability of LLMs to accurately discover known articles is found in multiple studies, along with inaccurate summarization [17–19]. The number of previous studies examining ChatGPT highlight its importance as the best-known AI chatbot, familiar to large numbers of users although not a scholarly tool. This paper builds on earlier works, comparing six AI tools to PubMed and providing data on hallucination rates,

provision of relevant citations, and consistency and duplication of results among participants. The current study attempted to approximate and evaluate the experience of a non-expert searcher requesting medical literature from several LLM tools. We were interested in how well these tools performed this task at a basic level, producing real articles relevant to the topic of interest; we did not assess accuracy or recency of information in the articles provided. While article quality is obviously a critical component of how well these tools perform on literature searches, it was outside the scope of this project.

METHODS

Study Design and Participants

This original investigation was conducted by 13 health sciences librarians representing 10 Massachusetts institutions; depending on availability and access, 4-7 librarians tested each tool. The study was designed to evaluate performance of six AI chat tools in retrieving peer-reviewed literature in response to structured prompts. While the generative AI field contains tools specifically for academic writing, (i.e. Research Rabbit, SciSpace, Elicit), we were interested in the experience of users relying on well-known general purpose tools. Previous studies of AI and medical students suggest these may be the tools most users rely on [11,20,21], and familiarity with a tool for one purpose (e.g. summary of a topic) may logically facilitate its use for other purposes (e.g., searching for relevant literature). We did not consider tools requiring paid accounts, though some offer more access with paid versions, or, in the case of OpenEvidence, are limited to healthcare providers and possibly inaccessible to some users.

We used PubMed as a comparison since, as a free resource, PubMed is the clearest counterpart to free AI tools, as well as the best-known medical literature database in the US.

Tools evaluated included ChatGPT, Claude, Copilot (formerly Bing AI), Gemini (formerly Bard), OpenEvidence, and Perplexity AI. Terminology was not established in advance, and participants reported chatbot versions inconsistently. Of 7 ChatGPT users, 2 reported 4o Mini, 1 4o Mini/'auto', 1 'auto', 2 unspecified, and 1 unspecified/'free'. Of 5 Claude users, 1 reported paid version, 2 reported 3.5, and 2 indicated 'free'/unspecified. Copilot at that time used OpenAI's ChatGPT model, so of 8 Copilot users, 1 reported Creative ChatGPT 4o Mini,/ChatGPT4, 3 reported Creative Chat GPT4, 2 reported Creative, 1 Creative/unspecified, and 1 Balanced. Six users of Gemini and 8 each of OpenEvidence and Perplexity all indicated 'free' or unspecified versions. Though inconsistency of versions used/reported, and of prompters per tool, limited data standardization, we chose to use what we had rather than discard input. Since our

goal was not to provide definitive information on any specific product, but rather to gain insight into the basic experience of using these tools for literature searching, we accepted a variety of versions, incorporating whatever tool variant was accessible to a particular user. While this limits what can be decisively said about any individual version (many of which have since been superseded), it allows us to examine more broadly the overall experience of using LLM tools for literature searches.

Research Questions

The team developed five questions for investigation:

1. For each tool, are the recommended article citations real or hallucinated?
2. For each tool, if the article is real, is it relevant to the prompt topic?
3. For each tool, how many times can we use the same prompt before duplication and/or hallucination occur?
4. Do multiple simultaneous users of the same tool get the same citations in their results?
5. For each tool, how do the results compare to the results from a PubMed search for the same topic?

Prompts

Two primary prompts were developed, simulating educational and clinical information needs.

- **Educational Prompt:** "Please provide peer-reviewed articles about Teach-Back for patient education at discharge."
- **Clinical Prompt:** "Please provide real peer-reviewed articles in APA format about the Neutropenic diet, low bacterial diet, or low microbial diets as they relate to sepsis or length of stay."

Each prompt was followed by three iterations requesting more articles on the topic with the word "additional" (i.e. "Please provide additional peer-reviewed articles about Teach-Back for patient education at discharge") making four total interactions per tool, per prompt. The exception, OpenEvidence, allowed only two follow-ups at the free level, making three total interactions per prompt.

Data Collection

Data collection was organized through email and Zoom meetings. Participating librarians submitted prompts to each AI chat tool and recorded responses. The first (educational) prompt was used in a group session Aug. 21, 2024; the second (clinical) prompt was used Sept. 18, 2024. Participants unable to attend the Aug. 21 session

completed prompts and sent results over the next week (on or before Aug. 28, 2024).

For database comparison, we ran simple PubMed searches using the queries (*teach-back*) AND (*patient education*) AND (*discharge*), date limit Aug. 21, 2024, and (*neutropenic diet* OR *low bacterial diet* OR *low microbial diet*) AND (*sepsis* OR *length of stay*), date limit Sept. 18, 2024. While our professional inclination would normally be more sophisticated search strategies, our goal was to retrieve results similar to those a non-expert PubMed user might receive. We felt this both a fairer comparison to our non-expert prompt texts, and more relevant to an average literature seeker's experience.

Evaluation Criteria for Each Research Question

- **Hallucinations** were defined as citations we could not verify. Researchers attempted to verify each unique citation a chatbot provided by searching PubMed, the journal if listed, and via web search. For purposes of analysis we counted as 'real' citations that we scored as 'correct' (fully matching an existing source) or 'partially correct' (mostly matching an existing source, but some missing/incorrect information, i.e. publication date or volume number). Any citation for which we found no matching source was considered a hallucination for the tool providing it. Total hallucinations for each tool were tallied. (Our second prompt requested articles "in APA format" hoping this would produce more complete citations, but we did not evaluate results on adherence to formatting guidelines: we counted as "real" any citation for which we found a close/complete match, regardless of its formatting in APA or another style. We also counted as "real" actual citations that were not peer-reviewed articles, e.g. dissertations, book chapters, and web pages.)
- **Relevance** was assessed qualitatively based on alignment with prompt topic. Each unique non-hallucinated citation was reviewed at the title level and, if needed, abstract level, by two researchers; a third was tie-breaker. Each citation was considered a relevant or irrelevant result for the tool providing it. Total relevant/irrelevant results were tallied. Rulings were based on topic, not format: a non-peer-reviewed article could be relevant, though not fully meeting prompt criteria. Number Needed to Read (number of results screened / number of results deemed relevant) was also calculated for each tool using the total unique citations it provided.
- **Duplication** was tracked for each tool, considering unique citations received in response to the initial prompt (P1) and three follow-ups

(P2–P4). We defined duplication as any prompter seeing a specific citation for the second+ time. Each citation was marked either 'duplicated' or 'new' in each prompt response. Total duplicated citations per iteration were tallied. Number of prompters seeing a citation again was not counted (2 people seeing 1 citation the second time each = 1 duplicated citation in that response), but repeated duplication over multiple responses was (1 citation provided in 3 total responses = 2 duplications total).

- **Consistency** was calculated for each tool using formula ($[(\text{number of unique views of non-hallucinated citations}) / (\text{number of non-hallucinated citations}) / (\text{number of prompters in session})] * 100$). A 100 score indicates complete consistency (all prompters seeing all citations); smaller numbers indicate less consistency (less likelihood of multiple people seeing a citation). This "consistency score" for each tool expresses the percent chance of any given prompter seeing any given citation that tool provided. Since number of prompters in each session varied, the consistency score's lower limit also varied, smaller in larger groups. This variability, as well as the variation in tool versions noted above, makes our consistency score a rough value: it should not be interpreted as a precise measurement.

Comparison to PubMed involved evaluating PubMed results for topic relevance following the same process used for chatbot results. All PubMed results were real. Searches were not repeated, so duplication was not considered (but would have been complete). Consistency will be 100 for anyone using these search strategies.

Data Analysis

Data was compiled and analyzed using Microsoft Excel to calculate total numbers and mean. Results were further analyzed using 2-factor ANOVA with replication, examining the performance of tools between the two prompts, with tool name and prompt type ('Teach-back' or 'Neutropenia') as factors. Proportion of real/non-hallucinated citations and relevant citations were analyzed as dependent variables. Duplication/repetition was assessed using 2-factor ANOVA with replication, with tool name and duplication over prompt iterations P2-4. Since OpenEvidence only allowed three total repeats of each prompt, for all ANOVA calculations we used the mean of the existing responses to impute data for a fourth prompt. Though conclusions are necessarily limited given our small sample sizes and inconsistent data, results are reported below.

RESULTS

Overall Trends and Behaviors

Every AI chatbot except OpenEvidence produced hallucinated article citations. Hallucinated citations could appear with any prompt in tools producing them, commonly in response to Prompt 1.

Every chatbot repeated real article citations, sometimes within the same response. Results could repeat both between prompt iterations for the same prompt (duplication), and between different prompts (consistency). Hallucinated citations were usually not repeated, but were occasionally duplicated between responses to one prompt, or, rarely, to different prompts.

We did not attempt to assess whether tools provided accurate information if asked to summarize the literature regarding our prompt topics, and while in some cases they provided a summary even though it was not requested, we did not include or evaluate this content. It may be that hallucination-prone tools could respond adequately to summary requests even while unable to “cite their sources” when asked for articles, but this determination was outside the project scope.

Any prompt using any AI chatbot could expect on average 4.9 article citations (including duplicate and hallucinated results) in response to any one prompt. Most chatbots gave similar numbers. The exception, Perplexity, averaged 7.5 citations/prompt. Excluding Perplexity, the average number of citations/prompt was 4.3.

Table 1

Number of real (R) and hallucinated (H) citations retrieved from each tool for each iteration of two prompts. Includes irrelevant results, repetition of unique results to multiple prompts, and duplication of results to individual prompts.

Educational Prompt (“Teach-back”)											
Tool	No. of Prompts	Prompt 1		Prompt 2		Prompt 3		Prompt 4		Total	
		R	H	R	H	R	H	R	H	R	H
ChatGPT	6	3	20	6	19	6	22	4	21	19	82
Claude	4	8	7	12	6	8	8	11	7	39	28
Copilot	7	30	0	17	18	14	11	15	15	76	44
Gemini	5	16	3	15	14	7	20	9	20	47	57
OpenEvidence	6	15	0	49	0	30	0	--	--	94	0
Perplexity	6	33	0	53	2	37	0	38	1	161	3
PubMed	1	36	--	--	--	--	--	--	--	36	--

Clinical Prompt (“Neutropenic diet”)											
Tool	No. of Prompts	Prompt 1		Prompt 2		Prompt 3		Prompt 4		Total	
		R	H	R	H	R	H	R	H	R	H
ChatGPT	5	7	10	9	10	10	11	7	12	33	43
Claude	4	15	0	20	1	17	3	10	5	62	9
Copilot	5	8	12	8	12	13	8	13	8	42	40
Gemini	4	2	10	4	15	2	12	1	9	9	46
OpenEvidence	5	20	0	23	0	26	0	--	--	69	0
Perplexity	5	43	1	42	1	40	2	38	3	163	7
PubMed	1	98	--	--	--	--	--	--	--	98	--

Real and Hallucinated Articles

Five of six AI tools included hallucinated citations in results (see Table 1). Only OpenEvidence provided entirely real citations, though Perplexity returned few hallucinations (10/334, 3.0%). ChatGPT's results were mostly hallucination (125/177, 70%), followed by Gemini (97/153, 63%). Copilot's citations were 42% hallucinated (84/202), and Claude's 27% (37/138). Deduplication changes the numbers slightly. Considering only unique citations, ChatGPT still produced most hallucinations, with 125/154 article citations (81%) hallucinated. Perplexity remains lowest after OpenEvidence, with 3/46 (6.5%) hallucinated. Copilot's citations were 73% hallucinations (72/99), Gemini's 72% (63/88), and Claude's 40% (31/78).

Two-way ANOVA showed a significant difference in the number of real results between the tools ($F(5,36)=43.7$, $p<0.001$), indicating some tools were more likely than others to provide real results, and a barely significant interaction between tools and prompts ($F(5,36)=2.57$, $p=0.04$), suggesting that some tools were more likely to provide real results for one of the two prompts. There was no significant difference in the proportion of real results between the two prompts ($F(5,36)=1.28$, $p=0.26$), suggesting that neither the clinical nor educational prompt was overall more likely to retrieve real results.

For fabricated results, ANOVA showed a significant difference in the proportion of hallucinations between the tools ($F(4,30)=13.53$, $p<0.001$), and between the two prompts ($F(4,30)=7.5$, $p=0.01$) suggesting that some tools were more likely to hallucinate overall, and that one of the two prompts was more likely to retrieve hallucinated results. There was no significant interaction between tools and prompts ($F(4,30)=1.19$, $p=0.33$), suggesting that no particular tool provided more hallucinations in response to either prompt.

These findings support the observations of our raw data in showing that some tools provided more real or hallucinated results than others, and may also indicate that the text of one of our prompts was less likely to receive hallucinated results in general, and more likely to receive real results from certain tools. Given the minimal differences in phrasing, it is unclear whether tools respond differently to requests for educational than for clinical literature, or whether adding "real" and/or "APA format" (as in our second, clinical prompt) may in fact be somewhat effective.

Relevant Citations

For citations determined to be real, the majority were relevant to the topic (see Figure 1). Overall relevance ranged from 78% (Copilot) to 100% (OpenEvidence): most tools returned at least 90% relevant citations. Hallucinated citations uniformly appeared relevant based on title, but, since articles did not exist, could not provide information relevant to the prompt.

We assessed relevance only for real citations, but researchers making LLM tools part of formal search strategy might consider "screening" as a process that includes eliminating both hallucinatory and irrelevant real works from results. In this case, an established metric like Number Needed to Read (NNR) is useful. We calculated NNR for each tool using the total unique citations it provided (see Table 2). Even including hallucinations, all scored well, likely because our searches were fairly specific and our relevancy criteria broad.

ANOVA testing showed a significant difference in the number of *relevant* results returned by each tool ($F(5,36)=46.66$, $p<0.001$) as well as a significant interaction between the tools and the two prompts ($F(5,36)=2.92$, $p=0.02$). There was no significant overall difference in the number of relevant results between the two prompts ($F(5,36)=2.59$, $p=0.11$). This suggests that some tools are more likely to provide relevant results than others, particularly in response to one of the prompts, but that neither prompt was more likely to receive relevant results overall.

There were also significant differences in number of *irrelevant* results ($F(5,36)=4.80$, $p=0.001$), number of irrelevant results per prompt ($F(5,36)=8.10$, $p=0.007$), and interaction between tools and prompts ($F(5,36)=3.99$, $p=0.005$), suggesting that some tools are more likely to provide irrelevant results (unsurprising given that some were more likely to provide hallucinations, which cannot be relevant), and that prompt text may matter when it comes to relevance (again perhaps linked to number of hallucinations).

Duplication and Hallucination when Repeating Prompts

Duplication of citations to individual prompts occurred for each AI tool (Figure 2), with some tools repeating a citation in the initial response. Hallucinations appeared in every AI tool except OpenEvidence and occurred with each prompt (Figure 3).

Table 2

NNR for each tool

ChatGPT	Claude	Copilot	Gemini	OpenEvidence	Perplexity	PubMed
6.16	1.81	4.71	3.66	1	1.09	3.26

Figure 1 Number of unique relevant and irrelevant citations for each AI tool (clinical and educational prompts combined). Duplicates and hallucinated citations excluded.

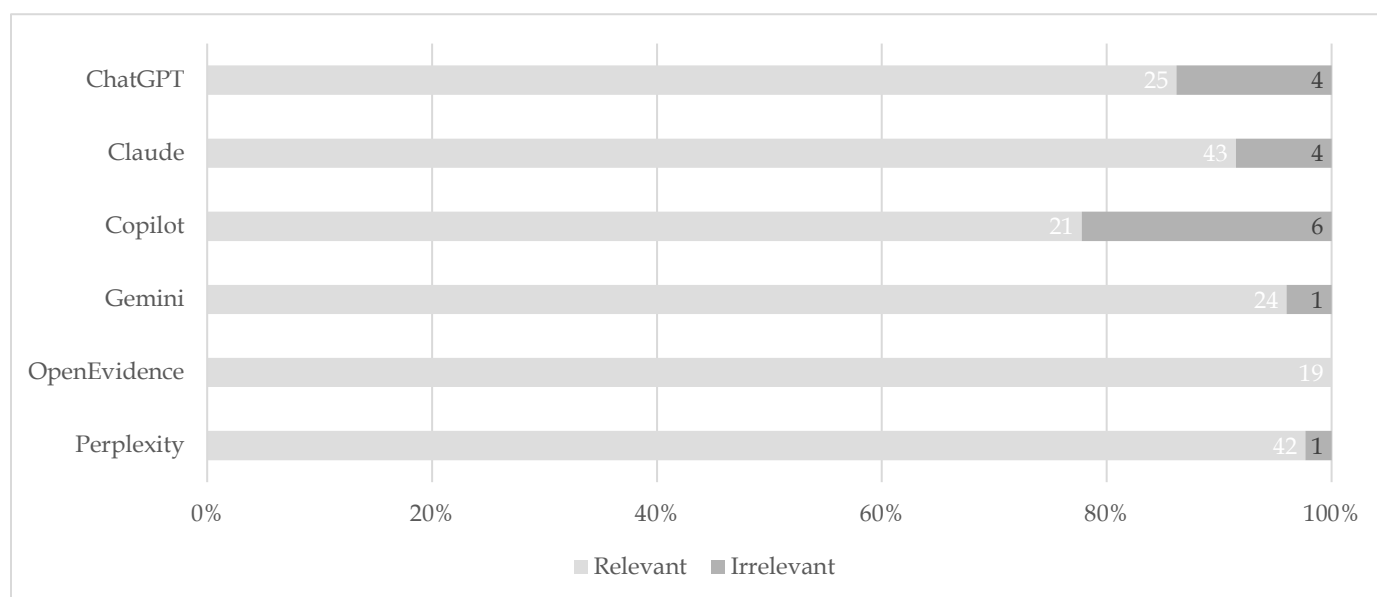
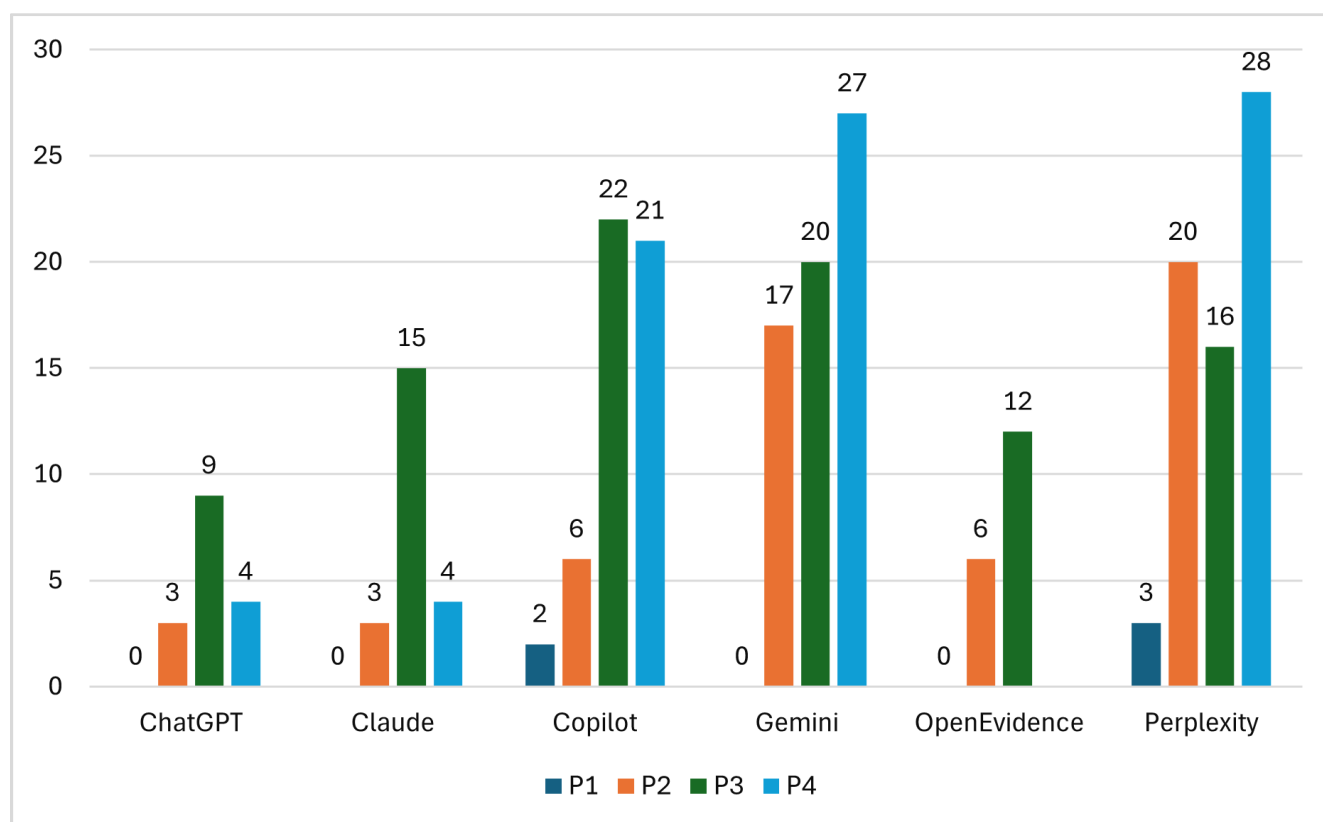
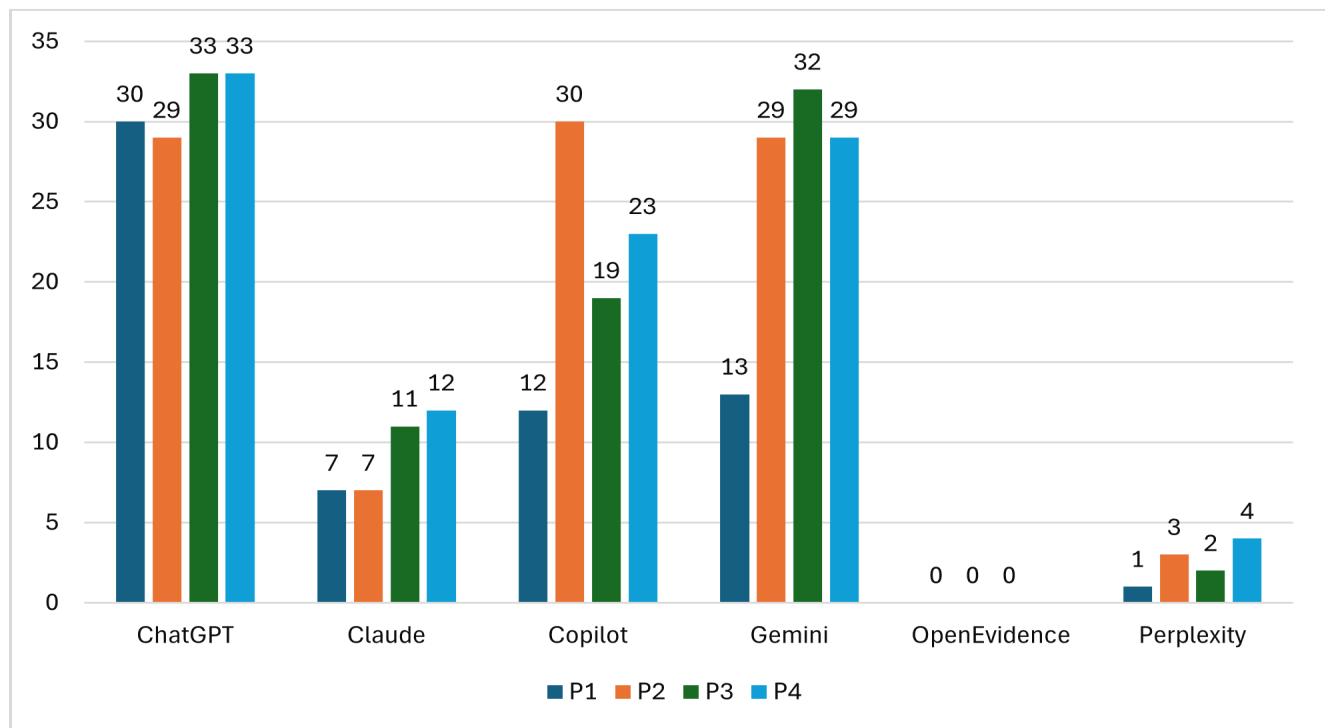


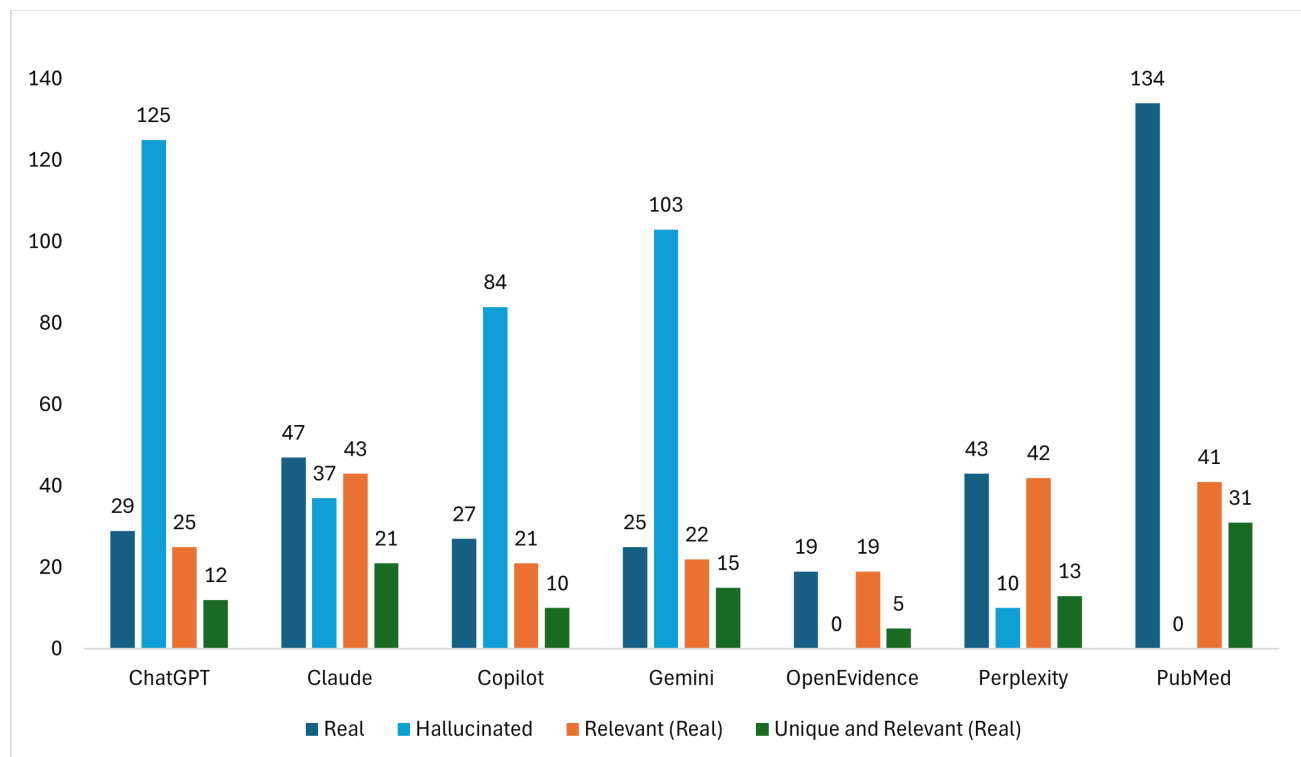
Figure 2 Times unique citations repeated to individual prompts and for which prompt iteration(s) repetition occurred. Clinical and educational prompts combined.



Note: OpenEvidence was prompted three times (P1-P3).

Figure 3 Number of hallucinated citations per prompt iteration. Clinical and educational prompts combined.

Note: OpenEvidence was prompted three times (P1-P3).

Figure 4 Total real, hallucinated, relevant, and unique results for each tool.

Repetition of Results when Repeating Prompts

ANOVA testing showed no difference between tools ($F(5,24)=1.53$, $p=0.21$) or between the numbers of new/repeated citations over the course of multiple iterations of the prompt ($F(5,24)=2.13$, $p=0.15$), and no interaction between the variables ($F(5,24)=1.71$, $p=0.16$) for the first, educational prompt. For the second, clinical prompt we did find a significant difference between tools ($F(5,24)=3.44$, $p=0.01$), as well as a significant interaction between tools and new/repeated citations ($F(5,24)=4.33$, $p=0.005$), but there was no significant difference in the overall number of new and repeated results ($F(5,24)=0.65$, $p=0.42$). This may suggest that while some tools may be more likely to provide new or repeated results generally, at least in response to one of the two prompts, each prompt iteration was, overall, as likely to retrieve a repeated result as a new one. We repeated prompts verbatim aside from the word “additional;” it is possible tools would have provided more new articles if we had modified prompts each time while maintaining key components of the topic, as we would do with databases or on the web.

Consistency of Results for AI Tools

OpenEvidence demonstrated 100% consistency with the clinical prompt (all six articles were retrieved by all five searchers); for the educational prompt, consistency was

73%. No other tool showed complete consistency for either prompt. Consistency scores for combined prompts: OpenEvidence 87; Perplexity 63; Claude 50; Copilot 32; Gemini 24; ChatGPT 21.

Comparing AI and PubMed Results

PubMed retrieved 134 results for both topics combined (36 educational, 98 clinical); 41 were deemed relevant, slightly below Claude’s 43 and Perplexity’s 42 (see Figure 4). PubMed retrieved 93 irrelevant results, for a relevancy score of 31%, lower than any AI tool (Figure 1). PubMed’s NNR fell between tools with fewer and those with more hallucinated results, suggesting that high hallucination rates may be analogous to high irrelevancy rates from the user perspective: both mean sifting through unusable results. PubMed retrieved considerably more results per query than the chatbots. While Perplexity and PubMed produced almost the same number of real, relevant citations (see Figure 4), and Perplexity included far fewer irrelevant citations, it took 44 total prompts (5 and 6 prompters each repeating prompts 4 times) to retrieve Perplexity’s 42 relevant results, while 2 searches retrieved PubMed’s 41 relevant results. This may be either an advantage or disadvantage depending on user need: retrieving many articles at once facilitates a broader view of available literature on a topic and more efficient discovery of multiple articles for a thorough search, but high retrieval of irrelevant articles may be frustrating for users with more limited information needs.

Figure 5 Real and relevant results unique to (gray boxes) and shared between (intersecting boxes) tools. Darker background indicates more shared citations.

	ChatGPT	Claude	Copilot	Gemini	Open Evidence	Perplexity	PubMed
ChatGPT	12						
Claude	5	21					
Copilot	6	2	10				
Gemini	1	2	2	15			
Open Evidence	4	6	5	2	5		
Perplexity	9	11	9	5	7	13	
PubMed	2	7	2	2	1	4	31

Unique and Shared References Between Tools

Each tool retrieved unique relevant citations in this study (see Figure 4). PubMed had the most unique, relevant results, with 31. Claude did best among LLMs, producing 21 real, relevant citations not retrieved by other tools.

Each tool also shared citations with others. Perplexity produced the most citations in common with other tools. Figure 5 depicts references shared by and unique to each tool.

DISCUSSION

Hallucinations

Based on our study, hallucination remains an issue for general AI tools providing article citations. Every tool except OpenEvidence returned hallucinated citations; OpenEvidence has not revealed source data, but is reported to have trained on collections of medical literature [22], and it is possible the tool accesses existing search features of these collections rather than using its LLM to generate citations. All other chatbots produced fake citations, usually generating hallucinated citations beginning with the first prompt response. Rate of hallucination was generally consistent across response iterations for each tool, suggesting that tools do not hallucinate more/less after multiple repeated prompts, at least for short conversations.

According to the Hallucination Leaderboard, hallucination rates of models used for this study likely ranged from 2–10% [23], but this is incomplete. OpenAI's GPT-4o-Mini, some version of which most prompters used in this study, has a reported hallucination rate of 1.7%, but hallucinated 81% of citations we received from it. This may be because Hallucination Leaderboard's reported rates reflect ideal circumstances, asking models to summarize documents and using a temperature of 0 (i.e., models were less likely to be "creative"). Since literature searches are not "ideal circumstances" for chatbots, and creating a hallucination-free LLM may be impossible [24], we suspect the problem of hallucinated citations will continue although newer models have lower reported hallucination rates.

Relevance

Relevance is seen as a strength for these tools, and in our study they did mostly provide citations relevant to our topics.

The fact that AI tool results are usually relevant to prompts is likely important to users, who prefer not having to sort through irrelevant citations [25]. With most tools, topic accuracy is tempered by hallucinations, which uniformly seem relevant based on title but are useless for legitimate research. Advertising in chatbot responses is a developing field with potential to further cloud usefulness of prompt results [26–28]. The AI tools in our study still

performed better in terms of relevance (for real results) than our simple PubMed searches, suggesting AI may be especially appealing to those non-expert searchers most likely to rely on basic searches in PubMed or other databases.

However, AI tools showed low return rate of real articles per prompt compared to PubMed searches, since they provided few results at once (averaging approximately 5 results per prompt iteration in this study, including hallucinations and duplications) and often hallucinated. Fewer results to review saves time for users with specific, limited information needs, but could make in-depth research more challenging since it is difficult to get a sense of the range of articles on a topic when retrieving only 4–5 citations at a time. Relevant articles per search were much higher in PubMed than with LLMs, suggesting that even for tools with few or no hallucinations, thorough scholarly work would ultimately save little if any time with AI searches, since repeating prompts to ensure coverage of a topic may equal the time needed to look through database result sets for those that are relevant.

Repetition

All AI tools had high rates of duplicate results. This is not necessarily a concern in principle, since retrieving the same articles with variations on search strategies is also common in database and web searches. However, repetition potentially has greater impact here than with traditional search methods, given the smaller number of results from a single prompt of an AI tool. If each prompt retrieves only 5 citations, the potential for new useful results is lower than in a database or web search where dozens to hundreds of citations might result with each query. Frequent duplication over multiple small results sets may cause searchers to prematurely conclude that no additional relevant articles exist.

Despite attempting to cue tools by requesting "additional" articles in each follow-up prompt, we saw minimal evidence of new citations being preferentially returned in later iterations of prompts, though more varied prompting might have shown different results.

Consistency

We observed low consistency of results between multiple users of AI tools, meaning a low likelihood of search replicability. While this may not concern an individual who is simply looking for an article on a topic, it could potentially hamper a shared, more complete understanding of the literature. If several people searching for information on the same subject with the same search terms see completely different articles, they could reach different conclusions by relying on AI tools. It is possible the tools would have shown more consistency if asked to summarize the literature on our topics rather than cite sources, but for researchers interested in going deeper

than an AI overview, lack of consistency is a concern. Also concerning is AI tools' lack of transparency: we have no way of knowing why any researcher saw the specific articles presented to them rather than those shown to someone else, meaning anything from random chance to stored information from previous prompts might influence which articles a researcher discovers.

Although our study took the viewpoint of an individual seeking literature on a simple topic, others have examined potential use of LLMs in various components of evidence synthesis projects [1,4,9,17]. The speed of AI chatbots could be valuable in these instances, where extensive work is required to locate and evaluate articles. However, reproducibility is a key component of systematic reviews [29], and the low consistency of citations produced by the LLMs we tested suggests they are currently inappropriate replacements for traditional databases such as PubMed. Systematic review teams should be advised to use LLMs only as a supplementary tool, perhaps useful for brainstorming search terms or phrasing queries, rather than for literature searching.

Unique Results in Tools

Since each tool produced some real, relevant citations not provided by the others, a possible conclusion is that thorough, extensive literature searches might benefit from prompting even those AI platforms which did not perform well at this task by our measures. However, this is balanced by the time it took us to input the multiple prompts and remove hallucinated, duplicate and irrelevant results. It is also likely that sophisticated database and web searches such as those already employed by review teams would in fact discover those citations not retrieved with our simple PubMed searches.

Potential Implications for Information Seekers

In academic settings, librarians have long promoted search skills training to students as time-saving, arguing that the more efficiently learners can locate articles relevant to their assignments, the more time they have for other components of their studies. Based on this metric and for this type of information need, it is difficult to frame an argument against the use of AI tools that is likely to resonate with students, since chatbots quickly provided relevant articles without need for advanced search skills. If an information seeker only wants a few articles on a topic to complete an assignment, an AI with minimal tendency to hallucinate may perform adequately.

However, for any in-depth information need, whether a systematic review project, historical retrospective, or simply a desire to understand the full scope of a topic, even low-hallucination AI tools demonstrated serious shortcomings due to their small results sets, lack of consistency, and tendency to repeat citations even when prompted for new ones.

Unlike PubMed and other scholarly databases, where the number of results for different searches can vary widely and is in part based on the amount of published literature for a topic, AI tools showed little variation in number of results for each prompt or topic. While more study is needed, we speculate that smaller retrieval from AI tools may promote a "flattened" perception of scholarly literature, suggesting an equal likelihood of retrieving a small number of relevant articles on any topic with a single request. Combined with the likelihood of seeing different articles than others investigating the same subject, even AI tools that do not hallucinate may contribute to a shallow and individualized understanding of a topic rather than a deeper, broader view that is more representative of the scholarly work.

At the same time, a cursory understanding is often preferable to no understanding, and chat tools' ease of use enables quick acquisition of a few articles on a topic that may provide a basic overview. If these tools can interpret individual queries in the style most comfortable to each user and demonstrate an acceptable level of accuracy in returning an article, they may provide value to a researcher with a very basic need.

Limitations

Study data was collected in August and September 2024. Since then, most of the LLM chatbots tested have released updated models with lower reported hallucination rates. Our study provides a broadly defined baseline to evaluate new models, not an assessment of current performance.

We considered only two questions, similarly worded. Different question types or more sophisticated prompt engineering could have produced results with fewer hallucinations and/or greater retrieval of new articles in later iterations. However, while both questions were medical in nature, one was clinically focused, and one educationally focused; we did not see meaningful differences in hallucination or duplication rates between them. We believe different question types will likely not lead to significant differences in hallucinated citations, duplication, or consistency of results.

Generalizability of data is limited by inconsistent numbers of prompts for each tool/prompt and inconsistent versions of tools. A more standardized dataset might have yielded different results and interpretations.

Finally, although the ability to translate and thereby facilitate sharing of information between languages is a potential strength of LLM tools, we considered prompts and results solely in English; findings of literature-searching projects in other languages might differ.

CONCLUSIONS

Future research will undoubtedly continue to assess performance of AI tools in literature searching. Other

research areas include the impact of AI tools on medical student information seeking, and the impact of prompt engineering on AI responses to literature requests (i.e., whether more sophisticated prompting skills deliver better results). Relatedly, if chat tools are accepted as standard resources for medical students seeking articles, librarians will need to teach patrons to effectively prompt for best results the way we now teach effective database and web searching: further study will determine best practices for both literature-search prompting and for presenting these skills in educational sessions.

Our results suggest that AI tools are not presently a viable replacement for PubMed or other academic databases for use in any in-depth literature searches; however, tools with little evidence of hallucination (in this study, OpenEvidence and Perplexity AI) may be adequate for limited information needs or as a complement to database or web searches.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in the Open Science Framework at <https://osf.io/5xpe4/>.

AUTHOR CONTRIBUTIONS

A'Llyn Ettien: conceptualization; project administration; methodology; investigation; data curation; formal analysis; visualization; writing – original draft; writing – review and editing. Kathleen Downing: conceptualization; methodology; investigation; writing – review and editing. Rebecca Drouhard: conceptualization; methodology; investigation; writing – original draft; writing – review and editing. Bridget Gunn: conceptualization; methodology; investigation; visualization; writing – original draft; writing – review and editing. Megan McNichol: conceptualization; methodology; investigation; writing – original draft; writing – review and editing. Kate Silfen: conceptualization; methodology; investigation; formal analysis; writing – original draft; writing – review and editing. Allie Tatarian: conceptualization; methodology; investigation; formal analysis; writing – review and editing.

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Six AI tools were used to generate citations for analysis, as detailed above. Grammarly was used to check for grammatical errors in some sections. AI was not otherwise employed in the writing of this paper. The authors take full responsibility for the content of the manuscript.

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Supporting researcher compliance: assessing institutional readiness for the 2023 NIH Data Management and Sharing Policy

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Objective: To assess researchers' understanding, readiness, and perceived challenges related to the 2023 NIH Data Management and Sharing (DMS) Policy and identify institutional support needs to facilitate compliance.

Methods: A mixed-method study was conducted using a 15-item survey distributed to 155 researchers at an academic medical center, with 55 responses (35% response rate). The survey evaluated familiarity with the DMS policy, confidence in performing data management and sharing tasks, perceived burden, and desired institutional support. Quantitative data were analyzed descriptively, and open-ended responses underwent inductive thematic analysis to identify key themes.

Results: Most respondents (67%) understood the DMS policy, yet fewer (47%) felt comfortable developing a DMS Plan. Only 29% had used DMPTool.org, while 87% requested tailored templates. Confidence in identifying appropriate repositories (40%) and budgeting for DMS activities (38%) was limited, with 68% perceiving plan execution as burdensome. Qualitative findings revealed two major themes: (1) Operational and Infrastructure Needs; emphasizing the need for centralized consultation, discipline-specific templates, equitable access to expertise, and budget guidance; and (2) Implementation Challenges and Perceived Burden; including perceptions of administrative overload, uncertainty in managing sensitive data, and calls for clearer institutional communication and cultural reframing of data sharing as a value-added activity.

Conclusions: While researchers endorse the principles of the NIH DMS policy, many lack the practical resources and institutional support necessary for effective compliance. Developing centralized infrastructure, standardized guidance, and targeted training may reduce burdens, promote equity, and strengthen a culture of responsible data stewardship. While researchers endorse the principles of the NIH DMS policy, many lack the practical resources and institutional support necessary for effective compliance. Developing centralized infrastructure, standardized guidance, and targeted training may reduce burdens, promote equity, and strengthen a culture of responsible data stewardship.

Keywords: NIH Data Management and Sharing Policy; Research Data Stewardship; Institutional Support; Data Sharing Compliance; Policy Implementation; Researcher Perceptions



See end of article for supplemental content.

INTRODUCTION

In January 2023, the National Institutes of Health (NIH) implemented a policy to enhance the management and sharing of scientific data [1]. This NIH Policy on Data Management and Sharing (DMS) mandates that all NIH-funded research projects include a concise, comprehensive plan for data management and sharing. This policy aims to accelerate the pace of biomedical discoveries, improve research integrity and reproducibility by facilitating the validation of research results, maximize sharing of research by ensuring accessibility to datasets, reduce

redundancy in scientific efforts, and boost citizen trust in science [2].

The DMS Policy represents substantive change from the previous 2003 NIH Data Sharing Policy [3], expanding its scope to encompass all NIH-supported research regardless of funding level. By promoting responsible data stewardship, the policy seeks to uphold scientific rigor and integrity while protecting the privacy of human research participants. Researchers are now empowered to choose the most appropriate methods for sharing scientific data, fostering broader collaboration and innovation

across the scientific community. Additionally, by ensuring the sharing of scientific data, the NIH anticipates an increase in the reusability of scientific data [4]. Before DMS policy implementation, up to 93% of researchers failed to comply with their own data sharing statements, in a variety of ways such as unresponsiveness, stating that they no longer have access to the data or simply rejecting the data request without providing a reason, among other reasons [5-7]. Consequently, adherence to the policy is expected to prompt changes within the scientific community [8].

A key aspect of the 2023 NIH DMS Policy is its alignment with the FAIR (Findable, Accessible, Interoperable, and Reusable) principles, which provide a framework for enhancing the utility and impact of scientific data [9, 10]. The 2023 NIH DMS policy adheres to these FAIR principles by emphasizing the importance of making data Findable using globally unique identifiers and rich metadata; ensuring that data are Accessible via facilitating seamless and long-term data retrieval; improving Interoperability by using shared vocabularies and formats, enabling data integration across diverse systems and workflows; and underscoring Reusability of data by advocating for detailed documentation and clear usage licenses, thereby maximizing the potential for data to be applied in various research contexts.

Although FAIR data principles have become more widely known since their introduction in 2016, not all research groups have expert data managers or prior experience in sharing their scientific data. Therefore, some teams may lack the necessary knowledge or skills to comply with the FAIR data principles. Acquiring the now-required skills, as well as undertaking the necessary data management and sharing activities to comply with the policy, will require a financial investment from researchers or their institutions. Moreover, the additional preparation of documents, such as DMS Plans, and the need to comply with various and potentially overlapping data-related policies may lead researchers to perceive an increased administrative burden [2]. This explains why the NIH has built an accessible and detailed list with examples of DMS Plans [11], and why online tools such as DMPTool.org—an online platform that contains several plan examples and templates that could be used to build a DMS Plan [12], have been adopted by multiple institutions.

To facilitate DMS policy compliance among researchers at our institute and allocate our institutional resources appropriately, we conducted a mixed-method study to assess researchers' understanding of the policy, identify factors that may facilitate successful engagement, evaluate their perceived readiness, determine whether the policy is perceived as adding a burden to the research process, and gather their overall opinions on the policy. This will allow an evaluation of potential support needs in training, DMS plan development, data curation, data repository consultation, and other areas. This study shares how we

evaluated researchers' needs and the findings, some of which may benefit other institutions.

METHODS

To assess the perceived impact of the NIH DMS policy on researchers at our institution and their research activities, we employed a mixed-method approach to collect both quantitative and qualitative data on their understanding of the policy, areas of concern, and suggestions for improvement. Nationwide Children's Hospital (NCH), with the Abigail Wexner Research Institute (AWRI), is a research-intensive, comprehensive pediatric hospital covering a wide range of pediatric specialties and research fields. This study was determined to not be human research by the Institutional Review Board (IRB) at Nationwide Children's Hospital (STUDY00004222).

We conducted a survey to evaluate participants' perspectives on policy requirements, challenges, and support needs. The survey included 14 questions designed to assess researchers' familiarity with the NIH DMS policy, including DMS Plan requirements and the tools needed to develop such plans (Questions 1 to 4); evaluate researchers' confidence in performing data management and sharing activities (Questions 5, 6, 8, and 9) and how to do so in compliance with policy requirements (questions 10 to 12); and identify areas where institutional support could help alleviate perceived burdens (Questions 7, 13 and 14). Participants rated their agreement on a 5-point Likert scale, with a "Not Applicable (N/A)" option provided. Responses were categorized as generally positive/agree (ratings of 4 or 5) or generally negative/disagree (ratings of 1 or 2). These questions were developed from previous informal interactions with researchers that had requested assistance to engage with the NIH DMS policy, and analysis of the policy, aiming to keep a short survey to maximize the number of respondents (see Appendix B).

The survey was distributed via email to 155 researchers across the institution, encompassing all members of faculty and staff that were determined to be research leaders at the institution, as they are principal investigators that meet a threshold amount of research funding support. These researchers belong to various fields of medical knowledge, and span basic, pre-clinical/translational and clinical research. Survey results were gathered between May and July 2024.

The survey also included an open-ended question that invited participants to share their perspectives and suggestions for enhancing institutional engagement with the policy, as well as areas requiring additional attention to support understanding and compliance. Open-ended survey responses were analyzed using inductive thematic analysis following Braun and Clare's six-phase framework [13]. This framework includes familiarization with the data, generation of initial codes, searching for themes,

reviewing themes, defining and naming themes, and producing the final analytic narrative. In this process, researchers move from close engagement with the raw data to the development, refinement, and interpretation of themes that capture meaningful patterns across the dataset. The framework was used as an iterative and recursive approach, allowing themes to be reviewed and refined while preserving the depth and context of participants' perspectives. Primary coding was conducted by a single researcher Thipkanok Wongphothipphan (TW) to support analytic immersion and interpretive consistency across the dataset. To strengthen the credibility and confirmability of the findings, we incorporated a formal audit trail and peer-debriefing/critical audit process with a second researcher Sergio Corrales-Guerrero (SC), who was familiar with the full dataset.

TW first familiarized themselves with the data through repeated readings and memo-writing, documenting preliminary impressions and early pattern candidates. TW then generated inductive, data-driven codes across the full dataset (totaling 13 discrete codes). Coding was flexible and non-exclusive; a single response could be assigned multiple codes where applicable. Codes were then collated into eight candidate themes, which were iteratively reviewed against the coded extracts and the full dataset to assess internal coherence and distinctiveness. Theme names and definitions were refined to capture each theme's central organizing concept. Finally, the thematic structure was consolidated by organizing the eight themes under two overarching themes comprising eight sub themes to produce the final thematic map (see Appendix A).

An audit trail was maintained to document analytic decisions and changes across stages (e.g., code generation, code merges/splits, and revisions to theme boundaries and definitions). Following development of the thematic map, SC conducted a critical audit by independently reviewing the proposed codes and theme definitions in relation to the raw survey extracts. TW and SC then held a structured peer-debriefing discussion to examine areas of interpretive divergence and refine theme boundaries and definitions. Revisions arising from this process were documented in the audit trail, and the thematic structure was finalized once themes were clearly defined and adequately supported by the dataset.

RESULTS

Of the 155 research leaders invited to complete the survey, 55 responded, resulting in a response rate of 35%. In instances where participants submitted multiple entries, only their first submission was retained for analysis. There were five instances of multiple submissions, likely because of the distribution method. An informal comparison of duplicate submissions demonstrated substantial

consistency between responses. The first submissions were retained because they more frequently contained comments for Question 15 and generally provided more comprehensive qualitative input.

The survey results revealed that while most researchers reported understanding the requirements of the 2023 NIH DMS policy (67% agreed vs. 13% disagreed), fewer felt confident in developing a DMS Plan, with only 47% expressing comfort compared to 22% who did not. Regarding available resources, the majority of respondents (71%) indicated they had never used DMPTool.org. There was also a strong demand for tailored templates, with 87% of participants expressing interest and only 9% indicating no interest.

When asked about data access, most researchers expressed confidence in their ability to determine which data should be shared (64% agreed vs 6% disagreed). However, confidence was lower regarding control over data access, with only 51% agreeing and 9% disagreeing. This pattern suggests that researchers may find it easier to determine whether data should be shared at all, rather than making more nuanced judgments about conditional sharing and the appropriate levels of access restrictions. Additionally, the majority of respondents (71% agreed vs 12% disagreed) indicated that institutional guidance on data sharing would be beneficial.

Researchers were also asked about their perceived level of expertise in performing tasks required for compliance with the DMS policy. More than half (56%) agreed that they possessed the expertise to document data, metadata, and tools, while 23% disagreed. However, only 45% reported confidence in their ability to curate data, compared to 23% who did not, indicating a gap in perceived preparedness. Furthermore, only 40% of respondents believed they had the expertise to identify an appropriate repository for data sharing, while 27% disagreed. Lastly, when asked whether their team could meet the NIH-required timeline for data sharing, only 39% agreed, and 24% disagreed, suggesting limited confidence in achieving timely data management and sharing compliance.

The final set of questions revealed researchers' main concerns related to DMS activities. Notably, only 20% expressed they know how to budget for DMS-related costs. While nearly half reported feeling comfortable overseeing their project's DMS activities (46% agreed vs 22% disagreed), most perceived the execution of a DMS Plan as a significant burden (68% agreed vs 12% disagreed).

As noted above, the survey included an open-ended question inviting researchers to share additional perspectives on the NIH DMS policy and suggestions for how the institution could best support compliance. A subset of 23 respondents provided qualitative feedback. Inductive thematic analysis of these responses revealed

Figure 1 Survey results: Cumulative percentage by response group for each survey question. Represented on the left neutral and N/A responses. On the right a comparison of disagreeing vs agreeing responses. For all questions n = 55, except questions 8 and 13 where n = 54.

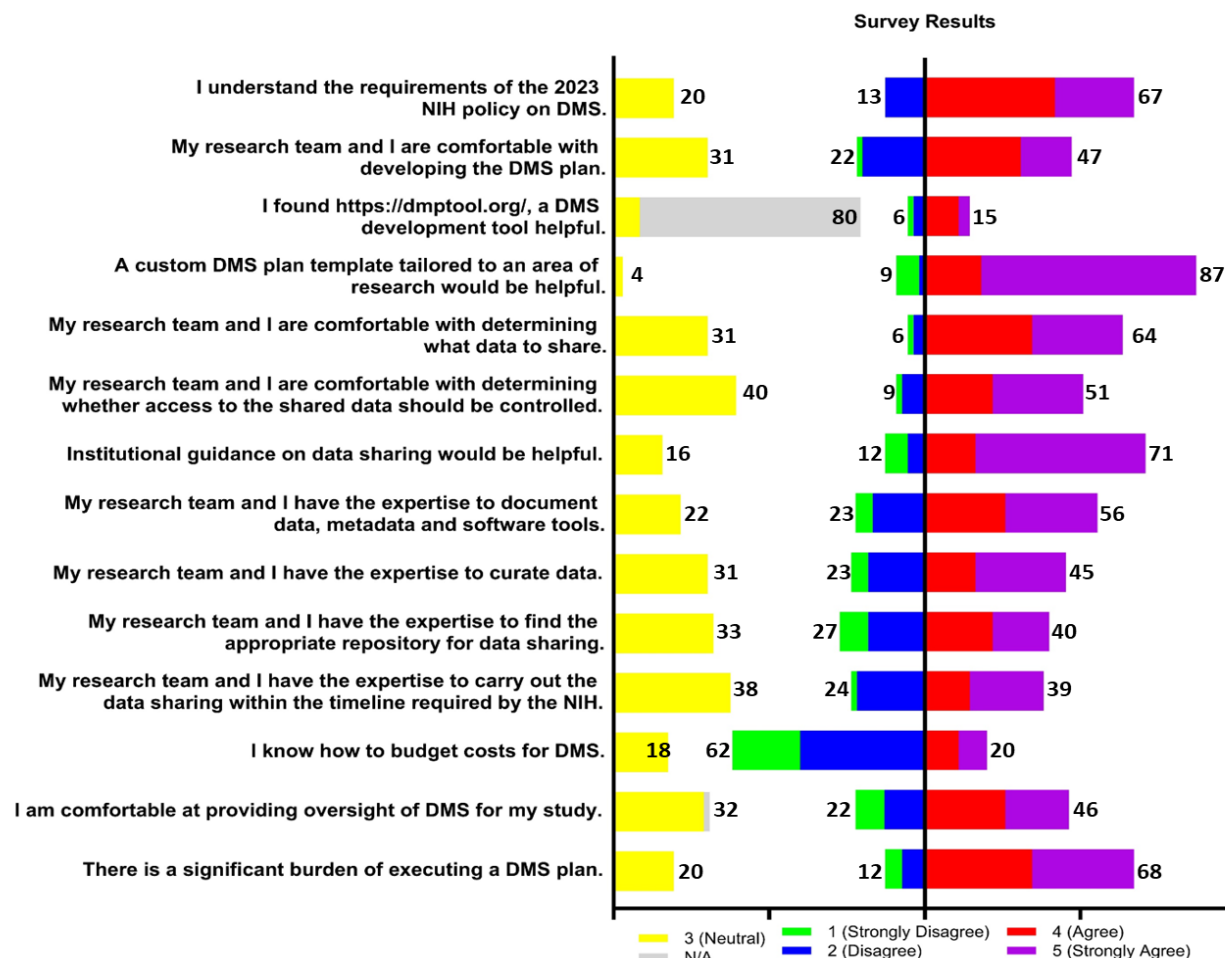


Table 1

Descending frequency of sub-themes in the open text responses.

Sub-theme	Frequency (%)
1.1 Institutional Infrastructure and Support	65.2
2.2 Data Sharing Complexity	39.1
2.3 Need for Clarity and Communication	39.1
1.2 Desire for Tailored and Practical Resources	26.1
2.1 Burden and Capacity Concerns	26.1
1.4 Financial and Budgetary Constraints	21.7
1.3 Expertise and Equity in Access	13.0
2.4 Cultural and Attitudinal Resistance	8.7

two overarching themes [13]: (1) Operational and Infrastructure Needs and (2) Implementation Challenges and Perceived Burden. Each theme comprises several subthemes that collectively illustrate researchers' perceptions, experiences, and support needs related to the NIH DMS Policy. The percentages in this section are calculated to represent the frequency among open-text answers and not total survey respondents, which can be found in the supplemental materials.

Theme 1: Operational and Infrastructure Needs

Participants expressed a strong desire for institutional support to facilitate compliance with the NIH DMS policy. This theme encompassed four sub-themes: *Institutional Infrastructure and Support*, *Desire for Tailored and Practical Resources*, *Expertise and Equity in Access*, and *Financial and Budgetary Constraints*.

1.1 Institutional Infrastructure and Support

Researchers want DMS services integrated into institutional infrastructure. This includes staff support, templates, repositories, and consultations.

Approximately 65% of the researchers (n = 15) responding to the open-ended survey question consistently emphasized the need for data management and sharing services to be integrated into institutional infrastructure. Many viewed DMS-related tasks, such as repository selection, metadata documentation, and plan development, as core services that should be supported by trained personnel, rather than managed solely by principal investigators. Participants also highlighted the need for access to consultative services during the grant preparation process. A survey respondent noted:

I wish that AWRI offers: 1) training, 2) templates, 3) personnel supporting writing a DMS plan for my grant applications, 4) identifying an appropriate data repository for my study, and 5) preparing and submitting my data.

1.2 Desire for Tailored and Practical Resources

Participants ask for field-specific templates, curated examples, and applied help with tools like DMPTool.

Over 26% of participants (n = 6) expressed support for the development of customized, discipline-specific resources to assist with both the creation and implementation of DMS plans. Many reported frustration with generic tools and templates, emphasizing the need for curated examples aligned with common study types reviewed by the IRB or representative of the local research context. For example:

The DMPTool is really not that helpful. A simple internal site where someone has curated examples from each of our centers would allow our team to pull parts relevant to their areas and see how others have done this.

1.3 Expertise and Equity in Access

Inequities in access to support are a concern, as is availability of DMS-specific expertise.

Three comments (13%) highlighted disparities in access to DMS-related support across research units. Participants noted that teams within our genomics research center (IGM) benefit from established workflows for depositing data, whereas others face challenges meeting similar requirements without institutional support or repository-specific expertise. These differences raised concerns about equity and consistency in policy compliance. As one survey respondent observed:

Depositing genomic data in NIH repositories is currently very difficult at AWRI for investigators who are not in IGM. Unclear

why different rules are applied to investigators in IGM vs. non-IGM investigators.

1.4 Financial and Budgetary Constraints

Concerns about costs, inflexible budgets, and unclear budgeting guidance related to DMS implementation.

Five participants (21.7%) expressed concern about the additional financial burden associated with the DMS policy, particularly within the context of static NIH budget caps. Some described data sharing expenses as unanticipated costs that further strain limited grant budgets. Others highlighted the absence of clear guidance on budgeting for compliant repositories and related services, which complicates financial planning and proposal development. To illustrate:

"Making a dataset ready for sharing is not easy.... It's a lot of work and therefore not cheap. Unfortunately, we are still living under the \$500,000/ year R01 limit that has not increased in decades! Just another expense NIH requires of us but says we must take it out of our allotted budget."

Theme 2: Implementation Challenges and Perceived Burden

In addition to structural challenges, participants described the implementation challenges and perceived burdens associated with implementing the DMS policy. This theme includes four sub-themes: *Burden and Capacity Concerns*, *Data Sharing Complexity*, *Need for Clarity and Communication*, and *Cultural and Attitudinal Resistance*.

2.1 Burden and Capacity Concerns

Researchers feel the DMS policy places a high burden on PIs, especially without dedicated support or expertise.

Many researchers (26.1%; n = 6) reported feeling overwhelmed by the new policy requirements, particularly in the absence of dedicated support or prior experience with data sharing. The perceived administrative burden was viewed as detracting from core research activities and contributing to inequities in researchers' ability to achieve compliance. As one survey respondent noted:

It seems each investigator will invest a significant amount of time developing best practices...I do think some of the burden could be removed from the PI by institutional systems.

2.2 Data Sharing Complexity

Researchers see the technical aspects of preparing and depositing data (especially human data or PHI) as complex and lacking support.

The technical and ethical challenges associated with sharing sensitive or human subjects' data emerged as a central concern. Almost 40% of participants (n = 9) working with clinical data or protected health information

(PHI) expressed uncertainty about how to appropriately de-identify datasets, select compliant repositories, or meet both IRB and NIH requirements. These concerns were particularly salient among researchers studying rare diseases or working with small sample sizes. For example:

The process for human data is very complex and would benefit from a staffed system that would walk investigators through IRB approval for depositing and actual deposit in dbGaP.

2.3 Need for Clarity and Communication

There's a strong desire for clearer institutional guidance and better communication about expectations, tools, and value of DMS.

Several comments (39.1%; $n = 9$) emphasized the need for clearer institutional communication regarding the expectations, purpose, and procedures associated with the DMS policy. Respondents reported uncertainty about what constitutes compliance, which tools are institutionally supported, and how to navigate overlapping data-related policies.

"Provide templates and better communication. We have sought insight from the OSU medical library because we have not been aware of any resources at NCH."

2.4 Cultural and Attitudinal Resistance

Some skepticism about institutional motives, DMS value, and overall policy burden reflects resistance to the change.

Finally, two comments (8.7%) reflected underlying skepticism or mistrust toward both the institutional response to the policy and the policy itself. These participants questioned whether data stewardship was being meaningfully prioritized or if compliance efforts were largely symbolic rather than substantive. Others expressed frustration with the top-down implementation of new mandates without corresponding support.

It would be helpful to understand the value of the DMS plan. At the moment, it feels like a tremendous burden that adds nothing to the research enterprise. Understanding that it actually has value, and how to capture that value, would be helpful in motivating adherence to the plan.

DISCUSSION

This study examined researchers' perceptions, preparedness, and support needs related to the 2023 NIH DMS Policy within our institutional context. Overall, the findings suggest that while most participants understand the NIH DMS policy, there are several areas of concern regarding how to engage with it. This presents an opportunity for institutional leadership to strengthen and expand existing data management practices, by framing the policy as a means to amplify research impact rather

than as an externally imposed mandate, which in turn may further strengthen engagement and compliance.

Despite broad understanding of the policy, many respondents reported gaps in practical knowledge and readiness for compliance. For instance, few expressed confidence in developing or implementing a DMS plan. Specific challenges included data curation, repository selection, budgeting, and meeting NIH-mandated timelines. These findings suggest that understanding the policy is insufficient as there may be barriers for its immediate generalized adoption, and effective compliance requires structured, practical resources that translate requirements into actionable steps. At NCH, addressing these gaps through structured institutional training, technical assistance, and standardized processes could substantially reduce barriers to implementation. Other institutions may likewise benefit from integrating similar resources into their research infrastructures.

A prominent theme emerging from the survey was researchers' call for a stronger institutional infrastructure to support DMS compliance. Respondents to the open text question stated the need for centralized consultation services during grant preparation, particularly for crafting DMS plans that align with both NIH expectations and local research practices. Such services were viewed as essential for reducing the administrative burden placed on individual investigators. This aligns with the survey results, in which a majority of respondents agreed that institutional guidance would be beneficial, underscoring a clear need for a coordinated institutional response to the challenges associated with policy compliance. Equally important was the call for dedicated personnel with expertise in data management who could provide direct assistance in DMS Plan development and repository selection. In the open text questions 26.1% of open-response participants also underscored the value of institutional templates and curated examples tailored to specific research disciplines and contexts. These comments are consistent with the survey findings, in which the desire for templates was rated very highly, and lack of confidence in selecting repositories showed the second highest level of disagreement, surpassed only by budgeting. Collectively, these requests highlight the importance of embedding DMS expertise within institutional systems rather than relying solely on individual investigators to interpret and operationalize policy requirements.

Another concern identified was the uneven level of preparedness for DMS-related activities across research centers. Three respondents pointed out that certain units, such as those engaged in genomics research, benefit from well-established workflows and familiarity with data repositories, whereas investigators in other departments often lack comparable resources, experience or guidance. This perceived disparity may contribute to perceptions of inequity and inconsistency in institutional DMS policy

implementation. This may also challenge notions of fairness and risk undermining collective compliance efforts, as smaller teams or less experienced investigators may face disproportionate administrative and technical burdens. These concerns further highlight the need for support in repository selection, as well as the gaps in expertise related to data curation and the handling and documentation of data, metadata, and associated tools identified in the survey. Addressing this gap will require development of standardized policies and support mechanisms to ensure equitable access to the expertise, tools, and infrastructure necessary for effective data and metadata management, curation, and consequently DMS compliance across all research teams.

A key finding was that researchers perceived the execution of DMS Plans as a substantial burden (68% agreement in survey and 26.1% in open responses), particularly regarding time and financial investment. At NCH, this perception may stem from the combination of budget limits and the limited availability of dedicated data management personnel within many research teams. This aligns with prior literature documenting tension between expanding compliance requirements and constrained grant budgets [2, 8]. Moreover, most survey respondents reported that they do not know how to budget for DMS-related costs, and only one-fifth indicated that they feel comfortable doing so. This further underscores the extent to which budgetary considerations represent a concern for researchers. Consequently, without explicit budgeting strategies and institutional overhead mechanisms to offset associated costs, the policy risks exacerbating inequities by disproportionately straining smaller or less-resourced teams. To mitigate this, NCH and similar institutions should provide clear budgeting guidance for recognizing DMS-related costs in grant applications and develop institutional initiatives that promote data reusability and shared infrastructure.

Participants also identified the complexity of managing sensitive data and the added burden of DMS compliance oversight as major challenges. Investigators working with human subjects or rare disease datasets expressed uncertainty regarding appropriate repository selection and in one comment about data de-identification. These findings may also help explain the relatively low survey scores related to researchers' confidence in determining whether data access should be restricted or in selecting an appropriate repository. These findings could potentially hint towards agreement with prior publications highlighting heightened concerns about privacy safeguards and intellectual property protections in research contexts [14, 15]. However, as noted earlier, intellectual property and data ownership was not identified among the open-text responses and perhaps these findings are reflective of the overall lack of expertise in repository selection, data curation and potentially participant privacy safekeeping. Within the NCH setting, this underscores the need for additional institutional

consultation services, particularly those providing guidance on repository selection, to strengthen researcher confidence and compliance. More broadly, these results suggest that generic federal guidance is insufficient, and institutional-specific support structures are essential to ensure privacy protections, regulatory compliance and researcher trust.

39.1% of participants of the open text response also indicated the need for improved institutional communication and clarity surrounding the DMS policy. Respondents expressed uncertainty about what constitutes compliance, and which institutional tools are officially supported. Such ambiguity may contribute to confusion and potentially resistance to engagement. Researchers suggested that clearer, coordinated communication strategies could reduce these barriers. Moreover, this enables a shift in how the policy is presented: rather than framing it as an external mandate, institutions should position data sharing as an opportunity to enhance research visibility, collaboration, and societal impact. This reframing could reduce potential attitudinal resistance by aligning compliance efforts with researchers' intrinsic motivations for scientific contribution and innovation, thereby transforming perceived obligations into shared institutional values.

To prepare an institutional response to the publication of the policy, NCH coordinated pre-existing resources, team members and added a new member to lead the response and provide the applicable expertise to help researchers engage with the policy. This led to the development of the present study. In response to the findings above, the team has implemented a suite of new services aimed at facilitating the transition to compliance with the NIH DMS policy. First, a website was developed using the institution's internal communications platform. The site provides a concise summary of the policy requirements, along with a curated collection of freely available resources, including templates, DMS Plan examples, and checklists.

Survey responses indicated that many researchers had not previously engaged with DMPTool.org, which offers additional tools and guidance for developing Data Management and Sharing (DMS) Plans). In response, the website highlights DMPTool.org and includes a step-by-step guide to support its use. Additionally, our team created and integrated supplementary guidance materials directly within DMPTool.org, ensuring that tailored support is available to researchers as they develop their DMS Plans using the platform.

Additionally, a presentation introducing the policy was developed and delivered through several institutional seminar series. The content was designed to address key concerns raised by researchers, including budgeting for data management and sharing, selecting an appropriate repository, and determining when data should be stored

under controlled access. The presentation was recorded, and both the video and slide deck were made available to researchers on the website for ongoing reference. Based on survey responses, we identified the research units with the highest representation and subsequently delivered tailored versions of the presentation to those groups, customizing the content to address their anticipated priorities and most pressing needs.

A consultation service was also established to support researchers seeking assistance with their DMS activities, particularly in the development of DMS Plans. Support is available via email, chat, and video conferencing. As part of the consultation process, a team member may conduct a “discovery” conversation with the researcher to assess their specific needs, identify potential solutions, and clarify relevant policy requirements. These consultations often include assistance with selecting an appropriate repository, connecting researchers to relevant resources, ensuring that proposed data-sharing approaches align with privacy and confidentiality protections, and reviewing or drafting compliant DMS Plans.

To support continuous improvement, a satisfaction survey is distributed following each consultation. In addition to assessing overall satisfaction, the survey gathers feedback on which components of the DMS Plan researchers find most challenging. This allows us to update the recurrent presentations on the policy by further explaining topics where confusion may prevail. Furthermore, several months after NIH proposal submission, researchers are invited to share any feedback received from NIH regarding their DMS Plans. This information enables the consultation service to adapt and remain responsive to evolving NIH priorities and evaluation criteria.

Finally, our institution continues to pursue broader initiatives to address concerns that extend beyond the scope of the services described above, including inequities in access to data management expertise and the inherent complexity of data sharing. These efforts include the development of data literacy training modules and the promotion of initiatives aimed at enhancing data reusability. Collectively, these initiatives represent a proactive institutional strategy to transform researcher concerns into opportunities for strengthening sustainable data stewardship capacity and promoting responsible research data sharing.

This study has several limitations. Although a 35% response rate was achieved, respondents represented a wide range of research units. As a result, subgroup analyses comparing individual units to the overall dataset, or to one another, were not feasible due to limited sample sizes within each unit. Moreover, at the time of this study we were not able to determine whether the number of respondents per research unit was a fair representation of all researchers in the unit, which limits the interpretation of representation by field of research. Additionally, to

encourage participation, the survey was intentionally kept brief to minimize the time burden on researchers.

Consequently, the scope of questions was limited, and some areas of inquiry that might have provided deeper insight into researchers’ needs and better informed the prioritization of support services were not explored.

Most recently, in May 2026, the NIH introduced a new DMS Plan format. This streamlined and user-friendly format is intended to facilitate the completion of DMS Plans by researchers. Although the revised format may address some of the concerns identified in this study, such as the need for standardized templates, it is important to note that templates were already available at the time the survey was administered. Furthermore, many of the concerns identified in this study extend beyond the creation of the DMS Plan itself and relate to the operational requirements of effectively implementing the policy throughout the research lifecycle and period of performance. These challenges include determining which data should be shared, securing institutional support, determining appropriate data access controls, curating data, developing appropriate budgets, addressing administrative burden, and selecting suitable repositories.

In summary, this study highlights both the opportunities and challenges associated with implementing the NIH DMS policy. The researchers suggest that institutional strategies should prioritize capacity building over persuasion. Priorities include developing centralized infrastructure, providing targeted training, ensuring equitable access to resources, and offering clear financial and procedural guidance. Through these efforts, institutions can not only facilitate compliance but also foster a culture of responsible data stewardship and amplify the scientific and societal impact of research.

DATA AVAILABILITY STATEMENT

All data associated with this article can be found in the supplementary materials.

AUTHOR CONTRIBUTIONS

Sergio Corrales-Guerrero: Conceptualization; methodology; investigation; data curation; visualization; formal analysis; writing - original draft; writing - review & editing. Xu Zhang: Conceptualization; methodology; visualization; formal analysis; writing of original draft; writing - review & editing. Thipkanok Wongphothiphan: Formal analysis; writing of original draft; writing - review & editing. Jinyu Xu: Methodology; investigation; writing - review & editing. Yungui Huang: Conceptualization; methodology; formal analysis; writing - review & editing.

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SUPPLEMENTAL FILES

Appendix A: Thematic Steps

Appendix B: Survey Instrument and Dataset

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Removing records on animals and nonhumans in Ovid Embase: a comparison of 11 filters

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See end of article for authors' affiliations.

Objective: To understand and compare the impact of 11 filters to remove records on animals or nonhumans in Ovid Embase, which are routinely used despite there being no performance data for them. To understand the indexing of relevant subject headings in Embase.

Methods: To assess filter performance, we screened and categorized 3,000 records as 'should be removed' or 'should be retained' and calculated the sensitivity, specificity, and overall accuracy for each filter. We also reported on the number of records with human participants or data that were incorrectly removed by each filter.

Results: Method 11 was the most sensitive, correctly retaining 90.6% records, whereas method 3 had the highest specificity, correctly removing 71.5% records. Of the records incorrectly removed by each filter, method 11 removed the fewest records with human participants or data at 10.9%, whereas method 3 removed the most at 14.3%. Filters that did not remove records indexed with 'nonhuman/' had higher sensitivity. Filter performance could vary by subject, publication type and language due to differences in indexing.

Conclusion: In choosing a search filter, information specialists and review teams should discuss whether animals or nonhumans could feature in relevant studies.

Keywords: Bibliographic database; Embase; MEDLINE; indexing; information retrieval; search strategies



See end of article for supplemental content.

INTRODUCTION

Evidence syntheses interested in humans as a subject or population often remove records on animals and nonhumans where certain studies (e.g., pre-clinical studies using animals) are ineligible for inclusion. These records are removed using search filters – pre-tested search terms designed to filter results to specific criteria such as the population or study type [1]. Filters described as 'validated' have been tested against a 'gold standard' or set of known relevant and irrelevant records, whereas 'non-validated' filters may have undergone limited testing [2]. In Ovid Embase, several non-validated search filters are routinely used to remove records on animals or nonhumans. Although the database contains an inbuilt limit to filter to results indexed with the Emtree subject heading 'human/', this risks exclusion of relevant records where this indexing term has not been applied. The same issue on Ovid MEDLINE can be mitigated with a widely used method, applied in the Cochrane highly-sensitive search strategies for randomized controlled trials (RCTs) [3]. This method removes records indexed with subject headings for animals that are not also indexed with

humans. It is therefore designed to limit records to those likely to be about humans by excluding records that are *only* about animals [4]. Many routinely used filters designed for this purpose in Ovid Embase also follow this structure.

As filters designed to remove records on animals or nonhumans are rarely credited in published evidence syntheses (including the widely used MEDLINE filter), many of those designed for Ovid Embase are of unknown authorship. Several such filters, which have been routinely used in Ovid Embase, can be found in a diverse range of sources. Some can be found in the appendices of published literature reviews, such as one used by the Cochrane Common Mental Disorders Group (CCMD) [5] and another used by York Health Economics Consortium (YHEC) [6]; some are found in the strategies used to populate the Database of Abstracts of Reviews of Effects (DARE) and the NHS Economic Evaluations Database (NHS EED) [7]; others appear in filter resources by the InterTASC Information Specialists' Sub-Group [8] and Canada's Drug Agency [9]; Ovid Embase has its own filter to remove animal or nonhuman records [10]; and another

is part of a validated filter to find RCTs in Ovid Embase [11], though we do not have separate data on its performance. The unknown authorship of many of these filters may reflect that these are custom-made, unpublished or non-validated. It also means we do not know the context in which they were developed and their exact intended purpose. There are numerous differences in the design of these filters, with many exclusively using Emtree terms but some also employing the title or abstract fields. There is also variation in the Emtree headings applied as well as other differences in approach.

The challenges of defining and removing records on animals have been highlighted by Finnegan et al. [12]. Issues such as how we define these records mean that understanding the efficacy of filters designed to remove them yields numerous complexities. Firstly, just as we cannot rely on all records that are relevant to humans to be indexed with 'human/', we also cannot rely on records relevant to both animals/nonhumans *and* humans to use this indexing term. Therefore, these records could be excluded from search results if desired Emtree terms such as 'human/' or 'human experiment/' are missing on records with humans as a subject or population. This is important to consider, as animals are involved in human health in animal-assisted therapies; in detecting conditions such as cancer or low blood sugar; as sources of disease transmission or injury; and in various other respects. Similarly, as the Emtree term 'nonhuman/' can encompass animals, bacteria, viruses, and plants, we may not consider the full breadth of this term during filter selection, despite the relevance of nonhumans to human health. This prompts us to consider several questions: how are indexers assigning Emtree headings to records; what are information specialists using the filters to remove; what types of animal or nonhuman records do research teams want removed (and how might this vary on a review-by-review basis); and do information specialists and review teams discuss if the use of a filter is appropriate?

The use of search filters to remove records on animals/nonhumans is a subject which has received little attention to date. In 2025, a study by Askin et al on the widely used MEDLINE filter applied in the Cochrane highly-sensitive search strategies, found that records machine-indexed with the subject heading 'humans/' were almost twice as likely to be incorrect compared with manual indexing [13]. Prior to this, a poster by Soudant et al. in 2021 questioned the reliability of three non-validated filters to remove animal records in both MEDLINE and Embase, and reported on records with human participants that had been incorrectly removed [14].

As there is no direct performance data on any of the routinely used filters designed for Embase, filter performance and reliability are important considerations. It would be valuable to understand how these perform

and compare to each other to inform discussion and decision-making about filter use.

OBJECTIVES

This is an exploratory study which aims to investigate the impact of 11 filters to remove records on animals or nonhumans in Ovid Embase. The study explores how the filters work and compare to each other to facilitate informed decision making about filter use. The main objectives are to:

- understand how records are indexed with Emtree subject headings and how this could affect filter performance;
- explore how the 11 filters compare in terms of the proportion of records correctly removed (specificity) or retained (sensitivity); and
- explore how many records with human participants or data were incorrectly excluded by each filter.

METHODS

A summary of the methodology is as follows, we:

- communicated with Elsevier to ask questions on how records are indexed with Emtree subject headings;
- double screened a sample of 3,000 records to judge whether records should be removed or retained, using three separate datasets; and
- determined how the filters compare in their recall of records in the 'should be removed' and 'should be retained' categories; and in the number of incorrectly removed records with human participants or data.

1. Understanding How Records Are Indexed with Emtree Terms

Elsevier's indexing guide for Embase was used to understand how indexing might affect filter performance. We also e-mailed Elsevier to enquire: if indexers at Elsevier use the scope notes in determining whether to use Emtree subject headings relating to humans, animals, and nonhumans, and the meaning and interpretation of the scope notes for the Emtree term 'human/' [15].

Embase records are automatically indexed with Emtree terms based on their titles, abstracts and author keywords [15]. However, records which meet certain criteria (according to an automated process), are then manually indexed using the full text by indexers at Elsevier with a background in biomedicine [15]. This occurs for records with one or more Emtree terms for diseases, drugs, or

devices, and records identified as: reviews, short surveys (for case reports only), meta-analyses, and systematic reviews [15]. During manual indexing, indexers at Elsevier use Emtree's taxonomy as well as some additional rules and internal notes to ensure consistency [16].

Automatic indexing is retained for pre-prints and conference abstracts, and records with the status 'in press' or 'in process' unless listed as 'published' or 'processed' respectively [15]. This means there are differences in the indexing of conference abstracts and pre-prints in comparison to other publication types commonly sought in evidence syntheses. Records published in languages other than English are indexed based on the English title and abstract only [15] and do not meet the criteria for manual indexing, except for those in the Embase French Local Literature Module [17].

The scope notes for the Emtree heading 'human/', includes wording to describe its application to records 'where humans are a feature'. Elsevier explained that this could be 'anything from a human patient in a case report to a rural area, from a major clinical study (human subjects) to an environmental study in an urban area' [18]. They noted that this wording was chosen 'to include situations where there is a human presence, without the study necessarily including human subjects' [18].

2. Screening Records on: Animals/Nonhumans; Humans; and Animals/Nonhumans and Humans

To create our datasets, we developed three search strategies for Ovid Embase designed to find records likely to belong to one of the following categories:

1. animals/nonhumans;
2. humans; and
3. animals/nonhumans and humans.

These categories were chosen to provide a more comprehensive set of records than might be retained or removed by the filters compared with searching for topics only relevant to humans. Results for datasets 1 and 3 are not individually reported in this paper but are available in Appendix B. This study focuses on data from the humans dataset (as this is the most representative of topics that would use a filter) as well as all three datasets combined.

Each of the three search strategies included 16 lines of search terms and applied the 'all fields' field code. We chose search terms to find records likely to belong to each category only (e.g., veterinary parasitology for the animals/nonhumans category; personality disorder for the humans category; and human-animal bond for the animals/nonhumans and humans category).

The search strategies employed a filter for systematic reviews [7] as well as a filter for RCTs [11], as these study types are commonly sought in evidence syntheses. The

study filters were adapted to exclude any lines that removed records on animals or nonhumans. The 11 filters (see Table 1) were then employed consecutively in each of the three search strategies. These were applied with the NOT operator and the AND operator, so we could export records that would be removed or retained by the 11 methods. All lines removing or retaining records were pooled together using the OR operator. For each of the three searches, we used a sample of 500 records removed by the filters and 500 retained by the filters, totalling 1,000 for each category and 3,000 overall. To obtain each of our samples of 500, we used the 'range' box on Embase to export a selection of record numbers and ranges, totalling 500. Many of the 11 filters were either known to or used within the Centre for Reviews and Dissemination (CRD), University of York, except for methods 8 and 9, which were adapted from method 7 for testing purposes. All search strategies are available in Appendix A.

Each record was screened by both authors using the titles and abstracts. Records were categorized as either 'should be removed' or 'should be retained', using the criteria and definitions in Table 2, with disagreements resolved through discussion. The definitions and screening criteria in Table 2 are subjective and were designed around the context of the record rather than the population, as this is the broadest and most sensitive approach. We chose this approach as definitions of animal/nonhuman studies that are ineligible and should be excluded (both in the searches and during screening) could vary depending on the review being conducted.

Table 1 shows 11 different methods for removing records on animals or nonhumans in Ovid Embase. Line 1 (not listed) is representative of the line the method is applied to.

3. Testing and Comparing the Performance of 11 Filters

To test and compare the performance of the 11 filters, we needed to find each filter's recall of records we screened and allocated to the 'should be removed' or 'should be retained' categories. This was performed for each dataset individually.

Using the 'an' field code, we entered the accession numbers of each record allocated to the 'should be removed' and 'should be retained' categories with the 11 filters applied consecutively. This was performed separately for each category. The filters were applied with the NOT operator as well as with the AND operator, so we could determine the exact number of records removed or retained by each filter. Due to duplicate removal and changes to the records since their original export from Embase, some of the 3,000 records could not be retrieved using the accession number, resulting in only 2,689 records being tested overall.

Table 1

Methods of removing records on animals or nonhumans in Ovid Embase

Method	Application	Fields Used	Removes Animals only or Animals/Nonhumans	Origin / Usage	Citation
1	2 (animal/ or animal experiment/ or animal model/ or animal tissue/ or nonhuman/) not exp human/ 3 1 not 2	sh	Animals/Nonhumans	used within YHEC, c. 2014	[6]
2	2 (animal/ or nonhuman/) not exp human/ 3 1 not 2	sh	Animals/Nonhumans	used within CRD's Database of Abstracts of Reviews of Effects (DARE)	[7]
3	2 animal/ or exp animal experiment/ or nonhuman/ 3 (rat or rats or mouse or mice or hamster or hamsters or animal or animals or dog or dogs or cat or cats or bovine or sheep).ti,ab,sh. 4 2 or 3 5 exp human/ or human experiment/ 6 4 not (4 and 5) 7 1 not 6	sh ti ab	Animals/Nonhumans	used within CRD's NHS Economic Evaluations Database (NHS EED)	[7]
4	2 animal/ or exp animal experiment/ or nonhuman/ 3 (rat or rats or mouse or mice or hamster or hamsters or animal or animals or dog or dogs or cat or cats or bovine or sheep).ti,sh. 4 2 or 3 5 exp human/ or human experiment/ 6 4 not (4 and 5) 7 1 not 6	sh ti	Animals/Nonhumans	adapted from method 3	[7]
5	2 ((animal or nonhuman) not human).sh. 3 1 not 2	sh	Animals/Nonhumans	used within CCMD, c. 2021	[5]
6	2 (exp animals/ or exp animal experimentation/ or exp animal experiment/ or exp models animal/ or nonhuman/ or exp vertebrate/ or exp vertebrates/) not (exp humans/ or exp human experimentation/ or exp human experiment/) 3 1 not 2	sh	Animals/Nonhumans	Canada's Drug Agency: Animal Studies - Standard - MEDLINE, Embase	[9]

7	2 ((exp animal/ or exp invertebrate/ or nonhuman/ or animal experiment/ or animal tissue/ or animal model/ or exp plant/ or exp fungus/) not (exp human/ or human tissue/)) 3 1 not 2	sh	Animals/Nonhumans	Embase (Excerpta Medica Database) Guide: Humans only (removes records about animals)	[10]
8	2 (exp animal/ or exp invertebrate/ or nonhuman/ or animal experiment/ or animal tissue/ or animal model/ or exp plant/ or exp fungus/) not (exp human/ or human tissue/ or human experiment/) 3 1 not 2	sh	Animals/Nonhumans	adapted from method 7 to add terms for human experiment	[10]
9	2 (exp animal/ or exp invertebrate/ or nonhuman/ or animal experiment/ or animal tissue/ or animal model/) not (exp human/ or human tissue/ or human experiment/) 3 1 not 2	sh	Animals/Nonhumans	adapted from method 7 to include terms for human experiment without plant and fungus terms	[10]
10	2 (rat or rats or mouse or mice or swine or porcine or murine or sheep or lambs or pigs or piglets or rabbit or rabbits or cat or cats or dog or dogs or cattle or bovine or monkey or monkeys or trout or marmoset\$1).ti. and animal experiment/ 3 animal experiment/ not (human experiment/ or human/) 4 2 or 3 5 1 not 4	sh ti	Animals only	Glanville et al., 2019	[11]
11	2 animal experiment/ not (human experiment/ or human/) 3 1 not 2	sh	Animals only	adapted from method 10	[11]

sh or / = subject headings; exp = exploded subject heading; ti = title field; ab = abstract field; \$ = truncation.

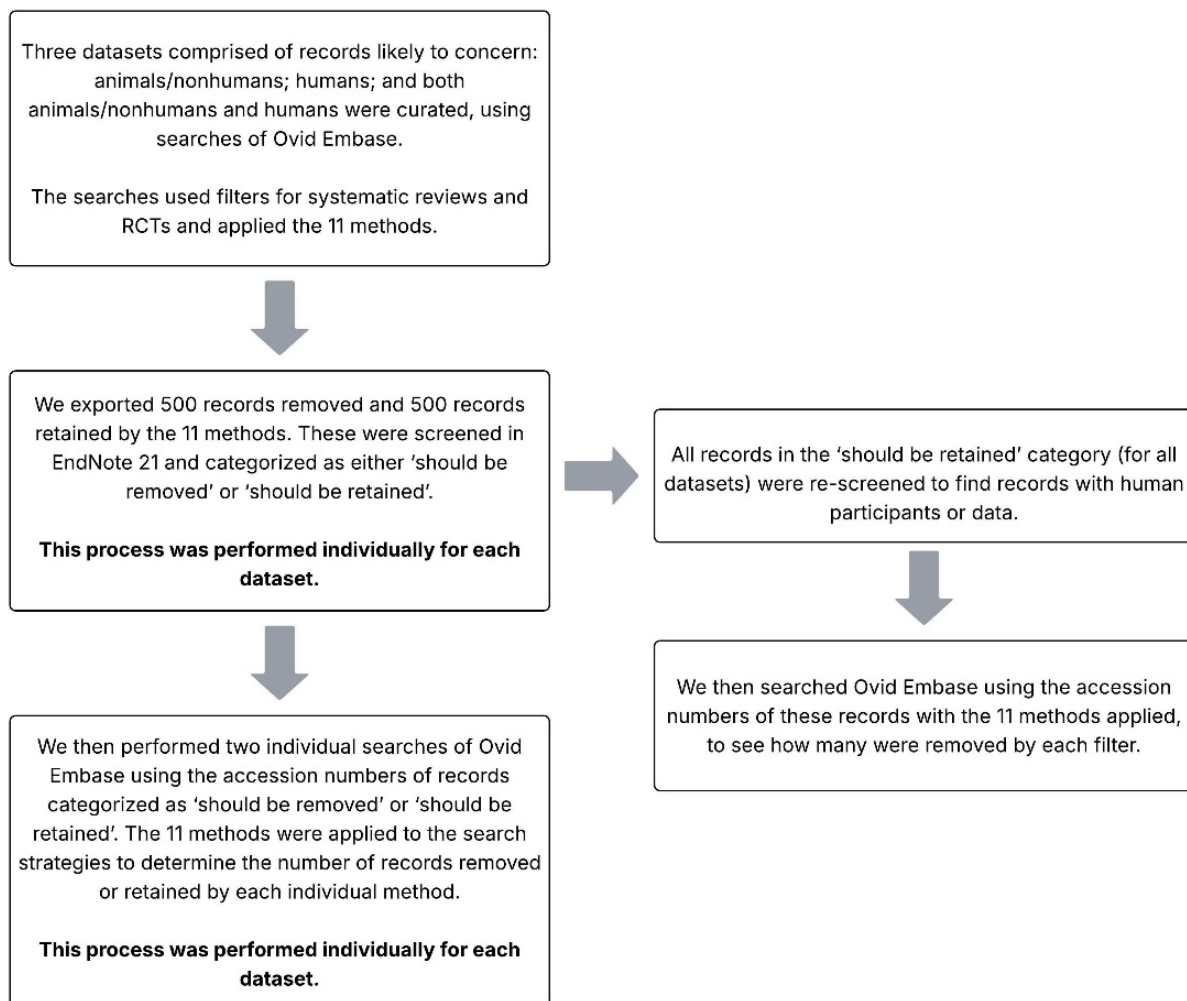
Table 2

Definitions and screening criteria

Definitions		Screening Criteria
Animal or Nonhuman Records	The primary focus or outcome is on, about, or for animals or nonhumans, and there is no relevance, impact or implication for human health (i.e., studies where humans are mentioned or compared in the study would be excluded from this categorisation if there is no relevance, impact or implication for human health). Pre-clinical studies investigating human health conditions by experimenting on animals whether wholly or in part (e.g., tissues, cells, etc), including studies also using human tissues or cells (unless human tissues, cells etc are tested separately and compared with animal tissues, cells etc). Studies that feature or use animals or nonhumans whether wholly or in part (e.g., tissues, cells, etc) with no relevance, impact or implication for human health, even if humans are mentioned or whole, living humans are compared (e.g., interns versus specialists). Studies on the properties, cultivation, use, health or diseases of nonhuman organisms such as plants, fungi, viruses, bacteria etc, where there is no relevance, impact or implication for human health.	Should be Removed: Meets criteria for Animal or Nonhuman records.

Not Animal or Nonhuman Records	Anything that does not meet the definition of an animal or nonhuman record above. Several examples include (but are not limited to): The focus is not on or about humans, animals or nonhumans (e.g., computers, the environment, etc). First-in-human studies. The primary focus or outcome is <i>on, about, or for</i> human health (except for pre-clinical studies investigating human health conditions by experimenting on animals). On, about, or involving animals/nonhumans or both animals/nonhumans and humans, where the focus or outcome is either split between humans and animals/nonhumans, or primarily about humans (e.g., training dogs to detect cancer in humans; studies of zoonotic diseases contagious to humans; nutritional value of animal products for humans).	Should be Retained: Meets criteria for <u>Not</u> Animal or Nonhuman records.
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Figure 1 Testing the performance of 11 filters to remove records on animals or nonhumans



For each of the 11 filters, we calculated the sensitivity, specificity, and the overall accuracy. Sensitivity, which is a measure of a filter's ability to correctly retrieve relevant records, was calculated by dividing the number of records retained by each filter by the number of records in the 'should be retained' category and then multiplying this number by 100. Specificity, which is a measure of a filter's ability to correctly exclude irrelevant records, was calculated by dividing the number of records removed by each filter by the number of records in the 'should be removed' category and then multiplying this number by 100. The term 'overall accuracy' is used to refer to the number of records that were either correctly removed or correctly retained by each filter. This was calculated by combining the number of correctly retained and removed records for each method, dividing this number by the combined number of records that should be removed or retained, and then multiplying this number by 100. Overall accuracy should be understood using the proportion of correct records in the 'should be retained' and 'should be removed' categories, as this weights the overall accuracy in favour of either sensitivity or specificity accordingly. For all calculations, percentages are shown to one decimal point.

We also sought to explore how many records with human participants or data were incorrectly excluded by each filter, using the following methodology. Across all datasets, 1,102 records in total had been categorized as 'should be retained'. These records were then screened on title and abstract by one author to find records that used human participants or data. In total, 735 records were found for this subset, which was the most valuable to report on compared with the other reasons records should be retained (e.g., those not on animals/nonhumans or human health directly, those relevant to factors affecting human health, etc).

To find each filter's recall of the 735 records with human participants or data, we created a search string of the accession numbers of these records with the 11 filters applied consecutively. We calculated the percentage of records removed for each filter. This was calculated using the number of records removed by each filter as proportion of the total number of records with human participants or data.

The process of testing the performance of the 11 filters is summarized in Figure 1.

RESULTS

Table 3 shows the recall of records in the 'should be removed' or 'should be retained' categories by each of the

11 filters for the humans dataset. Results with the highest percentages in each column are shown in grey and bold.

Method 11 was the most sensitive filter for this dataset, correctly retaining 88.3% records in the 'should be retained' category. A similar proportion was correctly retained by method 10 (86.9%), whereas all other filters retained similar amounts to each other, ranging from 75.4% to 78.5%.

Method 3 had highest specificity, correctly removing 91.7% records in the 'should be removed' category. All other filters correctly removed similar proportions of records (ranging from 90.1% to 91.3%), except for method 11 which had the lowest specificity at 73.4% and method 10 with second-lowest specificity at 80.4%.

Method 10 achieved 84.8% overall accuracy for the humans dataset. Similar percentages were observed for the other filters, which ranged from 80.5% to 83.6%.

Table 4 shows the recall of records in the 'should be retained' and 'should be removed' categories by each of the 11 filters for all datasets combined. Results with the highest percentages in each column are shown in grey and bold.

Method 11 was the most sensitive filter for all datasets, correctly retaining 90.6% records in the 'should be retained' category. A similar proportion was correctly retained by method 10 (88.3%), whereas all other filters retained similar amounts to each other, ranging from 75.2% to 78.9%.

Method 3 had highest specificity, correctly removing 71.5% records in the 'should be removed' category. All other filters correctly removed similar proportions of records (ranging from 68% to 68.5%), except for method 11 which had the lowest specificity at 41.2% and method 10 with second-lowest specificity at 49.9%. Method 3 achieved the highest overall accuracy at 73%. Similar percentages were observed for all other filters, (ranging from 72.2% to 72.6%), except for method 11 with 61.4% overall accuracy and method 10 with 65.6%.

Table 5 shows the number of records with human participants or data removed by each of the 11 filters for all datasets combined. The percentage is based on the number of records removed as proportion of all records with human participants or data. Results with the lowest figures in each column are shown in grey and bold, with the highest figures shown in white and bold.

Method 11 removed the fewest records with human participants or data $n=80$ (10.9%), whereas method 3 removed the most $n=105$ (14.3%). The mean number of records removed was 95.6 (13.1%).

Table 3

Comparing the performance of 11 filters to remove records on animals or nonhumans (Humans Dataset)

Method	<i>Sensitivity</i> Should be Retained	<i>Specificity</i> Should be Removed	Overall Accuracy
1	531 of 678 (78.3%)	281 of 312 (90.1%)	812 of 990 (82%)
2	532 of 678 (78.5%)	281 of 312 (90.1%)	813 of 990 (82.1%)
3	511 of 678 (75.4%)	286 of 312 (91.7%)	797 of 990 (80.5%)
4	530 of 678 (78.2%)	282 of 312 (90.4%)	812 of 990 (82%)
5	531 of 678 (78.3%)	281 of 312 (90.1%)	812 of 990 (82%)
6	529 of 678 (78%)	283 of 312 (90.7%)	812 of 990 (82%)
7	520 of 678 (76.7%)	285 of 312 (91.3%)	805 of 990 (81.3%)
8	520 of 678 (76.7%)	285 of 312 (91.3%)	805 of 990 (81.3%)
9	530 of 678 (78.2%)	281 of 312 (90.1%)	811 of 990 (81.9%)
10	589 of 678 (86.9%)	251 of 312 (80.4%)	840 of 990 (84.8%)
11	599 of 678 (88.3%)	229 of 312 (73.4%)	828 of 990 (83.6%)

Table 4

Comparing the performance of 11 filters to remove records on animals or nonhumans (All Datasets)

All Datasets	Method	<i>Sensitivity</i> Should be Retained	<i>Specificity</i> Should be Removed	Overall Accuracy
	1	868 of 1102 (78.8%)	1079 of 1587 (68%)	1947 of 2689 (72.4%)
	2	870 of 1102 (78.9%)	1079 of 1587 (68%)	1949 of 2689 (72.5%)
	3	829 of 1102 (75.2%)	1134 of 1587 (71.5%)	1963 of 2689 (73%)
	4	867 of 1102 (78.7%)	1085 of 1587 (68.4%)	1952 of 2689 (72.6%)
	5	869 of 1102 (78.9%)	1080 of 1587 (68.1%)	1949 of 2689 (72.5%)
	6	863 of 1102 (78.3%)	1086 of 1587 (68.4%)	1949 of 2689 (72.5%)
	7	855 of 1102 (77.6%)	1087 of 1587 (68.5%)	1942 of 2689 (72.2%)
	8	855 of 1102 (77.6%)	1087 of 1587 (68.5%)	1942 of 2689 (72.2%)
	9	865 of 1102 (78.5%)	1083 of 1587 (68.2%)	1948 of 2689 (72.4%)
	10	973 of 1102 (88.3%)	792 of 1587 (49.9%)	1765 of 2689 (65.6%)
	11	998 of 1102 (90.6%)	654 of 1587 (41.2%)	1652 of 2689 (61.4%)

Table 5	
Removed records with human participants or data (All Datasets)	
Method	Records Removed
1	95 of 735 (12.9%)
2	95 of 735 (12.9%)
3	105 of 735 (14.3%)
4	95 of 735 (12.9%)
5	96 of 735 (13.1%)
6	96 of 735 (13.1%)
7	97 of 735 (13.2%)
8	97 of 735 (13.2%)
9	94 of 735 (12.8%)
10	102 of 735 (13.9%)
11	80 of 735 (10.9%)
Mean	95.6 of 735 (13.1%)

DISCUSSION

How do the Filters Perform and Compare?

The filters with highest sensitivity and specificity (methods 11 and 3, respectively) were the same for Table 3 (humans dataset) and Table 4 (all datasets). The same findings were observed for each dataset individually, which can be seen in Appendix B. This suggests that the high sensitivity of method 11 and the high specificity of method 3 in comparison to the other filters, could be generalizable across a broad range of topics.

Following this pattern, the finding that the filter with the highest sensitivity (method 11) incorrectly removed the fewest records with human participants or data (n=80, 10.9%) in comparison with method 3, which removed more than any other filter (n=105, 14.3%), may be as we would expect. However, method 10, which was the second most sensitive filter overall, removed the second highest number of these records (n=102, 13.9%). This highlights the value of further insight into filter performance beyond sensitivity and specificity.

The filters which achieved the highest overall accuracy differed between the datasets. Method 10 had the highest percentage of correct records (84.8%) for Table 3 (humans dataset), whereas method 3 achieved the highest percentage (73%) for Table 4 (all datasets). This will be due to the different proportions of records in the ‘should be retained’ and ‘should be removed’ categories between the datasets, caused by the different topics that were sought

(i.e., animals or nonhumans; humans; and both animals/nonhumans and humans). Although we report on the overall accuracy of the filters, records on animals/nonhumans may be unlikely to make up a significant proportion of results for reviews interested in humans as a subject or population. Therefore, we recommend choosing a filter based on sensitivity rather than overall accuracy. Where specificity is an important consideration, this is best where sensitivity also remains high. As an example, if we compare filters 10 and 11 in Table 4 (all datasets), method 10 is 2.3% less sensitive than method 11, with 8.7% higher specificity.

Do the Different Approaches of the Filters Impact their Performance?

A key difference that affected filter performance is whether they were designed to remove records with subject headings for animals and nonhumans or for animals only. Table 1 shows that nine of the 11 methods employed subject headings to remove records on animals and nonhumans. The remaining two (methods 11 and 10) were unique in not applying the ‘nonhuman/’ subject heading. These filters, which were the two most sensitive, are also comparable in their sole use of the ‘animal experiment/’ subject heading, as ‘animal/’ appears in all other methods. Although other variations in subject heading choice can be seen across the filters, these had a much less noticeable impact on performance.

The similarities and differences in the design of the filters is reflected in the sensitivity and specificity they achieved. Although method 11 achieved the highest sensitivity at 88.3% for Table 3 (humans dataset) and 90.6% for Table 4 (all datasets), method 10 was close behind at 86.9% and 88.3%, respectively. All other filters achieved similar levels of sensitivity for both Table 3 (humans dataset) and Table 4 (all datasets).

This pattern was also observed for specificity: method 3 achieved highest specificity at 91.7% for Table 3 (humans dataset) and 71.5% for Table 4 (all datasets) but had a similar performance to most other filters, except for methods 11 and 10 which had the lowest and second-lowest specificity respectively.

Another notable difference in filter design that affected performance is the search fields. Table 1 shows that eight of the 11 methods solely employed subject headings; two employed the title field in addition to subject headings (methods 4 and 10); and one employed the title and abstract fields in addition to subject headings (method 3).

Method 3 was unique in employing the title and abstract fields in its approach to remove records. Notably, this filter had highest specificity and lowest sensitivity overall. Since terms appearing in the title and abstract fields may not necessarily reflect the content of a record, their use could have caused records to be incorrectly excluded. For example, some terms might be used to denote irrelevance

(e.g., 'animal studies were excluded') or might be used metaphorically rather than literally, as Finnegan et al. have observed [12]. Since this filter is almost identical to method 4 but unique in its application of the abstract field, it is this aspect of its design which led to it achieving highest specificity and lowest sensitivity.

For the other two filters that employed the title field and subject headings (methods 4 and 10), performance varied. Method 4 ranked sixth for sensitivity, whereas method 10 was the second most sensitive filter overall. Additional key differences between these filters in their use of subject headings (as described above) explain this difference in performance. A further difference is that method 10 removes records with animal terms in terms in the title where these occur with the 'animal experiment/' subject heading. As all 11 filters remove irrelevant free-text terms or subject headings unless they occur with a relevant subject heading, method 10 is unique in its structure to remove records with irrelevant free-text terms that occur with an irrelevant subject heading. However, this also means that it is possible for method 10 to remove records with the Emtree heading 'human/', in contrast to all other filters. To understand the implications of this difference, this led to the removal of a first-in-human study of porcine skin xenotransplantation for burns [19] (due to having 'porcine' in the title and 'animal experiment/'), and a study on autistic children's visual processing of the faces of humans and dogs [20] (due to having 'dog' in the title and 'animal experiment/'). This aspect of its design may also explain why method 10 removed the second highest number of records with human participants or data. If we compare the similar design and performance of methods 10 and 11, the unique differences in the structure of method 10 led to its correct removal of more animal records at a slight cost to sensitivity. Notably, there were only minor differences in sensitivity between methods 11 and 10 in Tables 3 and 4 (1.4% and 2.3%, respectively), with larger differences in specificity (7% and 8.7%, respectively).

Information about the origins or usage of the filters may reflect the context for which they were originally developed, which could explain some of the design differences between the filters. As an example, method 5's use by the Cochrane Common Mental Disorders group could mean it was developed using records on common mental disorders. Similarly, method 3's origins as part of the strategy to populate the NHS Economic Evaluations Database could mean it was developed using this study type. This might also explain aspects of its design, such as the use of the title and abstract fields, which may have been valuable for economic evaluations. In the absence of this information, it is useful to examine how the filters compare to each other for the study types used within this study (systematic reviews and RCTs).

As a further point on filter design, several Emtree headings for human study types listed in Elsevier's 2026

indexing guide are not routinely used in filters that remove animal or nonhuman records [15]. These include: 'normal human/', 'major clinical study/', 'clinical article/', 'case report/', 'human experiment/', 'human tissue/', and 'human cell/' [15]. Future studies could investigate the impact of incorporating these subject headings into a new or existing filter. Although some review teams may not be interested in Emtree terms such as 'human tissue/' or 'human cell/', where *in vitro* or *ex vivo* studies are not relevant, it is worth noting that some studies may involve human tissues and cells as well as including human participants. In comparison to the filters tested in this study, a wider variety of free-text terms for humans are searched in the Embase.com search strategy used to populate Cochrane CENTRAL. Designed by Julie Glanville, the animal studies filter includes terms such as patient, patients, children, man, men, women, woman, pediatric, paediatric, and other terms [21]. This approach could be investigated for Ovid Embase or filters designed for other databases and platforms.

How Might Indexing Affect Filter Performance?

A study by Soudant et al. reported that most of the records incorrectly excluded by animal filters in Embase were conference abstracts [14]. This finding may suggest that records which only receive automated indexing are more likely to be incorrectly excluded by animal filters. This includes the following types of record: certain non-English language records; pre-prints; conference abstracts; 'in press' or 'in process' records; records *without* one or more Emtree terms for diseases, drugs, or devices; and records *not identified as*: reviews; short surveys (for case reports only); meta-analyses; and systematic reviews. Information specialists should keep this in mind for review topics meeting these criteria (i.e., those interested in international evidence, conference abstracts, pre-prints, etc). As a result of this finding, Soudant et al. discourage the use of filters in strategies aiming to find conference abstracts [14]. However, information specialists could limit to these records (i.e., conference abstracts or pre-prints) separately in the search strategy and then use the OR operator to pool these records with results applying a filter to remove records on animals/nonhumans.

As each filter removed records with human participants or data (see Table 5), this provides evidence that records may not always be indexed as we might expect. The following examples were excluded by many (or all) of the filters as records were not indexed with 'human/': a study on the impact of an animal visitation program on students' mental health [22] (missed due to indexing with 'nonhuman/' and 'animal experiment/', despite the presence of 'university student/'); a review of drug-drug interactions of cannabis [23] (missed as cannabis is nonhuman); a trial of a vaccine in older adults [24] (missed as viruses are nonhuman); a review on smoking cessation [25] (missed as tobacco is nonhuman, despite 'health care

personnel/' being applied); a study on monkeypox [26] (as monkeypox is nonhuman, despite 'Bantu people/' and 'Aka (people)/' being applied); and a study on canine impactation [27] incorrectly indexed as 'nonhuman/'. These examples, which show the breadth of 'nonhuman/' and its relevance to human health, also highlight that records might be indexed with more specific terms for humans based on categories such as education or race instead of broader terms such as 'human/'. This justifies the need for filters to employ a wider variety of terms for humans, such as Glanville et al.'s filter for Embase.com [21]. Further investigation is warranted to understand what factors affect the removal of relevant records (such as topics, publication types, or automated indexing) and how these could be mitigated (e.g., with different techniques for different publication types or through increasing the sensitivity of filters).

How do we Define an Animal or Nonhuman Study?

In evidence syntheses, definitions of animal or nonhuman studies that are ineligible and should be excluded (both in the searches and during screening) could vary depending on the specific review being conducted and the level of evidence required. This suggests the need for discussions between information specialists and review teams about the types of animal or nonhuman studies they are aiming to exclude, and whether animals or nonhumans could feature in relevant studies.

In addition, review teams could consider the human records that are of interest, since various terms for humans appear in filters to retain records with these subject headings. As an example, the term 'human experiment/' is used for nonclinical experiments on humans such as psychological tests [15] but its nonclinical context is not immediately clear without reading the scope note. The individual meanings of subject headings is therefore an important factor in filter choice.

LIMITATIONS

This is an exploratory study in which only 2,689 Embase records were tested. As records were retrieved using filters for systematic reviews and RCTs, filter performance could vary for other study types. As we did not intend to test differences in filter performance by study type, we did not export the same number of records for systematic reviews and RCTs. For all datasets, only titles and abstracts were double screened.

As search results on Ovid Embase are ordered by the most recent records added to the database [28], our method of exporting our sample using a selection of record numbers and ranges would have introduced some variation in the records we obtained. However, this does not reflect a truly random sample.

Screening decisions about what is or is not an 'animal' or 'nonhuman' record were subjective, and definitions could vary. For these reasons, a broad approach was taken for greater generalizability of the findings.

The additional subcategorization of records that 'should be retained' with 'uses human participants or data' was based on the titles and abstracts and performed by one author only, which could have led to minor errors.

CONCLUSION

Between information specialists, review teams, and even on a review-by-review basis, there may be different criteria for excluding records on animals or nonhumans. Information specialists and review teams should discuss this in the context of the specific condition, phenomenon of interest, intervention, or level of evidence needed for the review. Detailed understanding of a review team's inclusion and exclusion criteria helps ensure relevant records are not removed through filter use.

Where filter use is considered appropriate to remove records on animals or nonhumans in Ovid Embase, we recommend the use of method 11 due to its sensitivity. Our investigation of how Emtree terms are indexed suggests that performance of the filters could vary by subject, publication type, study type, and language, which information specialists should keep in mind. Some relevant records could still be removed where subject headings such as 'human/' or 'human experiment/' have not been applied. Further research could test how the filters perform for conference abstracts, pre-prints, non-English language records and subjects that are unlikely to have one or more Emtree terms for diseases, drugs, or devices. Further testing and validation of the filters for different study types, such as qualitative studies or economic evaluations, would also be useful.

Overall, our findings are informative to help information specialists understand the impact of 11 different methods in Ovid Embase to remove records on animals or nonhumans, which are compared in terms of both performance and design.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in the supplemental files or can be obtained by contacting the first author.

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SUPPLEMENTAL FILES

Appendix A: Search Strategies

Appendix B: Supplementary Material

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Scholarly publishing literacy and perceptions of predatory publishing among educational partners at a chiropractic college: a case report

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Background: Chiropractors must find, appraise, and apply high quality, peer-reviewed information sources to make evidence-based clinical practice decisions. This case report describes perceptions of scholarly publishing practices, with a focus on predatory and deceptive publishing, among chiropractic educational partners at one chiropractic college.

Case Presentation: An anonymous, online, cross-sectional survey was administered to a convenience sample of 2,476 faculty, staff, and students. The 35-item questionnaire elicited publishing experience, critical appraisal skills, knowledge of scholarly and predatory publishing, and perceptions of chiropractic journals and information resources. Respondents (n=204, 111 students, 36 faculty, 16 administrators, and 41 staff) provided usable survey responses, though skipped items were common. Twenty-six percent had published one or more peer-reviewed publications. Most self-rated themselves as novice or intermediate in their ability to perform literature searches (87%) or critically appraise research articles (82%). Forty-six percent to 69% had not read or were unsure of the quality of scientific evidence for 11 chiropractic-related journals. Fifty-seven percent were unsure or unfamiliar with predatory journals and 51% lacked confidence in recognizing these journals. Predatory practices identified included insufficient or fast peer review, editorial board and impact factor issues, publication fees, plagiarized articles, and unsolicited request for paper submissions. Sixty-one percent requested training or resources on identifying quality academic journals for publication or research.

Conclusion: Chiropractic educational partners were unfamiliar with most chiropractic journals and had little familiarity with predatory publishing. Targeted training on identifying quality academic publications, conducting literature reviews and critically appraising research articles is recommended.

Keywords: Predatory Journals as Topic; Scholarly Communication; Information Literacy; Chiropractic; Education, Professional; Libraries, Medical; Library Surveys



See end of article for supplemental content.

BACKGROUND

Chiropractors need the ability to locate, evaluate, and use high quality, peer-reviewed information sources to make evidence-based clinical practice (EBCP) decisions [1–3]. Chiropractors must have sufficient information literacy skills, including knowledge of scholarly publishing practices and core chiropractic journals and reference materials [4,5]. The profession has struggled against anti-science sentiments from its founding and more recently saw unproven claims raised purporting protective mechanisms of chiropractic treatment during the COVID-19 pandemic [6,7]. While original research and scholarship generated by chiropractic faculty and students is an area of growing emphasis [8–12], chiropractic educational partners may lack research expertise and scholarly writing skills [13–15].

Chiropractic educational partners have engaged in numerous initiatives to increase practitioner and student knowledge and skills with EBCP, noting favorable gains in attitudes and use [2]. However, persistent barriers remain, including perceived lack of time, insufficient clinical evidence, and issues with locating, critically appraising, or interpreting the literature [2,4,16–23]. These barriers may lead chiropractors and students to rely on lower quality information sources, like websites and trade publications, instead of peer-reviewed sources of scientific evidence [2].

Faculty across higher education institutions often face intense pressures to publish [24,25] which may lead some faculty to publish their works within predatory journals [26,27]. Grudniewicz et al. within *Nature* offered a comprehensive, consensus definition of predatory journals, describing them as “characterized by false or

misleading information, deviation from best editorial and publication practices, a lack of transparency, and/or use of aggressive and indiscriminate solicitation practices” [28]. Predatory publishing is a persistent problem that promotes poor scientific practices and lowers editorial standards across academic fields [29].

In this case report, the authors describe a project designed to understand the training and support needs of potential health science library users at one U.S.-based chiropractic college regarding scholarly publishing, with an emphasis on journal quality and predatory publishing. Our team sought to answer the following questions:

1. What experiences have chiropractic educational partners in our institution had with scholarly publishing, including predatory publishing?
2. What resources do faculty, students and staff in our institution use and consider as reputable sources of information about chiropractic?

CASE PRESENTATION

This single-institution, cross-sectional survey evaluated perceptions of scholarly publishing literacy among educational partners at Palmer College of Chiropractic campuses in Iowa, Florida and California. The Doctor of Chiropractic program enrolls on a trimester basis, with hundreds of new student users introduced to the David D. Palmer Health Sciences Library each term. The library has two locations and is home to the largest collection of chiropractic works in the world, which includes books, journals, audiovisual materials, models, tools, and databases to support EBCP.

This project was timely and needed for several reasons. First, library resources were undergoing re-organization related to shifts in campuses and academic programs. Secondly, scholarly publishing was encouraged on multiple levels. Chiropractic students could participate in research honors programs and were encouraged to co-author research papers and case reports in collaboration with faculty. Academic and clinical faculty and staff members could receive financial incentives for authorship of scholarly publications but reported difficulties with selecting appropriate journals for their manuscripts. Thus, we hoped to identify knowledge gaps regarding predatory publishing and chiropractic journal quality.

We submitted the protocol to the Palmer College of Chiropractic Institutional Review Board, which deemed the project exempt. The 35-item online survey was adapted from prior research on publication literacy in academic health sciences [30,31] and designed within SurveyMonkey (San Mateo, CA, USA) using a feature that prevented recipients from completing the survey more than once. Most items were multiple choice, with some open-ended questions provided. The survey asked respondents to rank relevant journals based on perceived

quality of scientific evidence. Journal titles were selected based on history within the profession [5]; availability in the library collection; topical focus on chiropractic or spine care; impact factor (IF) as an indicator of rank within the field [32]; and known sources for faculty publications. Each question was optional, and survey completion was voluntary. Six librarians pre-tested the survey to ensure its clarity and flow (Appendix A). No incentives were offered. Descriptive statistics were summarized, including the number and percentages of responses. Skipped items ranged from 0 to 78 respondents for the quantitative questions, with more items skipped in the final third of the survey, suggesting survey fatigue [33]. Open-ended questions were coded by 2 authors (JS, SAS) using a conventional approach to content analysis [34].

We emailed survey invitations to a convenience sample of 2,476 potential library users from July to August 2024. In total, 210 people responded to the invitation, consent was received for 208 surveys, with 204 containing usable data (8.2% response rate). Respondents included 111 chiropractic students, 36 faculty (including 1 resident), 41 staff members, and 16 administrators.

What Experiences Have Chiropractic Educational Partners Had with Scholarly Publishing, Including Predatory Publishing?

Chiropractic educational partners in our institution described themselves as novice (24%), intermediate (32%), advanced (33%), or expert (10%) in their knowledge of chiropractic. Respondents rated their ability to perform literature reviews as novice (44%), intermediate (43%), advanced (10%), and expert (3%). Novice (36%), intermediate (46%), advanced (14%), and expert (4%) ratings were reported for critically appraising research articles. While 74% reported no publishing experience, 53 respondents had published at least 1 peer-reviewed journal article, including 7 staff, 9 administrators, 11 students, and 26 faculty.

When asked if they were familiar with predatory journals, 43% of respondents said yes, 42% said no, and 15% were unsure; among those replying no/unsure, 76% were students, 54% staff, 22% faculty, and 13% administrators. Respondents were divided evenly between confidence (49%) or not confident (51%) about identifying a predatory journal, with non-confidence reported by 64% of students, 50% staff, 35% faculty, and 13% administrators. 21% of respondents had received an email invitation to submit papers, 12% had colleagues/friends recommend articles, 7% were invited to join editorial boards, and 6% had read articles. The majority had not used Think, Check, Submit (93%) to assess if a journal title was predatory [35].

Table 1 depicts the characteristics of predatory journals identified in a survey checklist and described in open-ended responses. Respondents identified many characteristics ascribed to deceptive publications, such as

no/insufficient peer-review (71%), no/fake editorial board (68%), promise of fast publication (59%), high publication fees (55%), no/use of fake impact factors (53%), publication of plagiarized articles (53%), and unsolicited requests for articles (52%). Open-ended responses (n=120) added the characteristics of low quality of journal content, misinformation or ulterior motives for publishing decisions, and unethical practices.

What resources do faculty, students and staff in our institution use and consider as reputable sources of information about chiropractic?

Chiropractic academic journals were the most popular information sources for research or professional development (71%). DynaMed/medical platforms (54%) and health sciences journals (53%) also were referenced.

Table 1

Characteristics of predatory journals identified by chiropractic educational partners

Predatory journal characteristic	% Respondents		Open-ended response example
	Survey Items	Open-Ended	
No/insufficient peer-review	70%	25%	Journal that charges you but does not perform proper evaluation of the submitted work
No/fake editorial board	68%	0	--
Promise of fast publication	59%	3%	A business disguised as a journal that charges high publication costs in return for fast publication times due to a lack of proper peer-review.
High fees/publication on payment	55%	34%	A journal enticing authors to publish on their journals for a fee to receive peer review status or accelerate the publication of an article.
No/fake impact factors	53%	0	--
Plagiarized articles	53%	0	--
Unprofessional layout	53%	0	--
Unsolicited request for articles	52%	12%	Bush league journals that seek out authors to include in their publications (and charge fees).
Articles with poorly written English	48%	0	--
Low content quality	0	21%	Journal prioritizes collection of fees from authors at the expense of conducting appropriate peer review and/or ensuring the scientific integrity and/or quality of published articles (if they are published at all).
Misinformation or ulterior motive	0	18%	Journal that goes out of their way to spread misinformation
Unethical	0	6%	Journal that looks legit, but has practices that draw in articles, and then say you have to pay to get it published or does not properly cite the articles in it.
Publication schedule [#]	1%	0	--
Reputable publisher [#]	1%	0	--
Indexed in MEDLINE [#]	0.7%	0	--
Not sure/do not know	16%	17%	I have never heard the term predatory journal.
Skipped item	n=64	n=10	

[#]Item included as example of standard academic publishing practice

Within these publications and platforms, systematic reviews/meta-analyses (63%), case reports/series (56%), clinical practice guidelines (51%), clinical trials (51%), and review articles (50%) were the most frequently consulted sources. When evaluating resources for quality, respondents' top criteria were reported as the journal itself (64%), study design (57%), and publication status (i.e., peer-reviewed vs pre-print) (51%). Most (86%) correctly defined open-access as a manuscript published in a journal with peer-review and which is freely distributed online. Only 54% selected the correct definition of an article pre-print as a manuscript published in a digital version, but which has not gone through the peer-review process.

News about chiropractic, that is, information about the profession that is not necessarily based on research, was sourced from scientific journals and research databases (66%), social media (39%), professional or governmental websites (37%), DynaMed/medical platforms (32%), televised reports (10%), and Research Square/pre-print platforms (2%), while 'other' sources included professional associations, conferences, institutional communications, chiropractic educational institution websites, holistic health magazines, blogs, or podcasts. Nearly half (48%) reported checking 2 to 5 references before sharing information with colleagues, while 19% checked at least 1 additional resource.

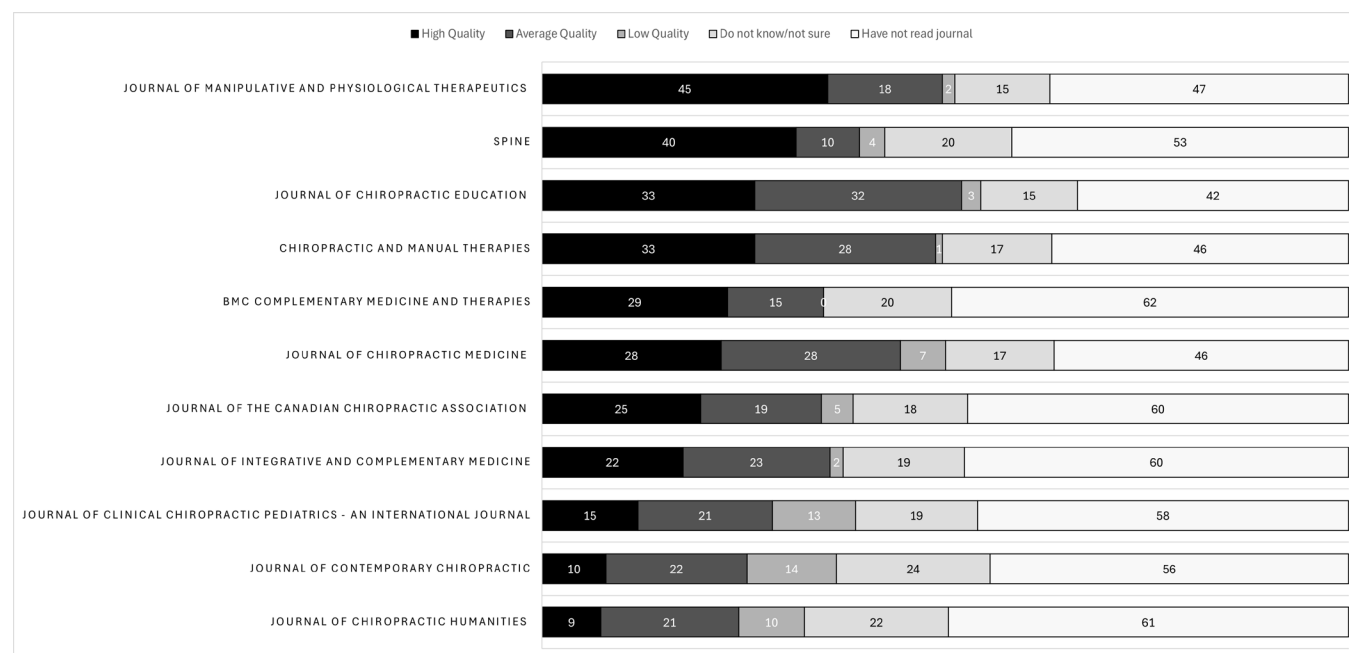
Figure 1 depicts chiropractic journals rated on the perceived quality of scientific evidence. Journals rated as

higher quality by greater than 30% of respondents were *Journal of Manipulative and Physiological Therapeutics* (IF 1.5), *Spine* (IF 4.6), *Journal of Chiropractic Education* (IF 0.7), and *Chiropractic and Manual Therapies* (IF 2), which generally aligned with the journal impact factors. Journals ranked of average or lower quality were often indexed only in the *Index of Chiropractic Literature* [36] and did not have IF ratings. These findings indicated respondents' unfamiliarity with many chiropractic journals (46% to 69% having no-to-little knowledge of various journals), with 61% interested in receiving training on how to identify quality academic journals.

DISCUSSION

This case report explored perceptions of scholarly publishing literacy among educational partners at one chiropractic college. Only 26% of respondents reported authorship of a peer-reviewed publication, although this included students, staff, faculty and administrators. Most respondents, especially students, considered themselves at the novice or intermediate level of ability in conducting literature searches and critically reviewing journal articles, which is similar to other studies within chiropractic [2,13,17]. Informal and formal training initiatives, support, and mentorship in scholarly activities may be helpful to develop these skill sets, as was noted in a recent scoping review of faculty scholarship in chiropractic [8]. Chiropractic educational partners were somewhat inexperienced with deceptive publishing practices, as

Figure 1 Chiropractic journal titles rated on the quality of their scientific evidence



only 43% were familiar with predatory journals and 49% expressed confidence in recognizing such publications. Swanberg and colleagues reported similar knowledge gaps as 40% of university and medical faculty in their institution could not correctly identify predatory journals [37]. Faculty across academic settings report high concerns and low familiarity with predatory publishers [38,39]. Although lacking confidence, respondents correctly identified common characteristics of predatory journals [40]. Librarians can instruct educational partners about the characteristics of predatory publishers, including the strategies used by such journals to solicit articles and the problems when such articles are integrated into clinical practice guidelines and similar reviews [37,41,42]. Librarians also can ensure that library collections do not contain these journals [43].

According to the 2018 Council on Chiropractic Education (CCE) Accreditation Standards meta-competency 6 “Information and Technology Literacy”, doctor of chiropractic programs have the curricular objective to prepare students to “locate, critically appraise and use relevant scientific literature and other evidence” with the outcome that “students will be able to use relevant scientific literature and other evidence to inform patient care” [44]. Chiropractic students have reported deficits in their research literacy, such as in their ability to access peer-reviewed journals, identify study designs, and select successful search strategies [13,45]. Respondents displayed low level of familiarity with many chiropractic journals (46% to 69%), as was noted in other recent publications [27,46]. Further, only 2 titles received quality rankings from the majority of faculty and administrators. While respondents reported using a variety of information sources, many had a high reliance on case reports, non-peer-reviewed resources, and social media. Not surprisingly, 61% of respondents expressed interest in training and resources on information literacy and scholarly publishing.

Health sciences librarians working in chiropractic academic institutions may be well placed to lead such efforts, as chiropractic students are receptive to educational interventions offered within the library setting [13,45,47]. Librarians in our institution have implemented initiatives aimed at increasing student and faculty awareness of high-quality publications, including regular newsletters highlighting recently published chiropractic research in prominent health sciences journals. Workshops and resources on scholarly publishing, including predatory publishing and how to select information resources may be warranted. Although not specifically surveyed in this study, we also foresee the need to incorporate information on artificial intelligence (AI) literacy into these tools and trainings [48].

One strength of this case report was its focus on scholarly publication literacy, including knowledge of predatory publishing practices, among chiropractic educational

partners, a population for which limited information is available. This survey had its limitations. Our response rate was 8.4%, which is consistent with low responses reported in similar surveys in health sciences settings [37,49]. Incentives, shorter surveys, survey administration timing, or tailored project information to subgroups might improve response rates. Targeted deployment, such as types of staff invited, may have improved the response. Selection bias is present in any convenience sample, so our results might reflect those with an interest in scholarly publication. Our team modified published survey instruments [30,31]. This modification could have benefited from pre-testing with students to ensure comprehension of item wording and to decrease the overall number of items, which might have led to fewer skipped questions. Future studies might build upon this single-institution case report to explore scholarly publication literacy at chiropractic training programs worldwide, which could increase generalizability.

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DATA AVAILABILITY STATEMENT

Data associated with this article are available in the Open Science Framework at <https://osf.io/sm8nw/>.

Registration: Open Science Framework, <https://osf.io/dspra>.

AUTHOR CONTRIBUTIONS

Jennifer Smith: Conceptualization; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Writing – original draft; Writing – review & editing. Edward Murphy: Conceptualization; Formal analysis; Investigation; Methodology; Writing – review & editing. Stacie Salsbury: Conceptualization; Formal Analysis; Investigation; Methodology; Supervision; Visualization; Writing – Review & Editing.

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SUPPLEMENTAL FILES

Appendix A: Survey Instrument

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Health sciences librarians' awareness and incorporation of informed consent standards for medical image publication: a preliminary study

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Objective: The objective of this study was to determine if health sciences library workers were aware of informed consent best practices and standards for the publication of medical images and if they incorporated the recommendations into their professional work.

Methods: A survey was developed by the authors to determine awareness and incorporation of informed consent best practices and standards for the publication of medical images. The survey was distributed via listservs of professional librarian associations in the United States. The results of the survey were tabulated in RStudio. Fisher's Exact Test was carried out to determine if awareness of informed consent influenced job responsibilities.

Results: A total of 91 respondents were included in the data analysis with all respondents reporting multiple responsibilities (instructional, collections, and/or digital initiatives). While the majority of library workers (59%) were aware of the best practices and standards, few (6.6%) incorporated the recommendations into their professional work. Over 50% of librarians with instructional responsibilities, over 70% of librarians with collections responsibilities, and over 60% of librarians with digital initiative responsibilities were aware of the recommendations but did not incorporate the recommendations into their job duties.

Conclusions: The professional work of health sciences library workers does not appear to include a significant incorporation of informed consent best practices and standards for the publication of medical images. There is a need for future research to better understand how library workers can better incorporate their knowledge of informed consent recommendations into their work.

Keywords: Consent; images; publication; health sciences librarians



See end of article for supplemental content.

INTRODUCTION

Health Professionals and Informed Consent

Photographs are commonly taken in medical settings to document clinical findings, especially in fields which specialize in conditions with primarily externally visible conditions, such as dermatology, plastic surgery, and maxillofacial surgery. Ensuring patient confidentiality, dignity, and autonomy are of paramount importance when disseminating these clinical images, including for the secondary or non-therapeutic purposes of education and publication [1–4]. The World Medical Association developed the Declaration of Helsinki, a global statement of ethical principles for medical research involving human subjects, to provide guidance on safeguarding identifiable patient data like clinical photographs [5]. De-identification

of images is an essential component of ethical clinical photography and is heavily advised [6–10]. When a clinician wants to publish a patient's photograph, but the patient's anonymity cannot be guaranteed via de-identification, obtaining informed consent is imperative to protect the patient from undue harm [1–4,6–9,11–18]. Informed consent is the ethical principle in medical treatment that ensures patients receive the necessary information to make informed decisions about their care and the use of their medical information [19].

The informed consent process must be transparent, documented in the medical record, and provide comprehensive information to patients regarding the purpose, risks, and potential outcomes associated with clinical photography. Obtaining explicit consent from patients for the use of their photographs is necessary to

ensure they fully understand how their images may be utilized and disseminated. If consent is given for one specific purpose, it is not transferable to other uses and patients should have the freedom to decline ways their photo(s) could be disseminated, along with being photographed altogether [3,6,7,11,16–18,20]. In the United States, section 164.522 of the Health Insurance Portability and Accountability Act (HIPAA) gives patients the right to restrict the use of their protected health information, including identifiable medical photographs [21].

Publishers and Informed Consent

Various professional associations have released recommendations and best practices regarding informed consent for the publication of patient photographs. Journal publishers most often cite [22,23] the International Committee of Medical Journal Editors' (ICMJE's) "Protection of Research Participants" [24] and the Committee on Publication Ethics' (COPE's) "Journals' Best Practices for Ensuring Consent for Publishing Medical Case Reports" [25]. Even though these recommendations and best practices have existed for years and a few publications have updated their processes to improve patient privacy and autonomy [1,2,26], medical journal publishers have overall struggled to align their publication practices accordingly.

A 2022 scoping review examined the policies and practices of publishing identifiable photographs in scientific articles. The authors concluded that in 95% of the included studies, the consent process was not conducted properly by clinicians who intended to include medical photographs in research publications. The consent practices used were often considered insufficient or did not fully implement professional guidelines in practice. Healthcare professionals in the studies largely considered verbal consent to be sufficient and some even thought it was acceptable to publish patient photographs without consent [23]. Studies for specific disciplines included an analysis of top dentistry, oral surgery, and otorhinolaryngology journals which found that only 52% had a posted policy on the publication of clinical images [27]. Similarly, for dermatology, a review of the top ranked journals revealed that only 58% had explicit patient consent requirements [13]. While the feasibility of applying and enforcing publication guidelines and informed consent procedures, especially internationally, has been questioned [26], there have been many calls for implementation of clear protocols and standardization from clinicians, researchers, authors, and ethicists as a way to eliminate confusion, risk, and improve patient confidentiality [3,4,6,8,10–17,28–32].

Technology and Informed Consent

The inconsistent application of informed consent guidelines and best practices is becoming increasingly problematic as technological advances are rapidly

increasing the ease of taking, disseminating, and discovering clinical photographs. It is largely agreed that the rapid ubiquitousness of the smartphone was the catalyst for this significant disruption [1,3,8,11,15,18,30,33–36]. Historically, clinicians often relied on professionally trained medical photographers to take pictures of patients, but smartphones have enabled clinicians to take images whenever and wherever they like, largely bypassing the medical photographer [3,8,12,33,34,37,38]. There is evidence that the use of smartphones by clinicians has also led to a relaxation in informed consent practices. A shift towards obtaining patient consent verbally instead of in writing has been observed [3,8,33,37–39].

Before the widespread use of the internet, it was rare for a patient to discover their image(s) in the literature. Health sciences journals were primarily distributed as print publications to libraries and health professionals, making access and reproduction cumbersome. Now that almost all journals are available online and many are publishing at least hybrid open access (OA), a patient's image can be copied and shared on the internet, including on social media, without the patient's or publisher's knowledge [1,14,18,27]. Clinicians and patients often do not review the platform's privacy settings and terms of use when uploading photographs to social media and so they are not aware of how their images can legally be reused [18,40]. In one study, even though 70% of top dermatology journals had an account on one or more major social media platforms, only 6% required the disclosure of potential social media use of images in their publication consent process [22]. This is just one way social media has created ethical and legal complications regarding patient consent.

There is evidence that patients do not always understand that OA journal articles are just as widely available as other content on the internet. Publishing images in an OA article enables access to the photographs via the public domain, similar to sharing via social media, and often lacks the proper corresponding consent [4,23]. Not only is the image viewable, but it could be reused in ways which were never intended when a Creative Commons license, especially CC BY, is applied [1,23,27]. One very popular and potentially damaging way images in OA articles can be discovered is through the image database, Google Images. Marshall et al. concluded that if an article with a medical image is freely available online, the image is nearly three times more likely to be found on Google Images than an image behind a paywall [30].

The rapid developments in artificial intelligence (AI) have raised further concerns among researchers. Now that numerous computer programs can identify a person with high levels of accuracy without full-face images, clinicians should anticipate these advancements complicating patient privacy, informed consent, and previous definitions of identifiable [15,23]. Because of these complexities, it is recommended that, for patient images

that are to be used for AI development, consent should explicitly include permission for this use [36].

Despite the overall benefits of OA, machine learning, and similar technological advances, these developments have compromised and will continue to compromise patients' privacy and autonomy in ways never conceived [6]. One such example is the fact that a clinician's inability to permanently delete a patient's image from the public domain goes against a fundamental part of informed consent: the right for the patient to revoke consent at any time. Essentially, a healthcare provider is asking the patient to surrender their right to revoke consent when they disseminate their photograph via the internet [40]. As medicine and technology both evolve, the ethical issues related to patient privacy and confidentiality will not improve without consistent iteration of established codes of practice. The risks associated with new technologies need to be included in the informed consent process so that patients truly understand to what they are consenting [1,3,6,8,11,15,18,28,30,33–36].

Effects of Unethical Dissemination of Medical Images

There is a risk, due to the unequal patient-provider power dynamic, that patients can feel as though they must agree to photography for treatment or to get the best care [4,11,12,16,32–34]. This dynamic can be intensified in environments where there are low resources, language and/or cultural differences, and vulnerable patient populations [11,32]. When identifiable photographs are shared for secondary purposes without the appropriate consent, it has the potential to cause not only legal trouble for clinicians, but psychological harm to the patient [6,8,16,34]. This is especially true for patients who belong to marginalized groups, such as the Lesbian, Gay, Bisexual, and Transgender Plus (LGBTBQ+) and Black, Indigenous, and People of Color (BIPOC) communities, as these betrayals further erode patients' tenuous trust in healthcare due to a long history of medical professionals taking advantage of such individuals.

Studies have been conducted which examine the effects on intersex and transgender patients, respectively, when their images are shared without their consent [16,30]. These two populations have historically experienced heightened rates of harassment, discrimination, and/or physical harm. The chance of incident would increase further if their identities were revealed to or pieced together by nefarious individuals via medical publications. The likelihood of this occurring is increased by the fact that there are a limited number of clinicians who provide healthcare to these patients. This limitation means that intersex and trans patients could be more easily identified using the author information in combination with photographs and case report descriptions [30]. The same can be true for patients with rare diseases [1].

A patient's identity and history must be taken into consideration when seeking informed consent. A scoping review of patient perceptions of dermatological photography discovered consistent disparities among ethnic groups. Non-white patients expressed greater discomfort with medical photography and were more likely to believe medical photography would not improve their care. These differences were attributed to the non-white patients experiencing the negative effects of the systemic inequities and implicit biases prevalent in healthcare [29]. The heightened interest in properly obtained patient consent is part of the increasing worldwide demand for human rights, equity, and empowerment [32]. Providing and enforcing consent standardization could be a step towards improving consistency and equitability in patient care in relation to photography, privacy, and autonomy [6].

Library Workers and Informed Consent

Another, often overlooked, player in the dissemination of medical photographs is health sciences library professionals. Librarians purchase and subscribe to resources for their users, including materials that may not abide by the established best practices and standards for informed consent. They then teach and encourage patrons to use these same resources. With or without their knowledge, health sciences library workers are perpetuating the use of unconsented images and, consequently, the harm inflicted on patients who did not provide consent for their images to be used. As of the writing of this publication, the authors could not find any peer-reviewed, published literature that addressed librarians' awareness of informed consent best practices and standards for the publication of medical images and how they incorporate the recommendations into their professional work. This surprised the authors given the abundance of research and publications on the topic of informed consent and the publication of medical images.

The authors hypothesized that this lack of publication signaled that library workers might not be familiar with these standards and best practices. They decided to investigate these topics with health sciences library workers, as the most likely group within the library profession to have been exposed to these concepts in their professional work. The research questions developed by the authors were: 1.) are health sciences library workers familiar with the informed consent best practices and standards for the publication of medical images? and 2.) if so, how are they incorporating the recommendations into their professional work? Sub-questions were created based on different types of library duties the authors hypothesized would most likely incorporate the standards and best practices. The authors broadly defined the types of work as instruction, collections, and digital initiatives. The sub-questions were: 1.) Does knowledge of the standards and best practices influence instruction

responsibilities? 2) Does knowledge of the standards and best practices influence collections responsibilities? 3) Does knowledge of the standards and best practices influence digital initiative responsibilities?

The goals of our research included understanding real-life phenomena and behavior and hopefully finding a way to improve lives. The paper will go on to describe the disseminated survey, the associated results, and the authors' opinions on said results.

METHODS

An exploratory quantitative study was conducted through a survey using Qualtrics software (Appendix A). Drafted by the authors, the survey investigated how aware our target population of health sciences library workers were of written, authoritative recommendations and best practices for obtaining informed consent to publish images of patients. Four non-health sciences librarians reviewed the initial drafted survey for face validity. Based on the testers' feedback, revisions were made.

Following the revisions, the survey project was approved by the University of California, San Francisco IRB (registration #22-38211). Following IRB approval, the survey was disseminated across 20 North American listservs (see Appendix B) between April 4 and 7, 2023. A reminder was sent to the listservs between April 20 and 21. The survey closed on April 30, 2023. The authors were members of the chosen listservs or were able to connect with members who posted on their behalf. The listservs included the main Medical Library Association (MLA) listserv (MEDLIB-L), nine MLA chapter listservs, seven MLA caucus listservs, and three other listservs: University of California Libraries' Health Sciences Selectors, the Association of College and Research Libraries (ACRL) Health Sciences Interest Group, and Electronic Resources in Libraries (ERIL).

Participation was voluntary, informed, and safe for the research subjects. The authors focused on disseminating the survey to health sciences library workers in the United States. The geographic limit was implemented because ethical standards and laws regarding medical image use and patient privacy vary widely across the world. If the respondent was outside of the United States, they were excluded. If a respondent was not a health sciences library worker, they were excluded and the survey ended. Incomplete responses were excluded. 91 respondents were included in the data for this paper, with 1 respondent removed from the dataset before analysis, as the respondent was not from the United States.

The survey consisted of 43 possible questions, 42 of which were multiple choice, and one was a free text response. Links to two informed consent guidelines were included at the start of the survey, COPE's "Journals' Best Practices for Ensuring Consent for Publishing Medical Case

Reports" [25] and ICMJE's "Protection of Research Participants" recommendation [24], so respondents could see examples of what was meant by informed consent standards and best practices for the publication of medical images. If the respondent said they were aware of these recommendations, the survey then asked how they incorporated that knowledge into instructional responsibilities, collections responsibilities, and/or digital initiative responsibilities, depending on what the respondent's stated job duties were. If the respondent was not aware, the survey asked if they anticipated incorporating the recommendations and best practices into their job duties in the future now that they were aware. The survey also asked several demographic questions. Multiple choice questions had the option of a write-in response. The final survey question was a free text response box for respondents to add comments or questions.

All the statistics were evaluated using RStudio with R version 3.4.2 [41]. When possible, tables and charts were generated with relevant counts. Chi-squared tests (or Fisher's Exact Test, the numerical alternative for chi-square, i.e., when any observed frequency was less than 5 in the table) were carried out to test if awareness of informed consent influenced the library worker's job responsibilities. The significance level for all the tests was 0.05. The authors would like to note that though some results were statistically significant, it does not imply causation. The authors did not receive enough data in open-ended questions to warrant qualitative analysis.

RESULTS

Demographics

A total of 91 respondents were included in this data analysis. Among these respondents, 31% were research and instruction librarians. The distribution of various reported positions is shown in Table 1.

Table 1

The distribution of the different types of library positions.

Current Position	Percentages (Count)
Research and Instruction Librarian	31 (28)
Collection Development Librarian	1 (1)
Scholarly Communications Librarian	1 (1)
Liaison Librarian	12 (11)
Library Administrator	15 (14)
Clinical Librarian	1 (1)

Hospital Librarian	14 (15)
Information Specialist	6 (6)
Other	18 (18)

All respondents indicated that they had multiple responsibilities (instructional, collections, and/or digital initiatives) within their reported position. Over 25% of the respondents had worked for six to ten years in libraries and 22% of them worked for over twenty-five years.

When asked whether they were aware of any written, authoritative standards and best practices informed consent for the publication of medical images, 59% of the respondents said yes and 41% said no.

Responsibilities vs. Awareness

Instructional Responsibilities

The authors then looked at the library workers who had instructional responsibilities (71 out of 91) and tested if awareness of the recommendations informed their instruction. The results of the Fisher's Exact Test ($p = [9.238e-09]$) indicate a significant association between awareness and librarians involved in instruction. In other words, being a librarian involved in instruction indicates an awareness of the best practices described above. The authors also wanted to see, if they were not aware of the recommendations prior to the survey, whether the respondent would now have intentions to incorporate the recommendations in their job.

It was observed that over 50% of the library professionals with instructional responsibilities who were aware of the best practices and standards did not incorporate the recommendations in their responsibilities. The counts and

percentages (shown in parenthesis) are provided in Table 2. The percentages were calculated using the row totals of 47 and 24 for each row.

Collections Responsibilities

Testing whether awareness informed collections duties (50 respondents out of 91), the authors again used the Fisher's Exact Test for independence ($p = [1.686e-05]$) indicates a significant association between positions that involve collections responsibilities and awareness of informed consent. Table 3 shows that over 70% of the library professionals who were aware of recommendations before the survey do not incorporate said practices in their responsibilities. The percentages were calculated using row totals.

Digital Initiative Responsibilities

Repeating the Fisher's Exact Test for independence ($p = [0.09]$) does not indicate a significant association between awareness and digital initiative responsibilities (13 respondents out of 91). Table 4 shows that over 60% of the library workers with digital initiative responsibilities who were aware of best practices before the survey incorporate them in their jobs. The percentages were calculated using row totals.

How Are Library Professionals Incorporating These Recommendations?

Respondents who had instructional responsibilities and were not aware of the standards (9.9%) indicated that they will incorporate the standards during one shot instruction sessions and by mentioning informed consent when advising others on research strategies, where to publish, and assessing journal quality. Respondents with digital initiative responsibilities who were aware of the standards (9.9%), reported that they will require informed consent

Table 2

Frequency distribution of library workers with instructional responsibilities and their intent to incorporate recommendations.

	Incorporates best practices/ recommendations	Does not incorporate best practices/ recommendations	Unsure	Total
Aware before survey	22 (46.81%)	25 (53.19%)	0 (0%)	47
Not aware before survey	9 (37.50%)	2 (8.33%)	13 (54.17%)	24

Table 3

Frequency distribution of library workers with collections responsibilities and their intent to incorporate recommendations.

	Incorporates best practices/ recommendations	Does not incorporate best practices/ recommendations	Unsure	Total
Aware before survey	9 (28%)	23 (72%)	0	32
Not aware before survey	4 (22%)	5 (28%)	9 (50%)	18

Table 4

Frequency distribution of library workers with digital initiative responsibilities and their intent to incorporate recommendations.

	Incorporates best practices/ recommendations	Does not incorporate best practices/ recommendations	Unsure	Total
Aware before survey	6 (67%)	3 (33%)	0 (0%)	9
Not aware before survey	2 (50%)	0 (0%)	2 (50%)	4

from future contributors that meet these standards and best practices. Respondents with both collections and instructional responsibilities, who were not aware of the recommendations and did not wish to incorporate them (5.5%), indicated that they were not teaching the standards and best practices because they felt they were not relevant to their areas of responsibility. Unfortunately, the number of respondents who provided data regarding how they actually incorporate the recommendations in their library responsibilities was small (6.6%) and this result did not lend itself to further analysis.

The results of the survey in response to the primary research question were unexpected by the authors, as the majority of respondents were aware of the standards and best practices. As the original research question explored whether participants were aware or unaware of the standards, the authors are unable to explore why the standards are not currently being used and encourage future research on this important topic. Future research could greatly benefit the library profession by exploring how the recommendations are being incorporated by professionals in health sciences library settings.

Additionally, further research is also needed to better determine the deterrents preventing library workers from applying these recommendations to instruction, collections, and digital initiative work.

DISCUSSION

The current incorporation of informed consent standards and best practices for the publication of medical images by health sciences library professionals appears to be limited. The data collected from the survey indicated that the majority of respondents (59%) were aware of the recommendations, but, with 41% of respondents not aware, there is significant room for further dissemination of the standards and best practices and for them to gain importance within librarianship. Since, in recent years, many libraries have committed to diversity, equity, and inclusion (DEI) initiatives and actions, including racial equity and social justice [42], the knowledge and application of informed consent standards and best practices for publishing medical images could be a key component of improvement within libraries. Specifically,

within health sciences education, librarians providing instruction and consultation on these recommendations to researchers, faculty, and students who want to adhere to the best practices and standards and ensure their published materials are not endangering their patients could be a step towards ensuring the sustainability for DEI work within medical education [43]. This would have the added benefit of aligning librarians' work within the larger framework of their institutions. Further, application of the recommendations could be developed into a possible standard to determine if DEI initiatives and actions are being met by libraries.

There were several limitations to this research, including a small sample pool, bias in the sample pool (i.e., lack of access to or awareness of other listservs could have caused sampling bias), and the general limitations associated with survey-based research. The authors strongly encourage future research on this topic, as there is a lack of richness in the data presented here. As is typical with survey research, a validated survey measurement would be helpful for future research as it would increase confidence in the quality of the data collected; however, there was no validated, appropriate measurement at the time that this research was conducted. In addition to suggesting the above first step of incorporating the recommendations into instruction and consultation, the authors believe that future studies could be extremely helpful for providing examples and improving the understanding of what library workers are currently doing successfully to incorporate informed consent recommendations for medical image publication into their professional work.

There are several options for further research on this important and timely topic, including where and how library professionals gained knowledge of the best practices and standards, as well as best practices for dissemination. The data presented here included 47% of respondents with instructional responsibilities who were aware of the best practices and standards, but did not incorporate them into their practice and, as this is exploratory research, this indicates this could be a fruitful area for future inquiry, particularly for qualitative research that explores why librarians do or do not incorporate informed consent recommendations into their instruction. The authors assumed instruction would be a key way for librarians to disseminate information regarding the recommendations, but dissemination through instruction was not widely reported among participants. Future research in this area could also focus on library professionals with roles other than instruction, collections, and digital initiatives to gain a better understanding of knowledge gaps. While this paper focused on health sciences library workers, future research could focus on general academic librarians who also have purchasing power for materials that include photographs of human subjects. The majority (68%) of respondents who had collections responsibilities also did not incorporate the best practices and standards into their professional

practice, which was surprising to the authors, given the analytical and discerning nature of collection development work. Research on how to improve the incorporation of informed consent recommendations by librarians making collection development decisions could be another valuable study. Looking outside of libraries, further research could include collaborations with research offices and/or ethics programs to create wider, institutional-wide awareness of informed consent best practices and standards in both education and practice.

Libraries, as the primary purchasers of scholarly content, are uniquely positioned to support the informed consent standards and best practices for publishing medical images. Using this purchasing power, they could improve the adherence of these practices not only within their institutions, but also within publishing. If libraries collectively agreed that they would not subscribe to or purchase any publication that did not comply with informed consent recommendations, it is probable that significant changes would be made to ensure that publishers did not lose their library customers. In recent years, libraries and the institutions they serve have committed to various forms of DEI initiatives and aiding in the enforcement of informed consent recommendations would be a concrete way to prove those commitments while also enhancing patient safety. The authors urge library professionals to start conversations about how to best leverage the power and influence libraries possess to help bring about change that benefits historically marginalized populations, protects patients, and proves that institutional DEI goals are more than just vague promises.

AUTHOR CONTRIBUTIONS

Sarah McClung: conceptualization, project administration, investigation, methodology, writing. Rachel Keiko Stark: investigation, methodology, formal analysis, writing. Megan DeArmond: investigation, methodology, writing. Sherli Chenthittayil: formal analysis, visualization, writing. All authors contributed equally to writing- all drafts, review and editing.

DATA AVAILABILITY

The survey results and code used to analyze the data are available via Dryad:
<https://datadryad.org/dataset/doi:10.5061/dryad.vmcvnd17>.

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SUPPLEMENTAL FILES

Appendix A Appendix B

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Pharmacist resource use across the United States: implications for teaching and practice

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See end of article for authors' affiliations.

Objective: To analyze practicing pharmacists' use of drug information (DI) resources in the United States.

Methods: An electronic survey was distributed to practicing US pharmacists through professional organization email lists and social media. The survey questionnaire asked respondents which subscription-based DI resources are provided through their employer, whether they personally pay for additional resources, how often they use subscription-based resources, and other related questions.

Results: The survey received 430 responses, 387 of which were able to be fully analyzed. The resources that respondents most frequently had access to through their employer were UpToDate (77.0%), Lexicomp (74.9%), and Micromedex (62.3%). Many respondents (40.8%) paid for subscriptions with personal funds, and 28.9% reported never experiencing access issues due to payment barriers. Respondents in community settings were more likely to have paid for resources with personal funds (57.1%, $p < 0.05$) and have less access to resources (51.4%, $p < 0.05$). In the open-text responses, the most desired resources were point-of-care tools (UpToDate) and DI databases (Lexicomp).

Conclusions: US pharmacists experience a varied level of access to DI resources through their employer. Pharmacy educators should focus their instruction on resources that are the most accessible to practicing pharmacists. Many, especially community pharmacists, pay out of pocket for desired resources, presenting an opportunity to advocate for increased resources.

Keywords: Drug information; electronic resources; pharmacy education; pharmacy practice; collection development



See end of article for supplemental content.

INTRODUCTION

The utilization of drug information (DI) is a crucial aspect of pharmacy practice. Pharmacists are asked to respond to a variety of DI questions every day, most of which directly impact patient care. Although these questions vary, responses are generally formulated through a systematic approach, typically taught in pharmacy schools by both pharmacists and librarians. In brief, the systematic approach involves gathering appropriate background information to formulate the appropriate question(s), systematically searching the literature to gather information, analyzing and synthesizing a response, disseminating the information, and following up [1]. Central to carrying out this process is access to and familiarity with using DI resources.

Exposure to DI resources often begins during pharmacy education, taught by both pharmacists and librarians. Librarians contribute to this process by teaching research

skills and introducing students to drug information databases, point-of-care tools, and larger compendia that support their learning [2]. However, the depth and extent of pharmacy trainees' exposure to these licensed information tools is contingent upon institutional access to them. Existing studies have researched pharmacists' preference for particular resources but few have examined the actual availability of specific resources in their practice settings [3–5]. Those studies that have examined resource availability are either not representative of current practice or are restricted to a local area (e.g. one US state) [6–10]. So although pharmacists' value within the health care system is well established, less is known about whether they are consistently provided with the resources required to practice at their full potential.

Understanding which resources pharmacists currently use in practice is important for several reasons. The primary purpose of this study was to identify resources that can guide DI instruction in pharmacy schools. Because time to

educate in pharmacy curricula is limited, there is a need for educators to select the most relevant resources for their students; information that is generally not available in the literature. Aligning educational exposure with use can narrow the gap between training and practice, ensuring that new pharmacists are prepared to use the resources most likely to be accessible in their work settings. Therefore, the present study seeks to inform DI educators of the current state of subscription-based resource availability to practicing pharmacists across the United States (US), with a long term goal of equipping future pharmacists with the knowledge and skills to effectively utilize the resources they will most often encounter in practice.

METHODS

Survey

We conducted a cross-sectional anonymous survey of US practicing pharmacists from April to May of 2024. The primary purpose of the survey was to inquire about the use and availability of pharmacy resources in various practice settings. Secondary outcomes included evaluation of resource use depending on if the employer provided access to the resource, the amount paid by respondents for resources, and resource use by year of pharmacy school graduation.

To accomplish this the authors developed a survey consisting of 12 items, including questions on practice/employment setting, subscription-based resources provided through employers, payment for additional resources with personal funds, frequency of use of subscription-based resources, and other related questions (see supplementary files for full survey instrument). Of note, the resource named "Lexicomp" in the survey has since been renamed UpToDate Lexidrug. This paper is using the name Lexicomp because that is what the resource was called for the duration of the study. Three survey questions allowed qualitative responses: 1) Which of the following subscription/fee-based resources are provided to you through your organization/employer? 2) In your current or most recent job, what resources did you use that were unavailable to you in pharmacy school? 3) If you could have your employer provide access to one paid/subscription based resource that is currently unavailable to you, what would it be and why?

The survey was piloted with a small number of pharmacist colleagues of the authors to identify any items that needed clarification. Authors utilized their professional and social organizations and networks, as well as institutional peers, to disseminate the survey. The recruitment information was distributed through email lists and social media. A full distribution list is provided in the supplementary materials. No compensation was

offered to participants, and no personally identifying information was collected. Data were collected and analyzed through Qualtrics, with additional analysis in SPSS vs. 29.0. This survey was approved as exempt research by the Concordia University Wisconsin Institutional Review Board.

Quantitative and Qualitative Analysis

Data were described using the mean and standard deviation or median with interquartile range for continuous data depending on the distribution of the data. Ordinal data were described using median with interquartile range. Categorical data were described using frequencies and proportions. Student's t-test was used to analyze differences between two means. The Mann-Whitney U test was used to assess differences between distributions of two independent groups when the data are not normally distributed or ordinal. The chi-square test was used to assess associations between categorical variables. Differences in responses were compared across practice setting and graduation year (which was collected in 10-year increments). A comparative analysis between pharmacists graduating prior to and after 2009, the year in which the PharmD degree became required, was conducted to explore potential differences with resource availability across larger groups. This date was selected for convenience and as an approximate cutoff for a generational shift in graduating pharmacists. Additionally, the relationship between access to resources and use of resources was evaluated. All data were analyzed using SPSS v. 29.0 and a predetermined alpha of 0.05 was used to detect statistical difference. A convenience sample of 100 was used as the minimum number of respondents.

For qualitative analysis, grounded theory (including line-by-line open coding and thematic analysis) was utilized by two independent reviewers for each of the three open-ended questions. Any disagreements were settled by a third reviewer. NVivo was used for assigning codes for thematic analysis.

RESULTS

Demographics

A total of 430 participants initiated the survey, with 10 participants being excluded for not being a practicing pharmacist. Of the remaining 420 participants, all completed the demographics section of the survey, 385 completed all questions, and 2 participants had partial completion of the resource use section. Participants that only completed the demographic section were more likely to be employed in an academic hospital pharmacy setting compared to other settings (9.8% vs 4.2%, $p=0.03$). There were no other differences in participants that completed the demographics section only. We excluded participants

who did not complete the full survey from the remainder of the analysis. Of the 387 full and partial respondents, 49 US states were represented (excluding Hawaii), 48.6% graduated after 2009, and 58.7% practiced in hospital, 18.7% in ambulatory care, 9% in community, and 14% in "Other." Forty-four percent of respondents either were a preceptor or were employed by a pharmacy school. Respondents in the "Other" category included government (2.1%), pharmaceutical industry (1%), and others that were provided via free text (10.3%).

Quantitative Results

Overall responses are provided in Table 1. Many respondents paid for subscriptions with personal funds (40.8%), with a similar percentage noting they used resources that were unavailable in school (41.1%). Of those that personally paid for resources (n=158), the number paid for was most frequently between 1 and 3 resources (88.2%), with most (58.2%) paying between \$101-\$500 per year. Only 28.9% of respondents never had access issues related to cost over the course of the year. There were differences in response depending on graduation year. Respondents that graduated before 2009 more frequently paid for resources with personal funds, had more access to

resources, paid a higher monetary amount for resources, and less frequently had access issues due to cost (Table 1).

Values described as n(%); *p<0.05; Questions related to number and amount of paid resources were limited to those who had answered that they paid for resources with personal funds; unsure responses not displayed in table. 2009 was used as the time frame because the PharmD became required in that year, and also represented an approximate cutoff for a generational shift in graduating pharmacists.

Questions related to number and amount of paid resources were limited to those who had answered that they paid for resources with personal funds; Unsure responses not displayed in table.

There were also differences in access to resources across practice sites. Respondents in the community setting were more likely to have paid for resources with personal funds, had less employer-provided access to resources, and paid a higher monetary amount for resources (Table 2). Specific employer-provided resources by site are provided in Table 3. The community pharmacy setting had on average a smaller number of resources provided

Table 1

Responses by graduation year

		Overall n=387	Before 2009 n=196	2009 or After n=188
Paid subscriptions with personal funds		158 (40.8)	94 (48)*	64 (34)
Used any resources that were unavailable in school		159 (41.1)	99 (50.5)*	60 (31.9)
Access to subscription & fee-based resources relative to school	More	120 (31)	90 (45.9)*	30 (16)
	Less	141 (36.4)	43 (21.9)	98 (52.1)
	Same	89 (23)	32 (36.4)	56 (29.8)
Number of resources paid for (n=161)	1-3	142 (88.2)	80 (85.1)	62 (92.5)
	4-6	14 (8.7)	11 (11.7)	3 (4.5)
	>6	2 (1.2)	2 (2.1)	0 (0)
Paid per year amount (n=158)	\$1-100	36 (22.8)	14 (15.1)*	22 (33.8)
	\$101-500	92 (58.2)	56 (60.2)	37 (56.9)
	\$501-1,000	27 (17.1)	21 (22.6)	6 (9.2)
	\$1,001-5,000	2 (1.3)	2 (2.2)	0 (0)
How often no access due to cost	Daily	14 (3.6)	5 (2.6)*	9 (4.8)
	Several times per week	37 (9.6)	19 (9.7)	18 (9.6)
	Several times per month	78 (20.2)	37 (18.9)	41 (21.8)
	Several times per year	144 (37.2)	67 (34.2)	77 (41)
	Never	112 (28.9)	68 (34.7)	43 (22.9)

Table 2

Responses by practice site

		Hospital n=227	Ambulatory Care n=72	Community n=35	Academia n=178
Paid subscriptions with personal funds		88 (38.8)	24 (33.3)	20 (57.1)*	76 (34.5)^
Used any resources that were unavailable in school		85 (37.4)	30 (41.7)	13 (37.1)	96 (43.6)
Access to subscription & fee-based resources relative to school*	More	62 (27.3)	22 (30.6)	10 (28.6)	83 (37.7)
	Less	90 (39.6)*	23 (31.9)	18 (51.4)*	58 (26.4)^
	Same	49 (21.6)	24 (33.3)	2 (5.7)	62 (28.2)
Number of resources paid for (n=161)	1-3	78 (86.7)	21 (84)	19 (90.5)	66 (85.7)
	4-6	8 (8.9)	2 (8)	1 (4.8)	9 (11.7)
	>6	2 (2.2)	1 (4)	0	1 (1.3)
Paid per year amount (n=158)	\$1-100	27 (17.1)*	1 (4.2)	2 (10.5)	23 (30.3)
	\$101-500	46 (51.7)	18 (75)	14 (73.7)	42 (55.3)
	\$501-1000	16 (18)	5 (20.8)	3 (11.1)	10 (13.2)
	\$1001-5000	0	0	0	1(1.3)
How often no access due to cost	Daily	10 (4.4)	3 (4.2)	1 (2.9)	14 (3.6)
	Several times per week	20 (8.8)	5 (6.9)	7 (20)	16 (7.3)
	Several times per month	54 (23.8)	14 (19.4)	4 (11.4)	26 (20.9)
	Several times per year	83 (36.6)	31 (43.1)	10 (28.6)	86 (39.1)
	Never	60 (26.4)	19 (26.4)	13 (37.1)	65 (29.5)

Values described as n(%); *p<0.05; ^p<0.05 for academia vs no academia.

Table 3

Employer-provided resources by site

	Hospital n=227	Ambulatory Care n=72	Community n=35	Academia n=178
AccessPharmacy*	51 (22.5)	34 (47.2)	1 (2.9)	106 (48.2)^
APhA Pharmacy Library*	19 (8.4)	14 (19.4)	5 (14.3)	42 (19.1)^
ASHP eBooks	25 (11.0)	5 (6.9)	0 (0)	28 (12.7)
Clinical Key	50 (22.0)	15 (20.8)	0 (0)	66 (30)^
Clinical Pharmacology*	52 (22.9)	25 (34.7)	7 (20)	73 (33.2)^
Cochrane Library	72 (31.7)	31 (43.1)	0 (0)	102 (46.4)^
Dynamed	53 (23.3)	16 (22.2)	1 (2.9)	69 (31.4)^
Epocrates (paid)*	1 (0.4)	3 (4.2)	1 (2.9)	5 (2.3)
Facts & Comparisons*	41 (18.1)	22 (30.6)	16 (45.7)	67 (30.5)^
Lexicomp*	185 (81.5%)	55 (76.4)	11 (31.4)	190 (86.4)^
MedicineComplete	3 (1.3)	2 (2.8)	0 (0)	4 (1.8)
Micromedex*	160 (70.5)	47 (65.3)	2 (5.7)	159 (72.3)^

Natural Medicines	78 (34.4)	36 (50)	5 (14.3)	102 (46.4)^
Pharmacists Letter	114 (50.2)	35 (48.6)	12 (34.3)	108 (49.1)^
PharmaPendium	0 (0)	1 (1.4)	0 (0)	1 (0.5)
Pyrls	1 (0.4)	2 (2.8)	1 (2.9)	8 (3.6)
Reference books*	125 (55.1)	29 (40.3)	9 (25.7)	131 (59.5)
Sanford*	110 (48.5)	16 (22.2)	1 (2.9)	80 (36.4)
Subscription journals	87 (38.3)	33 (45.8)	5 (14.3)	120 (54.5)
Stat!Ref	28 (12.3)	12 (16.7)	0 (0)	40 (18.2)
UpToDate*	200 (88.1)	59 (81.9)	11 (31.4)	187 (85)
VisualDx	4 (1.8)	5 (6.9)	0 (0)	11 (5)

Values described as n(%); *p<0.05; ^p<0.05 for academia vs no academia.

Table 4

Relationship between employer-provided access of resources and regular use

	No Employer-Provided Access	Employer-Provided Access
Clinical Pharmacology*	2/281 (0.7)	45/105 (42.9)
Cochrane Library*	5/257 (1.9)	29/129 (33.4)
Dynamed*	1/297 (0.3)	28/89 (31.5)
Epocrates (paid)*	2/378 (0.5)	2/8 (25)
Factors & Comparisons*	2/292 (0.7)	39/94 (41.5)
Lexicomp*	15/96 (15.6)	263/290 (90.7)
MedicineComplete	0/381 (0)	0/5 (0)
Micromedex*	8/145 (5.5)	164/241 (68.0)
Natural Medicines*	9/245 (3.7)	56/141 (39.7)
Pharmacists Letter*	21/199 (10.6)	85/187 (45.5)
PharmaPendium	0/385 (0)	0/1 (0)
Pyrls*	12/375 (3.2)	6/11 (54.5)
Reference books*	12/194 (6.2)	59/192 (30.7)
Sanford*	26/247 (10.5)	75/139 (54)
Subscription journals*	16/233 (6.9)	84/153 (54.9)
Stat!Ref*	2/338 (0.6)	10/48 (20.8)
UpToDate*	16/88 (18.2)	236/298 (79.2)
VisualDx	1/374 (0.3)	2/12 (16.7)

Values described as n(%); *p<0.05; Values indicate numbers of regular users over number without or with access

by employers (2.60) compared to the hospital (6.50) and ambulatory care (6.96). The most frequently used resources in participants that had employer-provided access were Lexicomp (90.7%), UpToDate (79.2%), Micromedex (68%), and subscription journals (54.9%). The most frequently used resources in participants without employer-provided access were UpToDate (18.2%), Lexicomp (15.6%), Pharmacist's Letter (10.6%), and Sanford Guide (10.5%). Lastly, we conducted a post hoc analysis evaluating the academic setting (Table 2, 3). Respondents with an academic affiliation had more access to resources and were less likely to pay for resources with personal funds compared to those with no academic affiliation.

Having employer-provided access to resources significantly increased use of those resources (Table 4). The notable finding in Table 4 is the number of resources that were used by people despite not being provided access through their employer. For example, 18% of the respondents whose employers did not provide access to UpToDate still regularly used this resource, which suggests the respondents pay out of pocket for a subscription.

Qualitative results

Five resource-specific themes emerged in qualitative analysis in response to the first question of "Which of the following subscription/fee-based resources are provided to you through your organization/employer?". These themes were tertiary compendia, journals/databases, professional association-related resources, specifically named resources including point-of-care tools, and nonspecific responses like "Google" or "Internet". Additionally, two perception-specific themes emerged: "I

have everything I need", and "I don't know what I might need". These seven codes were applied to all open-text responses. Additionally, the heatmap below (Figure 1) illustrates the most popular resources mentioned and their quantities.

Concerning the relationship between resource access and year of graduation, the quantitative results corresponded with the qualitative answers. In response to the question "In your current or most recent job, do you use any resources that were unavailable to you in pharmacy school?", 15% (n=33) of qualitative responses noted a lack of access due to their age at the time they attended school, noting that they primarily used paper resources at the time:

"Almost all of the online resources were not available when I was in pharmacy school - except I would buy Lexicomp books."

"I was in school pre-internet, so there are a LOT more available to me now. And they are electronic!"

"Online didn't exist when I was in pharmacy school so none of these were available - we used books only."

In the final open-ended question, "If you could have your employer provide access to one paid/subscription based resource that is currently unavailable to you, what would it be and why?" responses had a dynamic range. More specific responses included access to American Society of Health-System Pharmacists and Pharmacist's Letter, both mentioned for their continuing education (CE) resources. Journals listed by name included *The American Journal of*

Compounding Pharmacy, *Annals of Pharmacotherapy*, *The American Journal of Health Systems Pharmacists*, *The International Journal of Pharmaceutical Compounding*, *The Journal of the American Medical Association*, *The Journal of Clinical Pharmacology*, *The Journal of Pediatric Pharmacotherapy*, and *New England Journal of Medicine*. There were also many broad responses, such as:

"Access to ebooks"

"Access to the most common journals would be helpful"

"Anything to help us get access to ALL journal articles (pubmed)"

"Better direct access to primary literature. Our library is good at tracking down articles, but I hate feeling like I'm badgering them with requests."

DISCUSSION

This study is the first to survey a national sample of pharmacists evaluating subscription-based resource use in practice. Surprisingly, a significant proportion of pharmacists purchased their own resources. Unsurprisingly, not having employer-provided access to specific resources significantly decreased their use. Furthermore, many pharmacists reported not having access to resources due to cost. These findings suggest that for some pharmacists, resource availability may be inadequate, which has the potential to impact patient care. For pharmacists in those situations, these data have the potential to help them advocate for access to additional tools necessary for optimal patient care.

Figure 1 Heatmap of resources named in open-text responses in alphabetical order



*Increments in this map were made to differentiate less frequent responses from more frequently occurring responses, therefore the intervals are smaller for lower occurring responses.

While potentially inadequate access was identified across all settings, community access was lacking more than hospital or ambulatory care. This is especially problematic as community pharmacies impact a larger portion of the population comparatively, and are the most accessible to the public, often acting as a sole healthcare touch point for patients [11]. Identifying resources that are most frequently used in practice can help pharmacists advocate to their employers for resources that will be most useful. Additionally, it can help inform collection development budgets to align resources with those that are more likely to be used in practice.

These results have important implications for teaching DI in the pharmacy curriculum. Broader guidance is provided by the 2025 ACPE standards and the 2013 Entrustable Professional Activities; [12,13] however, specific topics and resources needed to meet this guidance are currently not standardized. As a result, students enter advanced rotations and clinical practice with widely varying experiences with resources such as drug information databases (e.g. Micromedex, UpToDate), literature databases (e.g. PubMed), and reference texts (e.g. *Drugs in Pregnancy and Lactation*).

The high usage reported for Lexicomp, UpToDate, Micromedex, and subscription journals indicates that these remain important resources on which to educate students. However, once students graduate, they are unlikely to have access to many of these resources. This suggests a need to introduce pharmacy trainees to a broader range of resources, including lower cost tools they will have access to as practitioners. Equipping students with foundational skills such as literature searching, critical appraisal, and reading drug monographs will prepare them to engage in lifelong learning and engage in information seeking in their workplace.

The wide variety in the types of paid/subscription resources that respondents want access to supports teaching students how to use the data that is presented on a broader level. For example, adverse drug reactions (ADRs) are presented in a variety of different manners depending on the resource [14]. Teaching students how to interpret presentation of ADRs, whether it be quantitative or qualitative, and considering whether comparator percentages are included in the resource would prepare students to interpret ADRs across a variety of sources. Lastly, access to free resources, such as those provided by government and professional organizations, should be presented in case subscription-based resource access is an issue.

In addition to teaching students how to utilize existing DI resources, the findings in this study underscore the importance of teaching students how to stay current with pharmacy resources overall. Respondents who attended pharmacy school prior to the creation and accessibility of electronic resources discussed solely being taught to use

textbooks and print resources for DI while in pharmacy school because many of these core electronic resources either did not exist, or were restricted to print copies. However, this issue is not isolated to those who attended pharmacy school prior to the development of online DI resources. The availability of electronic resources has changed even over the last five years with the addition of new databases (e.g. FirstLine), modifications to existing databases (e.g. name changes of titles or databases), and dissolution or merging of resources (e.g. ToxNet and LactMed are no longer individual databases). Changes to electronic resources are likely to continue as technology advances and artificial intelligence becomes more prevalent. Pharmacy educators must embrace the challenge of teaching students how to utilize existing resources while also equipping them with the skills to use new or changed resources.

This study has limitations to consider. Although survey respondents included pharmacists working across a variety of settings, hospital practice was more represented compared to other settings, such as community practice. A response rate was not calculable due to the online distribution methods used for sharing the survey, and responses to the survey do have a potential for response bias; the survey did not explicitly ask respondents if they had no access to any type of DI resources, meaning that the sample may have underrepresented pharmacists with a complete lack of access to DI resources. Additionally, the survey did not ask whether respondents felt they had sufficient access to the resources they needed. Lastly, the survey did not capture usage of free drug information resources and how use of those tools may impact use of paid resources. Future research should compare the use of paid and free resources, as well as investigate whether free resources provide sufficient information for high-quality pharmacy practice.

CONCLUSION

This nationwide survey found pharmacists frequently paid with personal funds to access subscription-based drug information resources. Disparities in access existed across specific practices, with community pharmacists more frequently paying for resources. Additionally, there was a strong preference for specific resources (e.g., UpToDate, Lexicomp), while other resources were used infrequently (e.g. PharmaPendium, Epocrates). The results of this survey can be used to inform teaching and resource allocation.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in OSF at <https://osf.io/p7uz6/files/osfstorage>.

AUTHOR CONTRIBUTIONS

Rachel Whitney: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review and Editing. Hilary Jasmin: Methodology, Investigation, Qualitative Analysis, Writing - Original Draft, Writing - Review and Editing. Christopher Giuliano: Conceptualization, Methodology, Investigation, Formal Analysis, Writing - Original Draft, Writing - Review & Editing. Audrey Kostrzewa: Conceptualization, Methodology, Investigation, Qualitative Analysis, Writing - Original Draft, Writing - Review & Editing. Melissa Hunter: Conceptualization, Methodology, Writing - Review & Editing. Christopher S. Wisniewski: Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review and Editing. Emily F. Gorman: Project administration, Conceptualization, Methodology, Investigation, Writing - Original Draft, Writing - Review & Editing.

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SUPPLEMENTAL FILES

Appendix A: Survey Distribution List

Appendix B: Survey

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Development and validation of a geographic search filter for PubMed for retrieving studies about Nordic countries

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See end of article for authors' affiliations.

Objective: This study describes the development and validation of a geographic search filter. The filter is intended to find references on the Nordic countries in PubMed. This type of filter enables efficient systematic literature searches for evidence that is relevant for the region, and no validated filter for these countries is publicly available at the time of this publication.

Methods: The Nordic countries are Denmark, Finland, Iceland, Norway and Sweden. References on one or more of these countries were identified by relative recall, using systematic and scoping reviews that did not limit searches to any geographic region but presented the countries of included studies. The references ($n = 288$) were equally split into a development set and a validation set. A combination of objective and subjective methods was used to identify relevant terms from the development set. The filter was then tested, first on the development set, then on the validation set. A sample of the reviews that were used to identify references for recall testing was also used to test precision.

Results: The final filter surpassed the threshold recall of 90%. Recall was 94.4% for the development set, capturing 136 of 144 references, and 96.5% for the validation set, or 139 of 144. Precision was 95.8% with one false positive of 24 retrieved references.

Conclusions: A validated filter has been developed that can be used to find studies on the Nordic countries when searching PubMed on topics related to human health.

Keywords: PubMed; information storage and retrieval; Scandinavian and Nordic Countries



See end of article for supplemental content.

INTRODUCTION

Systematic reviews and other types of evidence synthesis rely on systematic searches to retrieve as much of the relevant literature as possible, which minimizes the review's bias [1]. Search filters, also called hedges, are used in systematic literature searches to find literature with a common feature, such as a study design, publication type or subject area [2]. What sets search filters apart from other search strategies is that they are intended for reuse and usually systematically developed and tested.

One type of search filter is the geographic filter. To draw conclusions that are relevant for a country or region, research that is specific to that geographic location might be required. This type of filter has been developed for countries and regions such as the United Kingdom,

Germany and the Organisation for Economic Co-operation and Development (OECD) countries [3-5].

In this article, I describe the development and validation of a search filter for the Nordic region. The Nordic countries include the three Scandinavian countries Denmark, Norway and Sweden, and also Iceland and Finland. The term Scandinavia is sometimes used to refer to all five countries. The Nordics also include the autonomous regions of Denmark, which are Greenland and the Faroe Islands, as well as the autonomous region Åland Islands of Finland [6]. The Nordic countries are not just a geographically cohesive area in the northern part of Europe, but also a region with similar institutions and with close connections, for example in academia, politics and economy. The countries also collaborate on issues related to public health, through the Nordic Welfare Centre [7].

Limiting the geographical scope of reviews to the Nordic countries is done in health-related research, such as epidemiology [8], qualitative studies [9] and social determinants of health [10], to mention a few recent examples. The strategies used to limit searches to the Nordic countries vary, and although the ISSG Search Filter Resource compiles a list of validated geographic filters, there are none to be found for the Nordic countries or any of the constituent countries or regions [11].

To further investigate whether other Nordic countries filters are currently available, PubMed, Scopus and Web of Science Core Collection* were searched on November 13, 2025. The search strategies were inspired by the ISSG searches for existing tools in preparation of the search filter appraisal checklist [12].† No search filters were found, based on title/abstract screening of all search results.

Each Nordic country's public health authority was contacted, or when possible, information specialists working there were contacted directly, to ask if they were aware of any geographic filter for the Nordic countries. The same question was asked in online forums for librarians working with systematic searching: Bibliotekarar involvert i systematiske oversikter i Norge (BISON), Norway, and Nätverket för systematisk sökning i vetenskaplig kontext (SSIVK), Sweden. A geographic filter for the Nordic countries was identified. It was developed by Ragnhild Agate Tornes and Marita Heintz at the Norwegian Institute of Public Health [13]. It is designed for use in Medline (Ovid), Embase (Ovid), PsycInfo (Ovid), CINAHL (EBSCO), Web of Science and Scopus. Some testing of the filter has been done, but the filter is currently not validated [personal communication from M. Heinz to author, 6 Nov 2025].

The search filter that this study describes is intended for use in searches related to human health and has been developed with the purpose to be used to retrieve literature related to the Nordic countries in PubMed. PubMed is one of the most common databases to search when gathering evidence related to health, and since it is a free resource, this filter can be used irrespective of institutional subscriptions.

The aim has been to develop a balanced filter, with high recall and precision, without maximizing one or the other.

METHODS

The method used for development and validation of the filter was adapted from the guide to develop validated geographic search filters by Ayiku et al. [14]. This method consists of five steps: (i) defining the geographic region, (ii) finding references for the region, (iii) forming the gold standard set which is split into two sets for development and validation, (iv) developing the filter using the development set and (v) validating the filter using the validation set [14].

The performance of a search filter should be tested to ensure sufficient recall and precision. Recall, also known as sensitivity, is the number of matching records out of the total number of relevant records, while precision is the number of relevant records retrieved out of the total number of matching records [2].

Defining the Scope

The search filter developed and validated in this study is meant to retrieve references about the Nordic countries: Denmark, Finland, Iceland, Norway and Sweden.

Gold Standard Creation

A gold standard, according to Jenkins' definition, is the "set of relevant records identified against which the performance of the search strategy is tested and validated" [2]. In this study, a gold standard set of references was constructed, containing references that are known to be relevant to the geographic region. To create the gold standard, relative recall was used to identify the relevant references.

Relative recall is an information retrieval term and is a way of measuring recall when all relevant records are not known. When several different retrieval techniques with the same aim are combined and the relevant records are pooled, the relative recall of one specific technique is the relevant records retrieved from that technique divided by all of the pooled relevant records [15]. The relative recall technique for creating a gold standard entails using a number of published reviews, which used different retrieval techniques and work as a composite, to pool relevant records [16]. This approach is considered a more efficient way of identifying gold standard references than hand searching [16].

To limit bias, only reviews without geographically-restricted search strategies were used to create the gold standard. Reviews were selected using convenience

* The Core Collection used covers the Science Citation Index, Social Sciences Citation Index, Arts & Humanities Citation Index, Emerging Sources Citation Index, Conference Proceedings Citation Index and Book Citation Index.

† In PubMed: (nordic*[tiab] OR scandinavia*[tiab]) AND (filter*[ti] OR hedge*[ti] OR "search strateg*" [ti]); in Scopus: TITLE-ABS-KEY(nordic* OR scandinavia*) AND TITLE(filter* OR hedge* OR "search strateg*"); and in Web of Science: TS=(nordic* OR scandinavia*) AND TI=(filter* OR hedge* OR "search strateg*")

sampling, through searching Scopus, Google Scholar and *Cochrane Database of Systematic Reviews* for systematic and scoping reviews mentioning one or more of the Nordic countries. The reviews had to be relevant to human health in a broad sense, and the selected reviews span disciplines such as epidemiology, public health, mental health, nursing and lifestyle related to health. Reviews where it was unclear if searches were limited by geographic area were excluded. The reviews were screened for references that were classified in the review as being about one or more of the Nordic countries. Pooling of studies from reviews continued until over 300 references were found, which meant that 34 reviews were included.

When using relative recall, at least 100 references are needed to validate the filter, according to Sampson et al [16]. If the validation and development sets are of equal size, the gold standard could then consist of a minimum of 200 references. Ayiku et al recommend identifying 300 references, to have some margins since all references might not be available in the database used for the filter [14].

When 34 reviews had been screened, a sufficient number of references had been found. These reviews were published between 2012–2025 and for each review, 1–49 references were relevant to the Nordic countries. The median number of references was 5 and the average 9.5. In total, 309 unique references were found, of which 288 were available in PubMed and included in the gold standard. The gold standard set consists of these 288 references, from 158 different journals and spanning the publication years 1973–2024.

Of the 288 references included in the gold standard set, 71 pertain to Denmark, 56 to Finland, 30 to Iceland, 74 to Norway and 85 to Sweden. While most of the references were relevant to only one of the countries (272 of 288 references), seven of them involved two countries, seven others involved three, one reference involved four and another one involved all five countries. Since Iceland is a smaller country than the others, with under a tenth of the population of any other country in the group, finding a similar number of references about Iceland as the other countries proved difficult. Several of the included

references were relevant to more than one of the countries, and any reference specified in the reviews to concern at least one of the countries was included. References described only with supranational regions that include other countries than the Nordics were excluded, such as “Europe” or “Worldwide”.

The gold standard set was split in two equal groups using the randomizer in MS Excel (RAND), resulting in a development set and a validation set with 144 references each.

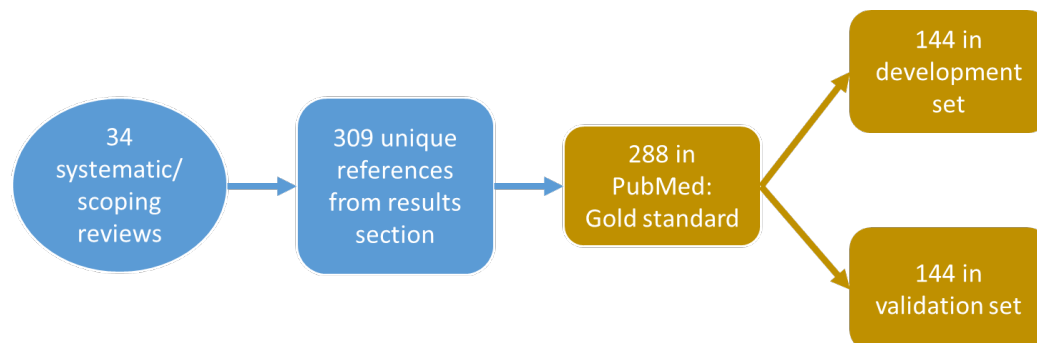
Filter Development

Geographical filters usually include the names of countries in English, and can also include country names in other languages, names of cities and regions, public health systems and population groups in the countries. The most common search fields that are used are affiliations and subject headings, followed by titles and abstracts. Some filters also use search fields for words in names of journals, all text or keyword fields [17].

In the development of this filter, text content from titles, abstracts, journal names and affiliations were used to identify terms. The final filter includes terms searched in the affiliation field, titles and abstracts, together with Medical Subject Headings (MeSH) and terms searched in the language field. Journal names are not part of the filter, since words in journal names are not searchable in PubMed. The fields used for filter development were selected based on the most relevant fields according to Ayiku et al [14].

To identify search terms, objective methods, such as term frequency analysis, can be used. This is done in order to create an evidence-based set of terms and reduce the risk of bias [2]. Other filter developers have used subjective methods, basing the search term selection on their own knowledge, research, or expert advice [2]. The development of this filter uses a combination of the two, an approach which has been noted as a practical way of ensuring objectivity while covering more aspects than a purely objective approach [17].

Figure 1 Flowchart of the gold standard, development set and validation set construction



A target corpus was created by combining the content from titles, abstracts, journal names and affiliations of all references in the development set. Using AntConc 4.2.4 [18], the target corpus was compared to the reference corpus “American English 2006: Learned” [19]. The keyword tool shows words that are statistically overrepresented (likelihood) in the target corpus compared to the reference corpus. All 485 keywords that appeared in the keyword tool were manually scanned for words related to Nordic geography and 32 terms were identified. No abbreviations were used.

The identified terms included the English names for all five countries, their adjectival forms and capital cities. All of these terms were included in the filter. Country names were also added in the countries’ main languages, as well as alternative names for the capitals where applicable. An exception was the name for Iceland in Icelandic, since “Ísland” is undistinguishable from the English word “island” when searching PubMed. Inclusion of this term would significantly worsen the filter’s precision. Names of regions comprising several of the countries were added (Scandinavia and Nordic), as well as names of autonomous regions within the countries. In addition to adjectival forms of the countries, demonyms were also added.

The remaining terms identified using the keyword tool were names of two hospitals, and 15 other names, of cities and/or municipalities and other geographic areas. Identifying all hospitals, all cities, or other such wide categories would bloat the filter and drawing the lines for what to include for each country could easily be an arbitrary decision. A category that covers almost all of these terms is “university hospitals”. 14 out of the 17 terms were covered by adding the names of university hospitals including their location. The three keywords not covered by the filter are Herlev, Gentofte and Nydalen. The first two are names of hospitals that are part of the Copenhagen University Hospital, and the last is one of the addresses of the Norwegian Institute of Public Health. None of these terms are used without other terms already included in the filter, when studied in context in the development set.

Ayiku et al recommend retrieving references by language for languages that are uncommon outside of the geographic area the filter is for [14]. This is true for the Nordic languages, and terms for the five Nordic languages that are available in PubMed were added to the filter, searched in the language field (“la”) by using the first three characters in the English name of the languages.

Two main terms in MeSH are of relevance to the Nordic countries. “Scandinavian and Nordic Countries” was introduced in 1999 and has replaced the earlier “Scandinavia”. The second main term is newer, “Scandinavians and Nordic People”, and was added to MeSH in 2023. The latter does not have any terms below it

in the hierarchy, but the former includes all of the Nordic countries, with specific terms for Greenland (Denmark) and Svalbard (Norway).

The MeSH terms appearing in the development set were identified using Anne O’Tate [20]. In Anne O’Tate, the development set was imported by searching the PMIDs combined with the Boolean operator “OR”. Using the Topics tool, MeSH terms from the set were collated, and then restricted by applying the semantic filter “Geographic Areas”. The terms that were related to the Nordic countries were each country’s MeSH term. These do not have to be included explicitly, as they are all already included as terms below “Scandinavian and Nordic Countries” in the MeSH hierarchy. MeSH terms in the current filter are searched in the standard, exploded form, not excluding narrower terms below.

Validation Methods

All records in PubMed have a unique ID. These PubMed IDs (PMIDs) were used in all validation testing as they are unambiguous, which might not be the case for titles or other information. Internal validation tests how well a filter performs on the set of references used to create it, and offers a chance to make adjustments to the filter before validating it against a new set of references that were not used during the development of the filter [17]. The development set was used to test the internal validity of the Nordic filter and recall was calculated by dividing the retrieved records with the total number of records in the development set, which solely consisted of relevant records. The missed relevant records were analyzed to see if the filter could be further improved.

External validity was assessed by testing the filter against the validation set and recall was calculated again. For both the development set and the validation set, at least 90% recall was considered sufficient, a threshold that is used in several previous studies [4, 21, 22].

Figure 2 Calculation of recall

$$\frac{\text{Number of relevant records retrieved by the filter}}{\text{Number of records in the gold standard}} = \text{Recall}$$

Precision Testing Methods

Precision is the fraction of relevant retrieved references of the total retrieved references. As the gold standard is solely made up of relevant references, it cannot be used to test precision, without also identifying references that are known to be irrelevant to the filter.

A selection of the same reviews used to identify relevant references in the gold standard creation was used to test precision, since they also included references specified to

be about other countries than the Nordics. One of the reviews, Balaj et al [23], was considered ineligible since its included studies were not all included in the review's list of references. Out of the remaining reviews (n=33), five random reviews were selected using MS Excel. The references of four of these could be retrieved automatically using Scopus, while one was handled manually. 223 references were found in total, and 172 of these could be connected to a PMID with the Scopus data or manually, respectively.

The filter was tested against all PMIDs from the five reviews in PubMed. Each matching reference that was not present in the gold standard set was examined to determine if it was one of the studies that were reviewed in the results part of the review, or cited for other reasons, such as background and discussion. Since references cited for other reasons (background articles) have not been classified by country in the reviews, they were not used in the precision testing as either relevant or irrelevant.

Precision was calculated by dividing the relevant retrieved references, present in the gold standard, by all retrieved references from the results of reviews.

Figure 3 Calculation of precision

$$\frac{\text{Number of relevant retrieved records}}{\text{Number of retrieved records}} = \text{Precision}$$

RESULTS

Internal Validation

Internal validation showed that the filter retrieved 136 references out of the 144 total references in the development set, or 94.4% recall. Eight references were not retrieved, two of these were missing abstracts entirely, and all but one lacked geography information in the searchable fields. The reference that could have been retrieved by a filter included a city and its county in the affiliation field of an author (Gävle and Gävleborg). To balance recall and precision, cities and counties have not been added to this filter. No changes were made to the filter as a result of internal validity testing. External validation followed as the threshold recall of 90% was surpassed during internal validation.

External Validation

External validation using the validation set showed that 139 references out of the total 144 were retrieved by the filter. This means that the recall was 96.5%. The five missed references in the validation set all lacked affiliation information and one of them did not have an abstract. None of them used any geography terms in their abstracts and only one had a MeSH term related to geography. As it was "Europe", it was too broad to qualify for a Nordic countries filter.

Table 1

Final filter

Line	Search string	Notes
1	"Scandinavians and Nordic People"[mh] OR "Scandinavian and Nordic Countries"[mh]	MeSH related to the Nordic countries
2	scandinavia*[tiab] OR nordic*[tiab] OR denmark[tiab] OR finland[tiab] OR iceland[tiab] OR norway[tiab] OR sweden[tiab] OR danmark[tiab] OR suomi[tiab] OR norge[tiab] OR noreg[tiab] OR sverige[tiab] OR aland[tiab] OR faroe*[tiab] OR greenland*[tiab] OR scandinavia*[ad] OR nordic*[ad] OR denmark[ad] OR finland[ad] OR iceland[ad] OR norway[ad] OR sweden[ad] OR danmark[ad] OR suomi[ad] OR norge[ad] OR noreg[ad] OR sverige[ad] OR aland[ad] OR faroe*[ad] OR greenland*[ad]	Terms for countries, supranational regions and autonomous regions, searched in titles, abstracts and affiliations
3	danish[tiab] OR finnish[tiab] OR icelandic[tiab] OR norwegian[tiab] OR swedish[tiab] OR danes[tiab] OR finns[tiab] OR icelanders[tiab] OR norwegians[tiab] OR swedes[tiab] OR alanders[tiab] OR danish[ad] OR finnish[ad] OR icelandic[ad] OR norwegian[ad] OR swedish[ad] OR danes[ad] OR finns[ad] OR icelanders[ad] OR norwegians[ad] OR swedes[ad] OR alanders[ad]	Adjectival forms and demonyms, searched in titles, abstracts and affiliations
4	copenhagen[tiab] OR helsinki[tiab] OR helsingfors[tiab] OR kobenhavn[tiab] OR reykjavik[tiab] OR oslo[tiab] OR stockholm[tiab] OR copenhagen[ad] OR helsinki[ad] OR helsingfors[ad] OR kobenhavn[ad] OR reykjavik[ad] OR oslo[ad] OR stockholm[ad]	Capital cities searched in titles, abstracts and affiliations
5	aalborg[tiab] OR aarhus[tiab] OR abo[tiab] OR akademiska[tiab] OR akershus[tiab] OR bergen[tiab] OR goteborg[tiab] OR gothenburg[tiab] OR haukeland[tiab] OR huddinge[tiab] OR karolinska[tiab] OR	Names of university hospitals and their locations, searched in titles, abstracts and affiliations

	kuopio[tiab] OR landspitali[tiab] OR linkoping[tiab] OR lorenskog[tiab] OR lund[tiab] OR malmo[tiab] OR norrland*[tiab] OR odense[tiab] OR orebro[tiab] OR oulu[tiab] OR rigshospitalet[tiab] OR roskilde[tiab] OR sahlgrenska[tiab] OR sjaelland*[tiab] OR skane*[tiab] OR solna[tiab] OR "st olav*" [tiab] OR stavanger[tiab] OR tammerfors[tiab] OR tampere[tiab] OR tromso[tiab] OR trondheim[tiab] OR turku[tiab] OR uleaborg*[tiab] OR umea[tiab] OR uppsala[tiab] OR aalborg[ad] OR aarhus[ad] OR abo[ad] OR akademiska[ad] OR akershus[ad] OR bergen[ad] OR goteborg[ad] OR gothenburg[ad] OR haukeland[ad] OR huddinge[ad] OR karolinska[ad] OR kuopio[ad] OR landspitali[ad] OR linkoping[ad] OR lorenskog[ad] OR lund[ad] OR malmo[ad] OR norrland*[ad] OR odense[ad] OR orebro[ad] OR oulu[ad] OR rigshospitalet[ad] OR roskilde[ad] OR sahlgrenska[ad] OR sjaelland*[ad] OR skane*[ad] OR solna[ad] OR "st olav*" [ad] OR stavanger[ad] OR tammerfors[ad] OR tampere[ad] OR tromso[ad] OR trondheim[ad] OR turku[ad] OR uleaborg*[ad] OR umea[ad] OR uppsala[ad]	
6	dan[la] OR fin[la] OR ice[la] OR nor[la] OR swe[la]	Nordic languages, searched in the language field
7	#1 OR #2 OR #3 OR #4 OR #5 OR #6	Combination of all lines

Table 2

Internal validation

References	Number	Percentage of development set
Development set	144	100%
References retrieved	136	94.4%
References not retrieved	8	5.6%
Not retrieved, without geographic information	7	4.9%
Not retrieved, with geographic information	1	0.7%

Table 3

External validation

References	Number	Percentage of validation set
Validation set	144	100%
References retrieved	139	96.5%
References not retrieved	5	3.5%
Not retrieved, without geographic information	4	2.8%
Not retrieved, with geographic information	1	0.7%

Precision

The references of five reviews were examined to determine the filter's precision. 172 references with PMIDs

were identified and 33 of these were retrieved by the filter. After removing references that were part of the gold standard set, 10 references remained that were retrieved by the filter. All but one were cited as background or for discussion purposes. A single reference was a false positive. It was part of the results of a review and classified there as not being about the Nordic countries, but was still retrieved by the filter. The reason was that one of the authors was affiliated with a Swedish university. Since one false positive was found out of the 24 references that matched the filter and were not background articles, the precision was 95.8%, or 23 relevant references out of 24 retrieved.

DISCUSSION

A balanced filter was created, with high recall and precision. Recall was tested on 288 references in total, and only one reference that could have been retrieved by a filter was missed.

This filter was developed for PubMed and is meant for use in searches related to human health. Geographic filters are often developed for use in health care resources, although they may not be designed for PubMed [17]. Systematic searching is common in evidence-based medicine, but also used in many other fields. In disciplines like the social sciences and in education research, a filter for the Nordic countries could also be of use, since there are similar societal institutions in the region. A valuable direction for future research would be the development of filters for this region in other health care databases as well as for databases for other disciplines.

Even though the recall was proven acceptable in this study, the filter should not be considered "highly sensitive", since the aim was to develop a balanced filter. Ideally, a recall-maximizing filter should be developed and tested on an even larger number of references, where the 100 reference threshold could be surpassed per

country. Gathering a large volume of references is a demanding task, and no Nordic organization is currently responsible for developing and validating search filters. Several existing geographic filters for other regions are developed by the United Kingdom's National Institute for Health and Care Excellence (NICE) where NICE guidelines were used to develop gold standard sets [3, 5, 24]. There is no corresponding institution for the Nordic countries, but one or more national institutions, for example the fairly similar institutes for public health [25], could be in an advantageous position when it comes to this type of development.

Other geographic filters have used the Boolean operator "NOT", which is not used in this filter. In the UK filters for Medline and Embase, locations containing UK related terms were excluded, such as "New England" and "British Columbia" [3, 26]. Similar uses are in the filters for Spain and Africa [27, 28]. Similar issues arise with the Nordic terms, for example the Nordic diet, Nordic walking, and the Nordic hamstring exercise, and several combinations with other more local geographic terms such as the Declaration of Helsinki or the ABO blood group system (which has nothing to do with Åbo/Turku, Finland). For the present filter, these issues were not deemed serious enough to warrant phrase exclusion, since the terms are not part of geographic names from the wrong part of the world and do not seem to be common phrases across many fields of health research.

Users of the filter can of course append exclusions of specific phrases if necessary for the specific topic that the filter is used in combination with. A systematic literature search on sleep in the Nordic countries could for example choose to exclude "Karolinska sleepiness scale" from "Karolinska" in titles and abstracts, while making sure to flag any such changes as their own alteration to the validated filter.

Some issues are impossible to avoid, such as geographical terms as last names, most notably "Lund". This was also noted by the developers of the UK filters, as well as the reduced precision caused by using the affiliation field, since authors don't necessarily write about the same country where they are affiliated [3, 26].

It is worth mentioning that the filter currently incites an error message in PubMed since some of the terms are not indexed in any references yet. This does not affect the search and the error message requires no action. If PubMed references are added in the future where these terms are present, they will be captured by the filter.

This filter is the first publicly available, validated filter for the Nordic countries. It can be used by information specialists, health librarians, health researchers and professionals in various health related fields who aim to collect evidence from the Nordic countries related to human health. This freely available filter for a database that is also free to search means that health care

practitioners in diverse circumstances can find evidence with relevance to the Nordic countries efficiently. For many librarians and information specialists, this validated filter will likely increase the recall of search strategies compared to ad hoc solutions. Ultimately, the consequences are that fewer relevant references are missed and that systematic searches related to the Nordic countries give a more complete picture of the available research. Using the filter will reduce the risk of missing relevant studies and save resources since it can be reused in many different contexts.

CONFLICT OF INTEREST

The author has no conflicts of interest to declare.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in the Open Science Framework at <https://osf.io/6ktva>.

AUTHOR CONTRIBUTIONS

Malin Barkelind: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Writing – original draft.

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SUPPLEMENTAL FILES

Appendix A: Executable Search Filter

Appendix B: Reviews

Appendix C: Unique Papers Identified from Reviews

Appendix D: Antconc Keywords

Appendix E: Gold Standard Papers

Appendix F: Read Me

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The state of library publishing in the health sciences in the United States and Canada

Gina Genova

See end of article for authors' affiliations.

Objective: Publishing initiatives led by academic libraries have grown over the past decade. They are often involved in the development of innovative publishing models and open initiatives, and a number of library publishers have worked in the health sciences. This study aims to assess the current state of library publishing in the health sciences (HS).

Methods: The Library Publishing Directory survey and Library Publishing Coalition's member directory were accessed to identify active library publishing programs in the U.S. and Canada. Survey responses on disciplinary specialties and top publications were assessed, and individual publisher websites were accessed to inventory HS titles. Journals were checked for whether they were actively publishing and indexed.

Results: One hundred eighteen survey respondents and 24 additional LPC members were assessed. Twenty-five percent of respondents named an HS subject as a disciplinary specialty, and 20% named an HS title as a top publication. Two hundred seventy-five individual HS titles from 81 different library publishers were identified. Fifty-three percent were journals, 39% open education resources, and 8% monographs. Medicine was the most common field for publications. Seventy-three percent of journals were actively publishing. Of those, 42% were indexed in DOAJ or a major HS database, and just over 10% appeared in PubMed or Scopus.

Conclusions: Library publishers have a track record of working with a wide variety of HS researchers. Indexing of library-published journals is an area for improvement. HS librarians may be able to collaborate with their institutions' publishing programs to further develop these services and build relationships with researchers.

Keywords: Library publishing; scholarly communication

INTRODUCTION

Scholarly publishing in the health sciences is an enormous enterprise, with over 1.5 million journal articles indexed just in PubMed in FY2023[1]. As with other disciplines, scholarly publishing in the health sciences is dominated by five commercial publishers: Elsevier, Sage, Springer Nature, Taylor & Francis, and Wiley, which combined publish a majority of journals indexed in Web of Science's SCI-Expanded, SSCI, and AHCI [2]. The operation of these commercial journals is guided by a combination of publisher policies and recommendations from professional organizations, which include the International Committee of Medical Journal Editors and World Association of Medical Editors, and the discipline-agnostic Committee on Publication Ethics. These bodies provide best practices on issues ranging from criteria for authorship and authorship disputes, disclosure of conflicts of interest, peer review, corrections and retractions, the use of artificial intelligence, and more[3-6].

Researchers in the health sciences commonly face a pressure to "publish or perish," with their opportunities for jobs, promotion or tenure, and funding often

contingent on their ability to produce publications, particularly peer-reviewed journal articles[7]. Several factors may influence researchers' choice of publishing outlet, including journal reputation and audience, personal experience with titles, the advice of colleagues or mentors, and the probability of acceptance for their article[8, 9]. Interestingly, researchers do not necessarily most frequently publish in journals that they regularly read, since readership habits skew more towards prestigious titles [10].

Recent trends in health sciences publishing mirror those in broader scholarly publishing. For example, the "gold" model of open access (OA) publication increased from 3% of scholarly publications in 2003 to 30% in 2022, in part due to requirements from funders like the National Institutes of Health [11, 12]. However, health sciences researchers' knowledge of OA remains variable [9]. A related concern in health sciences publishing in recent years has been predatory or questionable journals, which are journals that exploit the OA model, namely the collection of article processing charges, but do not provide

appropriate peer review processes and editorial services[9, 13, 14].

Over the past decade, academic libraries have become increasingly involved in scholarly communications services, including launching publishing programs of their own. Defined by the Library Publishing Coalition (LPC) as “the set of activities led by academic and research libraries and library consortia to support the creation, dissemination, and curation of scholarly, creative, and/or educational works,” library publishing offers an opportunity for libraries to establish themselves as leaders in scholarly communication and to support the development of open access and other innovative publishing models [15].

As early as 2008, 43% of ARL member libraries offered some type of publishing services, with another 21% of members planning to develop them. At that point, most library-published content was peer-reviewed, and library publishers aimed to develop new publishing models, not to duplicate traditional ones[16]. The LPC’s first *Library Publishing Directory* was published in 2014, which listed 116 individual publishers from five countries; the most recent version published in 2024 spotlighted 179 library publishers from 18 countries [15].

The scope of library publishers’ services vary widely, from that of a basic platform provider to much more in-depth publication services, such as obtaining DOIs or ISBNs, assistance with indexing in databases, copyright advisory, and technical production support[17-21]. As of 2024, a majority of library publishers offered DOI assignment, copyright advisory, metadata, training, ISSN registration, and non-copyright author advisory services[15].

The Role of Library Publishers

As service-driven rather than commercial ventures, library publishers are well positioned to play a unique role in the scholarly communication ecosystem. Common motivations and priorities for library publishing programs include promotion of open access, offering less restrictive licenses, collaboration across campus, and providing services tailored to campus communities[22, 23]. Open access in particular is a key value, with most publications produced by library publishers available open access [23-27].

Library publishers are often able to provide an avenue for research that is in emerging fields, produced by small scholarly societies, or that may otherwise be too niche or otherwise overlooked by traditional commercial publishers[24, 28-30]. This can include research on issues relevant to marginalized or underserved communities, whom are sometimes neglected by larger commercial publishers [31].

Library publishers also often provide services to students. One common activity is the publication of undergraduate

and graduate student journals, often with instructional programming to educate students about scholarly communications issues [24, 32-35]. Additionally, some library publishers produce open educational resources (OERs), which can help alleviate the burden of high textbook costs for students [21, 36-38]. Finally, library publishers provide a visible home for gray literature, such as conference proceedings, datasets, and dissertations/theses [22].

Challenges in Library Publishing

Library publishing is not without challenges. Costs and ongoing funding are major concerns, as are the related issues of the sustainability and scalability of services given available staffing and other resources [16, 19, 21, 22, 28, 35, 39-41]. Another major concern is the training and professional development of librarians to manage publishing-related activities [22, 35]. As Schlosser points out, many library publishing programs are “bootstrapped” with minimal resources and support and as such may not meet best practices in scholarly publishing [26].

Library publishing also lacks standardization in workflows and procedures [39]. Some of this is unavoidable due to the different service levels provided by library publishers, the numerous platforms utilized by them, and the reality that different publication types, such as open educational resources, require different processes than journals or scholarly monographs [21]. Managing relationships with journal editors and navigating roles and expectations is also a variable process given the level of service provided by the library publisher, the developmental stage of journals, disciplinary norms, and the continuity (or lack thereof) within editorial boards [24, 32, 42, 43].

Another issue is establishing credibility for library publishers and obtaining the acceptance of library-published journals and monographs in research assessments [35]. While indexing in the Directory of Open Access Journals or Directory of Open Access Books is common for library-published titles, indexing in services like Scopus is less so, which can deter scholars operating under a “publish or perish” paradigm from choosing less-established venues for their work [28].

Research Aims

Despite the number of library publishing ventures and the existence of partnerships between library publishers and health sciences researchers, there has been little discussion of library publishing within health sciences librarianship. This article aims to provide an assessment of the current state of library publishing efforts in the health sciences. How often are the health sciences a disciplinary priority for library publishers? How many health sciences titles

have library publishers produced, and what types of publications are they involved in?

METHODS

Publicly available data from the 2024 *Library Publishing Directory* survey (available at <https://librarypublishing.org/lp-directory/>) served as a key data source for this project, with several additional publishers identified using the Library Publishing Coalition's (LPC) member list[15, 44]. The Library Publishing Coalition is the main professional organization for library publishers, and their *Directory* of publishing programs provides a detailed annual snapshot of activity in the field. Publishers do not have to be members of the LPC to participate in the survey and be included in the *Directory*, so the survey included a mix of member and non-member programs. English-language responses from publishers based in the U.S. or Canada were considered to avoid language barriers.

Survey respondents had the option to list up to five "disciplinary specialties" and "top publications" for their programs. Disciplinary specialties and top publications in any health sciences field were recorded. It should be noted that the *Library Publishing Directory* survey does not define a "disciplinary specialty" or "top publication," so these designations may refer to number of publications in a discipline, disciplines with strong faculty-publisher relationships, the impact of publications, or other measures. "Health sciences" was considered broadly to encompass medicine, allied health fields, public health, medical humanities, clinical biomedical sciences, and so on. As such, life sciences or psychology titles with a clinical focus (e.g., mental health treatment, drug development) or for a health sciences audience (e.g., pre-medical students) were eligible for inclusion, but basic life sciences or general psychology titles were not.

Next, an inventory of health sciences titles published by library publishing programs was undertaken. Individual publisher websites, institutional repositories, and individual platforms (e.g., Open Journal Systems, Manifold) were accessed and their catalogs manually browsed for health sciences-related titles. Specific platforms used to publish journals or books were identified from survey responses about platform use, then located by searching Google with the key "institution name platform." Not all publisher websites provided listings of their publications or links to catalogs, so additional checks of institutional repositories and specific platforms were deemed necessary.

The title, publisher, publication type, and health sciences field of journals, monographs, and complete open education resources (textbooks or full courses) in any field of the health sciences were recorded. Digitized archival material, reissues of historical university press publications, rehosts of other institutions' open access

publications, multimedia projects, dissertations or theses, conference proceedings, previously published institutional repository deposits, and more "one-off" OERs such as syllabi or individual case scenarios were excluded to focus on publication types where in-depth publisher support was most likely. Titles with multiple editions or translations were only counted once.

Additional data was recorded for journal titles. Their websites were accessed to determine their open access status and if the journals were active, which they were considered to be if they had published at least once in 2024 or 2025. Notes about several journal characteristics were also gathered from active journals' websites: article processing charge, peer review, editor affiliation (internal vs external to the institution), student focus (run by students and/or dedicated to publishing student research), and subject coverage. Active journals' ISSN registration and indexing status in Scopus, Web of Science, the Directory of Open Access Journals, MEDLINE, PubMed Central, CINAHL, and PsycINFO was assessed with the ISSN Portal, DOAJ web search, National Library of Medicine catalog, and database source lists [45-51].

The Carnegie Classification of U.S. institutions that published in the health sciences were recorded, and both U.S. and Canadian institutions that published in the health sciences were checked against lists of accredited programs in medicine, dentistry, veterinary medicine, optometry, and pharmacy [52-61].

Searches were initially done in March 2025 and updated in June 2025. All data was recorded in Excel.

Lastly, *Library Publishing Directory* data from 2014 (the first available) and 2019 were accessed, and data on programs' top publications (2014 and 2019) and subject specialties (2019 only) were compared with current trends.

RESULTS

Survey Respondents

One hundred forty-two library publishers based in the United States or Canada were assessed for current library publishing activity. This included 118 respondents to the 2024 *Directory* survey and 24 additional Library Publishing Coalition members who had not submitted an updated entry for the most recent *Directory*. One hundred thirty (92%) of these publishers were academic libraries, and 10 (7%) were library consortia.

Of the 142 library publishers, a majority (86 / 61%) had a medical, dental, pharmacy, veterinary, and/or optometry school based at their institution or a member institution (in the case of consortia). Slightly over half (73 / 51%) specifically had a medical school at their institution or a member institution. Additionally, one program was based at an independent medical school, the University of Massachusetts Chan Medical School.

Disciplinary Specialties and Top Publications

Of 118 evaluated 2024 survey respondents, 38 (32%) indicated some level of health sciences focus through a disciplinary specialty, top publication, or both. Fifteen (13%) named both a disciplinary specialty and a top publication in the health sciences, 14 (12%) named one of more health sciences disciplines as a disciplinary specialty but did not highlight specific publications, and nine (8%) listed a health sciences title as a top publication but did not describe themselves as specializing in the health sciences.

Of the 29 publishers (25%) who named one or more health sciences subjects as a disciplinary specialty, medicine or a medical specialty was most commonly named specialty, followed by general health sciences and public health (Table 1).

Additionally, 24 publishers (20%) named one or more health sciences publications as a top publication. These publications were most often in medicine or a medical specialty, medical humanities, nursing, or public health (Table 1). Clinical specialties of top publications in medicine included lymphology, neurology, obstetrics/gynecology, and radiology. Of the 32 individual health sciences publications identified as a top publication, over two-thirds (22 / 69%) were journals, and most of the remainder (8 / 25%) were open education resources (OERs). One monograph and one dissertation in the health sciences were named as top publications.

Of the 86 survey respondents that had at least one health professional school based at their institution or a member institution, 29 (34%) named a health sciences discipline as a program specialty and/or a health sciences publication as a top publication.

Of the 32 respondents without an institutional health professional school, nine (28%) indicated some level of health sciences focus through disciplinary specialization, a top publication, or both. These publishers named specialties in health sciences fields that are not typically based at professional schools, such as nursing, medical humanities, kinesiology, and occupational therapy.

When publisher-identified disciplinary specialties and top publications are considered across time, library publisher involvement in the health sciences has been relatively consistent over the past decade. Roughly one-fifth of respondents named roughly 30 health sciences titles as a "top publication" in the 2014, 2019, and 2024 *Library Publishing Directory* surveys.

Similarly to 2024, medicine was the most-identified specialty for top publications in 2014 and 2019, but medical titles never comprised more than one-third of named top publications. Other fields represented in 2014's top health sciences publications included biomedical sciences, general health sciences, health policy or law, kinesiology, medical humanities, mental health

professions, nursing, pharmacy, and public health. In 2019, audiology, biomedical sciences, consumer health, general health sciences, health policy or law, health sciences librarianship, medical humanities, mental health professions, pharmacy, public health, and veterinary medicine were also represented among top publications.

Table 1

2024 Library Publishing Survey Responses Related to Health Sciences

Health Sciences Discipline	Publisher Specialty	Top Publications
Medicine (or medical specialty)	9	6
Health Sciences (general or unspecified)	6	2
Public Health	6	5
Nursing	5	5
Medical Humanities	3	5
Kinesiology/Sports Science	2	1
Biomedical Science	1	-
Health Science Education	1	-
Optometry	1	1
Allied Health Professions	-	4
Mental Health Professions	-	2
Consumer Health	-	1

However, the publication formats of publisher-identified top publications in the health sciences have shifted over time. Although journals have consistently been the most common format for top publications, they have become more common over time, and other publication types have changed. In 2014, as many theses or dissertations were called top publications as monographs. Additionally, in 2019, while journals and monographs were the most common top publication types, conference proceedings, dissertations or theses, exhibitions, newsletters, and OERs also all appeared once or twice. By 2024, journals and OERs were the most common top publication types.

Publication Inventory

Two hundred seventy-five unique titles in the health sciences were identified from 81 individual library publishers' websites, institutional repositories, and publishing platforms. A description of publisher demographics can be found in Table 2.

Table 2

Institutions Involved in Library Publishing in the Health Sciences

	Publishers with HS Titles (%) (N = 81)	Publishers With HS Focus* (%) (N = 38)
Country		
United States	67 (83)	33 (87)
Canada	14 (17)	5 (13)
Health Professional School		
Yes	56 (69)	29 (76)
No	25 (31)	9 (24)
Carnegie Classification		
R1	44 (54)	23 (61)
R2	7 (9)	3 (8)
Special Focus-Health Sciences	1 (1)	1 (3)
Special Focus-Arts and Sciences	2 (2)	–
Doctoral	1 (1)	1 (3)
Masters	2 (2)	2 (5)
Associate	1 (1)	–
Canadian, Health Prof. School	13 (16)	6 (16)
Canadian, No Health Prof. School	3 (4)	1 (3)
Consortium or University System	7 (9)	1 (3)

*Survey respondents that listed a health sciences field as a “disciplinary specialty” and/or a health sciences title as a “top publication.”

Publishers that have published in the health sciences published anywhere from 1 to 17 health sciences titles. Most publishers (42 / 52%) only published one or two health sciences titles, while a handful (4 / 5%) published ten or more health sciences titles. However, how prominent health sciences titles were in publishers’ catalogs varied somewhat by publisher size. Some programs with only a handful of available titles were heavily focused on health sciences (e.g., University of Massachusetts Chan Medical School), while some large, established programs produced larger numbers of health sciences titles but did not have a particular health sciences focus (e.g., the University of California System) [62, 63].

A slight majority (145 / 52%) of titles were journals. Most of the others (107 / 39%) were OERs, and a small number

(23 / 8%) were monographs. Monographs included a mix of consumer-oriented titles, such as memoirs; scholarly monographs on topics like history, policy, and social issues; and clinical manuals.

Across all publications, over a dozen health sciences disciplines were represented. Medicine (59 / 22%) was the most-represented discipline, followed by general health sciences, biomedical sciences, nursing, and public health (Table 3).

Among the 145 journals, medicine was more of a dominant discipline (43 / 30%), although it still comprised less than a third of total publications. General health sciences, public health, mental health professions, and the medical humanities were also prominent in this subset of titles (Table 3). Of note, several of the represented mental health professions were smaller fields, such as financial therapy, music therapy, and sand therapy.

Nearly all journals (143 / 99%) were open access. One hundred six (73%) journals were identified as active, including 28 (85% of) student-run journals. Additional notable journal characteristics are highlighted in Table 4.

Among OERs, biomedical sciences (22 / 21%) and nursing (21 / 20%) were the most common fields, followed by medicine, general health sciences, and veterinary medicine. Most of the biomedical sciences OERs (15 / 68%) were anatomy/physiology textbooks aimed at health professional students. Overall, fewer fields had OERs published by libraries than journals (Table 3).

Indexing & Operations of Active Journals

Of the 145 identified journal titles that had ever published, 106 (73%) published at least once in either 2024 or 2025 and were therefore considered to be active. Eighty-five (80%) of active journal titles had an identifiable ISSN. One hundred four (98%) active journals were open access, of which most (60 / 58%) could be confirmed not to charge article processing fees. Additionally, the vast majority were peer reviewed (92 / 87%), with double-blind review being the most commonly utilized (47 / 44%). Journals that were not peer-reviewed were often student-focused and employed an editorial review process (Table 5).

Only 43 (42%) active journals were indexed in at least one of the sources inspected. The Directory of Open Access Journals (DOAJ) was by far the most common place journals were indexed (33 / 31% of all journals, 32% of OA journals). Only eleven journals (10%) were indexed in PubMed, and only five (5%) were indexed in Web of Science and thus had an impact factor (Table 6). The most-indexed journals were the *Journal of the Medical Library Association* hosted by Pitt Open Library Publishing and the *Western Journal of Emergency Medicine* hosted by eScholarship University of California, which were both indexed in all evaluated sources but PsycINFO.

Table 3

Health Sciences Disciplines of Library-Published Titles

Discipline	Publications (%) N = 275*	Journals (%) N = 145	OERs (%) N = 107
Medicine (or medical specialty)	59 (22)	43 (30)	12 (11)
Health Sciences (general or unspecified)	38 (14)	25 (17)	11 (10)
Biomedical Sciences	27 (10)	5 (3)	22 (21)
Nursing	27 (10)	6 (4)	21 (20)
Public Health	23 (8)	16 (11)	7 (7)
Mental Health Professions	21 (8)	13 (9)	8 (7)
Medical Humanities	18 (7)	12 (8)	-
Veterinary Medicine	14 (5)	1 (1)	11 (10)
Nutrition/Dietetics	9 (3)	3 (2)	6 (6)
Kinesiology/Sports Science	8 (3)	5 (3)	3 (3)
Health Sciences Librarianship	7 (3)	3 (2)	-
Health Policy/Law	6 (2)	4 (3)	1 (1)
Consumer Health	5 (2)	-	-
Pharmacy	4 (1)	1 (1)	3 (3)
Dentistry	3 (1)	2 (1)	1 (1)
Speech-Language Pathology/Audiology	2 (1)	1 (1)	1 (1)
Complementary/Alternative Medicine	1 (<1)	-	-
Occupational Therapy	1 (<1)	1 (1)	-
Optometry	1 (<1)	1 (1)	-
Physical Therapy	1 (<1)	1 (1)	-

*including 23 monographs.

Table 4

Selected Journal Characteristics

Trait	Journals (n = 145) (%)	Fields
Student-Run/Student Research	33 (23)	Medicine (14), General Health Sciences (10), Public Health (2), Biomedical Sciences (1), Health Law/Policy (1), Kinesiology/Sports Science (1), Medical Humanities (1), Nursing (1)
Health Professions Education	10 (7)	Allied Health (3), Medicine (2), General Health Sciences (2), Nursing (2), Mental Health Professions (1)

Local/Regional Focus or State Scholarly Society (excl. student journals)	9 (6)	Public Health (7), Medicine (1), Mental Health Professions (1)
Global Health	7 (5)	General Health Sciences (5), Medicine (1), Mental Health Professions (1)

*Journals on “global health” broadly were classified as general health sciences since most appear to publish in medicine and public health broadly.

Table 5

Operational Characteristics of Active Library-Published Health Sciences Journals

Trait	Journals (n = 106) (%)	Non-Student Journals (n = 78) (%)
Article Processing Charge		
Yes	7 (7)	7 (9)
No	60 (58)	51 (65)
N/A (non-OA)	2 (2)	2 (3)
Unclear	37 (35)	18 (23)
Peer Review		
Blinded (details unclear)	11 (10)	8 (10)
Single-Blind	11 (10)	10 (13)
Double-Blind	47 (44)	37 (47)
Optional Double-Blind/Open	2 (2)	2 (3)
Open	1 (1)	1 (1)
Unspecified Peer Review	20 (19)	17 (22)
Any Peer Review	92 (87)	75 (96)
Not Peer Reviewed	6 (6)	0
Unclear	8 (8)	3 (4)
Editor Affiliation		
Internal	65 (61)	38 (49)
External	37 (35)	36 (47)
Unclear	4 (4)	4 (5)
Society/Organization Affiliation		
Yes	24 (23)	24 (31)
No	82 (77)	54 (69)

Table 6

Indexing of Active Library-Published Health Sciences Journals

Source	Journals (n = 106) (%)	Non-Student Journals (n = 78) (%)
CINAHL	15 (14)	13 (17)
DOAJ	33 (31)	29 (37)
PsycINFO	4 (3)	4 (5)
PubMed	11 (10)	10 (13)
MEDLINE	6 (6)	5 (6)
PubMed Central Only	5 (5)	5 (6)
Scopus	11 (10)	10 (13)
Web of Science	5 (5)	5 (6)
Emerging Sources Citation Index (ESCI)	2 (2)	2 (3)
Science Citation Index Expanded (SCI-E)	2 (2)	2 (3)
Social Sciences Citation Index (SSCI)	1 (1)	1 (1)

DISCUSSION

Most existing library publishers are based at institutions with at least one health professional school, and thus many health sciences librarians already work at institutions with an active library publishing program. This presents several opportunities for collaboration between library publishing colleagues and health sciences researchers interested in publishing.

There are some promising signs as to the strength of library publishing ventures in the health sciences. For example, nearly all non-student journals are peer-reviewed, and nearly a third of non-student journals are affiliated with an external professional organization or scholarly society. However, only one third of library publishers with a health professional school based at their institution identify the health sciences as a disciplinary

specialty or area of top publication, which suggests room for growth in building relationships between academic health sciences librarians and their patrons and library publishers.

Responses to the *Library Publishing Directory* survey indicate that library publishers' involvement in the health sciences has been relatively consistent over the past decade. However, the particulars of their involvement appear to have shifted. Earlier survey responses indicated that publishers' work in the health sciences was frequently with grey literature like dissertations/theses. Currently, programs highlight more formal health sciences publications like journals and open educational resources (OERs) when asked to name "top publications."

One area of frequent involvement for library publishers is student research. One-fifth of identified journal titles were student-focused, of which the vast majority are active. Related to this, journals dedicated to health professions education research are somewhat common from library publishers, with ten titles (nine active) published in multiple fields. These two journal trends, combined with the growing prominence in health sciences OER publications in recent years, highlight the role of library publishers in advancing health professions education.

Library publishers also seem to have developed a niche in place-specific public health research. This is seen in titles like *Journal of Appalachian Health* from the University of Kentucky and the publication of their state public health association's journal by library publishers at Georgia Southern University, the Ohio State University, Grand Valley State University in Michigan, and James Madison University in Virginia. This makes sense—if local public health research is considered too niche for mainstream journals, or if local- and state-level public health associations are hesitant or unable to contract with a major commercial publisher to produce their journal, partnering with library in the area can ensure that relevant research is still made accessible to the community.

Related to local interests, library publishers are sometimes offered as promising partners for small or emerging fields, and this has been observed to some extent in the health sciences [29]. Library publishers have published journals on topics such as graphic medicine, financial therapy, Muslim mental health, music therapy education, optometry history, sand therapy, and veterinary forensic sciences. These highly specialized titles indicate that library publishers can be viable partners for these types of projects.

It is notable that library publisher involvement in the health sciences spans multiple disciplines. Although medicine is the most common field for health sciences titles produced by library publishers, it accounts for less than one quarter of their total health sciences publications. This suggests that working with library publishers need not be limited to health sciences librarians in medical

school settings, but can also include librarians working with nursing, public health, or allied health faculty and students at less research-intensive institutions.

However, there may be challenges in expanding library publisher involvement in the health sciences. Library publishing programs frequently grapple with issues related to costs, sustainability, and the scaling of services [16, 19, 22, 28, 39, 40]. Although there are no health sciences-specific reports of these challenges, it can be expected that similar issues will be encountered while developing library publisher partnerships with health sciences researchers. Another challenge that is not specific to the health sciences but may be especially salient for health sciences researchers is the indexing status and impact factors of library-published journals [28]. Many health sciences faculty are evaluated not only on the amount of research they publish, but *where* they publish it, and indexes like Scopus and metrics like impact factor are frequently used, however problematically, as proxies for outlet quality.

However, library-published health sciences journals are infrequently indexed, despite best practices like peer review being the norm. Part of this is likely because many library-published journals are relatively new and have not established the track record required for indexing. However, there is at least one example of a library-published journal being rejected by an indexing service, partly due to reviewers' misunderstanding of the journal's relationship to the library and the publishing platform used [64]. Helping faculty editors understand indexing requirements and assisting with the indexing process could be a valuable role for health sciences librarians and library publishers interested in growing their services to the health sciences researchers.

Overall, it is clear that health sciences researchers across disciplines work with library publishers with some frequency, both at institutions with health sciences professional schools and those without. Although the resources and staff needed to implement a publishing program de novo is probably beyond the reach of most individual health sciences libraries, health sciences librarians could collaborate with non-health sciences or consortial partners to further library publishing work. This could include raising awareness of library publishing outlets among health sciences researchers; connecting would-be journal editors or OER authors to publishing services, especially in niche or local-interest fields; and providing guidance to journal editors on issues salient to health sciences researchers, such as indexing.

Limitations

One limitation of this study is the sample selection. This study relied on the *Library Publishing Directory* and the Library Publishing Coalition's (LPC) member directory to identify active library publishing programs in the U.S. and

Canada. Publishers do not have to be LPC members to be included in the *Directory*, so the sample is not restricted to LPC members, but there are likely some library publishers that are not LPC members and did not participate in the *Directory* survey and therefore were not evaluated. Additionally, while the decision to focus on English-language U.S. and Canadian publishers was made to avoid potential language barriers, library publishers do exist worldwide and in languages other than English, and library publisher work in the health sciences may differ in other countries. A more global survey utilizing additional data sources may surface additional trends.

Other limitations exist with the data sources. The *Library Publishing Directory* survey asks questions about publishing programs' structure and staffing as a whole, so while some insights can be gleaned from those responses, they are not specific to publishers' work with health sciences researchers. Given that health sciences publishing is a small portion of most publishers' work, there may be additional opportunities, challenges, or other nuances to these publishing ventures that are not reflected in program-wide survey data.

Survey responses also don't capture how involved library publishers are with any given title. Library publisher services range from simple platform provision to professionalized, full-service publication support, and publishers may provide different levels of services to different projects within their portfolios. As such, the details of exactly *how* library publishers support health sciences publications, and what barriers or opportunities exist for different support models, cannot be determined by the data available for this paper.

Finally, it cannot be guaranteed that all health sciences publications from the assessed publishers have been evaluated. Certain publication types were deliberately excluded due to this project's scope, and it is possible that eligible publications were missed during the inventory. There is no standard website design for library publisher webpages and no standard organization for institutional repositories that host library-published content. The author visited websites multiple times and supplemented website links with Google searches to attempt to fill as many gaps as possible, but it is possible some omissions still occurred. Additionally, some journals that were identified as inactive for this study but were not officially "archived" may resume publishing in the future.

CONCLUSION

Academic libraries and library consortia have growing involvement in the provision of publication services. As interest in open access publication and innovative publication models increases, library publishers offer an intriguing alternative to traditional commercial publishers. These publishers have a track record of working with health sciences researchers in multiple

disciplines to disseminate scholarship and open educational resources, with notable involvement in areas like student research, local public health research, and health sciences education. Health sciences librarians have the opportunity to collaborate with their colleagues working in library publishing to raise awareness of these publishing opportunities and, potentially, to provide guidance on health sciences-relevant issues during project development, such as database indexing.

DATA AVAILABILITY STATEMENT

Library Publishing Directory survey data is available at <https://librarypublishing.org/lp-directory/>. Data related to the inventoried health sciences publications are available in the Open Science Framework at <https://osf.io/nxbqz/>.

AUTHOR CONTRIBUTIONS

Gina Genova – Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Writing – original draft; Writing – review & editing

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Sound solutions: expanding access through digital audiobooks in an academic health sciences library

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See end of article for authors' affiliations.

Background: As digital audiobooks gain popularity among the general public, academic health sciences libraries have the opportunity to provide access to supplemental nonfiction titles in this format which while often found in public libraries has not been traditionally offered in this setting.

Case Presentation: An academic health sciences library serving students and faculty in the colleges of medicine, nursing, pharmacy, and public health piloted a collection of nonfiction health sciences audiobooks through OverDrive's Libby app. We launched an initial collection of over 500 titles using the cost per circ (CPC) pricing model, including a focus on four content areas: popular nonfiction, first person experiences, history of healthcare, and study helps. Over the first year of the project, we saw 123 total checkouts of 64 titles across 74 unique users, spending \$351.84 US on CPC checkouts.

Conclusions: The OverDrive title library includes sufficient offerings for academic health sciences libraries to create targeted nonfiction audiobook collections. Challenges of which other libraries should be aware include planning budgets around adding funds each year and determining local workflows to keep the collection updated. Though usage was low in the first year, it was consistent and varied, making the project beneficial and sustainable.

Keywords: Audiobooks; OverDrive; Libby; academic health sciences libraries



See end of article for supplemental content.

BACKGROUND

Though audiobooks have a long history (e.g., Talking Books and Books on Tape), it is only recently due to technological advancements that they are becoming a mainstream way to consume books. A 2023 survey of U.S. adults found that 53% percent of respondents reported ever having listened to an audiobook; the percentage had remained steady at 44-46% for the three years prior [1]. Audiobook sales revenue is also steadily growing, showing the increased interest in and usage of audiobooks among consumers. In 2018, audiobook sales revenue was \$0.94 billion, increasing to \$2.2 billion in 2024 [2]. Dali and Brochu shared that "readers with print disabilities are no longer the primary or the largest audience for audiobooks, and ... the popularity of audiobooks has grown tremendously" [3].

Overall increased demand for audiobooks has included an increased demand for audiobook availability in libraries. Though public libraries have been leading this charge due to a focus on audiobooks for leisure reading [3], the value of audiobooks for academia, and thus academic libraries, is also worth exploring. One study found that audio

recordings of course lectures helped undergraduate students improve their understanding of biochemistry topics [4]. Though some researchers have explored the question of the effect of reading versus listening on mental load and comprehension for individuals without learning disorders [5], no definitive answer has yet been discovered [6-8].

However, that some modern students prefer consuming information via audio, including audiobooks, has been established. For example, a recent study of health sciences students at a Florida university found that 97% had read for leisure within the last 6 months, including 45% of those via audiobook [9]. Within the same group of respondents, two-thirds were interested or very interested in the health sciences library offering health-related leisure or supplemental books for students. The age group most typically found on college campuses—18 to 29 year olds—was also the age group who reported the highest proclivity for listening to audiobooks. Of 18 to 29 year old respondents in a 2021 survey, 30% reported that they had listened to an audiobook within the last 23 months (versus 27% of 30-49 year olds, 22% of 50-64 year olds, and 12% of 65+) [2]. Students responding to a leisure reading survey

at Sam Houston State University indicated that they used the public library to get audiobooks (22.9%), and 45% of respondents said they would like to see audiobooks available through the university library [10].

As students in higher education, including medical and health sciences students, become ever-busier, audiobooks could be a great way for them to squeeze reading – whether required course reading, areas of interest supplemental to their studies, or leisure – into their schedules. Audiobooks have become a way for people to “keep up on the books they want to read while they’re going about their day – be it while they’re commuting, or doing housework, or exercising, or winding down for bed” [11]. The data confirms this assertion: according to a 2020 study, 43% of adult audiobook listeners in the U.S. listened most often in the car; 73.4% of women and 66.1% of men reported multi-tasking while listening to audiobooks [2].

In this study, we provided students and faculty in health sciences programs with access to nonfiction, digital audiobooks related, but supplemental to, their fields of study through OverDrive’s Libby app as a pilot project. We tracked usage and cost of content areas and specific titles to help identify interest in audiobooks in our libraries and how to grow our collection in the future.

CASE PRESENTATION

USF Health Libraries primarily serve the four colleges that comprise USF Health: medicine, nursing, pharmacy, and public health. The health libraries operate separately from the USF Libraries with our own dedicated leadership and budget, reporting directly to USF Health to prioritize the needs of the approximately 6,000 students under the USF Health umbrella.

In March 2024, we were inspired by a presentation at the Florida Health Sciences Library Association annual meeting about a hospital library using OverDrive’s Libby app to provide audiobook access to their patrons [12]. We decided to pilot an audiobook collection through OverDrive for our library population because audiobooks would be a new format not previously offered. Additionally, the Libby mobile app is easy to use and many patrons may already be familiar with it through the public library. Audiobooks could be a way for us to provide students and faculty with nonfiction content supplemental to the curricula. Finally, we know our health sciences students are busy, so we anticipated that audiobooks might be a way for students to consume content while doing other things.

Vendor Options

While some competition exists for OverDrive in providing audiobooks to libraries, OverDrive is the “largest commercial provider” of such content [13]. Hoopla, while

second to OverDrive in providing electronic and audiobook content to public libraries in the United States, does not seem to have much purchase among academic libraries, though some may provide access through statewide library cooperatives that also serve public libraries, such as UNC Pembroke through NC LIVE [14]. Additionally, Baker & Taylor’s Boundless product, which provided digital media options for libraries, is currently winding down operations along with its parent company [15]. While this closure was not yet announced when we began the project, Boundless was not well known to us. In all, OverDrive was the most robust and simplest choice for our project.

However, an early consideration revolved around whether OverDrive would provide the specialized content we need as an academic, health sciences library. We met with the vendor, who gave us trial access to their Marketplace platform. From there, we were able to search the available title options. We identified that the options provided met our collection development standards and our focus on nonfiction audiobooks related to the health sciences for this project.

Our next step was to investigate the several pricing models offered by the vendor and determine which best met our needs. The “one copy / one user” (OC/OU) model is a purchase model where the library owns the content, but, as the name suggests, each copy is only available to one user at a time. Users may therefore need to join waiting lists for popular titles, or the library would need to purchase multiple copies to meet demand. Another concern with this pricing model for our pilot program was that it required a large up-front expense with no guarantee that the content would be used.

The second pricing model we explored was the “cost per circ” (CPC) model. With CPC, the library selects an unlimited number of titles to add to their collection and then is charged fees as users borrow the titles. The “per circ” cost is a fraction of the cost to purchase a title outright and comes with the advantage of allowing multiple users to access a title simultaneously, with the library charged for each circulation of that title. Two other advantages with CPC for our purposes were that it would allow us to offer a wide selection of titles to our patrons and the library would only pay for the titles that patrons actually use. One disadvantage, however, is that fewer titles are available as CPC than in the OC/OU model.

We decided to use the CPC model as our primary pricing model, though we have purchased some titles through OC/OU when they weren’t available through CPC.

Regardless of pricing model, OverDrive requires a “content credit” deposit from which funds are deducted as purchases are made or titles are circulated. We started with the minimum content credit amount, which has been more than enough for the amount of circulation we’ve seen from our patrons.

Selecting Titles

The overall focus for the pilot program was nonfiction health sciences audiobooks. Though OverDrive provides access to a wide variety of e-books through the Libby app, we decided to use the platform for audiobooks only. One reason was because with the many disparate platforms and sources the library already provides for e-books, paired with the self-contained nature of the Libby app, we were concerned patrons would search for specific e-books on Libby and assume that no result in Libby meant the library could not provide the book. We advertised the Libby app as a source for audiobooks and, because it is our only audiobook platform, patrons can safely assume that no result in Libby means the audiobook title is not available through the library.

We further narrowed our focus to include CPC titles that fell into one of four content areas: popular nonfiction, first person experiences, history of healthcare, and study helps. We later added an additional area: wellness. Popular nonfiction encompasses titles about health and medicine written for general audiences. First person experiences include memoir-type books giving the perspective of a health practitioner or patient. History of healthcare includes works detailing medicine throughout history. Study helps incorporate reference, review, and test prep materials. Finally, wellness encompasses titles related to self-care, stress management, and personal well-being.

These content areas were chosen because they closely align with the mission of the library of providing state-of-the-art biomedical information while also providing

options that support student development and learning supplemental to the curricula. We purposely excluded most consumer health titles, such as those touting diet and exercise plans, because of the difficulty verifying the credentials of the authors and the trustworthiness of the information.

The research and education unit librarians assisted in selecting titles: they were given access to Marketplace to search the available titles and created “carts” of suggestions for the content management staff to evaluate, largely to ensure the titles were available in the CPC pricing model. We did add a limited number of titles that did not fall into any of the focus categories only if the research and education unit librarians recommended them.

Ultimately, we launched the pilot with 530 titles available for our patrons to borrow.

Setting Up the Platform

With titles selected, the next step was to set up the Libby platform and customize it to our library. We activated automated lists or created curated lists for each of the content areas. These lists flow into the libraries’ Libby landing page, where the covers of select titles appear in visual carousels and thumbnails to encourage browsing and check out (see Figures 1 and 2).

We also customized rules and policies such as loan limits and lending periods. Because of the experimental nature of the pilot, we viewed our initial choices for these settings

Figure 1 Browser view of USF Health Libraries Libby landing page.

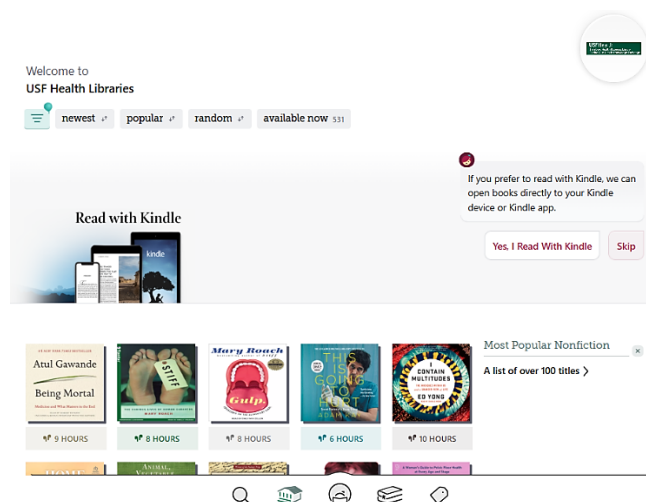
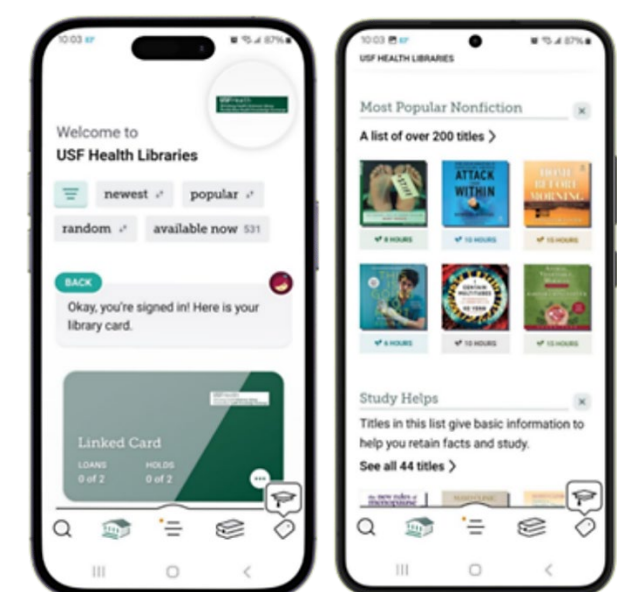


Figure 2 Mobile view of USF Health Libraries Libby landing page.



as starting points, with the intention to adjust as needed as we got a better understanding of our patrons' needs and the rate of spending. We started by limiting borrowers to two checkouts at a time and three total per month.

We set the default lending period to 21 days, though individual users can choose from a drop-down menu giving them the options of 7, 14, or 21 days each time they check out a title. Because we were relying on the CPC pricing model, we determined that setting the default lending period to the longest available might save the library money because it would make it less likely that a user would need to check out the same book twice due to running out of time.

Cataloging and Access

Though Libby is a stand-alone mobile app and we anticipated that most users would access our libraries' Libby content through the app, we also wanted to catalog the individual audiobook titles so that they would be discoverable through our libraries' catalog and discovery layer.

OverDrive offers several ways to acquire MARC records, including both paid and free options with different levels of full or brief records. We chose the free MARC Express record option provided by OverDrive because the records were full enough for our needs. Institution-specific links to the audiobooks were provided in the 856 MARC field. This made it easy for our cataloger to download the MARC records directly from the OverDrive Marketplace site and batch upload them into our integrated library system.

To provide additional access points to the audiobooks, we also added Libby to our libraries' A - Z database list.

Marketing and Launch

We officially launched Libby audiobooks to our library community on August 1, 2024, ahead of the fall semester. We saw our first checkout later that afternoon.

Our marketing strategy revolved around advertising Libby audiobooks on as many university communication channels as possible. We promoted the service in the libraries' monthly "Library Letter" email newsletter, created digital and physical flyers to post on bulletin boards and digital signage around campus, and encouraged our research and education librarians to mention Libby audiobooks in their classes and presentations.

We customized colors, graphics, and information on the standard marketing materials provided by OverDrive to ensure they reflected our branding and focus.

Soon after we launched the collection, a web and digital content developer joined our staff and has since helped us with refreshed marketing content and avenues for the

Libby audiobook collection such as social media marketing and updated flyers and signage, including table tents and stall signs.

We utilized promotion campaigns targeted for Libby audiobooks approximately every other month in the first year of access, in November 2024, January 2025, March 2025, April 2025, May 2025, and July 2025.

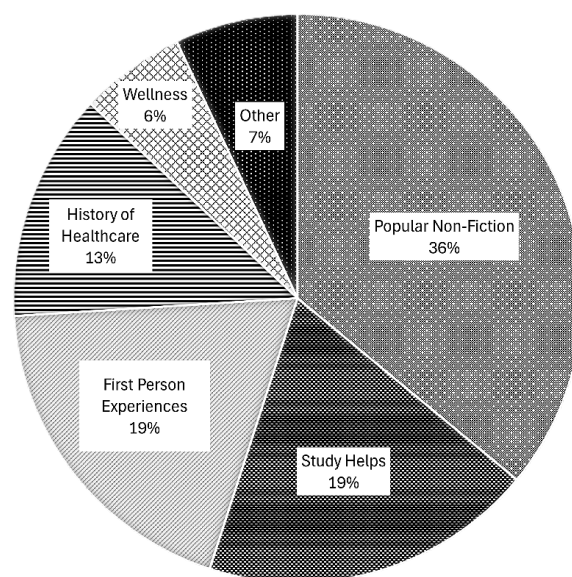
RESULTS

In the first year (August 2024 through July 2025) of offering audiobooks to our patrons, we saw 123 total checkouts of 64 titles across 74 unique users. Of our initial content credit, we spent \$351.84 US on CPC checkouts.

Usage

We saw the greatest number of checkouts in the popular nonfiction content area, with 45 total checkouts across 24 titles. See Figure 3 for a breakdown of checkouts across all content areas. The most frequently checked out popular nonfiction title was *Well: What We Need to Talk About When We Talk About Health* by Sandro Galea with 12 unique borrowers. This was also the title with the greatest number of checkouts overall during the first year.

Figure 3 Libby audiobook checkouts per content area in the first year of access.



Two content areas tied for the second greatest number of checkouts: study helps and first-person experiences, with 23 checkouts across 12 titles each. The study help title checked out most often was *The New Rules of Menopause: A Mayo Clinic Guide to Perimenopause and Beyond* by Stephanie Faubion with 9 unique borrows. The first-

person experiences title checked out most often was *This is Going to Hurt: Secret Diaries of a Young Doctor* by Adam Kay with 8 unique borrows.

“Other” refers to titles included in our collection, but that don’t easily fit into one of the primary categories. This includes six checkouts of a title we added to support a library-hosted book club and one checkout each for three titles related to leadership or education that our research and education librarians recommended but didn’t fall into one of the focus categories.

Cost

We started August 2024 with \$3,000 in content credit. We spent \$351.84 of that deposit on the monthly CPC charges; an average of \$29.32 per month. We spent an additional \$430.80 on OC/OU e-book and audiobook purchases to support the library-hosted book club that met once per semester. Some titles the book club chose to discuss were not available under the CPC model or were not available as e-books through other platforms the libraries were already using. In all, we purchased eight e-book copies and one audiobook copy of three book club titles.

DISCUSSION

Almost two-thirds of the titles used were checked out just once during the year, indicating that users were accessing a variety of titles from the available collection, even though only about 12% of the total available titles were checked out at all. These data confirm the decision to use the CPC pricing model to provide a wide selection of titles and only pay for what is used.

We finished the first year with more than \$2,000 in content credit remaining and were then required to add more to that deposit amount for year 2 with OverDrive, so we added the minimum amount required.

On the one hand, it is positive that we did not exceed our budget, which was a plausible scenario due to the unpredictable nature of the CPC model. However, we finished the year with money still available to spend, meaning that the service was not used to capacity. We expect usage, and therefore cost, of the service will continue to increase as more patrons are made aware of it. So far in year 2, the monthly average spend for CPC checkouts is slightly higher than in year 1, at \$30.87 per month based on the first six months of year 2 data.

The specific focus of our collection – nonfiction audiobooks related to health and medicine – versus the overall breadth of formats and content available through Libby limits the spending capacity of our project. Because of this, OverDrive’s requirement to add content credit each year could be a future limitation for us.

One limitation is that we have not yet incorporated feedback directly from patrons, though subject librarians

participated in selecting the titles in our collection. In retrospect, finding a way to incorporate input from students and faculty in selecting titles would have been beneficial. When we selected the titles for the initial collection, we weren’t sure which areas would have the most demand, so we made broad selections. Now that we have some checkout data, we can be more targeted in the titles or collecting areas we choose going forward. Our next steps include gaining insight directly from our libraries’ Libby audiobook users to understand how their preferences and levels of satisfaction might shape the program going forward.

Another lesson learned was that we need to develop a process for refreshing the content available in the CPC audiobook collection. For one, titles may leave OverDrive or the CPC program without notice and therefore be removed from our collection unexpectedly. We need to be aware of these changes so that we can remove the title from our catalog manually. Additionally, as new titles are published or become available that meet our collection goals, we want to be able to make them available.

Through this project, we discovered that OverDrive’s title library includes sufficient offerings for academic health sciences libraries to create targeted nonfiction audiobook collections. The consistent and varied usage of the audiobook collection at USF Health Libraries in the first year indicates that it is benefitting some students or faculty members. The low average cost associated with the program thus far means that it is sustainable, though we understand that if interest and usage increases, so will the cost.

In all, this project directly supports one of our library’s strategic pillars: strengthening library collections. It does so in a way that offers supplemental health and medicine content in a modern format popular among the demographics of our students.

DATA AVAILABILITY STATEMENT

Due to privacy concerns, circulation data are not available. Aggregate data related to circulation is available in the appendix.

AUTHOR CONTRIBUTIONS

Julie Evener: Conceptualization, Methodology, Writing – original draft, Writing – Review & Editing; Melinda H. Berg: Conceptualization, Methodology, Writing – Review & Editing

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SUPPLEMENTAL FILES

Appendix A: Sound Solutions Aggregate Data

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Resident resource use in clinical settings: an institutional survey

Nell Aronoff; Laurel Mueller

See end of article for authors' affiliations.

Background: We explored which point of care (POC) resources medical residents at the University at Buffalo use in clinical settings. We specifically sought to gather feedback from residents who help train medical students to see how they discover, use, and promote resources to support patient care.

Case Presentation: We developed an eight question Qualtrics survey. Residency program coordinators emailed the survey to approximately 445 residents in the following programs: Family Medicine, Internal Medicine, Combined Internal Medicine and Pediatrics, Neurology, Child Neurology, Obstetrics and Gynecology, Pediatrics, Psychiatry, Surgery, Plastic Surgery, and Vascular Surgery. The programs we targeted all correspond to required clerkship rotations. The survey was open for two weeks in June 2025. Thirty-nine residents (8.8%) completed our survey. Thirty-five, or nearly 90% of respondents, reported that they frequently use UpToDate, followed by twenty-three (59.0%) that use OpenEvidence, and seventeen that use MDCalc (43.6%). The residents we surveyed were inclined to recommend similar resources to medical students. They most often hear about new resources from other residents and attendings, via announcements on social media or podcasts, or by attending grand rounds and conferences.

Conclusions: Our results highlight the continued popularity of UpToDate among medical trainees but also suggest that residents frequently use OpenEvidence in clinical settings. Further studies are needed to determine the impact of artificial intelligence tools on patient care and learning outcomes.

Keywords: Graduate medical education; internship and residency; medical residents; medical libraries; surveys and questionnaires; resource use; clinical decision making



See end of article for supplemental content.

BACKGROUND

The Accreditation Council for Graduate Medical Education (ACGME) Common Program Requirements for Residency Programs includes proficiencies in the acquisition and application of Medical Knowledge (4.6) and Practice-Based Learning and Improvement (4.7) [1].

In addition to the ACGME requirements, the Association of American Medical Colleges' thirteen core Entrustable Professional Activities (EPAs) for graduating medical students includes the ability to "form clinical questions and retrieve evidence to advance patient care" [2]. Based on these expectations, residents must develop the ability to recognize when a clinical scenario calls for information and identify where to find the answers to their clinical questions.

Providers use POC resources to educate themselves and others, including patients and learners, and to make clinical decisions [3]. Previous studies have looked at where students, residents, and other clinicians find

information to support patient care. They illustrate the enduring popularity of UpToDate, PubMed, the Cochrane Library, and drug information sources, but it is important to note that they were all published before generative AI tools were readily available [4-10]. For example, Blake and Tong surveyed Pediatrics, Pediatric Infectious Disease, Trauma, and Family Medicine residents after a month-long rotation and found that they relied most heavily on UpToDate, PubMed, and LexiComp [4]. Brassil et al.'s survey of practitioners at Baystate Medical Center found that 80% of respondents used UpToDate and 65% used PubMed, followed by Epocrates, Micromedex, Google Scholar, and Cochrane [5]. Petersen, Earl, and Wilson's review of library usage trends over a sixteen-year period at the University of Tennessee showed that residents and fellows consistently used UpToDate, PubMed, and the Cochrane Library [9].

Part of the challenge of determining what resources to use is that there are more options than ever before. Bernstein et al.'s survey of 662 internal medicine residents in the US

revealed that residents used an average of seven traditional resources and two novel resources [11]. Traditional resources included broad categories like digital clinical resources (i.e., UpToDate), clinical experience, journal articles, textbooks, and guidelines. Novel resources included blogs, podcasts, and YouTube videos. Cook et al. suggest that a lack of awareness about where to search and the exponential amount of information physicians must wade through are barriers to POC learning [12]. Along with the exponential increase in medical information, there has also been an influx of new tools and resources. This so-called tyranny of choice may overwhelm residents and lead them to return to familiar tools even if better resources exist [13].

The use of artificial intelligence (AI) has exploded in the past few years, further complicating where residents should turn when deciding where to search for clinical information. Some AI tools are easier to access, easier to use, or more reliable than others. As of this writing, ChatGPT is perhaps the best-known AI chatbot. As Lahat and colleagues state, while ChatGPT has the potential to improve patient outcomes, it must be used in tandem with human knowledge [14]. A more recent addition to the AI landscape is OpenEvidence, an AI chatbot trained on content from JAMA and The New England Journal of Medicine. As more and better AI tools are available, clinicians will find new ways to address POC questions.

CASE PRESENTATION

Institutional Context

The University at Buffalo (UB) is a large public research institution. UB has over sixty resident and fellow training programs with over 800 residents and fellows [15]. Until August 2024, there was one primary library liaison to the Jacobs School of Medicine and Biomedical Sciences. At that time, a second library liaison was hired to support the school which has faculty, staff, undergraduate, graduate, medical, and PhD students, residency, and fellowship programs, and twenty-six basic science and clinical departments. Since there is no dedicated university teaching hospital, residents are located at nine affiliated hospitals and in various UBMD clinics across Western New York, leading to limited interactions between residents and their assigned liaison librarians [16]. Librarians have interacted with residents at new resident orientations and have been invited to present during grand rounds and academic half day sessions. Some hospital partners provide their own library resources and services, which means that residents may also be receiving assistance from full time or circuit hospital librarians.

Purpose

We sought to explore which POC resources medical residents at our institution use in clinical settings.

Exploratory questions that guided our survey design included: 1) Are they still relying heavily on UpToDate?; 2) What changes have there been since previous studies?; and 3) Have the emergence of artificial intelligence tools changed their workflows?

Survey Population

We sought to query residents that regularly interact with medical students in required clerkships to learn how residents discover and promote resources to support patient care. The core clerkships consisted of Family Medicine, Medicine, Advanced Medicine, Neurology, Obstetrics and Gynecology, Pediatrics, Psychiatry, and Surgery so we targeted residents in the following programs: Family Medicine, Internal Medicine, Combined Internal Medicine and Pediatrics, Neurology, Child Neurology, Obstetrics and Gynecology, Pediatrics, Psychiatry, Surgery, Plastic Surgery, and Vascular Surgery. This amounted to approximately 445 residents.

Survey Instrument and Distribution

Our protocol was approved by the UB Institutional Review Board in May 2025. We shared a draft of the survey with seven residents for feedback about how to bolster the response rate. They suggested that residency program coordinators email the survey on our behalf and mentioned that a survey incentive could help. Another resident suggested that we could promote the survey during grand rounds or academic half days; however, we could not schedule visits with every program during the survey period. We were also concerned that promoting the survey to certain programs would result in response bias.

The final Qualtrics survey instrument contained eight questions. The full survey is available in Appendix A. Given the demands on potential respondents' time, we intended for the survey to take less than ten minutes to complete. Program coordinators emailed the survey twice during a two-week period in June 2025. We offered three \$50 gift cards as an incentive to participate.

Response Rate and Respondents' Program Demographics

Using resident lists from Graduate Medical Education (GME) program websites, we estimated there were 445 residents across the eleven programs affiliated with required medical student clerkships in academic year 2024-2025. Forty medical residents responded to the survey. One response was disregarded from analysis because they did not provide any usable information besides their program name. With 39 completed responses, there was an 8.8% response rate. Due to the low response rate, we were also unable to provide in-depth analysis of specialty-specific resource use.

The survey began with one demographic question that asked participants to identify their program affiliation. The resident response breakdown is as follows: Internal Medicine (n=16, 41%); Family Medicine (n=6, 15.4%); Pediatrics (n=6, 15.4%); Neurology or Child Neurology (n=4, 10.3%); Obstetrics/Gynecology (n=4, 10.3%); Surgery, Plastic Surgery, or Vascular Surgery (n=2, 5.1%); and Psychiatry (n=1, 2.6%).

Resources Used for Clinical Decision Support

Next, we asked respondents what information resources they use most frequently to answer clinical questions (Figure 1). Frequency was defined as resources they engage with on a daily or weekly basis, and information resources were defined (but not limited to) medical apps, websites, databases, calculators, textbooks, and AI tools. This was an open-ended question with no set limits on the number of responses to include, and respondents were not offered a list of resources to select from to reduce response bias.

Nearly all survey takers listed two or more tools. In total, 136 tools were listed among the thirty-nine respondents. This is an average of 3.5 resources per resident at our institution, with a population standard deviation of 1.6. Four respondents (10.3%) only consulted UpToDate for clinical decision-making. The other 35 residents (89.7%) reported using more than one resource. Thirty-five respondents (89.7%) used UpToDate for clinical decision support. Over half of the respondents (n=23, 59.0%) frequently consulted OpenEvidence, the AI-powered medical support platform. One other AI platform, ChatGPT, was used frequently by three participants (7.7%). The third most referenced tool used for clinical decision support was MDCalc (n=17, 43.6%). AMBOSS, Epocrates, and PubMed were each mentioned by 5 (12.8%) respondents. Four participants (10.6%) consulted the CDC vaccine schedule and Lexidrug. Guidelines from professional associations like the American College of Obstetricians and Gynecologists and the Infectious Disease Society of America, as well as general or specialty medical journals like JAMA and Obstetrics & Gynecology were listed by 3 (7.7%) or fewer people. One respondent (2.6%) mentioned Google, and another participant listed Google Scholar. Participants responded with 36 unique POC resources, ten of which are available through the UB Libraries. See Appendix B for a full list of resources.

To understand how residents support medical students' clinical education through resource sharing, participants were asked an open-ended question about what resources they recommend to medical students during their required clerkships (Figure 2). Notably, the question did not define or limit responses to tools only used for clinical-decision support, so respondents could reference any resources that would help medical students in their educational and clinical training. Residents listed similar resources to the ones they consulted for their own use.

UpToDate was again listed as the top resource (n=25, 64.1%), and OpenEvidence was the second most suggested resource (n=8, 20.5%). Respondents recommended test preparation materials, such as UWorld and AMBOSS. Survey takers also indicated specialty-specific textbooks, YouTube videos, and podcasts to support medical student learning and training. See Appendix C for a full list of resources.

Figure 1 Top resources used frequently by residents for clinical decision support

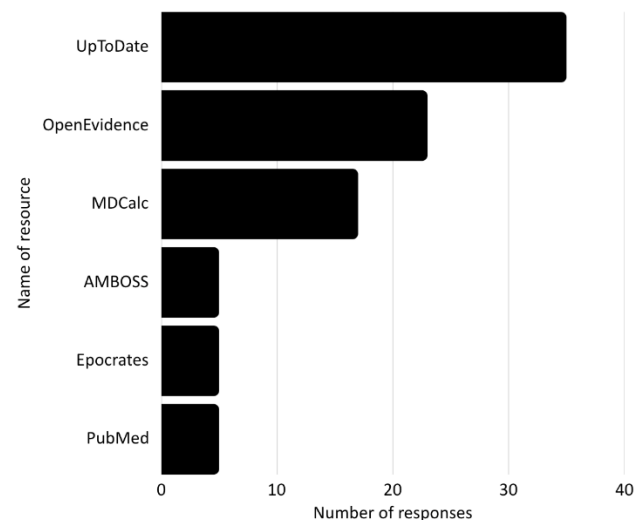
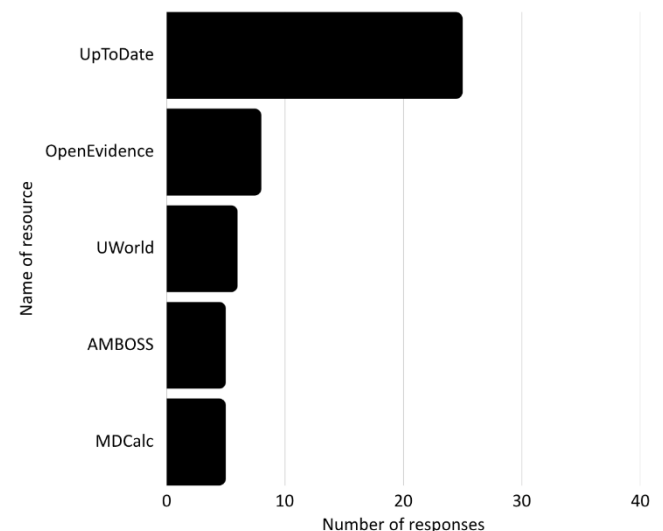


Figure 2 Top resources shared by residents with medical students during clerkships



Learning about New Resources

To explore how residents learn about new resources, one survey question asked residents who tells them about new resources. Regarding the who, residents were given seven choices as well as an "other" option. Participants could select all that apply. Nearly all the respondents (n=36, 92.3%) reported learning about new resources from other residents. Attendings were also frequently selected as a source for tool sharing (n=29, 74.4%), followed by medical students (n=10, 25.6%), other healthcare professionals such as nurses and administrators (n=4, 10.3%), and librarians (n=4, 10.3%). One respondent filled out the write-in option and listed "Internet" (n=2.6%).

In conversation with the previous inquiry, respondents were asked to identify where they find out about new resources. They were given a list of options and an "other" write-in box and asked to check all that apply. Almost half of participants said that they used social media to learn about new resources (n=18, 46.2%). Other top selections included podcasts (n=17, 43.6%), grand rounds (n=16, 41%), conferences (n=15, 38.5%), journal articles (n=12, 30.8%), and professional associations (n=9, 23.1%). One person wrote in "Almost always word of mouth." One participant (2.6%) selected library guides.

To determine how residents accessed fee-based resources and gauge if they were purchasing resources themselves, we asked residents to report on how they accessed subscription-based clinical resources. Two-thirds of respondents used hospital subscriptions to access paid resources (n=26, 66.7%), nearly equal to those who utilized them through the UB Libraries (n=25, 64.1%). Six residents bought their own (15.4%). Four respondents (10.3%) indicated "other." Two respondents left the write-in blank, one resident wrote "n/a," and another indicated they only use free options.

The last question invited respondents to relay anything else about their clinical resource use they wanted to share with their liaison librarians. Nine residents opted to provide additional information. Several residents highlighted the growing reliance on OpenEvidence to support clinical reasoning. Access limitations were also mentioned, including issues using resources off-site at home addresses, along with financial restrictions like having to pay up front for professional association memberships and board studying materials before being reimbursed by a program. Another person explained that the usefulness of each resource depends on the learner and the situation based on the degree of diagnostic or clinical uncertainty.

DISCUSSION

We sought to determine what resources medical residents at our institution without a designated teaching hospital consult on a daily or weekly basis for clinical decision

making. Residents at our institution reported using around 3.5 resources on a frequent basis. This is lower than the results from a nationwide survey of internal medicine residents, which found that residents consulted an average of nine resources for POC and general medical information [11]. One explanation for this is that we did not inquire about what resources residents used to support their education and training or research endeavors.

Results showed that residents continue to rely on UpToDate in clinical settings. According to one respondent, "UpToDate is the most important." Preference for UpToDate is consistent with other articles that studied resident resource use [5-10]. While UpToDate was the most frequently listed tool in survey responses, four residents did not engage with the platform on a regular basis. One resident noted UpToDate is useful for its high-quality summaries when physicians are more certain of their clinical diagnosis but explained the product "loses its helpfulness when your certainty of the culprit diagnosis is low."

Though we did not provide a pre-determined list of resources, similar trends appeared in medical resident responses across programs. Notably, residents cited medical specialty-specific professional associations, journals, textbooks, and podcasts as frequently consulted resources. Residents are relying on these tools when in search of specialized information. While the low response rate prevented us from performing further sub-analysis on programmatic resource use, other studies have addressed resource use among residents in specific programs [6, 11, 17].

Recent research illustrates that medical students and professionals use popular websites like Google and Wikipedia as well as databases including PubMed, Medline, and Google Scholar to answer clinical questions [5, 6, 8-10]. In Duran Nelson et al.'s study on resource use among internal medicine residents at POC, researchers found that residents were more distrustful of information provided by Google and Wikipedia but engage with these resources during the "discovery phase" before searching for additional information through a trusted source [6]. Our results show less frequent reliance on these tools; despite the efficiency and public accessibility these tools offer. The shift could be due to evolving clinical decision support technologies or a greater emphasis in medical and resident education on using high-quality evidence-based sources.

Residents are increasingly relying on AI-powered tools in clinical settings. As demonstrated by our results, residents have begun to identify AI tools like OpenEvidence as among their most frequently consulted POC platforms. While we did not include questions on how residents determine which tools to use in medical decision making, previous scholarship on resource use among medical

professionals found speed and ease of use were paramount [6, 10, 18]. Residents seek efficient means to locate high-quality, evidence-based medical information to answer clinical questions. Because AI tools synthesize large amounts of information almost instantaneously, they often reduce the time needed to search within individual databases or journals. This suggests that AI tools may continue to gain popularity among medical trainees.

Communication among residents, attendings, and medical students is essential for resource sharing, as residents are learning about new resources from other medical professionals. Brassil et al. found communication with colleagues was one of the most popular methods in finding an answer for a clinical question, so it follows that residents would learn about new resources most often from their peers [5]. As to where residents are learning about new resources, they discover new tools in academic and online contexts. Bernstein et al. found internal medicine residents are relying more on audio-visual media, including video streaming platforms and podcasts, for general and POC medical information compared to earlier studies [11]. Specialty-specific podcasts were included as frequently used resources among residents, and these podcasts, along with the video streaming platform YouTube, were recommendations residents shared with medical students during their required clinical rotations.

One of our goals was to assess how residents are accessing resources and if residents are paying out of pocket for subscription-based resources. Most residents utilize subscription-based tools provided by the UB Libraries or through their hospital affiliations. Less than one-fifth of respondents reported paying for subscription-based sources themselves. A remaining question is whether residents are finding what they need for free or through their university or hospital connections, or whether they are going without other beneficial tools because they can't afford to purchase them.

Implications for Practice

Data gathered from the survey has informed how we meet the information needs of residents at our institution. Though over half of the respondents disclosed that they access clinical resources through the UB Libraries, very few residents learned about new tools from librarians or via library guides. This suggests that we could be better at promoting our subscription resources to this dispersed user group, and further publicizing efforts can occur through instruction sessions and presentations given to residents. As an example, while we provide VisualDx, it was not mentioned as a frequently used resource.

Given the growing popularity of OpenEvidence for POC information, we contacted OpenEvidence customer service to provide us with unlimited access to the platform since it is currently only available to verified healthcare

professionals with a National Provider Identifier (NPI). We hope expanded access will allow us to incorporate it into resident instruction sessions, while also highlighting current POC library subscriptions. We have adjusted literature searching lesson plans to demonstrate other AI-powered tools, like the scientific literature searching platform Consensus, to address interest in AI products for faster literature searching. Results from this study will impact resources listed on our libraries' clinical resources and AI research guides. As usage and reliance on AI products increases, librarians may consider surveying their users to better meet user needs and make collection development decisions.

LIMITATIONS

There were several limitations to the study. Despite our efforts, the survey response rate was low, representing less than one tenth of the total population to which the survey was distributed. Therefore, we are unable to assess the full scope of resources residents consult for clinical care. Alternate time frames and expanding promotional efforts may have helped increase the response rate.

Offering open-ended responses for questions rather than providing a list of resources reduced response bias. However, some respondents listed general publication types, like review papers or case files, rather than identifying specific products they use to access medical information for clinical decision support. Inputting resources manually may have led to residents listing fewer resources than they actually use.

Finally, although this was outside the scope of our study, we did not investigate how residents are using these tools to make clinical decisions or how they appraise and integrate evidence to promote better patient care. The impact that the resources have on health outcomes is a separate matter that has been studied by Marshall and others [8, 19, 20] but would be worth pursuing again considering the changing information landscape.

CONCLUSION

Our findings suggest that medical residents at UB tend to rely on a few select tools that they hear about through other residents and attending physicians. Prior studies have also demonstrated a preference for UpToDate, but our results indicate that AI tools are becoming more popular in this cohort. Further investigations should consider how medical residents are integrating AI resources in their clinical decision-making process alongside more traditional tools like UpToDate and MDCalc. We posit that technological developments offering more efficient access to high-quality information will continue to drive information-seeking behavior among medical residents.

DATA AVAILABILITY STATEMENT

Data associated with this article are available in the Open Science Framework at <https://doi.org/10.17605/OSF.IO/RS98Y>.

AUTHOR CONTRIBUTIONS STATEMENT

Nell Aronoff: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; validation; writing – original draft; writing – review & editing. Laurel Mueller: Conceptualization; formal analysis; investigation; methodology; validation; visualization; writing – original draft; writing – review & editing.

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SUPPLEMENTAL FILES

Appendix A: Resident Resource Use Survey

Appendix B: Summary of Resources Used for Clinical Decision Support

Appendix C: Summary of Resources Shared with Medical Students

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Evidence-based design of vaccine hesitancy information resources for health care providers

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Background: The University of Florida Health Science Center Libraries (HSCL) sought to address the increasing challenge of vaccine hesitancy during the COVID-19 pandemic by developing evidence-based information resources for health care providers. To do this, HSCL librarians assessed the vaccine hesitancy information needs of local health care providers to design a resource that could be used to support conversations with vaccine hesitant patients at the point of care.

Case Presentation: A team of six librarians, supported by student research assistants, conducted interviews with 20 health care providers in north central Florida. The interviews, conducted via Zoom, focused on providers' experiences with vaccine-hesitant patients. Content analysis of the transcribed interviews identified key themes, including trust, individualized conversations, and the impact of misinformation. The team developed a resource guide based on these findings, featuring curated information to support providers in vaccine discussions.

Conclusions: The results highlighted the importance of trust in patient-provider relationships and the challenges posed by misinformation. Providers expressed a need for diverse, accessible resources to aid in conversations about vaccines. The resulting resource guide, disseminated through local health networks, aims to enhance providers' ability to address vaccine hesitancy effectively. This project underscores the critical role of librarians in public health initiatives and the value of collaborative efforts to combat vaccine hesitancy.

Keywords: Vaccine hesitancy; clinical information resources; evidence-based librarianship; qualitative data analysis



See end of article for supplemental content.

BACKGROUND

The University of Florida Health Science Center Libraries (HSCL) are committed to engaging with local communities and promoting access to trustworthy health information. However, the libraries' position serving academic and clinical populations means that the librarians have little direct contact with the public. Instead, through HSCL's community engagement strategy, library personnel have focused on developing strong partnerships with public-facing local health and social service organizations who are trusted by community members. Libraries, as information providers, are well placed promote access to scientific research and writings on vaccination and on historic concerns about vaccination processes. [1] Prompted by the COVID-19 pandemic, in 2021-2022 a team of HSCL librarians was awarded an internal grant to assess the vaccine hesitancy information needs of health care providers [2].

The University of Florida is in Alachua County located in north central Florida. North Central Florida's population

is often categorized into three groups: 1) the small town and university area of Gainesville, which is demographically younger, more diverse, and more highly educated; 2) the retirement area south of Gainesville that has a higher proportion of elderly residents; 3) and the rural counties to the north, east, and west of Gainesville. Like many other rural areas, access to health care is a challenge, exacerbated by the percentage of families living at or under the federal poverty level and the number of immigrants, particularly rural migrant laborers [3]. These populations also contain groups who are skeptical of health care providers and may be vaccine hesitant [4].

The goal of this project was to develop a resource to help improve the quality of conversations that health care providers have with their patients. We aimed to design the resource by obtaining a better understanding of the reasons for vaccine hesitancy and the sharing of information resources addressing these reasons. This was done through an information needs assessment in which local health providers and advocates were interviewed and those interview transcriptions analyzed. The project

team sought to interview a variety of individuals who regularly have conversations with patients about vaccines, with a goal of twenty interviews that represented at least three different provider or advocate types.

CASE PRESENTATION

Methods

The grant funding allowed for the hiring of student research assistants to collaborate with the librarian project team members. The six librarians focused on developing the project plan and methodology, using professional connections to recruit and make initial contact with potential study participants, conducting interviews, and leading data coding and analysis. The project team targeted providers who were known to have regular conversations about vaccines with their patients, such as primary care providers, but were broad in their definition of 'provider' and reached out to contacts in various medical specialties at UF Health and health advocates in the surrounding community. Use of an onboarding checklist and training session ensured that the research assistants understood the context of the project, as well as the process of conducting qualitative research. While the concept of validity in qualitative research has been considered controversial, Maxwell [5] discusses strategies to prevent validity threats, several of which were utilized in this project, including the use of rich data (meaning detailed and in-depth data that can be used to deeply understand the meaning behind experiences or phenomena) and applying numbers to assess the amount of evidence in the data. The research assistants participated in drafting the interview questions, facilitated the logistics of scheduling interviews with study participants, recorded and transcribed the interviews, and participated in the coding and qualitative analysis of the transcripts. The project plan was submitted to the University of Florida's institutional review board and was categorized as exempt (IRB #202101941).

Data Collection

To make interviews as accessible as possible to busy health care providers, and to take advantage of computer-generated transcription features, the project team conducted interviews over Zoom. The project lead developed a protocol document (see Appendix) that was used to guide interview setup and procedure, ensuring consistency across all interviews. It also helped the team remember important details like ensuring that the online consent form was completed, recording the interview, and asking for contact information to deliver the participant incentives. As a semi-structured interview, the team developed a list of core questions to ask about provider experiences with vaccine conversations, particularly ones in which patients are vaccine hesitant:

1. Do you talk to your patients about getting vaccines for: 1) themselves, 2) their children, or 3) other loved ones (parents, etc.)? How do you approach these conversations?
2. Do you encounter people who hold beliefs that may make them hesitant to get vaccines? What strategies do you use to discuss their beliefs with them?
3. Where do you think patients receive the most influential information about vaccines from?
4. What factors have you seen/ do you think influence a person's decision on whether to get a vaccine or not?
5. How do you decide which resources are most suitable to recommend for particular patients, in relation to vaccines?
6. In your opinion, what are the best ways to present vaccine information to patients?
7. What resources or tools would make these conversations easier for you?

The protocol also included a list of supplementary questions that interviewers could use to elicit additional information, depending on how detailed and informative the initial responses were. Interviewers had the flexibility to pursue additional areas of inquiry based on participant responses.

Librarians identified potential participants through existing contacts who were likely to work with vaccine hesitant patients. This included people from the team's liaison groups and past projects who were either institutionally affiliated or community-based health care providers. Health care provider was defined broadly as any professional involved in the health care process who has conversations with patients about vaccines on a consistent basis.

Data Analysis

Zoom transcripts were corrected to capture verbatim conversations. The use of full transcripts and "rich data" is one of several strategies for dealing with threats to validity in qualitative research. [5] To best fit the type of data and project goals, the research team elected to use a collaborative approach to qualitative data analysis. [6] The process included multiple rounds of coding, review, and triangulation to ensure consensus amongst the coders and consistency of code application (Figure 1). The full coding protocol is available at: <https://osf.io/f875j/files/t8a6k>.

To obtain additional direction related to the design of an information resource, the team performed a secondary analysis of the interview questions targeting information resources. As a first step, one team member created a new document collating excerpts from each interview transcript that specifically mentioned particular

information resources. The rest of this process was a streamlined version of the primary analysis with some high-level themes and recommendations being derived from the more focused dataset.

Findings

Participant Demographics

The team interviewed a total of 20 individuals, including clinicians, administrators, community health workers, and community health advocates. Many of the physician participants who responded are in specialties in which recommendations about vaccines feature regularly in clinical settings, such as pediatrics and family medicine. Several of the physician participants also spoke about their experiences in the context of vaccine-related projects or outreach work that they had begun during the pandemic.

Data Analysis

Using iterative content analysis for the primary analysis, the team created 86 unique inductive codes that were applied to interview transcripts. Those codes were tagged to transcripts a total of 1,725 times, with an average of 86 code instances per transcript. The same code could be tagged multiple times within each transcript.

Several codes were grouped into larger categories. These broader categories include the following:

- **Demographics:** age, education, socioeconomic status, race/ethnicity, religion, rural/urban
- **Information Content:** patient experiences/testimonials, data
- **Information Format:** audio, infographic, language, messaging, phone, print, video
- **Information Sources:** celebrities, experts, government websites, news media, research data, scholarly literature, social groups, social media
- **Reasons for Vaccine Hesitancy:** access/logistics barriers, conspiracies, fear, ID requirement, medical intervention hesitance, low individual risk, survived COVID, patient family/friends' experiences, political ideology, safety concerns, religious beliefs, skeptical of effectiveness, social groups, side effects
- **Reasons for Vaccination:** multiple/complex/overlapping rationale, high individual risk, patient family/friend experiences, protecting friends/family, religious beliefs, vaccine mandate

The most commonly applied codes across transcripts were: "providers reducing barriers: reframing the conversation" (93 instances), "individualized conversations" (73), and "trust" (62), and "patient provider relationship" (57). All codes used at least 20 times are shown in Figure 2.

Figure 1 Approach to Qualitative Data Analysis

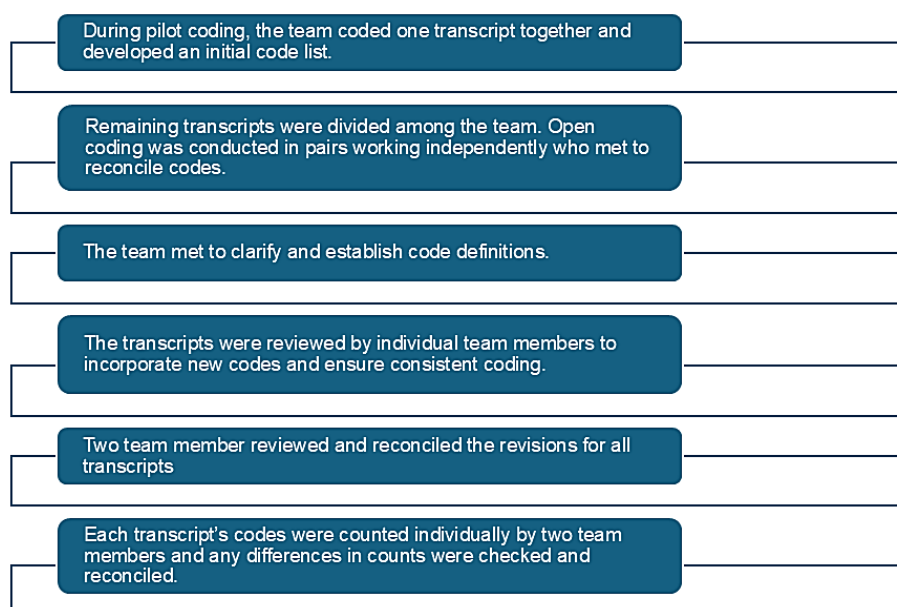
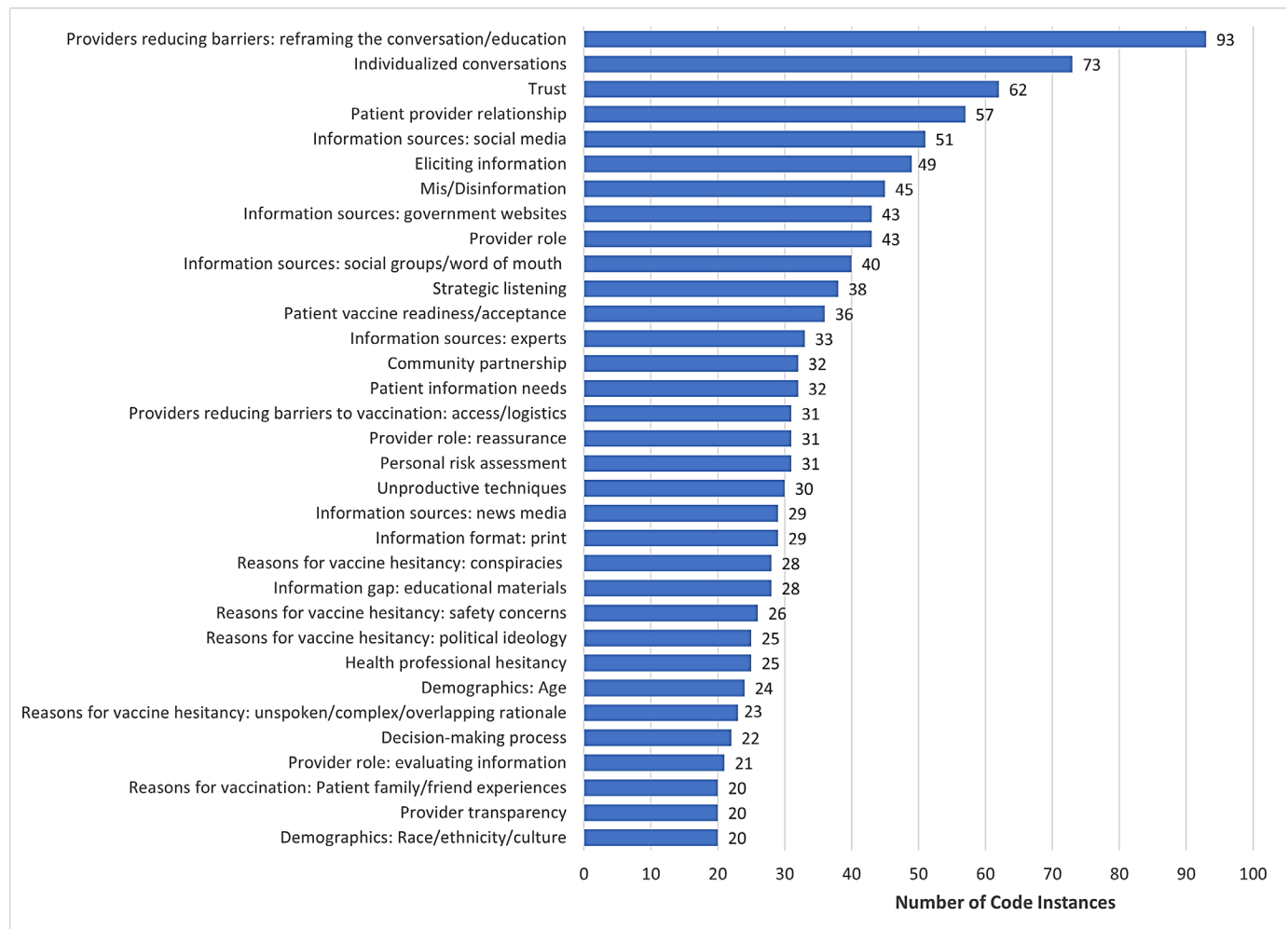


Figure 2 Number of Uses of Codes Across All Transcripts. Only codes with 20 or more uses are included.

The code "individualized conversations" was defined as "interviewees customizing the vaccination conversations based on their own individual experiences and beliefs". For example, one interviewee mentioned that sharing personal experiences one-on-one to establish a connection is essential:

"I think for really difficult, intractable issues like this, then the effort of going and trying to talk to people individually and trying to share those experiences, one on one. You know not talking at people and not trying to get them to come to one place, but really meeting them where they are, is super important - [and] worth the effort that it takes." - Interviewee #17, Community Health Worker

Another interviewee discussed the importance of having genuine conversations with people instead of having a canned response that could across as inauthentic:

"I approach all my vaccine conversations based around what the individual person specifically has questions about or is hesitant about. So, I don't give some canned spiel about how vaccines are

safe and effective, I ask people 'What questions do you have? What is [the] cause in your hesitation?' and I try to invite them to share anything and everything and I say that there is no concern that is too silly, there is no question that is at all a bad question." - Interviewee #20, Medical Director of a local clinic

Interviewees' responses pertaining to this code suggest that tailoring "individualized conversations" was considered an essential aspect of successful provider-patient communications related to vaccine hesitancy, particularly in terms of establishing personal connections and addressing specific concerns and questions.

The code "providers reducing barriers: reframing the conversation" was defined as "providing information in a way that helps patients better understand the benefits and risk of vaccination". Examples included asking patients why they were not completely vaccine-averse and reminding them of the potential impacts of vaccination on family members.

"I'll ask if they're interested in talking about the COVID vaccine like 'Where are you on a scale one to 10 for readiness to get the COVID vaccine?' If they're a 2, then, sometimes you'd like to get some positives out of them you'll say 'Okay, well, why aren't you a 1?'" - Interviewee #2, Pediatric Endocrinologist

"You're pretty healthy, but your elderly mom who you live with, who has contact with you daily who's not going out and being exposed to anybody else but you're going out and being exposed to everybody else, if you got it [the vaccine], you could really help her." - Interviewee #6, Community Medicine Doctor in a rural area

The code "trust" was defined as "indicates a specific mention of either the presence or lack of [trust], often as an element of a patient/provider relationship". Discussed further below in the context of information sources, trust was considered a key element of successful vaccine conversations.

"For my specific patients...who have long standing trusting relationships with me, a lot of these folks ending up getting vaccinated despite how concerned they were about a lot of things because of the level of trust. Like it was the trust; the trust was the most important thing. It wasn't even how well I made the argument or the logic behind it. It was really, at the end of the day, it was they trusted me." - Interviewee #20, Medical Director of a local clinic

Another important information-related code our team found was that of "misinformation and disinformation". According to the American Psychological Association [7], misinformation is information that is false or inaccurate whereas disinformation, is false information that is created intentionally with the purpose to mislead through intentionally misstating factual true information. Out of the 19 interviews, our team had 43 counts for the code of misinformation and disinformation. Interviewees acknowledged that the issue of misinformation and disinformation in medicine existed prior to COVID. However, interviewees discussed how misinformation in general was exacerbated by the misunderstanding and misuse of professional research terminology by the public.

"I don't know just in general with misinformation, I mean it was already an issue in medicine before the pandemic and I think the pandemic just brought out all of our issues with misinformation because...we [scientists and researchers] use certain language with each other about things that I think doesn't always translate to the community" - Interviewee #2, Pediatric Endocrinologist

Other interviewees spoke of misinformation related to COVID vaccine risks that misconstrued the potential harms and the rise and spread of misinformation on social media.

"YouTube has been a horrible proponent of disinformation, a lot of them cite all of the YouTube conspiracy theorists that have really gotten major play during COVID." Interviewee #4, Internal Medicine Doctor

The results of these different elements of information were the same: an increase of distrust in COVID vaccinations.

Secondary Data Analysis

The secondary data analysis focused on responses to the interview question, "What resources or tools would make these conversations easier for you?" as well as interview excerpts tagged with the codes "information gap" or "patient information needs."

This yielded many ideas about what kinds of resources would help participants have better conversations with vaccine hesitant patients. Formats of interest ranged from handouts to providers reviewing materials with a patient, to short videos, websites, infographics and diagrams, advice on social media, testimonials from other patients, and waiting room literature, as shown by the quote below.

"common issues with the common concerns people have with the vaccines, like the best way to approach those might be helpful. Either as like in the form of a training or in the form of a handout that then we can summarize for patients" - Interviewee #2, Pediatric Endocrinologist

Participants also pointed out the value of curated information from authoritative and trusted local sources, such as the library or the health care system.

"it's good for the library to have something curated because there's a lot of information about that out there. And some form of curated information to again dispel misinformation about the effect of vaccines and people with long COVID" - Interviewee #13, Integrative Medicine Doctor

"if UF had our own website I don't know if patients would trust that more versus the CDC because I feel like if it's political reasons, then, some people might feel like CDC is biased. So if it came through this institution where they get the majority of the healthcare, maybe it would be different." - Interviewee #14, Internal Medicine Doctor

Participants indicated that resources should be catchy, printable, visual, colorful, eye-catching, and available in Spanish. For example,

"if, doctors and the CDC and all these people could have a little bit more pretty, catchy, things out there for why you should get the vaccine instead of boring websites" - Interviewee #2, Pediatric Endocrinologist

"I think generating more eye-catching infographics presenting simple facts in less technical language would be really effective." Interviewee #9, Community Health Worker

They also addressed multiple constraints that were outside the scope of this project: time, additional training on communicating with patients, more vaccination locations in rural areas, and television commercials, among others.

Designing a Resource Guide

As a result of the secondary analysis, the team identified a need to gather key information in a single place. Given the lack of interview data about the specific mechanism for sharing resources, a LibGuide was chosen, as LibGuides are convenient, customizable, accessible, familiar to the project team, easily updated, and can lead to additional information in a way that paper resources cannot. While incorporating resources into the affiliated medical center's electronic health record system would have been convenient for health care providers, the project team does not have direct access to the system, and this would have excluded community-based health and social service providers from accessing the resource.

The resources selected for review were all broad information portals from a variety of governmental and non-governmental sources. We anticipated that these sources would include a variety of types of resources designed for diverse audiences, so were most likely to meet our criteria. Resources reviewed included: the University of Florida HSCL and other libraries' COVID-19 LibGuides [8], the Smithsonian's Vaccines & US Campaign [9], the CDC-funded and Urban Institute-managed Partnering for Vaccine Equity Resource Hub [10], the University of Washington's Center for Informed Public Resources page [11], the NNLM Misinformation

Symposium [12], and the Office of the Surgeon General's Community Toolkit for Addressing Health Misinformation [13].

In reviewing these clearinghouses and information portals, the team used the following criteria to identify specific resources for inclusion in the guide: a focus on COVID vaccines rather than general COVID information, primary sources of information rather than secondary, locally-developed sources created by trusted organizations where possible, sources addressing specific reasons for vaccine hesitancy identified in the interviews, designed for diverse audiences, and available in multiple languages.

Ultimately, this work resulted in the following resource guide: <https://guides.uflib.ufl.edu/vaccinehesitancy>.

In the interest of balancing a clean overall look and feel with including a useful selection of the best resources, the team designed the guide with two tabs, one for general vaccine hesitancy resources and one for resources specific to various reasons for vaccine hesitancy identified in the interviews (Figure 3). On the general resources tab, information is divided into two sections: one collection of resources for direct patient use and another of resources to help providers prepare before and after speaking with patients who may be hesitant to receive a COVID vaccine.

Figure 3 Screenshot of the vaccine hesitancy library guide pages.

The figure displays two screenshots of a LibGuide titled "George A. Smathers Libraries" and "Vaccine Hesitancy Resources: General Resources".

Left Screenshot (General Resources Tab):

- Vaccine Hesitancy Resources: General Resources**
 - A collection of resources to assist in understanding the reasons for vaccine hesitancy and the barriers to vaccine uptake.
 - General Resources** (Selected) | Reason-Specific Resources
 - Resources for Patients**
 - Partnership for Vaccine Equity - Resource Hub**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: Partnership for Vaccine Equity is a program funded by the CDC that brings national, state, and community-level organizations, for each resource listed, language and accessibility of any people or languages is included. Over 10 languages are included. It is also available in Spanish for health equity conversations with community-based individuals.
 - Audience: Patients (multilingual)
 - Great! That COVID: The Conversation: Healthcare Workers on The COVID Vaccine Video FAQs**
 - Format: Video
 - Description: A healthcare worker's view of the COVID-19 vaccine topic, with questions raised for different topics and types of health care workers.
 - Audience: Patients (multilingual)
 - Rural Women's Health Project COVID-19 Materials**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for rural women's health project, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients (multilingual)
 - CDC: Signs and Symptoms of COVID-19**
 - Format: Web Page
 - Description: A list of common signs and symptoms of the virus, with links to related resources.
 - Audience: Patients
 - American Academy of Pediatrics - COVID-19 Vaccines**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for pediatricians, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients (multilingual)
 - How to Talk to Your Children about COVID-19 Vaccines**
 - Format: Web Page, video
 - Description: A collection of resources for parents, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients (multilingual)
 - Resources for Clinicians Before and After Talking with Patients**
 - CDC Vaccine Receptor Education**
 - Format: Web Page
 - Description: A collection of resources for clinicians, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Providers
 - Burgess's General Community Toolkit**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for community-based organizations, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Providers
 - HSCL COVID-19 Public Education Campaign: Pediatricians and Family Physicians Toolkit**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for pediatricians and family physicians, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Providers

Right Screenshot (Reason-Specific Resources Tab):

- Vaccine Hesitancy Resources: Reason-Specific Resources**
 - A collection of resources to assist in understanding the reasons for vaccine hesitancy and the barriers to vaccine uptake.
 - General Resources** | **Reason-Specific Resources** (Selected)
 - Reason: Safety Concerns**
 - Safety of COVID-19 Vaccines (CDC)**
 - Format: Web Page
 - Description: A collection of resources for safety concerns, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients and Clinicians
 - CDC: COVID-19 Vaccine: What to Expect or Beware of (CDC)**
 - Format: Web Page
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients and Clinicians
 - Wisconsin Department of Health Services: Family/Pharmacy & COVID-19**
 - Format: Web Page, localized video
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients and Clinicians
 - Reason: General Medical Intervention Hesitance**
 - COVID-19 Vaccines: The Government & Our Community**
 - Format: Video (2:38 minutes)
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients
 - Easy to Read: COVID-19 Vaccine**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients
 - Reason: Side Effects**
 - Information About COVID-19, Myocarditis, and Vaccines**
 - Format: Print, video, website, social media graphics, video, talking points, FAQs.
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients
 - Great! That COVID: What Side Effects do Kids Get from the COVID-19 Vaccine?**
 - Format: Video (4:00 minutes)
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients and Clinicians
 - Other Reasons**
 - Reluctant to Get COVID-19 Vaccine**
 - Format: Video
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients
 - How COVID-19 May Affect Your Health**
 - Format: Video
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients
 - Federal Trade Commission: Consumer Advice for Consumers**
 - Format: Web Page
 - Description: A collection of resources for COVID-19 vaccine, including video, print, and social media. All resources available in 4-6 languages, including English, Spanish, and Vietnamese.
 - Audience: Patients

The reason-specific resources tab identifies resources for each of the most frequent reasons for vaccine hesitancy that arose in the interview data. One of the team's most significant challenges was finding authoritative resources that were accurate without being offensive or patronizing, especially ones addressing misinformation about the COVID vaccine.

Overall, the team limited the number of resources on each page to avoid overwhelming busy providers. Rather than being an inclusive page of every potential resource available, the goal was to have a more limited curated list of the most relevant and useful items. Similarly, only particularly high-quality embedded videos were included.

Local dissemination included email messages to primary care facilities and clinics, especially those working with underserved communities, and other organizations that provide vaccinations in a range of settings. This included groups like the Safety Net Collaborative, a group of more than 25 health organizations, primarily low and no-cost clinics, run by both University of Florida and community organizations. Dissemination also occurred through University of Florida patron groups and departments with which HSCL librarians liaise. These groups could use the guide themselves to provide information to their patients, as well as pass it along to students and other providers.

A goal of this project is continual improvement involving regular site maintenance with up to date and relevant information. Some of this maintenance will be addressed by the team with regular updates. The guide also contains an embedded feedback widget, giving users an opportunity to bring additional materials to public attention.

DISCUSSION

Content Analysis

The interviews provided rich data about many aspects of conversations between providers and their patients about vaccines. Of particular note were the themes of mis- or disinformation, trust, and information sources.

The quick and pervasive spread of mis- and disinformation about COVID and vaccines was described by many of the interviewed providers and is noted in the literature [14]. Sources of mis/disinformation included social media, friends, family, community members, and news outlets. This echoes findings in the literature related to the role of social media in exposing people to COVID-19 vaccine-related misinformation [15], as well the erosion of public trust in scientific recommendations during this time [16, 17]. The World Health Organization declared misinformation as a threat to public health in 2021 and this problem has become exacerbated since then by the rise of artificial intelligence [18]. The types of mis/disinformation mentioned during

the interviews revolved around whether COVID existed, the potential treatments for COVID, and efficacy and safety concerns surrounding COVID vaccines. Interestingly, providers indicated a desire for a list of mis/disinformation types so they could be prepared when patients bring them up in conversation. This aligns with Bourgault's recommended strategies for health providers to identify and navigate misinformation, some of which include "pre-bunking" and "debunking" misinformation using a combination of critical appraisal, trusted sources, and professional communication skills. [17] The importance of recognizing digital literacy and health literacy as significant challenges for patients has also been noted in the literature. To ameliorate this issue, multiple authors have developed or recommended frameworks to guide conversations about misinformation. [18, 19, 20, 21]

During the interviews, trust was discussed in the context of both the presence and absence of trust, most commonly in the context of the patient-provider relationship, but also in specific information sources. While the literature suggests that individuals' level of trust towards their physicians consistently relates to their acceptance of vaccination [22], our interviewees had varying opinions about the amount of influence that providers have compared to relational and social sources of information. Some interviewees were confident in their authority as medical providers to influence patient decisions:

"She really just needed a doctor, somebody with a badge who could kind of speak in some plain language, just to explain to her what these vaccines really were. Because I could speak in an authoritative way, I seemed like I really did know what I was talking about; she felt she could trust me more than the YouTube video that she saw and that was enough." - Interviewee #20, Medical Director of a local clinic

The potential influence of healthcare providers as trusted authorities is echoed in the literature: Wynn encourages nurses to engage patients in the online spaces where they may be getting health information, in order to better understand patients' information environment and promote trustworthy sources of information. [21]

Other interviewees felt that their advice was being disregarded in favor of other relational and social sources:

"Helping to educate family members who have that influence on their college age kids I think would be helpful...because I don't know if there would really be any source that they would believe over something their parents said or their friends said or something they read on Twitter or Facebook." - Interviewee #5, Doctor at a university student health care center

In contrast to this interviewee's apprehension, both Sharman and Southwell encourage providers to elicit information from their patients about potential other sources of information about conditions and treatments, as an opportunity to learn more about the patient's

perspective and to start a conversation where misinformation can be addressed. [23, 24]

Providers also described struggles with sharing health information from traditional authoritative sources because of the distrust that patients had developed, particularly of governmental sources, over the course of the pandemic. For example,

"I've given them the FDA fact sheets on the vaccines I've given them CDC COVID 19 resources, but they don't trust those resources. If they're vaccine hesitant, whatever resources I may give them they don't know that they trust them because they're not sure if they came from the FDA or the CDC- they've already written those agencies off." - Interviewee #4, Internal Medicine Doctor

This was not limited solely to the United States; Abbasi et al found in their interviews with British providers a perception that patients felt the government was telling them what to do to the extent they felt they had no voice or agency, eroding trust in public health officials even more. [25]

Limitations

The team sought a diverse sample of participants to interview, as the project scope purposefully defined "provider" very broadly, but ultimately half of the participants were faculty from the University of Florida College of Medicine. The limitations from our participant demographics have skewed our findings towards mainly academic providers in the College of Medicine. We know that vaccine hesitancy is an issue that requires interprofessional collaboration and although our team tried to solicit participants from other profession to provide a much-needed holistic view, we were unable to. As is typical of many library-based research projects, the sample also consisted of those with pre-existing relationships to the library which creates another limitation; the opinions of providers who do not make use of library resources could differ.

CONCLUSION

This project provided valuable lessons on best practices for efficiently conducting team qualitative research (data collection and analysis), yielded interesting insights regarding patient-provider communication, and informed the creation of a useful provider-focused resource guide.

This project also showed the importance of health sciences librarians conducting and participating in research to support the development of patient education information resources for providers, especially in response to rising public health concerns. Vaccine hesitancy, combined with rapid misinformation, is a growing threat to public health and wellbeing [26]. Providers and patients should collaborate with information professionals to find vetted,

verified, and quality resources to help the public make informed unbiased decisions about their health.

In the future, the team will share a detailed description of the methodology used in this project for the use of other librarians and qualitative researchers. Other team goals are to continue disseminating the resource page and to conduct usability testing to maximize value.

DATA AVAILABILITY STATEMENT

The interview protocol, coding protocol, and coded, anonymized transcripts are available through the project's repository on Open Science Framework: https://osf.io/f875j/?view_only=7d01a78c7a15481c80e9e94229ac329f. Some of the quotes in the manuscript received minor editing to remove repetition.

AUTHOR CONTRIBUTIONS

Margaret Ansell: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Writing – original draft, Writing – review & editing. Lauren Adkins: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. Mary Edwards: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. Jane Morgan-Daniel: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. Hannah Norton: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. Nina Stoyan-Rosenzweig: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing.

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SUPPLEMENTAL FILES

Appendix A: Interview Session Protocol

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Head to head searching: the Search&Destroy card game in the health sciences classroom

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See end of article for authors' affiliations.

Background: Games are a promising way to make health sciences education more engaging and improve synthesis for learners. There have been some successful implementations of game-based learning for health sciences library instruction [1], but there is room for development of games tailored specifically for teaching database searching skills to health sciences students.

Case Presentation: The authors developed a biomedical edition of the existing library instruction card game Search&Destroy. The original Search&Destroy was developed as an alternative way to teach a one-shot instructional session on search skills using a discovery layer in an academic library for undergraduates. The biomedical edition modified the game to work with PubMed and incorporate health science-specific searching skills. Keyword cards were updated with biomedical terms and new cards were added with filters and actions related to health sciences literature searching (e.g., last five years, systematic reviews, randomized controlled trials filters). The new version was play tested internally by the authors and then piloted in classes with nurse residents. The game is now available through the print-on-demand service The Game Crafter and teaching materials are available online.

Conclusions: Feedback from our pilot test group of nurse residents was overwhelmingly positive. Informal conversations with nurse educators responsible for the program were also positive, and the game has been incorporated in the curriculum for the future. The Biomedical Edition joins a growing family of Search&Destroy games designed for a variety of library instruction needs.

Keywords: Game-based learning; games; card games; game design; gamification; game development

BACKGROUND

Problem Statement

Health sciences education is still a relatively traditional field, with slides and large group lectures being the predominant format [2, 3, 4], despite growing attempts at reform [5]– for example, incorporating more case-based learning and flipped classroom formats [6]. This has also permeated health sciences library instruction on literature searching [7, 8, 9].

As librarians, many times our classroom experience is limited to one-shot instruction. The one-shot instruction session is limiting, often forcing the librarian to choose between searching skills instruction or content evaluation in a short amount of time and commonly in an exhausting (and boring) lecture setting. Moreover librarians typically can't spend the same amount of time cultivating the trust and respect of students that their instructors do. Game based learning presents an alternative and an opportunity to use games for the same benefits they provide outside of an educational setting [10].

The authors wanted to take advantage of the increasing openness of health sciences education to new teaching methods and try a game-based learning intervention to increase student engagement in library literature searching instruction. One way to innovate on health sciences library instruction is to borrow ideas from academic librarians, who have historically had more leeway to try new teaching modes [11].

Literature Review

Game-Based Learning as a Solution for Student Engagement

The power of games to hold attention and inform has been discussed at length in game design literature and game studies. Gamification in particular is widespread, whether it be loyalty points at a grocery store or hotel [12], collecting digital badges [13], or with spinning wheels and games of chance in online marketplaces [14]. This benefits educators to more easily implement gamification, as students are familiar with game concepts [15,16]. This prior experience encourages quicker adoption and reduces learner frustration. Because gamification and game-based

learning are incorporated into many aspects of modern life, students are often familiar with game mechanics regardless of whether they know these terms or are interested in board games or video games.

Game design is primarily studied through the lens of positive psychology. The core concept of positive psychology is that focus and engagement comes from a match between a person's skill and the challenge of an activity. If these two are not in harmony, the person will become bored, anxious, or frustrated [17]. Through this model, we can view games as tools to modify the difficulty of a task, making them perfect for changing students' perceptions of subject matter [18].

It is through this positive psychology framework that game-based learning is used, seeking to create games that impart learning outcomes through the act of play, rather than using game elements only to increase motivation and task completion [19]. By directly connecting learning and play in this way, instructors are able to create bespoke, meaningful experiences for students.

Game-Based Learning in Health Sciences Education

A growing body of literature examines the use of games in health sciences education. Recent systematic reviews suggest that games can improve learning outcomes, such as knowledge acquisition, and learner engagement [10, 20, 21, 22]. Analog games, such as board and card games, have a history of use with healthcare trainees [23]. Digital serious games (games where-in the designer's goal is beyond creating an entertaining experience), often incorporating new technologies like Artificial Intelligence (AI), Virtual Reality (VR), and Augmented Reality (AR), can show positive effects on learner knowledge, skills, and confidence [24, 25, 26].

However, the efficacy of games compared to other educational interventions is not consistent. A recent meta-analysis showed an overall inconclusive effect on learner skills, attitudes, and behavior [27]. Limitations such as small sample sizes, lack of rigorous control groups, and inconsistent reporting of theoretical frameworks mean that further research is necessary to improve game design, implementation, and evaluation [1, 28, 29, 30]. While the use of games in health sciences education continues to expand, there is still a need for more examples of games being incorporated into existing curricula and healthcare environments [31]. There have been two studies implementing game-based learning for literature searching and information literacy that demonstrated learner skill improvement [32, 33]. This successful use of games to improve skills for instructional topics relevant to libraries shows that there are potential benefits from incorporating games-based learning into library instruction.

Health sciences libraries are well positioned to champion game-based learning within their institutions. Games have

the potential to support specialized clinical and research skills training [34]. Teaching strategies like escape rooms are one-way games can be adapted across different learning environments for learner needs [35]. With some training, librarians can partner with health sciences educators to develop, implement, and assess these learning experiences. It is possible for Library and Information Science programs to provide these instructional design skills [36]. An interactive special workshop, at the 2018 Medical Library Association annual meeting, successfully trained librarians to create and implement low-tech games for health sciences library instruction [37]. Through collaboration and with guidance, health sciences libraries can integrate games into existing curricula and spaces to improve the learning experience of healthcare professionals.

Card games provide a readily accessible, low-tech, and familiar format for educational games. A 2024 scoping review found that card games were the second most common format used in analog game-based learning in medical education [23]. A 2007 review identified various card games used in medical education, covering diverse topics [38]. Recent examples of medical education card games include the "Pit Crew Card Game" for improving EMS performance [39], "CARBGAME" for teaching clinical enzymology [40], and a game for teaching anatomy of the liver [41]. These examples demonstrate how card games can be used for teaching both medical concepts and practical skills. Card games focused on specific topics, like white blood cells [42] or viral hepatitis [43], show their use for specialized learning and knowledge reinforcement.

CASE PRESENTATION

Game Play of Search&Destroy

Search&Destroy is played in groups of 4-6 players, with each person accessing a library database. Students use cards to build search strings with keywords and place limiters (or facets) on one another, performing a search in a library database every turn. This search takes place in the actual discovery layer or database, thereby making the game immediately relevant to the students' research. Players continue until they get zero results, causing them to lose, one-by-one. Typically, players last 3-4 rounds of play, so every student is getting to practice with the database several times and will watch their classmates do the same.

To set up the game, you need 4-6 players, with each player able to reach the cards. They also need space in front of them to place the cards that make up their searches. Each student will also need to access the library database. Ideally, the students can gather around a single computer and web browser, with each student having their own browser tab for their searches, but students can also play on their own laptops, phones, or tablets if needed.

There are three types of cards in the game:

1. Keyword Cards (68): These are cards with words or names that are combined to create the search string that students will use to search the research database
2. Play Cards (51): these are further broken down into two types of cards
 - a. Modification Cards (abbreviated to MOD Cards in game): These are limiters or facets that students will need to apply to their search strings
 - b. Action Cards: These cards are one time use cards that impact play directly. Some examples are that students may skip their next turn or they must draw entirely new keyword cards
3. Rules reference cards (6): These cards have no impact on gameplay, but explain the rules of the game in a truncated way so that the full rulebook does not need to be consulted during play

At the start of the game each player is given a rules reference card. The Keyword Cards are shuffled and placed face down to form the Keyword Deck, and the Play Cards are likewise shuffled to make their own deck. Then each student should draw four Play Cards to form their hand, but these should be kept secret.

After this set-up, the librarian teaches the students how to play with a live demonstration or with a presentation. This saves time and avoids confusion, instead of asking students to read the rules on their own.

Gameplay follows 5 steps (listed in Figure 1 below), which students must take in order. First the student will draw the top two cards from the Keyword Deck and choose one by placing it face-up in front of them, placing it on the end of all the other Keyword Cards they already have (if any). The other is discarded by placing face-up in the discard pile. Students are most successful if they choose their keywords strategically based on what they already have, to maximize the number of results the database returns.

The student then has the opportunity to play an Action or MOD Card. Action Cards are played once, do the effect listed on the card and then are discarded. MOD Cards are added to any student's Keywords and must be included on their next search. These cards are what give students the most control of the game and have the most impact on their opponents. Some cards will make the game last longer (skipping turns or searches) or shorter (adding more keywords to a player's search, making a player filter their results to only French language). This step is skipped on each student's first turn.

During step 3 the student will then take all the keywords in front of them and search them as a single string in the library database. This might look like, "rats AND naps AND Darwin," or "asian AND carp AND star AND crown." This is also where they should add the facets from MOD cards, such as "Items must be published before 1965" or "Items must be in French." There is no limit to the number of keywords or facets that a student has to search. If the database returns zero results, the student's turn ends and they are out of the game.

After searching, the player draws back up to four Play Cards and then passes the turn to the next player.

Figure 1 Search&Destroy rules summary.

SEARCH & DESTROY RULES

On Your Turn

1. Draw two keyword cards and select one to keep.
2. Play 0-1 Action or Mod cards.
3. Search in the database.
4. Draw cards from the Play Deck until your hand is full with 4 cards.
5. Game moves counter-clockwise to the next player.



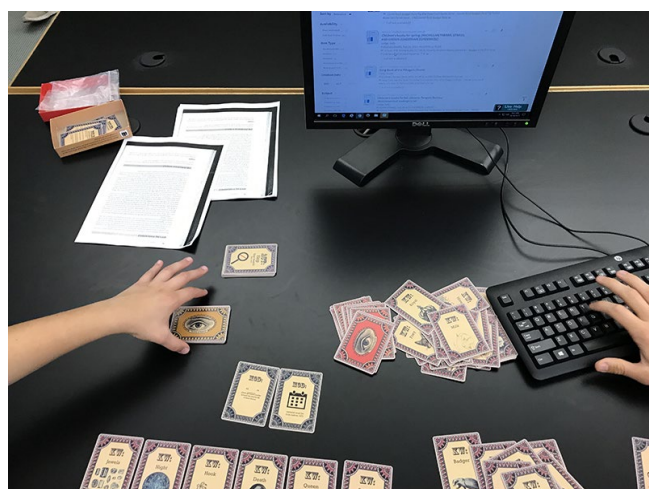
While rehearsing with a database is helpful, the real power of Search&Destroy is that to play effectively, a student must pay attention to their searches and the searches of their opponents. They are able to do this by playing Action or MOD cards, which change an opponent's search (e.g. "Results must be a Book") or add more keywords to a student's search string. The incentive of winning makes all searches more immediately interesting to the players, even when it's not their turn.

Ultimately this makes Search&Destroy a fun and meaningful way to teach discovery level searching. It acts as an upgrade over other exercises that might be done class-wide, such as working through prepared example searches or asking students for topic ideas (favorite band, research topic, etc.).

Development of Original Search&Destroy

The original edition of Search&Destroy was developed by Kermit-Canfield and Maixner as an alternative to teaching basic discovery layer search skills in one-shot classes at the collegiate level at Ferris State University. Ferris State is a public university in Big Rapids, MI, with 12,000 students. One-shot library classes can be challenging to teach, as students may be completely new to the academic world and library searching in general.

Figure 2 Playing the original Search&Destroy



Kermit-Canfield and Maixner's goal was to fundamentally change the way they were teaching and interacting with students – to entirely replace classroom lectures with game-based learning. Learning outcomes for the game would include:

- Students will practice database use
- Students will employ limiters and facets in library databases

- Students will use Boolean operators to expand their searches
- Students will construct Search Strings for Database searching
- Students will identify and select library materials
- Students will recognize peer review as a concept

Game design is an iterative process - the designer must build a functional prototype, test it, take that feedback, and improve upon it. It is widely understood that a game will be refined by repeating this process as many times as possible [44]. In the case of Search&Destroy development started with a deck of keyword cards. From there, the designers sketched out the basics of the game and then competed against one another and then played with student workers to ensure that the game design was on the right track. After these initial tests more specific decisions about the game were made, such as the order of play, exactly what keywords would be included and how many cards a player interacts with at a time were made. A good example of this is in the opening of a turn, where a player draws two keyword cards and selects one to keep. In the very first tests of the game, players simply drew the top card, meaning there was no decision making at this step and keyword strings were completely random. The change to selecting a card was implemented as players felt that they had too little influence on their success in the game.

This design process is more challenging while maintaining the connection to learning outcomes - every action that a player can take should reinforce learning outcomes as much as possible, while still allowing space for fun and discovery by players. To this end, the designers made sure to include cards in the game that, while not directly reinforcing the learning outcomes, lead to fun moments. An example is the card, "Skip your Search," an Action card that a student can play on themselves. This card allows the player to completely bypass the step in the game where they could be eliminated. Even though this card skips over the core learning outcome of the game (searching in the database), the designers found that adding options for players to disrupt the game was important to add more elements of competition and fun. Dialing the right ratio of "fun" elements to "learning" elements is something that can only properly be explored through playtesting, and updated editions to the game have adjusted these ratios after playing the game in class more often.

Development of Biomedical Game Version

The idea for creating a biomedical edition of Search&Destroy came through conversation between the three health sciences librarians on the team (CK, LB and RV). East Tennessee State University was already using the original edition of Search&Destroy in its library instruction, and the librarians were inspired to try it out

on PubMed to see its potential for health sciences library instruction. East Tennessee State University is an R2 state school with both nursing and medical schools in Johnston City, Tennessee. Northwell is a large health system made up of 27 hospitals in the New York City metro area that employs 80,000+ people. After testing, the basic mechanics of the game worked, but it needed modification to work well in a medical or health sciences setting.

Since the project seemed doable, the three health sciences librarians approached the original creators of Search&Destroy to gauge interest. Fortunately Kermit-Canfield was working on sabbatical to develop a Spanish language of the game and thought it was possible to work on a Biomedical Edition concurrently. It seemed that a collaboration was possible, with the health sciences librarians contributing knowledge of medical education and databases, to create a modified version. Librarians from other institutes have requested specific versions of the game (e.g. medical, science, etc.) of Kermit-Canfield and Maixner in the past, but because of the sabbatical of one of the founding members and the expertise of the health sciences librarians, it could finally come to fruition.

Changes for the Biomedical Edition

The health sciences librarians had specific requests for creating a biomedical version of Search&Destroy. They primarily envisioned the game being used with PubMed as the demonstration database but wanted it to be compatible with other common health sciences databases

such as Embase and CINAHL. In addition, they also wanted to cover search filters that would appear in a traditional lecture on literature searching from a health sciences librarian.

In order to accomplish this, the Biomedical Edition required specific adaptations:

1. Additions to and modifications of the keyword deck (search terms) to biomedical/health sciences terms (e.g., skull, suture, pregnancy).
2. Addition of more boolean operator cards to the Play Deck as modification/action cards.
3. Creation of new “Med” Action Cards to the Play Deck with the most commonly used biomedical database filters (e.g., filter for published in the last five years, filter for systematic reviews, filter for RCTs).

All of these changes were meant to make the game more directly applicable to health sciences patrons.

Locating and building the digital materials and original content for Search&Destroy, piecing the parts together, and creating updated packaging and documentation into a material product are a precise, labor intensive, and time-consuming process with a tremendous creative payoff. The physical development of each Search&Destroy edition is extensive, each requiring the sourcing, creation, and assembly of over a hundred cards. Cards are paired with public domain imagery, either icons that direct gameplay

Figure 3 Search&Destroy Biomedical Edition. Photo by Jason Peercy.



in the Play Deck or pictorial images for the Keyword Deck. The pictorial images are majority pre-1900 engravings and etchings with the new additions from period medical books and documents and illustrate each card's concept (e.g. the "Nausea" Keyword Card is represented by a bucket). Art for a game is important, aesthetics being one of the four main elements of a game [44].

Playtesting

The game went through three distinct rounds of playtesting:

1. Testing within the group developing the medical version of Search&Destroy.
2. Testing with librarians from Northwell and East Tennessee State University who were not on the development team.
3. Testing with nurse residents.

The first two rounds of testing both led to iterative rounds of improvements. The authors discovered that the game ran too long as we originally designed it and compensated by changing the numbers of different types of action cards – eliminating some that lengthened the game and increasing the number of those that shortened them. The team also changed some of the keyword cards to be more unexpected, since forcing people to choose a non-optimal keyword also shortened the game (and increased the fun).

Nurse residents at Northwell were the first patrons to test the new edition. At Northwell, the librarians teach literature searching to nurse residents often, so they were one of our primary audiences for the game. This playtesting allowed for refining the process of teaching the game in a healthcare setting and doing evaluation with nurses.

Figure 4 Nurse residents playing Search&Destroy.



Printing

Search&Destroy is currently produced by the print-on-demand company The Game Crafter, which also acts as a Content Management System for all of the game materials: cards, rulebook, box, etc. [45]. Games are sold at cost and do not turn a profit for the designers. When Search&Destroy is purchased, The Game Crafter prints a copy of the game and ships it. This kind of instant ordering allows game developers to easily make changes to a game. While developing the multiple editions of Search&Destroy this has proven useful to fix mistakes, but it has been better to make major changes in a single large update simply to keep track.

In order to maintain the privacy of the buyer, The Game Crafter provides the game designer only with the city and country name of the location where they are shipping the product. Kermit-Canfield has tracked these locations on Google Maps since Original Search&Destroy was published and has found it satisfying to observe the game's spread but also frustrating to be unable to perform further assessment with the purchasers of the games.

Supplemental Teaching Materials

In order to make adopting the game as easy as possible for librarians, the authors also wanted to release a complete package of teaching materials to go along with the game [46]. Ultimately, this came to include a slide deck, a printable handout, a lesson plan, and a best practices sheet for instructors. These were developed and refined in our playtesting with nurse residents.

DISCUSSION

Evaluation/Feedback

Because the Northwell librarians frequently teach literature searching to cohorts of nurse residents, we decided to pilot test the Search&Destroy Biomedical Edition with them. The game was overwhelmingly positively received by both the nurse residents and the nurse educators who helped to facilitate the sessions. The students were much more engaged when using the game than previously, when the activity had been a simulated clinical searching exercise. Nurse educator feedback suggested limiting gameplay to under 40 minutes and providing librarians with microphones for improved audio. Nurse resident feedback recommended more thorough gameplay demonstrations and the use of a scoreboard so that teams could more easily track who was ahead.

As the librarians running the pilot, Vitiello and Bohman reflected that the game capitalizes on the fact that health science students are often competitive. Many of the teams enjoyed trash-talking each other, debating the best next move, or occasionally arguing about rules interpretations

with the librarians. Even those students who are less engaged with the topic of literature searching don't want to let their team down in the competition. When teaching with the game, there was often a "light-bulb moment" when one team's search went from a huge number of results (100,000+) to a tiny number (1,000+) over the course of only one turn, which helped teams understand the power of facets and Boolean operators (often to many "oohs" and "aahs").

Doing a more in-depth assessment of any type of one-shot instruction is challenging. Health professionals' time is limited, and librarians often only see the students once. It would be very difficult to do an assessment comparing how well game players remembered literature searching lessons longitudinally compared to a control group due to logistical challenges. One potential avenue that the authors did not explore would be a pre- and post-test of literature searching skills for students, primarily because the nurse residency program conducts their own pre- and post-test. However, the authors do not have access to that data.

Based on the positive pilot experience, the game is now integrated into the evidence-based practice component of the nurse residency curriculum. The game is also expanding into other hospitals in the Northwell network through librarian colleagues, and Bohman recently used it successfully to teach Internal Medicine residents as well.

CONCLUSION/FUTURE DIRECTIONS

Search&Destroy began only as a way to improve the in-class instructional lives of a pair of librarians teaching at a small Midwestern university but has grown to be so much more. As of the time of writing, a Spanish Language Edition (Buscar&Destruir) is nearing completion and the filming of instructional videos for all three editions has begun. An Advanced Boolean Booster Pack will be introduced that will function with any Search&Destroy game, along with subject-specific booster packs that can also be used with the Biomedical Edition. Kermit-Canfield and Maixner have several other higher-ed game projects on deck and are always looking for ways to further the Search&Destroy project. All Search&Destroy games are available for purchase at the Wunderkind Games website.

Despite the value of literature searching skills for medical and health sciences students, librarians often face barriers when working to add these and other information literacy skills to tightly packed curricula. It can be an additional challenge to bring non-traditional learning methods into a library instruction session once established. However, the authors hope that Search&Destroy Biomedical Edition will, in keeping with current trends in health sciences education, be a helpful tool to enliven staid lectures and engage students in active learning through brisk gameplay and friendly competition.

DATA AVAILABILITY STATEMENT

The game described in this article is available for purchase at cost via The Game Crafter: <https://wunderkind-games.com/searchdestroy-medical-edition/>.

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AUTHOR CONTRIBUTIONS

Lena Bohman: Investigation; Methodology; Project Administration; Writing - Original Draft; Writing - Review and Editing. Regina Vitiello: Investigation; Methodology; Visualization; Writing - Original Draft; Writing - Review and Editing. Christiana Keinath: Investigation; Writing - Original Draft; Writing - Review and Editing. Gary Maixner: Conceptualization; Investigation; Writing - Original Draft; Writing - Review and Editing. Mari Kermit-Canfield: Conceptualization; Investigation; Writing - Original Draft; Writing - Review and Editing.

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Journals that accept case reports 2025

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Background: For medical students and residents writing and publishing a case report is a common entry point into scholarly publishing. However, finding a journal that accepts case reports can be challenging. This project updates the 2023 list of journals that accept case reports. Shared on the Open Science Framework (OSF), the original list is a highly used, openly available list of English-language, MEDLINE-indexed journals that publish case reports, providing librarians and authors with a vetted, current open resource for discovering journals.

Case Presentation: A list of 2,199 journals was extracted from PubMed using the same method from 2023. The methodology was updated to exclude journals that rarely publish case reports (n=721) resulting in 1,478 journals to review for inclusion on the updated list. The team excluded 290 titles due to ceased publication (n=1), submission restrictions (n=1), non-English publication (n=13), lack of MEDLINE indexing (n=4), and not publishing case reports (n=271). The final list includes 1,188 journals. This is an additional 160 journals over the 2023 list. Nearly half of eligible journals (49%) offered free-to-author publishing options, either through traditional publishing models, open access that did not charge article processing fees, or through hybrid publishing models.

Conclusion: The Journals that Accept Case Reports list is an open resource available on the Open Science Framework and serves as a tool to support librarians and authors in identifying appropriate journals for publishing a case report.

Keywords: Publishing; case reports; scholarly communication



See end of article for supplemental content.

BACKGROUND

Research and publishing are actively promoted as essential for undergraduate medical education [1]. The transition of the United States Medical Licensing Examination (USMLE) Step 1 to pass/fail scoring from numerical scoring in 2022 shifted the residency application landscape, increasing the importance of research and scholarship participation for medical students and residency program directors. This is particularly true for medical students looking to match with more competitive specialties and higher-tiered programs [2]. As a result, accessible forms of academic productivity are crucial early in training, and case reports are often the introduction to publishing for medical students, residents, and junior faculty [3].

Despite their lower position in the evidence hierarchy, case reports continue to have a role in the advancement of medical knowledge [4]. Unique cases can highlight successful diagnosis and care of not only novel diseases and newly discovered variants, but also new approaches to standard of care. Their findings can be the basis for future research studies, thus promoting higher levels of research and evidence synthesis [5].

The medical education value of case reports goes beyond their contribution to medical knowledge. Case reports have been identified as one of the first opportunities for medical scholars to actively engage in researching, constructing, editing, and submitting a manuscript. As part of the publication process, students and residents practice critical thinking, team work, and medical writing skills within a short time period [6,7]. Additionally, unlike other article types, case reports usually are institutional review board (IRB) exempt. They typically do not require statisticians, long-term follow up, or exhaustive research while juggling long hours in a clerkship or residency program.

The first list of journals that accept case reports was published in 2016 and included 160 journals [8]. In 2023, a second list of journals that accept case reports was published, and included 1,028 journals [9]. In 2024, Gaggero published a list of 39 open-access, no fee journals discoverable in PubMed and Scopus that publish image reports [10]. These lists demonstrate a need to support authors in finding journals that publish a specific article type.

The 2023 Journals that Accept Case Reports (JACR) list has been a valuable resource for the promotion of undergraduate medical research and a highly visited resource [11]. Since the list was posted, it has been viewed over 8,000 times and the authors are aware of the list being included on 11 library websites. With the shift toward open access publishing, maintaining an updated list is critical for recognizing journals whose APC (article processing charge) could be prohibitive for students lacking access to dedicated research funding [12]. One of the limitations of the project is the changing publication landscape, making the list less accurate over time. Therefore, this project is being updated to make sure the list remains useful and up to date.

This project updates the 2023 list of journals with the objective to create an extensive, but not an exhaustive, list of journals that are indexed in MEDLINE, are published in English, and actively publish case reports. This vetted list is being updated to help medical students or resident authors, and the librarians who support them, find journals that accept case reports. The list is freely disseminated on the Open Science Framework.

CASE PRESENTATION

Journal Search

A list of journals was extracted from PubMed by conducting an all field search for ("case report*"). The title/abstract field was not used, as it excluded journals that published case reports without abstracts or "case report" in the title. The limiters: article type case reports, English, and MEDLINE were applied. The same rationale from the previous study was used for selecting the limiter of MEDLINE. This includes the indexing requirements of journals to be included in MEDLINE and the ability to search MEDLINE from multiple databases and search engines [5]. To identify journals that were currently publishing case reports, date limiters were used to pull records from July 1, 2024 to June 30, 2025. Because PubMed's export limit is 10,000 records, records were pulled in six batches July 1, 2024 to August 31, 2024 (n=9,459), September 1, 2024 to October 31, 2024 (n=8,542), November 1, 2024 to December 31, 2024 (n=6,608), January 1, 2025 to February 28, 2025 (n=6,976), March 1, 2025 to April 30, 2025 (n=5,819), May 1, 2025 to June 30, 2025 (n=4,549). This search resulted in 41,953 results. The results were exported as csv files and compiled in Microsoft Excel.

Journal Selection

Because journal title abbreviations are a controlled vocabulary in PubMed, a pivot table was created in Excel to remove duplication and to determine the number of case reports published in each journal. As a result, 2,199 unique journal titles were identified. This is an increase in

the number of journal titles to vet from the 2023 list (n=1,874). One of the issues with the 2023 list was the inclusion of journals that rarely publish case reports. The 2023 final list included 202 journals that stated on their website that they accepted case reports but only under certain circumstances or rarely accepted case reports. Since the 2025 list is for authors who are searching for a journal that is actively seeking to publish a case report, journals that rarely publish were excluded. Therefore, journals were included if they had published three or more case reports between July 1, 2024 and June 30, 2025. Journal titles that had only published one or two case reports were excluded (n=721). Resulting in 1,478 unique journal titles.

The 2025 list of journals to vet was compared to the 2023 list of journals to vet. The 2025 list of journals to vet included 1,224 titles that were included on the 2023 list, and an additional 254 new journal titles that were not vetted in 2023. There were 650 journals on the 2023 list to vet that were not included on the 2025 list to vet. These were compared to the final results of the 2023 list, 446 of these titles either did not accept case reports or only accepted case reports under certain circumstances. The remaining 204 journals were compared to the 2025 list that were excluded for only publishing one or two articles, 108 of the 2023 journal titles had only published one or two case reports during the 2024-2025 time period. Further supporting the decision to up-to-date the list, ninety-six journals who had published a case report in 2023, had not published a case report during the 2024-2025 time period.

Data Collection

The following data points were collected using a Microsoft Form: Journal title abbreviation, full journal title, MEDLINE inclusion status, Broad Subject Term (specialty), does the journal accept case reports, and publishing model.

The National Library of Medicine (NLM) assigns broad subject terms to journals that are indexed in MEDLINE providing a controlled vocabulary of 130 specialty areas [13]. Journals may be assigned multiple broad subject terms and all terms for a journal were recorded.

The PubMed records for journal titles only include the abbreviated title. The team used the NLM catalog to search for the journal title abbreviation. From the journal record the full journal title, and the broad subject terms were obtained. In addition, the inclusion in MEDLINE was also confirmed, and the electronic links were used to navigate to the journal websites. If a link was broken, the team searched the internet for the journal title. From the journal's website, team members navigated to the author's guideline to confirm the journal accepted case reports, to collect the link to the author guidelines, and to collect the publishing model information (subscription with no

author fees, subscription with author fees, open access with no fees, open access with fees, or hybrid).

RESULTS

Of the 1,478 journal titles reviewed, 1,188 journals were found to accept case reports, covering 111 subject areas, 290 titles were excluded: one journal that had ceased publication, one journal that did not accept submissions, 13 journals whose websites were not available in English (these website did not have an option to translate into English and an attempt to use Google's translate did not result in a usable translation), four journals that were not indexed in MEDLINE, and 271 did not accept case reports, or only accept case reports under certain circumstances, for example the website used phrases such as "case reports are strongly discouraged," "case reports are unlikely to be accepted" or "case reports are of low priority". These journals still published three case reports, so they were on the list of journals to vet, however, it is unclear as the circumstances in which they accept and publish case reports.

During the JACR 2023 review process, 803 journals reviewed did not accept case reports. In comparison, in 2025 only 271 journals reviewed did not accept case reports. The new method of eliminating journals that rarely publish case reports, may have improved the accuracy of discovering journals that are actively publishing case reports. Sixty-six journals that were included on the 2023 list that were reviewed for 2025 no longer accept case reports, discourages case report submissions, or suggested sending case reports to their "partner journal".

Publishing Models

Nearly half of journals, 49% (n=549) offer a free for authors publishing model (Table 1).

Table 1

Publishing models.

Publishing Model	Total	Percentage
Open Access (charges author fees)	262	22%
Open Access (no author fees)	89	7%
Optional Open Access (author chooses subscription may be charged fees or is charged fees for open access)	349	29%

Optional Open Access (Author chooses subscription, no fees, or is charged fees for open access)	414	35%
Subscription (charges author fees)	28	2%
Subscription (charges no author fees)	46	4%
Total	1,188	

The publishing models remained relatively consistent between 2023 and 2025.

Table 2

Comparison of publishing models from 2023 to 2025.

Publishing Models	2023 Total	2023%	2025 Total	2025%
Subscription	144	14%	74	6%
Hybrid	581	57%	763	64%
Open Access	303	29%	351	30%

DISCUSSION

Case reports continue to be an introductory publication avenue for entry level healthcare providers. Their educational value has been identified as providing students and residents with the opportunity to practice critical thinking, teamwork, and medical writing skills [6,7,14]. Jha et al's single-institution study on the value of case reports found fourth year medical students perceived case reports as improving their scientific writing, presentation and critical thinking skills [15]. Packer et al. studied case reports published by medical students in the Veterans Administration hospital system between 2008 and 2015. Based on the team's data analysis and student feedback, they propose five educational benefits: "(1) observation and pattern recognition skills; (2) hypothesis-generating skills; (3) understanding of patient-centered care; (4) rhetorical versatility; and (5) use of the case report as a rapidly publishable 'mini-thesis,'" [6]. To build on Packer's benefits, case reports can serve as proof of concept. Albrecht et al examined 103 case reports and case series published in the Lancet between 1996-1997. Of the 103 studied, 96 were cited an average of 17 times and 22% led to further clinical research [16]. The educational value of case reports rests in their being viewed as the first stage of research, not the last.

As research productivity becomes increasingly prominent in residency selection, identifying accessible and feasible

avenues for scholarly output among medical students becomes essential. Being able to identify journals that accept case reports facilitates the scholarly process for students who are building their scholarship for their residency applications. Websites catering to medical students eager to make their ERAS application stand-out to residency program directors, promote case reports as one of the first steps towards building a publication portfolio [17]. One or two case reports published in a quality journal can demonstrate to program directors that a student can identify a unique case, work as part of team, and see a project through from the beginning to the end [18]. In late 2025, the Association of American Medical Colleges (AAMC) announced changes to the Electronic Residency Application Service (ERAS), which puts more focus on peer-reviewed scholarly work [19]. As MEDLINE journals, the titles included on the list are peer-reviewed.

Distinctions between open access and subscription-based journals have important implications for students, residents, and fellows as the rising costs of APCs are a barrier to publication [20]. Booth et al quantified the staggering cost associated with APCs, including monetary implications such as shifts to non-peer-reviewed pre-prints as authors attempt to avoid rising costs of publishing [21]. Librarians, who advise authors, can utilize the publishing model aspect of the list when helping authors to find journals that do not charge authors for publication.

Despite fewer journals explicitly refusing case reports in 2025 compared to 2023, this does not equate to increased accessibility. Some journals that were vetted did not accept case reports, instead offering to transfer authors' case report submissions to "partner journals" which were open access journals that charged article processing fees, not indexed in MEDLINE, and cited less often [20,22]. As case reports are non-funded publications this tactic results in financial barriers that disproportionately affect students, residents, and early career clinicians who rely on case reports as an entry point into scholarly publishing [21].

In the current publishing landscape, predatory journals continue to be a challenge. Their schemes are so pervasive, that in 2025 an editorial written by editors and members of the International Committee of Medical Editors (ICJME) was published simultaneously in 14 journals [23]. The editorial discussed how predatory journals engage in aggressive solicitation, false promises related to publication timeline, and lack transparency about cost and fees. Early career scholars may not yet have the experience and knowledge needed to discern the credibility of a journal. Due to concerns of predatory journals, and the goal of this list to support early career scholars, the JACR list limits journals to those indexed in MEDLINE.

To put the MEDLINE subset selection process into perspective, only 8% (n=11/145) of the journals evaluated

for MEDLINE inclusion in 2025 met the scientific review standards [24]. Providing the authors with confidence, but not a guarantee, that the JACR list promotes legitimate journals. MEDLINE journals are considered the gold standard of vetted publications with measurable evaluation criteria, including the use of CARE for case reports [25]. The CARE Guidelines was adopted at the 2013 International Congress on Peer Review and Biomedical Publication to strengthen the completeness and transparency of case reports [26]. In part due to the growth of case report journals, there have been calls to update CARE guidelines to improve the quality of submissions [27].

The JACR list is freely available on the Open Science Framework under a creative commons license. This tool can help librarians and authors identify appropriate journals for publishing case reports in an increasingly complex and cost-driven publication landscape.

LIMITATIONS

Using the MEDLINE filter may have excluded some journals that are actually indexed in MEDLINE, just as the list to vet included some journals that were not currently indexed in MEDLINE. As with the 2023 list, this list will also become outdated. Therefore, this list should be used as a starting point for discovering journals that accept case reports, and not as a definitive list.

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DATA AVAILABILITY STATEMENT

Journals that Accept Case Reports 2025 is available on Open Science Framework (OSF), <https://osf.io/fx28d> under the CC-BY Attribution 4.0 International Creative Commons license.

AUTHOR CONTRIBUTIONS

Terri Gotschall: conceptualization, supervision, project management, methodology, data collection, writing - original draft, writing - review and editing. Elizabeth Irish: supervision, project management, methodology, data collection, writing - original draft, writing - review and editing. Emily Hannum: methodology, data collection, writing - original draft, writing - review and editing. Kryslynn Collazo: methodology, data collection, writing - original draft, writing - review and editing. Alyssa Snyder: methodology, data collection, writing - original draft, writing - review and editing. Jacquelyn

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SUPPLEMENTAL FILES

Appendix A: Data

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Academic librarians as navigators of institutional data policies: developing resources to facilitate compliant research data management

Michelle Yee; Nicole Contaxis

See end of article for authors' affiliations.

Background: Proper research data management requires complying with data policies that ensure the ethical, effective, and efficient collection, storage, and sharing of research data. Medical librarians have made increasing inroads to leading research data management instruction and institutional efforts to comply with federal policies like the NIH Data Management and Sharing Policy. However, there has been less discussion about how medical librarians can support researcher compliance with institutional data policies. After observing patterns in requests for guidance, two data services librarians developed decision-making tools to help researchers identify appropriate local resources for their data sharing and re-use needs.

Case Presentation: The paper describes four projects that were developed with a similar methodology for the purpose of guiding patrons through institutional policies and processes: (1) a decision tree for determining when a data transfer or use agreement is required; (2) a matching tool that identifies appropriate data transfer platforms for specific data characteristics or scenarios; (3) a decision tree for determining whether a researcher needs to seek out Institutional Review Board (IRB) review for a project that uses secondary data analysis; and (4) a flowchart detailing data de-identification processes and institutional tools available for specific data formats. The creation of each resource entailed information gathering from local experts as well as review of internal policies to produce action-oriented guidance to solve common researcher problems.

Conclusions: These efforts demonstrate how librarians can utilize their skills and develop cross-departmental collaborations to help patrons navigate an increasingly complicated data ecosystem, particularly where that ecosystem is informed both by external policies (e.g., policies for de-identification) and internal tools (e.g., data transfer tools). The decision trees have helped researchers make choices about their own data management approaches so that they comply with external and internal policies. These documents also enable stakeholders to identify gaps in institutional policies and resources. The development of these resources has had the additional benefit of strengthening partnerships and positioning librarians as collaborators for policy decisions involving research data.

Keywords: Data management; academic librarians; data policy; federal regulation; educational guidance



See end of article for supplemental content.

BACKGROUND

In 2011, the New York University Health Sciences Library (NYUHSL) established a data services team to centralize research data management expertise and services for a large academic medical center. Beginning as three librarians with additional liaison duties and one staff member, the data services team today has four data librarians and two staff members. The team provides consultations and training for a range of topics, including data management, data sharing, and how to use institutionally supported tools like REDCap (1,2). Additionally, they built and maintain a data discovery

platform called the NYU Data Catalog, which houses metadata for research data and instructions for data access (3). Their work mirrors a trend in health sciences libraries broadly speaking with an increasing number of libraries offering data services and the establishment of the National Center for Data Services (NCDS), a center from the Network of the National Library of Medicine (NNLM) that is meant to teach librarians about providing data services (4). Over time and through these services and tools, the [redacted] team has grown and developed significant expertise in data sharing and data management as well as relationships with researchers and research support personnel across the institution.

Through these relationships with stakeholders, the development of subject matter expertise, and ongoing interactions with the research community, the two members of the Data Services team were made aware of various needs for guidance on implementing data management best practices that aligned with institutional data policies. Institutional data policies may describe what data is considered confidential, impose requirements on tools for storing and transmitting data, and inform security protocols. These institutional policies typically expand on federal policies, such as the Health Insurance Portability and Accountability Act (HIPAA) Privacy Rule, with more specific local requirements.

This paper describes a novel aspect of data management services: helping researchers understand data policies and how to implement those policies within their pre-existing data workflows (e.g., data sharing). To provide this type of guidance, the authors created decision trees as institutional resources. As frequent collaborators with departments like Information Technology (IT), General Counsel, and the Institutional Review Board (IRB), librarians are well-placed to gather information on data policies, engage with stakeholders across the institution, and apply their expertise in data management in the creation of these resources (5). Furthermore, creating decision trees, as opposed to providing time-consuming consultations and referrals to other departments, are a sustainable approach for librarians to address these information needs. The decision trees created in this use case include information on institutional-specific policies, so to be used at other institutions, these resources would need to be revised to match institutionally specific policies. The approach for developing and disseminating this type of resource is generalizable.

Relevant Policies

Some key US federal policies formed the basis of institutional data policies described in the case report. Main drivers include the Health Insurance Portability and Accountability Act (HIPAA) and the Federal Policy for the Protection of Human Subjects, frequently referred to as the “Common Rule” (6, 7). In order to develop guidance on institutional data policies based on federal policies, librarians needed to understand these federal policies.

The implementation of HIPAA in 1996 established national standards and practices for protecting health information. In particular, the Privacy Rule limits the uses and disclosure of protected health information (PHI) while placing no restrictions on de-identified health information (8). Two broad methods for de-identification are described in the Privacy Rule. The Common Rule predates HIPAA and governs research conducted on human beings, including the roles and responsibilities of Institutional Review Boards (IRB). The Common Rule focuses on ensuring research participant autonomy and regulates how informed consent is obtained from research

participants. An example of the Common Rule’s role in data policy is that research data cannot be shared – even if de-identified – if a research participant is not properly consented to that data sharing (9). Both HIPAA and the Common Rule may shape how institutions police appropriate and inappropriate data management practices.

Internal policies can extend these external policies. For example, the local IT department tests and implements technologies that enable HIPAA-compliant transfer of data with PHI. An internal policy requires researchers to utilize these approved tools, thereby ensuring that they comply with federal guidelines as well. Another type of internal policy is the determination of whether sharing a specific dataset would require a Data Use Agreement (DUA) or Data Sharing Agreement (DSA). While HIPAA outlines requirements for sharing identifiable or limited datasets, an institution may decide to require DUAs or DSAs for non-HIPAA protected data if that data is understood to be commercially viable or sensitive for reasons not related to HIPAA or the Common Rule.

CASE PRESENTATION

Over the years, a number of information needs were expressed to two Data Services librarians at [redacted], including the following: (1) understanding what internal policies and procedures applied to sharing research data, including creating a DUA or obtaining IRB approval; (2) determining which data transfer tools would be appropriate for legally and ethically transferring data that may contain PHI; (3) identifying when IRB approval is needed for a research project that uses secondary or pre-existing data; and (4) understanding what institutional tools or workflows are available for data de-identification. These four cases were chosen for a variety of factors including interest from institutional stakeholders and frequency of library consults around the issue. Each use case represents a situation where non-compliance with institutional policies could put patient or research participant data at risk. Protecting patient and research participant data is a priority shared by many at any academic medical center. This shared goal provides a stable foundation for collaborations to produce informational resources on data policies and research data management best practices. These four scenarios also presented an opportunity to deepen relationships with other research stakeholders like IT or Risk Management.

Examples of each of these use cases will be used throughout our discussion of the generalized approach to creating guidance for data policies.

For each of these use cases, the authors decided to create decision trees, a form of flowcharts. The format is designed to help researchers and research staff walk themselves through each logical step of a problem. As an alternative to dense documentation, this type of resource

is meant to highlight the key decision points of any situation (e.g., whether data was obtained from human subjects data or not) and the ramifications of that decision (e.g., de-identifying human subject data prior to sharing). One of the two data librarians would take the lead for a specific decision tree with the other consulting and providing feedback. Nicole Contaxis led efforts for the decision trees on internal policies for data sharing and tools for data transfer. Michelle Yee led efforts for the decision tree on de-identification and secondary data analysis.

Approach

The authors created decision trees to provide researcher guidance by following a similar five step methodology, as illustrated in Figure 1. This method developed organically and in an iterative fashion as the authors learned how best to engage other stakeholders and collaborators.

Step 1: Identify Need

Information needs surfaced during research data management consultations, within the library ticketing system, or during outreach meetings for open science initiatives like the NYU Data Catalog. For example, the data librarian who eventually led the creation of the data sharing policies flowchart noted that researchers appeared to struggle with these policies when asked to share their data through the NYU Data Catalog. In particular, there was a lack of clarity about when DUAs were needed, when data sharing might be limited by past informed consent paperwork, and when an IRB would need to be involved.

Similarly, data librarians discovered gaps in understanding ethical secondary data use while providing data reference services. Secondary data, pre-existing data that has been collected by someone other than the primary

user, may vary in availability and accessibility (10, 11). Through various means, including workshops, individual consultations, the NYU Data Catalog and library guides, the data librarians have connected researchers at all career levels with relevant data and/or search strategies for locating such data. In the course of providing these services, researchers frequently asked whether they would need IRB approval prior to requesting or utilizing secondary data. Typically, they were referred to contacts at the institution's Human Research Protections (HRP) office and the IRB for further discussion. However, wanting to enable researchers to understand and navigate relevant policies more easily, one of the two data librarians on the project initiated a collaboration with HRP.

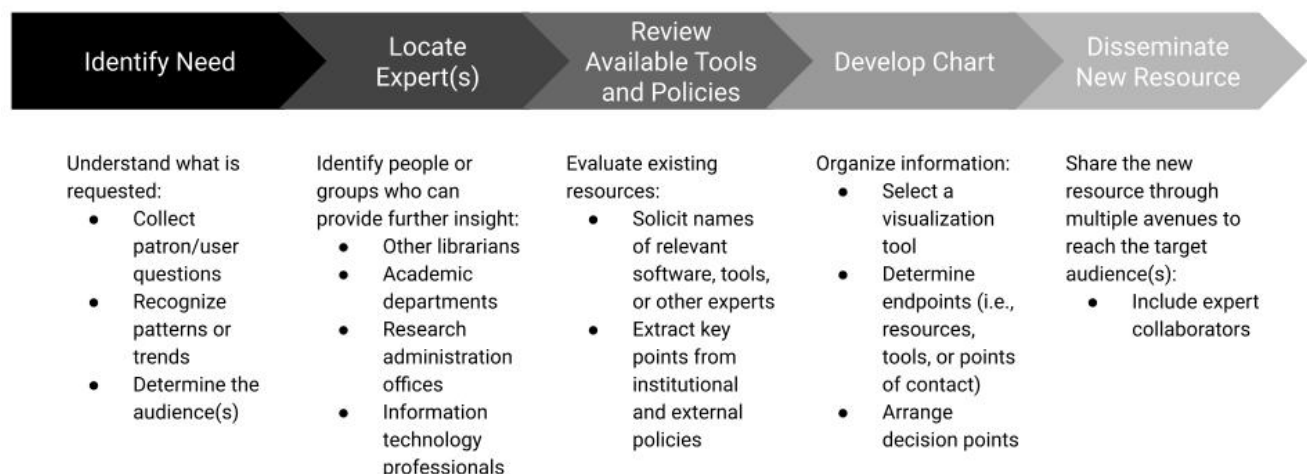
In some cases, these information gaps were identified by an existing collaborator or local expert. For example, separate guidance on data transfer tools was produced while creating the data sharing decision tree.

Step 2: Locate Experts

After identifying a specific information need, the data librarians located experts in that area within the institution. They sought out stakeholders to provide helpful perspectives from other disciplines and departments. Sometimes stakeholders were also active collaborators, providing feedback on decision trees in development and engaging in dissemination of the final products. Further information on how needs and experts were identified is included in Figure 1.

To produce a decision tree on data sharing policies, it was clear that two kinds of expertise were needed: expertise on the regulatory and policy environment for research data sharing and expertise on researchers' data sharing practices and culture. Data librarians had significant knowledge of research data sharing practices and culture,

Figure 1 Workflow for decision tree generation



but the input of General Counsel was necessary to address the regulatory and policy environment. In particular, the lead librarian collaborated with a lawyer who had experience with data policy and had written the institution's data retention policy. Similarly, when preparing a decision tree for describing IRB involvement in secondary data analysis projects, the lead librarian sought out an expert from the IRB to interpret the language in federal policies.

To provide guidance on data de-identification processes and tools, a wider array of experts and collaborators was needed. The librarian in charge consulted leaders in various research areas, including directors of clinical informatics and data analysis teams, to compile examples from their own experience in which various types of data required de-identification before being transmitted to another party. This list would eventually be incorporated into the decision tree.

Step 3: Review Available Documentation and Tools

Next, both librarians collected information on available tools and policies. This information was used to identify key decision points for shaping the flowchart or decision tree. The process of locating experts, pre-existing policies, and tools may be iterative. A new piece of documentation could point to a new expert not previously consulted or a new expert could point to documentation that the librarians did not previously know existed.

For example, when developing a flowchart on policies related to secondary data analysis projects, the leading librarian located resources created by the United States Department of Health and Human Services (HHS), including the Human Subject Regulations Decision Charts (12), and a self-certification worksheet from the institution's HRP office that incorporated information from HHS. These materials were used as a starting point for the creation of the flowchart, which eventually underwent several rounds of editing between the librarian in charge and the HRP office.

Sometimes clear documentation did not yet exist. While investigating the suitability of data transfer tools in various contexts, the librarian found little documentation on data transfer tools at the institution. To remedy this issue, there were several in-person meetings between data librarians, the General Counsel, and several members of the institution's IT departments, including members of the cyber-security, research technology, and desktop support teams.

These meetings began as fact-finding endeavors to relay needs and concerns around current researcher data sharing practices. To facilitate discussions, the lead data librarian presented a list of past instances where researchers needed to transfer data. This allowed her to highlight the need for clearer documentation on policies and technical procedures and to gather information on

available tools. The listed common data transfer scenarios included sharing internally, sharing externally, sharing data that included PHI, and sharing data at set intervals during multi-institutional clinical trials.

At the time, the institution had several data transfer tools at hand, including secure file transfer protocol (SFTP), email attachment encryption, and internal cloud workspaces. However, it was not clear which tools were suitable for the transfer of identifiable information in ways that were compliant with federal mandates like HIPAA. This knowledge was documented by IT in their internal security standards, and data librarians worked with IT to locate those standards and then expand them into a decision tree.

Step 4: Develop the Flowchart

Finally, flowcharts were created in Microsoft Visio or Canva, tools selected according to the librarian's preference. Drafts were shared with experts and stakeholders for feedback and revisions. Considering the deeply collaborative nature of these projects, feedback and revisions frequently took several rounds. For example, with the flowchart about IRB approval, staff from HRP assisted in ensuring that the language in the flowchart matched policy as much as possible. For the decision tree on internal policies for research data sharing, General Counsel provided feedback on specific data types or sharing use cases that were missed in prior drafts.

To develop guidance for data de-identification, librarians explored several options on how best to organize the information by referring to external resources from HHS and National Institute of Standards and Technology (NIST), as well as input from local experts. The team explored multiple potential starting points for a decision tree: categorization of the data format or modality (e.g., tabular, imaging, unstructured text), specific features of the data source or destination (e.g., cloud-based, controlled access), and characteristics of the data recipient (e.g., external collaborator, institutional affiliates, general public). The most approachable pathway appeared to be linking data formats to de-identification tools and techniques, which eventually formed the basis of the decision tree. Additional screening questions to assess the risk of re-identification were added to the start of the decision tree to help users determine the applicability of the guide.

Two of the four flowcharts are available as supplemental materials. Appendix A contains the flowchart that demonstrates which internal policies apply to specific instances of data sharing and Appendix B contains the flowchart that demonstrates when IRB approval is necessary for data sharing. Flowcharts that discuss internal tools for data transfer and data de-identification are considered confidential.

Step 5: Disseminate New Resources

Dissemination is a key final step. Resources can be shared through traditional routes like library guides, newsletters, and workshops. The data sharing and transfer tool flowcharts are included in a subject guide that has been viewed over 1000 times. The collaborative nature of flowchart development provides additional avenues for dissemination. Having been engaged throughout the information gathering and flowchart creation process, stakeholders have been keen to disseminate the flowcharts through their own channels. For example, after collaborating on the development of the data transfer tools decision tree, the IT department used and circulated the flowchart so thoroughly among their own staff that it was eventually sent back to the library as a useful resource that “they should know about”.

DISCUSSION

Compliance with institutional data policies is embedded within the practice of research data management. These policies, particularly when implemented by multiple departments or offices across an institution (e.g., IT, Human Research Protections), can be difficult to locate, understand, and apply. Librarians can facilitate compliance with these policies by making them easier to understand and implement. With an understanding of research data management, librarians are well-suited to work across departments and provide educational offerings and guidance on how to implement data policy requirements in day-to-day data management practices.

Creating data policy decision trees provides a series of benefits to library patrons, librarians, and the institution. First, the library helps researchers implement research data management practices in ways that comply with institutional policies. This can be indirectly measured by the number of views of associated library guides and the circulation of decision trees within the medical center. Institutions benefit with the reassurance that the potential for non-compliant practices is reduced.

Second, by working with other departments to create these flowcharts, the team established and built upon new partnerships. For example, after developing a flowchart on data transfer tools with IT, the library was invited to contribute to further projects, including devising documentation on data storage to help IT analysts better refer researchers to appropriate technologies. Additionally, in cases where there were insufficient tools, policies, or documentation to complete a decision tree, working with other departments brought these gaps to their direct attention. These interdepartmental partnerships also allowed librarians to showcase their expertise and improve communication about key policies and procedures that impact research data management

This approach, however, has several limitations and challenges. Although collaboration can strengthen interdepartmental relationships, progress is dependent on collaborators’ priorities and responsiveness. Keeping stakeholders on track can be a challenge, particularly if other demands emerge over the course of the project. An additional challenge is maintenance of these decision trees to reflect changes to policy or available technologies. This is particularly an issue with software and tools; institutions obtain, replace, or end licenses without broadly communicating these changes. Sometimes it is possible to rely on partners in other departments to keep the library up to date. Finally, in the course of developing many of these decision trees, the team encountered a lack of established institutional policies or guidelines. For example, to develop charts for selecting strategies for data transfer or data de-identification, IT leadership had not yet decided which technologies were best to use in which cases. Discussions that were initially scheduled to create the flowcharts thus became meetings for IT leadership to talk through various facets of data sharing and de-identification. While ultimately helpful for the research community, this process can be time-consuming for librarians.

For librarians considering undertaking similar projects to assist researchers with their institution’s data policies, it is vital to be patient but firm with inter-departmental collaborators. For example, a librarian may work with General Counsel on resources for institutional data retention policies. If the partner in General Counsel is pulled away to address a lawsuit, the librarian can set an alert to touch base with their collaborator in a month or two when the higher priority task has been addressed. Taking this type of approach with collaborators can also help build future relationships, as the librarian is able to demonstrate that they are an effective but understanding partner.

Moving forward, the library plans to continue to work with other departments to produce similar guidance to help researchers manage their data in policy-compliant ways. If insufficient resources exist, librarians are then placed to better inform the creation of new policies and or acquisition of new tools. By doing so, librarians can ensure that the needs of both researchers and the institution are met. This approach affirms the library’s central role in an academic medical center’s research ecosystem, helping researchers navigate complex data management challenges to contribute to scientific advancement.

DATA AVAILABILITY STATEMENT

There are no data associated with this article.

AUTHOR CONTRIBUTIONS STATEMENT

Michelle Yee: Conceptualization, Writing – original draft.
Nicole Contaxis: Conceptualization, Writing – review & editing.

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SUPPLEMENTAL FILES

Appendix A: Policy Flowchart

Appendix B: IRB Approval Flowchart

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Advancing library roles in research analytics: a case study of data-driven grant proposal support service

Fei Yu

See end of article for authors' affiliations.

Background: This case report demonstrates how a health sciences librarian designed and delivered a data-driven research analytics service to support a multi-institutional pre-award proposal.

Case Presentation: The librarian was invited to join a multi-institutional research team. After defining the project scope, the librarian developed and executed a structured search strategy in a key research database for collaborative research publications across the participating institutions. After two reviewers independently screened search results for relevance, the librarian applied validated measures and metrics and conducted quantitative data analysis and visualization with bibliographic metadata collected from the included research publications. The findings offered quantitative evidence that illustrates the dynamics and patterns in research productivity, collaboration networks, and topic distribution within the collaborative research effort. This librarian's work contributes to a timely delivery of actionable insights, directly informing the research team's proposal strategy and preparation.

Conclusion: This case presents a replicable framework for embedding research analytics services within library practice to support research performance evaluation. Leveraging librarians' expertise in literature search, research databases, bibliometrics, and data-driven workflows, librarians demonstrate their growing prominence as essential partners in research proposal development and research analytics.

Keywords: Pre-award support; research analytics; research collaboration; bibliometrics



See end of article for supplemental content.

BACKGROUND

Academic and research libraries have always strived to remain essential partners in the academic research enterprise [1,2]. Particularly, medical and health sciences librarians are known for engaging in collaborative and interdisciplinary research [3], teaching in curricula and workshops [4], and supporting accreditation processes and funding opportunities [5]. As the research paradigm becomes increasingly data-intensive, librarians have explored various approaches to support research analytics, including research data management and research impact evaluation [6]. The latter has emerged as a high-demand service in health sciences and medical libraries over the past decade [2,7]. Librarians apply their expertise in research literature search, bibliometrics, scientometrics, or network analysis to help researchers and institutes understand the research landscape, scholarly influence, collaboration patterns, and trends from bibliographic metadata [8–10].

However, most reported library support has focused on research output resulting from funded projects – post-

award evaluation or retrospective studies on research patterns and impact [8,11–13]. Little is known about whether or how librarians contribute during the pre-award phase of grant proposals, where timely data-driven evidence can strengthen proposals and demonstrate existing research capacity in a competitive funding environment. While librarians are well-positioned to contribute to research analytics, few case studies document workflows, resources, tools, deliverables, and practical applications needed to operationalize such data-driven services.

Therefore, this case report presents a real-world project in which a health sciences librarian collaborated with a multi-institutional research team to provide data-driven analytics supporting the pre-award proposal preparation and submission. While techniques such as bibliometrics, altmetrics, and collaboration network analysis have been documented in existing literature [10,14–16], the integration of secondary data from a state-of-the-art research database and the use of advanced analytics to promptly meet specific proposal requirements have rarely

been documented or reported in the library science literature. This project targets three aims as follows:

- Aim #1: To illustrate how a health sciences librarian leverages expertise and skills to design and deliver data-driven research analytics to support pre-award grant proposal preparation
- Aim #2: To report the workflows, tools, and metrics that can be effectively used, as well as example deliverables resulting from the service
- Aim #3: To summarize lessons from this project and inform the development of the research impact service in libraries.

CASE PRESENTATION

In 2020, the US National Institutes of Health (NIH) awarded a Research Center grant to a multi-institutional collaborative initiative focused on diabetes research. The participating institutions included Duke University (Duke), University of North Carolina at Chapel Hill (UNC-CH), Wake Forest University (Wake Forest), and North Carolina Agricultural and Technical University (NC A&T) [17]. As the initial grant term approached its conclusion, the partnering institutions sought to renew the grant in the summer of 2024. The new proposal expanded the collaboration to include three additional partners: North Carolina Central University (NCCU), North Carolina State University (NCSU), and the University of North Carolina at Greensboro (UNCG). The renewal application also aimed to assess whether and how the COVID-19 pandemic affected diabetes research activities at these institutions.

A librarian was enlisted to assist with the proposal preparation. The specific tasks were as follows:

- Conduct a systematic publication search and screening of diabetes publications co-authored by researchers from the seven participating institutions in North Carolina.
- Analyze the research productivity, top researchers, collaborations, and the impact of the identified publications in two periods: 2017-2019 vs. 2021-2023, which are three years before and after the COVID-19 outbreak in 2020.
- Demonstrate research collaboration patterns among the participating institutions.
- Complete the project within a four-week timeframe.

Publication Search

The librarian utilized Dimensions, a research database that offers a vast collection of scholarly publications across various disciplines, along with advanced analytics

features for research analysis [18]. Particularly, Dimensions indexes the entire MEDLINE database maintained by the National Library of Medicine, making it highly relevant to biomedical, health sciences, and interdisciplinary studies.

The librarian first identified all organizational IDs for the seven participating institutions in Dimensions and developed a comprehensive publication search strategy by connecting identified Medical Subject Heading (MeSH) terms (i.e., “Diabetes Mellitus” and “insulin”) and key terms (i.e., “diabet*,” and “insulin*”) with organizational IDs (e.g., Duke University – grid.26009.3d). The full search strategy and results are outlined in Appendix A. After retrieving search results for each institution, the librarian extracted the Publication ID fields from the seven datasets and identified duplicate records representing co-authored or collaborative works. Although relying solely on Dimensions may not capture all relevant publications, it was selected as an appropriate option given the project's time constraints and analytical requirements.

Publication Screening

The identified collaborative publications were exported from Dimensions in CSV format, and manually screened by both the librarian and one of the Primary Investigators (PIs) from the Diabetes Research Center. The librarian excluded the publications that were either (1) pre-print and corrections/errata, or (2) published before 2017. The PI further screened the subject content, eliminating irrelevant publications. The screening process concluded when reviewers agreed on a final set of publications and used it as the master dataset in CSV format for subsequent analysis.

Data Analysis

Based on previous bibliometric and data analytics studies in biomedical and health sciences [9,10,16], key measures and metrics were selected for metadata analysis (See Table 1). First, the librarian focused on the total number of collaborative publications, categorized by year and by seven participating institutions. Top contributing authors were identified by name, affiliation, and the number of publications.

For a more detailed comparison between the 2017-2019 vs. 2021-2023 periods, the following metrics were adopted: the number of collaborative publications, top contributing authors, number of co-author countries, collaboration networks, and citation impact. Regarding the citation impact analysis, three metrics were applied based on similar studies in the health sciences [19,20]: raw citation counts, Field Citation Ratio (FCR), and Relative Citation Ratio (RCR). The FCR, provided by Dimensions, measures the scientific influence of a publication by comparing it to the citation counts of similar articles in the same field and year [21]. Like FCR, the RCR is also an advanced citation

impact metric, developed by the NIH Office of Portfolio and provided through the NIH iCite interface [22]. RCRs benchmark an article's citation influence by comparing it with publications in the same field and timeframe indexed in PubMed. Both FCR and RCR are time- and field-normalized metrics that use 1.0 as a benchmark, with values above 1.0 indicating above-average citation influence and values below 1.0 indicating below-average citation influence. The key difference between FCR and RCR is that FCR is applied to publications in Dimensions, while RCR is most often used for NIH-funded publications indexed in PubMed. Although these two metrics use different approaches to define an article's field, both provide normalized benchmarks for comparing citation impact of publications across disciplines.

Furthermore, this project utilized Altmetric Attention Scores (AASs), a metric that quantifies the amount and type of digital attention that a publication receives across various online platforms, news outlets, social media, and policy documents, providing a measure of broader digital impact beyond traditional citation counts [23]. An AAS score of 20 or more indicates the publication receives greater digital attention than comparable publications in health sciences research [24]. Dimensions web application provides composite AAS values, while Altmetric Explorer breaks down digital attention counts by source.

A Mann-Whitney U test was conducted to assess differences between two time periods for FCR, RCR, and AAS, which were not normally distributed. Lastly, a MeSH term co-occurrence network was constructed in

VOSviewer to map the distribution of research topics across the two time periods. VOSviewer is a widely used bibliometric network analysis and visualization tool, visualizing co-authorship networks, citation networks, or term co-occurrence networks [25].

RESULTS

Overall (2017-2024)

A total of 370 co-authored (collaborative) publications by researchers from the seven institutions were included in the data analysis. The workflow is depicted in Figure 1. The number of collaborative publications across the seven institutions in chronological order from 2017 to 2024 was 54, 59, 58, 41, 37, 55, 50, and 18. Since 2024 represents a partial year in this study, only publications through May 2024 were included. The overall distribution indicates a decline in productivity in 2020 and 2021, followed by a resurgence in 2022.

UNC-CH, Wake Forest, and Duke produced the highest numbers of collaborative publications, with 301, 191, and 185, respectively. Researchers from NCSU, NC A&T, NCCU, and UNCG contributed 64, 7, 5, and 2 collaborative publications, respectively. Ranked by individual contributions, UNC-CH and Wake Forest researchers produced more collaborative publications than those from other institutions (See Supplementary Figure 1).

Table 1			
Data Analysis Framework			
	Measures & Metrics	Data Sources	Analysis Tool
Overall 2017-2024	Total collaborative publications by year & institution Top contributing authors	Dimensions Web App	Dimensions Web Analytical Views
2017-2019 vs. 2021-2023	Number of collaborative publications Top contributing authors Co-author countries Collaboration networks Citation impact (raw citation counts, FCR, RCR) Altmetric Attention Score (AAS) Research Topic Mapping	Dimensions Web App Altmetric Explorer	Microsoft Excel VOSviewer

Figure 1 Publication Search and Screening Flow

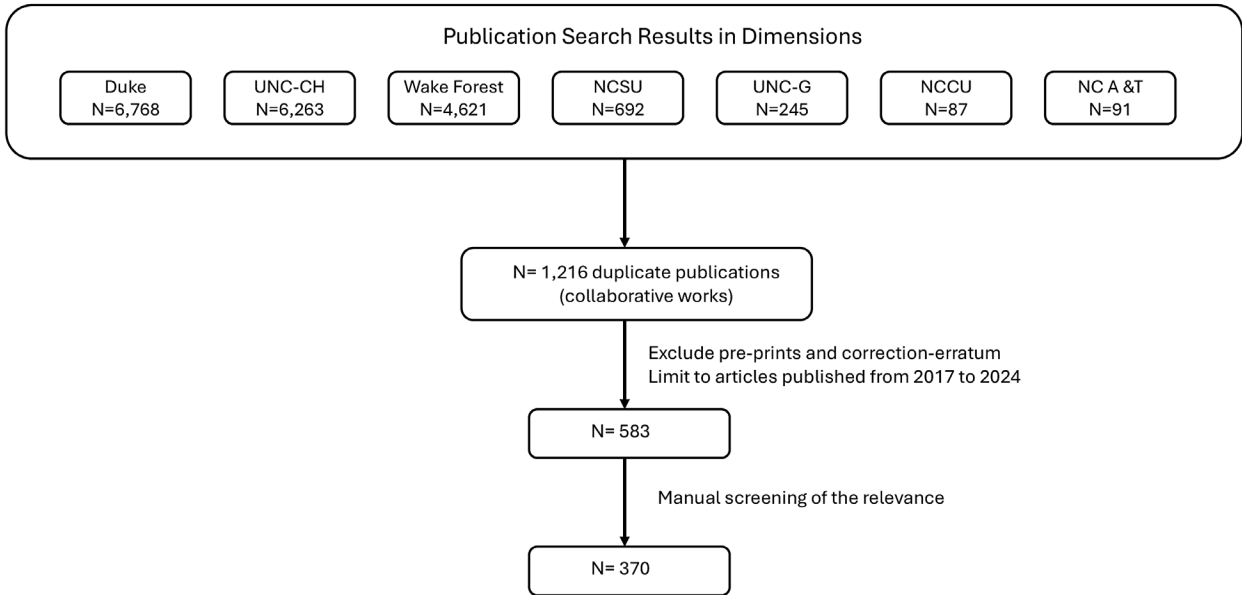
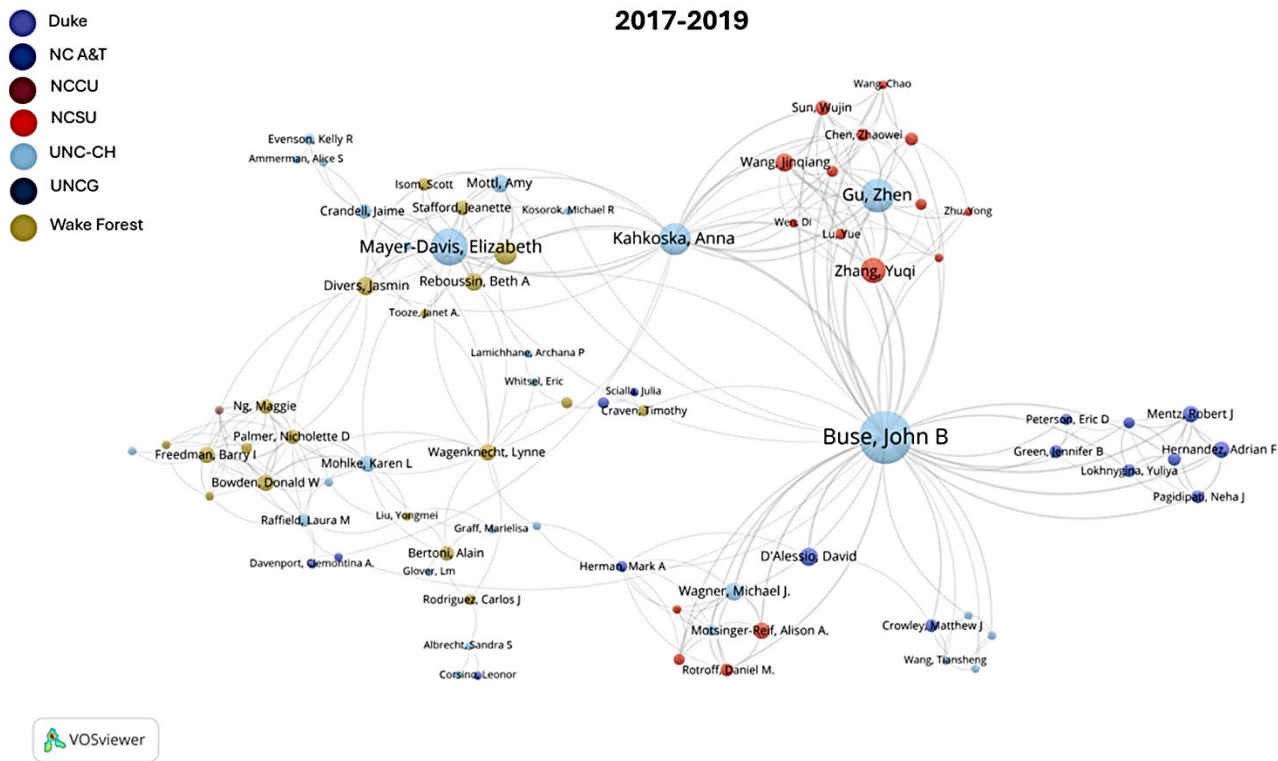
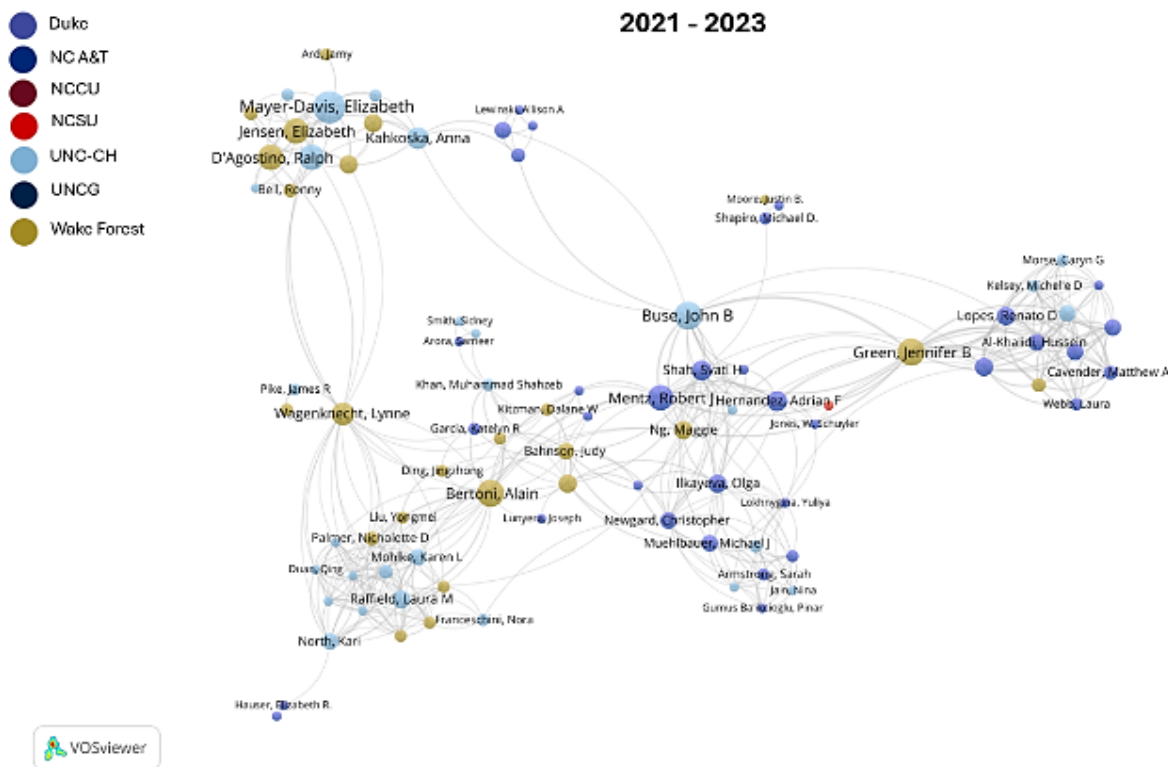


Figure 2 Institutional Collaboration Networks (2017-2019, Nauthor=112; 2021-2023, Nauthor=102; Each Author ≥ 2 publications)





Time period Comparison

The seven institutions collaborated on 171 publications during 2017-2019 and 142 publications during 2021-2023. In both periods, UNC-CH researchers published more than those at other institutions. However, UNC-CH collaborative publications decreased in the second period (2021-2023) to 105, compared with 150 in the first period (2017-2019). In contrast, researchers from Wake Forest and Duke increased their collaboration in the second period, producing 83 and 85 publications, respectively, compared to 74 and 73 in the first period. The other institutions (i.e., NCSU, NC A&T, NCCU, and UNCG) collaborated on fewer publications in the second period compared to the first.

Despite the lower overall number of collaborative publications in the second period, 13 additional researchers contributing to five or more publications appeared during the 2021-2023 period. Particularly, the majority of these researchers were affiliated with Duke and Wake Forest Universities (See Supplementary Figure 2).

International Collaboration

The total number of collaborating countries increased from 39 during 2017-2019 to 57 during 2021-2023. Despite a decline in the total number of publications by the United States (from 171 in 2017-2019 to 142 in 2021-2023), it remained the top collaborating country in both periods.

The United Kingdom, Canada, and China also continued to hold strong positions as leading collaborators, though their contributions slightly decreased in the second period (See Supplementary Table 2).

Collaboration Network

During 2017-2019, 454 authors from seven institutions collaborated on 171 publications. Among them, 112 authors contributed to two or more publications (Figure 2). On average, each author had about seven direct connections with other authors in this network, with an average total link strength of 16, indicating the combined strength of their connections with other authors [26]. In addition, UNC researchers were central nodes in the network, with key contributors such as “Buse, John B,” “Kahkoska, Anna,” and “Gu, Zhen” serving as connectors between different clusters.

During 2021-2023, 443 authors from seven institutions collaborated on 142 publications, with 102 authors contributing to two or more publications (Figure 7). On average, each author had about ten direct connections with other authors, and their average total link strength increased to 21, indicating a stronger combined strength of their connections. Additionally, central nodes in the second-period network included more researchers at Wake Forest (e.g., “Berton, Alain”) and Duke (e.g., “Newgard, Christopher,” “Ilkayeva, Olga”).

Citation Impact and Digital Attention

The total number of raw citation counts and the mean and median are significantly different between the two time periods, largely due to the natural accumulation of citations over time (See Supplementary Table 3). FCR and RCR are time- and field-normalized metrics. The mean and median of FCR for 2017–2019 were slightly higher than those for 2021–2023, but the difference was not statistically significant ($p > 0.05$). For the RCR, the mean and median were slightly lower in 2017–2019 than in 2021–2023, but the difference was not statistically significant ($p > 0.05$). Nevertheless, the majority of collaborative publications in both time periods were above the benchmark of 1.0, indicating above-average citation impact.

During the 2017–2019 period, 135 publications had AASs, compared to 107 publications during 2021–2023. Despite fewer publications with AAS in the second period, the mean AAS increased from 58.8 in 2017–2019 to 96.2 in 2021–2023. However, the Mann-Whitney U test shows no statistically significant difference between the two periods ($p > 0.05$). Since AAS is not a time-normalized metric, the results indicate that a small number of highly influential publications drove AAS to a high level in the second period. Notably, in both periods, approximately 30% of publications had an AAS greater than 20.

Topic Mapping

The subject-topic mapping for 2017–2019 revealed a total of 188 MeSH terms with a co-occurrence of ≥ 2 (See Supplementary Figures 3 and 4). For the 2021–2023 period, the mapping revealed 129 MeSH terms with co-occurrence of ≥ 2 . Several new MeSH terms appeared in the second period that were not present in the first period, including Ethnicity (10 occurrences), Hypertension (9 occurrences), Prediabetic State (6 occurrences), Diet (5 occurrences), Minority Groups (4 occurrences), Chronic Disease (4 occurrences), and Stroke Volume (4 occurrences).

Data Preparation for Proposal

After completing data analysis and visualization, the librarian compiled and shared a PowerPoint report with the multi-institutional research team, including comprehensive documentation of the method, results, and major findings. Additionally, upon the research team's request, the librarian assisted with compiling a collaboration table required for proposal submission. The librarian entered the number of collaborative publications for each of the 221 center members based on the master dataset and co-authorship collaboration networks generated from the analysis.

DISCUSSION

Aim #1

This project illustrates how a health sciences librarian designed, executed, and completed a data-driven bibliographic analysis within four weeks to support the preparation of a collaborative grant proposal, leveraging expertise in literature searching, bibliometrics, network analysis, and statistical testing. The librarian identified existing research collaboration patterns among the participating institutions without requiring manual data collection from individual investigators or their collaborators, reducing the time and effort typically required of PIs and research staff during proposal development, and contributing to the successful grant renewal [27]. In an increasingly competitive funding environment, demonstrating established research collaborations and institutional capacity can strengthen grant proposals. As health sciences research continues to shift towards team-based and interdisciplinary approaches, there is a growing demand for similar library-led services to identify and present evidence of existing collaborations or co-authored research outputs in proposal writing and submission.

Aim #2

An effective and replicable workflow presented in this study integrates secondary data collection from research databases, manual screening for quality control, and bibliometric and network analysis using the advanced visualization tool VOSviewer. The workflow incorporates key measures and metrics commonly used in biomedical and health sciences evaluation studies, such as RCR and AAS. As academic and research libraries increasingly provide similar services [5], this project offers a concrete model, workflow, and examples of deliverables that can be adopted and adapted to local contexts. Future studies should continue to document and report similar cases, tools, and services to build a shared evidence base on how librarians support research analytics and impact evaluation in academic research enterprises, strengthening knowledge exchange across professional communities.

Aim #3

Research analytics and impact evaluation support have become growing service areas, particularly in medical and health sciences libraries [7], as funders and institutions increasingly rely on evidence for decision-making and to demonstrate accountability for research investment [8–10,20]. As libraries continue to expand research support services, it is critical to prepare the current and future workforce with the skills and expertise needed to deliver these services effectively. The competencies demonstrated in this project include knowledge of bibliographic databases for secondary data collection, literature searching, expertise in research tools such as VOSviewer,

familiarity with the advanced database features, proficiency in collaboration networks visualization, and the ability to select and interpret appropriate metrics and measures, as well as effective communication with PIs and research staff. Combined with strong time management, these competencies are essential for meeting the needs of PIs during proposal preparation and submission. We call on library leaders, professional organizations, and library and information science (LIS) programs to provide targeted continuing education and professional development to build these capacities among library staff and within the LIS curricula to better support funders, administrators, and researchers.

In addition, the model presented in this project, which outlines the workflow, tools, resources, and deliverables, is transferable to other library-led research analytics support across disciplines and institutional contexts, such as annual grant reviews and reporting, research impact evaluation, faculty promotion review, and conference presentations on the research landscape and patterns in a specific field. Given variability in institutional resources, the measures and metrics used in this study can be adapted to local contexts. For example, RCR can be collected from the freely accessible NIH iCite platform, and VOSviewer is freely downloadable. Other databases (e.g., Scopus) and journal platforms also provide access to altmetric data. Libraries can tailor appropriate measures and metrics based on resource availability and staff expertise. As such services continue to grow and evolve, libraries are strengthening their position as indispensable partners in the academic research enterprise and shaping new directions for workforce development and career opportunities.

CONCLUSION

This case report highlights how a health sciences librarian provided timely support in preparing a pre-award grant proposal. By leveraging expertise in research databases and analytical tools, the librarian mapped the recent landscape of collaborative diabetes research in North Carolina, identified collaboration patterns, and highlighted key trends, contributing to a successful grant renewal and demonstrating the valuable role of librarians in facilitating multi-institutional and interdisciplinary research efforts.

DATA AVAILABILITY STATEMENT

Data associated with this project can be shared with permission from the multi-institutional Diabetes Center in North Carolina. Request for data access can be directed to the corresponding author at feifei@unc.edu.

AUTHOR CONTRIBUTIONS

Fei Yu: Conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing – original draft, review and editing.

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SUPPLEMENTAL FILES

Appendix A: Search Strategy in Dimensions and Results (May 15-16, 2024)

Appendix B: Supplementary Tables and Figures

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Author profiles in Web of Science, Scopus, Dimensions, ORCID, ResearchGate, and Google Scholar: a case report

Kimberly R. Powell, AHIP

See end of article for authors' affiliations.

Background: This study aimed to benchmark the availability and accuracy of author profiles for 45 faculty members within the Auburn University College of Nursing. Profile availability in the database platforms Web of Science, Scopus, and Dimensions were analyzed alongside the author-driven platforms ORCID, ResearchGate, and Google Scholar to set an understanding for the potential efforts needed for profile curation, publication tracking, and research impact assessments moving forward.

Case Presentation: Each of the six platforms were manually searched for faculty and name variations alongside both current and past institutional affiliations. All identified profiles were collected. Associated publication counts were recorded and database results were screened for accurate author identification. Among the author-driven platforms, ORCID had the highest adoption rate, with 64% of faculty, while ResearchGate and Google Scholar trailed with 38% and 16% faculty adoption, respectively. Web of Science offered profiles for 82% of faculty; Scopus offered profiles for 80% of faculty, and Dimensions only 53%. However, 53% of the associated publications were misattributed in Web of Science profiles compared to just 1% misattribution in Scopus and none in Dimensions.

Conclusions: Among our faculty, Scopus offered the most efficient author profile platform, balancing profile availability, minimizing misattribution, and including avenues for early identification of new authors. While largely in line with previous study findings, this effort provided important contextual understandings of profile data availability which can be used to inform research impact assessments and library services supporting author profiles for highlighting scholarly influence.

Keywords: Web of Science; Scopus; Dimensions; ORCID; ResearchGate; Google Scholar; author identifiers; author disambiguation; researcher impact



See end of article for supplemental content.

BACKGROUND

In recent years academic librarians across disciplines have become more involved in author tracking, curation of author profiles, and publication reporting (1-4). As experts in bibliographic databases, librarians are well positioned to offer specific support in using and managing database-driven profiles available in literature databases such as Web of Science and Scopus. These bibliographic databases automate author profile creation as part of the bibliometric discovery features. Author-driven profiles available through ResearchGate and Google Scholar have also come to be widely acknowledged and recommended for increasing research visibility (5-8). These author-driven profiles are website platforms in which individuals elect to create and maintain research and publication profiles outside of the curated literature.

Database-driven author profile automation was first introduced by Scopus in 2006 (9). Profile creations are automated based on listed author name, email, institutional affiliation, and patterns of citations, co-authorship, and subject domains (10). Web of Science followed suit with their Researcher ID, which launched initially as an author-driven identifier in 2008 (11). In 2019, Web of Science moved its Researcher ID profiles to primarily machine-learning driven methods (12). While profiles are automatically created and publications are automatically added, individual researchers are still able to claim or verify their profiles, as well as merge duplicate accounts and submit corrections to identified records and name variations. The Dimensions database was launched in 2018 with researcher profiles included in the freely available publications module. Uniquely, Dimensions profiles provide automated linking to public Open

Researcher and Contributor ID (ORCID) profiles (13). Notably, Web of Science and Scopus also make their author profiles, including searching, claiming, and managing (including connections with ORCID), freely available without need for full database subscriptions or licensing (10, 14).

In addition to database-driven author profile algorithms, web-based platforms like ResearchGate and Google Scholar offer authors a chance to gather and highlight their work on public web pages by creating individual user accounts. Once authors create an account, both platforms will add or suggest additional records, including non-traditional record types and citations scraped from web content such as abstracts, datasets, thesis, syllabi, etc. ResearchGate launched in 2008 as a social connection platform and remains popular for full-text document sharing (6). Google Scholar user profiles, launched in 2012, is another popular choice, particularly for those looking to capture high citation counts and activity as a result of the non-traditional citation tracking such as those made by abstracts, datasets, thesis, dissertations, syllabi, and personal webpages (15, 16). Neither of these two profile sites offer third party curation options or interoperability with other platforms; these are stand-alone platforms and cannot currently be linked with outside platforms.

Since launching in 2012, ORCID sits in a space between the automated database author identifiers and the author-driven webpages. As an author-driven profile system, researchers must choose to create and maintain an account. However, individuals can also allow delegates or trusted organizations, including literature databases and universities, to write data to their ORCID record. The ORCID platform has gained recognition as the unique author identifier required for an increasing number of federal funding compliance and data security guidelines (17, 18). All three of the major bibliometric databases, Web of Science, Scopus, and Dimensions, allow for ORCID integrations. In the case of Dimensions, ORCID iDs are automatically linked to the researcher profiles created by the platform. In Web of Science and Scopus, researchers have the option to link their ORCID iD to their researcher profile in the database once they have claimed their profile. Claiming a Web of Science or Scopus created profile also allows the researcher to verify or reject publications linked to their profile.

Faculty authors have a variety of platforms to choose from when trying to collect and showcase their research and scholarly outputs. Universities and research organizations face similar challenges when trying to track and aggregate their researchers' efforts. Librarians are natural partners when looking to collect and assess the available literature, but the accuracy of available author profiles across platforms has not yet been fully compared or assessed.

Case Presentation

The case presented here aimed to evaluate the availability and accuracy of author profiles for a convenience sample of the 45 faculty members which made up the 2024 Auburn University College of Nursing (AUCON) faculty. In 2019, the university was recognized with the highest research classification (R1) Carnegie Classification status, denoting it as a doctoral institution with very high research output (19).

Relatedly, AUCON has shown significant research growth in recent years, and in 2024 was one of three nationally ranked programs at Auburn by US News and World Report (20). The 2024 university strategic plan articulates a continued commitment to research growth with a goal to double publication outputs by 2034 (21).

Even prior to these formal research recognitions and strategic goals, the library has been increasingly called upon to provide expert publication tracking and affiliation searching in support of institutional publications assessments. Since 2022, the library has offered ORCID profile support and tracking, helping to ensure affiliated researchers are meeting federal and publication requirements [see more: <https://libguides.auburn.edu/ORCID/>]. However, prior to 2025, there had not been any campus support of author-level profile systems outside of ORCID. When consulted, librarians within the institution would recommend Web of Science or Scopus for publication assessments, as these both are included in institutional subscriptions. However, Dimensions has also been used in recent assessment projects and licensed through the Provost's office. Similarly, an expert finder project launched in 2025 uses profiles available through Google Scholar (see more: <https://ausme.auburn.edu/>). As the library is becoming more involved in the analysis of and recommendations for author profiles, this study sought to benchmark faculty profile availability across six platforms to inform potential profile curation and publication tracking efforts moving forward.

Profile Identification

A total of six platforms were searched for affiliated author records to 45 nursing faculty members, including name variations and previous affiliations. These platforms were: Web of Science (free profile URL: <https://www.webofscience.com/wos/>), Scopus (free profile URL: <https://www.scopus.com/freelookup/form/author.uri>), Dimensions (free database URL: <https://app.dimensions.ai/auth/base/landing>), Google Scholar (<https://scholar.google.com/>), ResearchGate (<https://www.researchgate.net/>), and ORCID (<https://orcid.org/>). When available, the unique profile ID was collected. Additionally, it was noted if the profile was "claimed" or "verified" by the represented author,

and if the profile had been linked to an ORCID profile. For Google Scholar and ResearchGate, which do not assign a unique identifier, the direct URL was collected in its place.

A spreadsheet was created for all nursing faculty members listed in the institutional directory, which included tenured, tenure-track, and clinical faculty. Author profiles were then manually collected from each of the platforms in October 2024. Columns were added to the spreadsheet to track identified profile ids and URLs. Profile identification was completed in an iterative process as name variations, affiliations, and record details were discovered in subsequent platform searches. A second review was completed in April 2025 to capture additional profiles, verification status changes, or ORCID links through the 2024 calendar year. Several additional author profile accounts were uncovered at the time: 1 ORCID profile, and 3 additional author profiles in Dimensions.

As of April 2025, a total of 192 author profiles were collected for the 45 AUCON faculty. Table 1 shows the identification of faculty associated profiles across each platform. Overall, 40 faculty members (89%) had a profile on at least one platform, with 38 (84%) appearing with at least one database-driven profile. There were 19 (42%) unique authors represented with an author-driven profile on either Google Scholar or ResearchGate platforms. Only 6 (13%) authors appeared with profiles across all platforms. Among the 5 individuals with no profile on any platform, all were assistant ranked clinical faculty who are less likely to have formal publication records than tenured, tenure-track, or later career (associate and full ranked) faculty. However, these five make up only 19% of the 26 total assistant clinical faculty included in the sample.

Of the database-driven platforms, faculty most frequently appeared with Web of Science Researcher IDs (n=37, 82%), followed closely by Scopus author profiles (n=36, 80%).

Dimensions offered profiles for the least number of faculty (n=27, 60%). All database platforms had multiple associated profiles for at least one faculty author. The problem of multiple associated profiles was most pronounced in Web of Science where 15 (41%) of the available faculty in the database were represented under more than one identifier.

For author-driven profiles, faculty most frequently appeared in ORCID (n=30, 67%) followed by ResearchGate (n=17, 38%) and lastly Google Scholar user profiles (n=7, 16%). No profile duplication was found on ORCID or Google Scholar. One individual had 3 ResearchGate accounts under their name and institutional affiliation, but none were associated with any publication records or data.

Profile claiming

Faculty were most likely to have claimed their respective Scopus profiles (n=8, 22%) as represented by profiles manually linked with an ORCID iD. Available Web of Science profiles showed only 3 (8%) with a linked ORCID iD among the total of 6 (16%) claimed records. While Dimensions offered the lowest availability of author profiles, it also offered the highest proportion of profiles linked to ORCID profiles (n=12, 50%). ORCID linking is a uniquely automated process for Dimensions, with the ORCID linking on this platform done without requiring author verification or claiming. Individuals are not able to claim, verify, or modify author accounts themselves within the Dimensions database as they can on the other platforms (22). Figure 1 illustrates the proportion of researchers with verified or ORCID linked profiles within each of the database platforms.

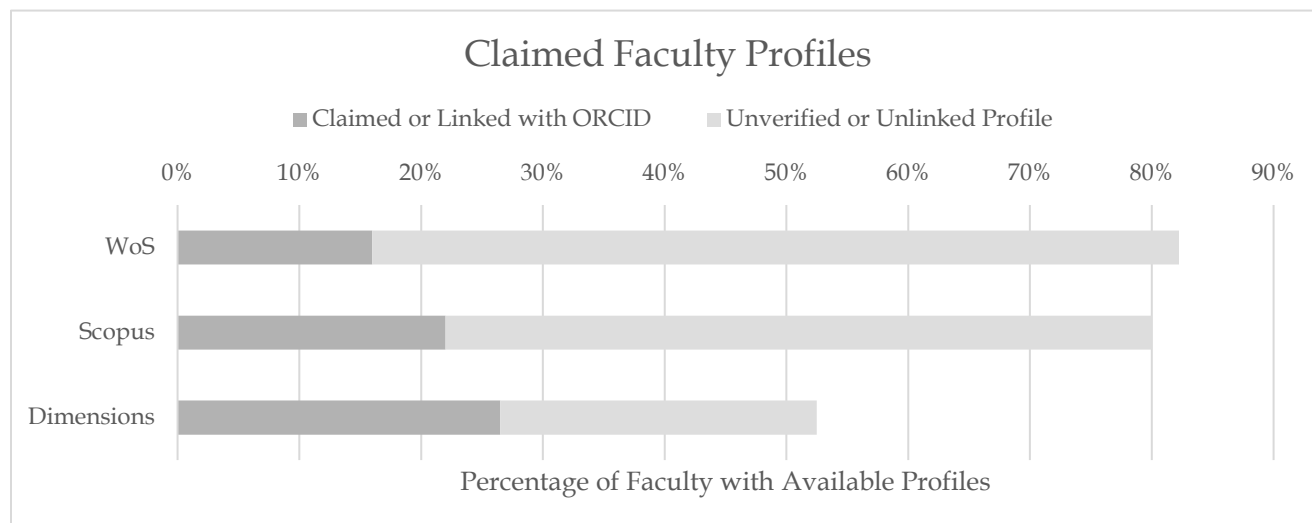
Publication record completeness

Publications affiliated with each of the Web of Science, Scopus, and Dimensions profiles were collected in April

Table 1

Summary of author profile availabilities.

	Web of Science	Scopus	Dimensions	ORCID	Google Scholar	ResearchGate
faculty with no available profile	8	9	18	15	38	28
faculty with 1 associated profile	22	28	19	30	7	16
faculty with 2 associated profiles	11	5	8	0	0	0
faculty with 3 associated profiles	4	3	0	0	0	1
unique faculty with available profiles	n=37	n=36	n=27	n=30	n=7	n=17

Figure 1 Percentage of author profiles in each database with breakout of those claimed or linked with ORCID.

2025 and saved to Endnote groups (version 21.5, Clarivate Analytics) for deduplication and manual verification of correct authorship attributions. When authorship could not be confirmed by the available record metadata, internally provided CVs were consulted. Exports from Scopus and Web of Science were limited to articles, books, book chapters, conference/proceedings papers, and reviews. Publication records were deduplicated using both manual and automated features to identify unique indexing across the database and create a total unique count of publication records for each faculty author. Dimensions was the only database to return preprints & conference and poster abstracts, which were removed manually. The remaining unique publications attributed to each author, gathered across these three databases, were used to calculate the percentage of database coverage.

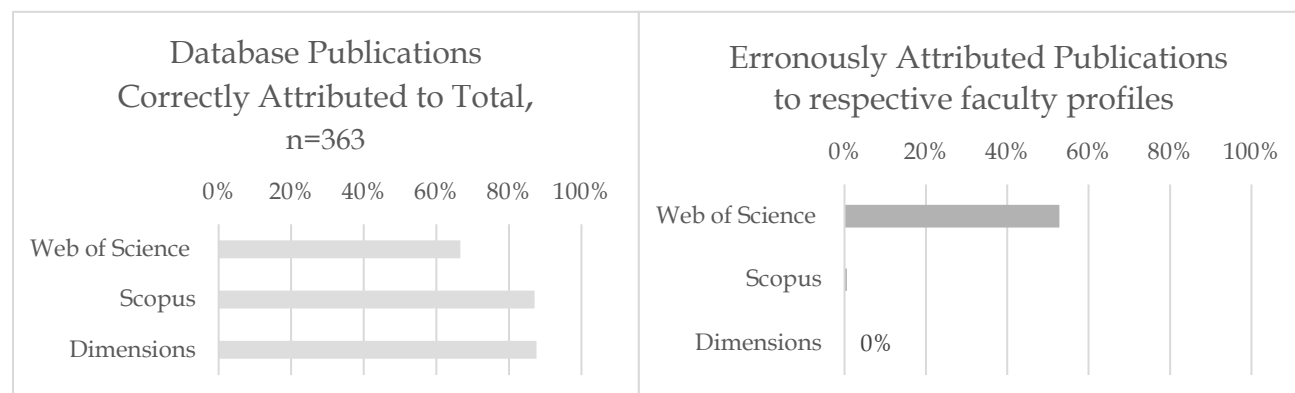
For ORCID, ResearchGate, and Google Scholar only the count of claimed publications was recorded, with no effort made to verify authorships. Each of these platforms allow for expanded record types such as abstracts, posters, datasets, and preprints which do not easily allow for independent verification and were explicitly excluded from the collected database publications. For identified ORCID profiles, it was further noted if data were set to private or public view. If public, the number of listed works/publications and current affiliation availability were also noted.

A unique total of 363 verified publication records were collected across all database author profiles (Web of Science, Scopus, and Dimensions), with publication years

ranging from 1979 through 2024. As author profiles are typically intended to offer tracking across the full spectrum of a researcher's career, these counts include all authored records regardless of institutional affiliation at the time of publication.

The Dimensions platform returned 318 publications records associated with the identified author profiles; 28 of these records were uniquely indexed in Dimensions and not available through Web of Science or Scopus. An additional 31 records were later identified as available in Dimensions, but the listed institutional author was not associated with an available author profile. Within Dimensions, no publications were misattributed to their respective author profiles. Scopus also returned 318 publication records associated with their author profiles, with 4 uniquely indexed in Scopus. There were 2 misattributed publication records, both associated with the same profile, which were removed. Web of Science returned 513 publication records. However, author misidentification was highest here, with 53% (n=271) of associated records being misattributed to their listed author profile(s). The majority of misattributions appeared to be due to the conflation of authors with similar surnames and initials working in related fields. After removing these erroneous records, Web of Science captured 242 faculty publication records. None of the identified records were unique to Web of Science. The percentage of the total verified faculty publications within each of these database profiles is displayed in Figure 2a (left), while Figure 2b (right) showcases the extent of publications erroneously attributed to the respective author profiles in each database.

Figure 2 Authorship attribution within each database. A) The percentage of total identified publications correctly attributed by database profiles. B) The percentage of publications in each database erroneously attributed to collected author profiles.



While 67% (n=30) of faculty had an identifiable ORCID iD, 4 of these had no data publicly available in the account. Additionally, 8 ORCID profiles did not include any authored publications, despite having a combined authorship count of 95 publications for these authors identified from the database profiles. Across all 45 faculty members, 27% (n=12) had an ORCID profile with at least 75% of their total publication count listed. ResearchGate similarly provided a mean of 72% of the total publication count for participating authors. However, this is likely an inflated estimate as ResearchGate records include preprints, data files, meeting abstracts, and other record types not included in the counts identified through Dimensions, Scopus, or Web of Sciences. While the expanded record types can be controlled for in ORCID's associated "type" data for each record, they cannot be controlled for through ResearchGate or Google Scholar associated metadata.

Google Scholar offered a mean 63% increase over the database identified records for each author. The highest profile discrepancy had 22 identified publications from the database-driven profiles and 51 listed records in Google Scholar, a 132% increase. While reconciliation of the Google Scholar listing is outside the scope of the present efforts and reporting aims, many of these additional records appeared to be abstract, poster, and conference listings excluded from the collected database counts.

DISCUSSION

Tracking author profile adoption and associated publication records is an important exercise in understanding the discoverability and potential measures of scholarly impact. Benchmarked data, such as presented here, give insight into faculty output representations over time as well as an awareness of potential data cleaning and curation efforts needed before author profile platforms can be reliably used for highlighting faculty efforts and institutional reporting. The current

documentation of author profiles at our institution informs potential patterns in the availability of author assessment data across the various platforms and underscore the continued limitations of author-driven profiles such as ORCID for assessment purposes.

Among the author-driven profiles, AUCON faculty had the highest adoption of ORCID profiles. This is likely linked, in part, to campus outreach and curation efforts following US federal funding requirements and the National Security Presidential Memo 33 (NSPM-33) recommendations for persistent identifiers (23, 24). ORCID adoption by Auburn college of nursing faculty is slightly lower than a recent broader report of 31 academic institutions which showed an overall faculty adoption of 72% across research disciplines, and 85% adopt in "health professions and related clinical services" (17). However, even for those authors that do have public ORCID profiles, robustness in both studies still falls short of being able to use faculty ORCID profiles for reliable publication metrics or institutional reporting. The average AUCON profile reported less than three-quarters of the available publication records and less half of faculty could be discovered by current affiliation listings. These missing elements are crucial impediments to accurate and robust impact reporting and assessments severely undermining the potential of using ORCID for local assessments.

Fortunately, Web of Science, Scopus, and Dimensions platforms all allow for data sharing with linked ORCID accounts. Library services and institutional efforts around supporting more complete ORCID data or publication reporting can leverage these connections to increase discoverability and inclusion of identified publications in author impact measures and reporting analytics. Neither ResearchGate nor Google Scholar allow for ORCID connection or integration.

Following ORCID, Auburn nursing faculty were most likely to have created ResearchGate profiles, which follows trends previously reported in the literature (2, 3,

25). Early evaluations of ResearchGate highlighted the potential influence of academic social networks to disrupt existing hierarchies, allowing earlier career researcher and those from the Global South to better highlight their scholarly works, but more recent studies have largely found the dominate hierarchies to be reinforced (26). Studies among university faculty have since found document sharing to be a leading motivation for ResearchGate participation (27, 28). Notably, ResearchGate provided metrics were not generally seen as an accurate reflection of research impact and were, in fact, discontinued in 2022 (29, 30).

Among the database-driven platforms, Scopus seemed to offer the best balance of accuracy and efficiency for Auburn nursing faculty. This is in line with previous findings comparing and assessing the representation of nursing publications and impact measures (31-33). Among the three automated profile platforms examined here, Scopus outperformed Dimensions in the availability of automated faculty profiles. Scopus also outperformed Web of Science for faculty-claimed or ORCID linked profiles and tied with Dimensions for the highest count of identified publications. Scopus also offered third-party correction submissions, with a specific toggle for librarian curation efforts, a feature likewise available in Web of Science, but not available in Dimensions. All Web of Science and Scopus corrections uncovered as a result of the analysis presented here were processed and available in their respective platforms within seven days of librarian curation submissions. Like the profiles themselves, claiming, linking, corrections and modifications are accessible in Web of Science and Scopus regardless of institutional subscription access.

This investigation also uncovered that database-driven profiles may have important implications for early career researchers that was not found to be reported elsewhere. Notably, Dimensions does not provide author profiles or assign author identifiers until two associated records are available. The finding of associated publications available in the database yet unlinked with discoverable author profiles does echo previous findings with affiliation profiles. Guerrero- Bote et al. (2020) noted in their study that over 25% of Dimensions records remained unlinked to institutional affiliation profiles (34). Conversely, Scopus does assign an identifier to single-record authors, but these are only discoverable from the publication record itself; single-record author profiles will not be returned in author search results lists. In yet another approach, Web of Science profiles allow individuals to create accounts prior to publications records but were also found the most likely to append erroneous records to these profiles resulting in misattributed publications.

CONCLUSIONS

The comparisons discussed here are a case study offering a snapshot of author profile adoption and database accuracy in a single faculty setting at one institution. While many of the findings are in line with previous reports from the literature, the profile identification and verification exercise was an essential effort in understanding the local faculty representations. This lays the groundwork for further institutional assessment recommendations. The comparisons discussed here offer greater contextual understandings when recommending platforms, and the associated curation efforts and time allocations for supporting librarians.

Among our faculty, Scopus offered the most efficient automation of associated author profiles, balancing profile availability, minimizing misattribution, and including avenues for early identification of new and early-career authors. As evidenced by growing federal and publisher support, ORCID iDs have tremendous potential to incorporate author-driven representation as well as integration across the database platforms. However, its practical application for author assessments remains ineffective due to low adoption and incomplete publication data. At Auburn University, campus initiatives have been launched relying on Google Scholar available profiles, and ResearchGate still remains relatively popular among our faculty authors. While these have been also shown to be inadequate platforms for assessing faculty authorship profiles, they cannot be discounted. Similarly, Dimensions offered a high level of associated record accuracy as well as the automated ORCID linking, making it an important emerging resource that many librarians and information professions should consider for exploring their own author contexts.

DATA AVAILABILITY STATEMENT

The data associated with this article are available in the Open Science Framework (OSF) at <https://osf.io/ypa76>.

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SUPPLEMENTAL FILES

Appendix A: Data

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Beyond database training: reconceptualizing information literacy and reading competence as a shared cognitive architecture in medical education

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See end of article for authors' affiliations.

Medical librarians have long observed that medical students who struggle with reading complex textbooks also demonstrate weak information literacy skills. For decades, these have been treated as separate problems requiring separate solutions—offering reading workshops and database training sessions with limited lasting impact. This commentary proposes a reconceptualization: textbook literacy and information literacy are not sequential competencies but rather parallel manifestations of the same underlying cognitive architecture. Drawing on research in medical education, cognitive psychology, and educational neuroscience, this commentary argues that both literacies depend on three interconnected cognitive capacities: metacognitive self-regulation, working memory management, and epistemic sophistication. Understanding this shared foundation has profound implications for how health sciences librarians design interventions, plan instruction, and position themselves as essential contributors to medical education. This commentary presents a framework and outlines practical implications for library instruction, assessment, and collaboration with medical educators.

Keywords: Information literacy; medical education; metacognition; cognitive load theory; epistemic development; health sciences librarianship

INTRODUCTION

Medical librarians have long observed a troubling pattern, that medical students who struggle with complex textbooks also demonstrate weak information literacy skills [1, 2]. Those who avoid dense scientific texts or who highlight passively, show poor source evaluation and also search unsystematically [2, 3]. Traditional library instruction has treated these as separate problems requiring separate solutions, with limited impact. What if we've been addressing symptoms rather than causes?

Before presenting this reconceptualization, it is worth clarifying two terms that anchor the discussion. By textbook literacy, we mean the discipline-specific reading competence required to engage productively with medical and scientific texts, a capacity that goes beyond general reading ability to include navigating technical vocabulary, interpreting complex textual structures, and integrating information across dense sources [1, 4]. Information literacy (IL), as defined by the Association of College & Research Libraries (ACRL) Information Literacy Framework, encompasses the reflective discovery of information, the understanding of how information is produced and valued, and the use of information in the creation of new knowledge [5].

Yet in medical education, this expansive conception of information literacy has been operationalized narrowly.

The closest IL has come to meaningful curricular recognition in medical education is through Evidence-Based Medicine, where it functions as a core clinical competency [6, 7]. But even there, instruction tends to collapse around its most visible and measurable component, database searching. This is not without reason. Searching is concrete, teachable, and maps readily onto clinical workflows. The ACRL Framework envisions something considerably broader. Its frames describe learners who treat research as iterative inquiry rather than a linear retrieval task (*Research as Inquiry*), who recognize that knowledge is produced through ongoing scholarly debate rather than deposited in authoritative sources (*Scholarship as Conversation*), and who develop critical judgment about how authority is constructed and why it varies across contexts (*Authority is Constructed and Contextual*) [5]. These are not peripheral extensions of IL; they are its conceptual core. When medical education reduces IL to search mechanics, it teaches students to retrieve information without developing the cognitive capacities needed to interrogate, situate, or synthesize it.

The shared cognitive architecture this commentary proposes is an architecture for that fuller conception of literacy. Specifically, we argue that textbook literacy and information literacy are not sequential competencies — where reading ability enables effective information engagement — but rather parallel manifestations of the

same underlying cognitive foundations. Understanding this shared architecture has profound implications for how health sciences librarians design interventions, structure instruction, and position themselves as essential contributors to medical education

THE TWO CONVERGING LITERACY CRISES

The Challenge of Discipline-Specific Reading in Medical Education

Medical students arrive with general literacy skills adequate for undergraduate success yet consistently struggle with specialized reading demands of medical and scientific texts. This reflects the transition from general academic reading to discipline-specific literacy, a transition medical education has largely failed to explicitly address.

Medical schools operate under what researchers term a 'problematic assumption', that students possess the background knowledge and skills to comprehend scientific texts without targeted instruction [1, 8]. Ivanitskaya et al. argued that "medical schools have wrongly assumed that students have the background knowledge and skill to understand scientific texts at an appropriate level" [1]. Students report difficulty with technical terminology and textual structures characteristic of scientific papers; challenges stemming not from poor general reading skills but from unfamiliarity with discipline-specific conventions [1, 4]. Another factor is what researchers identify as a "paucity of reading comprehension strategies and metacognition" [9]. Students haven't been taught strategic approaches to complex scientific material.

Research on students' actual reading practices reveals the scope of the instructional gap. Students demonstrate avoidance patterns, preferring lecture notes and review materials over textbooks and primary literature. Research on the rationale for this avoidance points to several intersecting factors. In a multi-institutional study of clerkship reading habits, Kind et al. found that students identified time as the primary barrier to reading, with question banks and board review books rated as most useful for exam preparation [10]. Eighty percent of students ranked classmates and senior students as most influential in resource selection, suggesting that avoidance cultures propagate through peer networks. Dense scientific texts require readers to build, test, and revise mental models of complex physiological and pathological processes. These acts of schema construction build the organized knowledge structures that underlie expert clinical reasoning [8, 11].

This leads us to believe that when students substitute condensed review materials for sustained engagement with primary sources, they may acquire testable facts without developing the interconnected knowledge

networks that support transfer to novel clinical problems. They spend minimal time with the complex texts that should form the foundation of medical knowledge, thus undermining the development of the deep, integrated understanding necessary for clinical reasoning and lifelong learning [8, 12].

The Parallel Challenge of Information Literacy

While students struggle with textbook reading, medical educators have also observed persistent information literacy deficits despite years of library instruction. Medical students and residents demonstrate persistent information literacy deficits that extend well beyond the mechanics of database searching such as difficulty evaluating the credibility and context of sources, the inability to recognize knowledge as contested and evolving rather than fixed and retrievable, and an inability to synthesize meaningfully across multiple conflicting sources [13-16]. These deficits persist even among students with strong MCAT scores and academic records [17].

This persistence suggests that skills-based training overlooks the true nature of information literacy. From a cognitive perspective, IL is a complex form of information problem solving – a metacognitively-driven process of identifying a knowledge gap, formulating a search, and integrating new information to construct meaning [2]. Foundational LIS models, such as Kuhlthau's Information Search Process, describe this as an intensive cognitive and affective journey where learners must manage uncertainty to build new understanding [18]. Modern standards reflect this model. The *Framework for Information Literacy* posits that learners must cross conceptual thresholds, such as understanding "Searching as Strategic Exploration" (a process of self-guided inquiry) and "Authority is Constructed and Contextual" (a judgment about the nature of knowledge) [5].

In the medical context, the cognitive process is not abstract, it is the foundational engine of EBM. The seminal definition of EBM requires that physicians engage in the "conscientious, explicit, and judicious use of current best evidence in making decisions about the care of individual patients" [19]. This entire process, formulating a clinical question, searching for evidence, and critically appraising evidence, is an act of information literacy, one that is formally recognized as a core competency of practicing medicine [6, 7].

Therefore, a deficit in IL is not a peripheral "library skills problem," it is a direct barrier to practicing EBM, the standard of modern medical care. It is these foundational cognitive skills, the "self-guided inquiry" and "judgment about knowledge," that medical education must begin to teach and health sciences librarians need to better incorporate into instruction.

The Puzzle of Co-Occurring Deficits

The puzzling question is, "Why do textbook literacy difficulties and information literacy deficits so consistently co-occur?" Both textbook literacy and information literacy are multidimensional constructs shaped by prior knowledge, disciplinary socialization, effective responses to uncertainty, and instructional context. We do not intend to reduce either to a single skill. Rather, we argue that specific cognitive capacities emerge as shared foundations that help explain patterns of co-occurring difficulty across both domains.

Traditional explanations treat these as independent problems; students who can't read well naturally can't engage effectively with information either. But this sequential explanation fails to account for key observations. Students with adequate general literacy still struggle with understanding medical texts and critically appraising the evidence they find. Interventions targeting reading alone don't improve evidence synthesis. Conversely, instruction in formulating clinical questions doesn't improve textbook comprehension.

These are not separate deficits with incidental co-occurrence, but parallel expressions of shared underlying cognitive mechanisms. This "puzzle" is largely an artifact of siloed professional disciplines. Cognitive scientists and literacy researchers have argued that the distinction between textbook literacy and information seeking is artificial in complex learning environments [20, 21]. The cognitive task of building a mental model from multiple, complex, often conflicting sources, known as multiple document comprehension, is the shared architecture, whether those documents are textbook chapters or database search results [20, 21].

The Shared Cognitive Architecture

A reasonable objection is that the capacities described below are foundational to most forms of learning, not just reading and information practice. We concede the point. These are general cognitive capacities. What current instruction overlooks, however, is their simultaneous expression across two domains that medical education treats as separate. When a student reads a pathophysiology chapter without monitoring comprehension, that same student might search PubMed without monitoring search effectiveness. When a student is overwhelmed by the density of a pharmacology text, that same student may be overwhelmed by the task of synthesizing multiple search results. The contribution of this framework is not in identifying novel cognitive capacities but in making visible the shared architecture that connects these parallel deficits, and in providing a unified instructional rationale rather than separate remediation strategies for separate problems.

Both textbook literacy and information literacy depend on three interconnected cognitive capacities. Understanding

these as foundational, rather than peripheral, reframes how we approach "library" instruction in medical education. As illustrated in Table 1, the cognitive deficits students demonstrate when struggling with textbooks are functionally identical to those they demonstrate when struggling to critically appraise clinical evidence.

1. Metacognitive Self-Regulation: Monitoring and Directing One's Own Learning

Metacognition encompasses both metacognitive knowledge (understanding what strategies work and why) and metacognitive regulation (actively monitoring and controlling learning processes) [22, 23]. Zimmerman's self-regulated learning theory demonstrates that successful learners plan, monitor, and evaluate their learning through cyclical processes of forethought, performance, and self-reflection [24]. In medical education, metacognitive skills predict academic performance better than many traditional aptitude measures [25-27], with metacognitively aware learners consistently outperforming peers even when matched on prior knowledge and general cognitive ability [28-30].

Implication for librarians: Teaching students to first articulate their goals, monitor whether the process is meeting their information needs, and evaluate whether to modify their approach teaches universal metacognitive practices applicable across the full range of information literacy behaviors. This is the cognitive core of *Research as Inquiry*, the recognition that engaging with information is an iterative, self-directed process of building understanding rather than a single retrievable act.

2. Working Memory Management and Cognitive Load

Working memory, the cognitive system for temporarily holding and manipulating information, is a multi-component system with limited capacity [31, 32]. Building on this model, Sweller's Cognitive Load Theory [33, 34] defines three load types that can overwhelm the system: intrinsic (the task's inherent difficulty), germane (load for building schemas), and extraneous (load from poor instructional design).

The theory is rooted in our understanding that limited working memory capacity can be easily overwhelmed when processing complex information simultaneously. Recent applications to medical education demonstrate that instructional design ignoring cognitive load principles consistently produces poor learning outcomes [35-37]. When working memory is overloaded, learning cannot occur effectively regardless of motivation or prior knowledge.

These types of loads manifest in recognizable ways across both domains. Intrinsic load in textbook reading stems from the material's inherent complexity. A paragraph on cardiac electrophysiology requires holding multiple ion channel states in mind simultaneously. In information gathering, intrinsic load appears differently but

analogously. Formulating a clinical question into searchable components while maintaining awareness of the clinical context requires juggling multiple conceptual elements at once. Germane load, the productive effort of building schemas, looks like a student connecting a textbook passage on renal physiology to a previously learned concept in cardiac output. In searching, it is akin to a student recognizing that two search results describe the same mechanism from different clinical perspectives and constructing a coherent model from both. Extraneous load, or wasted effort from poor design, includes unnecessarily complex textbook layouts in one domain and cluttered database interfaces in the other.

Implication for librarians: Teaching students to document their reasoning process, use structured evaluation criteria, and chunk complex information into manageable units teaches cognitive load management principles applicable across the full range of information literacy behaviors. This includes not only searching, but also reading primary literature, appraising conflicting evidence, and situating a source within an ongoing scholarly conversation. A student overwhelmed by the density of a pharmacology text may well be the same student who struggles to hold competing claims from multiple systematic reviews in mind long enough to synthesize them. Research suggests the cognitive bottleneck is shared even when the task looks different [32, 33, 38]. Recent studies support this approach, showing that instruction addressing cognitive load produces better outcomes than traditional skills-based training [39, 40].

3. Epistemic Sophistication: Understanding Knowledge as Constructed and Contextual

Epistemic cognition refers to individuals' conceptions about the nature of knowledge and knowing. William Perry first described students' intellectual development from simplistic, dualistic views of knowledge ("there are right answers that authorities know") to complex, contextual, committed relativism ("knowledge is constructed, contextual, and requires evidence-based judgment") [41, 42]. This pillar is directly "braided" with metacognition. As Hofer and Pintrich argued, a student's epistemic beliefs directly influence their use of metacognitive strategies [43]. Research shows that students with naive epistemic beliefs adopt rigid, surface-level strategies in both reading and information seeking, failing to tolerate the ambiguity inherent in clinical evidence [44-46].

It is worth noting that the educational structures preceding medical school may actively reinforce this epistemic stance. The MCAT and the multiple-choice formats that dominate preclinical and licensing examinations reward single-best-answer selection, precisely the dualistic orientation that Perry identified as

the earliest stage of intellectual development [41]. Students arrive having been rewarded for finding "the right answer" and are then expected to navigate a landscape of probabilistic, contextual, and often conflicting clinical evidence. Interventions aimed at developing epistemic sophistication must reckon with this structural reinforcement.

Implication for librarians: When we teach source evaluation, we implicitly teach epistemic concepts about evidence and knowledge construction in medicine; helping students understand why we privilege peer-reviewed literature, how evidence hierarchies work, and why expert disagreement exists. Making these concepts explicit develops epistemic sophistication applicable to both reading and searching. This is precisely what *Authority is Constructed and Contextual* and *Scholarship as Conversation* demand of learners. It isn't merely the ability to locate a credible source, but the capacity to understand why credibility is constructed differently across contexts, and to recognize that the conflicting expert voices they encounter in the literature are not a problem to be resolved but a feature of how medical knowledge evolves. Research has argued that medical students should learn basic terminology and methods of epistemology as they're introduced to EBM concepts [13], positioning librarians as natural partners in this epistemic development.

Synthesis: The Integrated Framework

These parallels are not coincidental; they are two manifestations of the same cognitive-constructivist process. Kintsch's *construction-integration model* posits that readers build mental representations by integrating new text with existing knowledge [11]. This mirrors the information gathering process, where students must construct coherent mental models from multiple, often conflicting, sources.

Both literacies are acts of schema construction governed by the same working memory limitations and guided by the same metacognitive judgments. Consequently, traditional interventions fail because they treat symptoms rather than causes. Teaching students to locate sources without developing the cognitive capacity to interrogate, situate, or synthesize them is like teaching vocabulary without comprehension strategies: it provides tools but not the architecture to use them.

Practical Implications for Health Sciences Librarianship

Understanding the shared cognitive architecture of reading and information literacy has immediate practical implications for how health sciences librarians design instruction, assess student competencies, and position themselves within medical education.

Table 1

The Shared Cognitive Architecture of Literacy Deficits: Mapping the Parallel Cognitive Demands of Reading and Searching

Cognitive Pillar	The "Textbook Literacy" Deficit	The "Information Literacy" Deficit	The Shared Instructional Solution
1. Metacognitive Self-Regulation (<i>Monitoring & Directing</i>)	The Unaware Reader: Continues reading despite loss of comprehension; fails to re-read or look up unknown terms; lacks "fix-up" strategies for confusion [47, 48].	The Unreflective Inquirer: Clicks links without planning; accepts initial results without evaluation; reads a clinical guideline without questioning its applicability; fails to recognize when an information strategy is not meeting a need [2, 38, 49].	Teach Monitoring: Require students to articulate goals before starting, periodically check if results/text match goals, and evaluate strategy effectiveness.
2. Working Memory Management (<i>Processing Capacity</i>)	The Overwhelmed Reader: Attempts to memorize isolated facts without schemas; overwhelmed by complex syntax; fails to use structural cues (headings) to chunk data [50-52].	The Overwhelmed Synthesizer Juggles sources without organizational criteria; Trial-and-error searching; opens tabs randomly; cannot hold competing claims in mind long enough to synthesize them; struggles equally when searching or appraising evidence [38, 39].	Teach Structure: Provide external scaffolds (graphic organizers, search logs, evidence appraisal templates) to offload working memory and reduce extraneous load.
3. Epistemic Sophistication (<i>Nature of Knowledge</i>)	The Fact-Seeker: Views texts as repositories of absolute truth; frustrated by nuance or conflicting physiological theories; seeks "the right answer" [46].	The Certain Knower: Seeks single authoritative sources; accepts clinical guidelines uncritically; paralyzed or dismissive when experts disagree; lacks framework for understanding why authority varies across contexts [53, 54].	Teach Complexity: Explicitly discuss evidence hierarchies, the probabilistic nature of medical knowledge, and the value of expert disagreement.

Rethinking Instructional Design

Many skilled health sciences librarians already incorporate elements of what we describe. Experienced instruction librarians routinely teach students to decompose research questions, evaluate sources critically, and reflect on search effectiveness. These practices naturally align with the cognitive architecture outlined above. However, the available evidence suggests this kind of instruction remains the exception in medical education. Smith and Sanger described their multi-year, scaffolded IL program at McMaster University as a "rarity" in undergraduate health sciences, noting that one-shot, skill-based instruction remains the dominant model despite its acknowledged limitations [55]. Similarly, Hartman et al.

documented persistent reliance on inappropriate resources among medical students even after standard library instruction [3].

The framework we propose does not introduce entirely new teaching practices. It provides a theoretical language, grounded in cognitive science, that makes explicit the rationale for the kind of integrated, metacognitive instruction that effective librarians already practice. This language serves two purposes: 1) it offers a design framework for librarians moving beyond skills-based instruction, and 2) it provides the vocabulary necessary to advocate for embedded IL instruction in the terms that medical educators and curriculum committees use.

Since reading and information engagement share cognitive foundations, instruction addressing both

simultaneously might be more effective than separate approaches. Library sessions could explicitly connect database searching strategies to textbook reading strategies, helping students recognize that the metacognitive monitoring skills used while reading (Do I understand this? Do I need more information? How does this connect to what I know?) apply directly to formulating a clinical question or synthesizing conflicting sources (Is my search strategy working? Do I need to modify my approach? How does this source relate to others I've found?).

Expert librarians execute sophisticated cognitive processes automatically, monitoring search effectiveness, managing cognitive load by chunking results into categories, and applying epistemic frameworks to evaluate sources. Novice students don't see these processes. Instructional design should make invisible cognitive processes visible through think-aloud demonstrations, metacognitive prompting, and explicit discussion of epistemic frameworks underlying source evaluation.

Reimagining Assessment

Many information literacy assessments already incorporate measures of critical engagement with sources, and this represents important progress beyond simple task completion. The cognitive architecture framework suggests a further extension, assessing not only whether students engage critically, but also questioning the underlying processes that enable that engagement. A student may identify a high-quality systematic review while relying on a surface-level heuristic (choosing the first Cochrane result) rather than genuine epistemic reasoning about evidence hierarchies. Process-level assessment asks not only "Did the student find an appropriate source?" but "Can the student articulate why it is appropriate, monitor whether their search strategy is working, and recognize when to change approach?"

If reading comprehension and database searching share cognitive foundations, information literacy assessments should also include strategic reading assessments. Students who cannot effectively read and integrate information from scientific texts fundamentally lack a core information literacy competency, even if they can execute database searches. This provides an opportunity to reframe how the scope of information literacy in medical education is conceptualized.

Positioning Librarians in Medical Education

Understanding that information literacy depends on fundamental cognitive capacities positions librarians not only as service providers teaching technical skills, but also as educational partners addressing core learning competencies. When a medical educator observes that students "can't evaluate sources," it may reflect a deficit in metacognitive monitoring, cognitive load management,

and epistemic sophistication, the same deficits resulting in reading comprehension difficulties. This positions library instruction to address fundamental educational objectives rather than only peripheral research skills.

Many medical educators recognize that students struggle with reading comprehension but feel ill-equipped to address it. Librarians, equipped with this cognitive framework, can partner with medical educators to develop integrated interventions addressing both reading and information practice. Problem-based learning sessions could incorporate explicit instruction in metacognitive monitoring applicable to both textbook study and evidence searching. Clinical reasoning exercises could explicitly address epistemic sophistication in ways supporting both clinical decision-making and information evaluation.

When advocating for information literacy instruction, librarians can articulate their value in the cognitive and educational language that medical educators use. Rather than arguing that students need to "learn how to utilize PubMed," students instead need to develop metacognitive self-regulation, manage cognitive load in complex information environments, and develop epistemic sophistication about medical evidence. These cognitive capacities serve as foundational competencies that can help predict future clinical competence and lifelong learning capability.

Future Directions and Research Questions

This reconceptualization opens several research questions that health sciences librarians are primed to pursue. Intervention studies comparing integrated cognitive instruction against traditional skills-based sessions would test whether the framework improves outcomes across both reading and information engagement. Librarians designing new IL programs could embed such comparisons within existing instruction. Transfer studies would test whether metacognitive strategies learned in one domain (e.g., search strategy monitoring) would improve performance in the other (e.g., textbook comprehension), validating the shared architecture claim and informing instructional design. Finally, practical assessment instruments measuring metacognitive monitoring, cognitive load management, and epistemic reasoning could identify at-risk students early and target interventions before deficits compound.

CONCLUSION

Understanding this shared cognitive architecture has immediate practical implications for instructional design, assessment, and positioning within medical education. Rather than teaching discrete information skills in isolation and hoping students will transfer them, students should be taught the underlying cognitive strategies enabling both effective reading, searching, and critical

engagement of evidence. Rather than positioning librarians as service providers teaching peripheral technical skills, they should be considered educational partners addressing fundamental learning competencies that predict clinical success.

In most medical schools, information literacy instruction currently takes the form of limited, session-based training focused on database mechanics, search syntax, and source identification [3, 55]. Even when these sessions incorporate critical evaluation, they are rarely integrated into the broader medical curriculum, rarely scaffolded across preclinical and clinical years, and rarely designed with explicit attention to the cognitive processes that determine whether students can transfer what they learn. The framework proposed here envisions a concrete shift. From isolated sessions to longitudinal cognitive instruction embedded within medical courses, from teaching search mechanics to teaching metacognitive monitoring as a transferable clinical skill, and from assessing whether students can complete a search to assessing whether they can regulate their own learning across both domains. This shift does not require librarians to abandon existing expertise but to reframe it in terms that articulate its value to medical educators and curriculum committees.

The evidence supporting this framework comes from multiple disciplines including cognitive psychology's models of reading comprehension and information processing, educational research on metacognition and self-regulated learning, medical education research on clinical reasoning development, and information science research on information-seeking behavior. By integrating insights from these fields, educators can move beyond treating symptoms and address the underlying causes.

This reconceptualization doesn't diminish the importance of technical skills like Boolean operators or reading techniques like SQ3R. Rather, it situates these technical skills within a broader cognitive framework that explains when, how, and why to deploy them. Students need both the cognitive architecture and the technical tools, but without the architecture, the tools remain inert.

Medical education faces increasing complexity, expanding knowledge bases, proliferating information sources, growing emphasis on evidence-based practice, and emerging challenges from AI-generated content. In this environment, the fundamental cognitive capacities described become more critical, not less. Students must learn not just how to think, but how to monitor their understanding, manage cognitive complexity, and evaluate knowledge claims in an uncertain, evolving evidence landscape.

Health sciences librarians are ideally positioned to lead in developing these capacities. They work at the intersection of information, learning, and evidence-based practice. These librarians understand both the technical

requirements of information access and the cognitive requirements of information synthesis. By embracing this broader understanding of a librarian's educational role, not as purveyors of database skills but as developers of fundamental cognitive competencies, instruction can be made more effective, assessment more meaningful, and value more apparent to medical educators and students alike.

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Still a filtering failure? A follow-up commentary on automated MeSH indexing

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See end of article for authors' affiliations.

We previously found that automated indexing in PubMed and Medline increased the risk of inappropriately excluding human studies when using the human studies filter from the Cochrane Highly Sensitive Search Strategy (HSSS). Following the National Library of Medicine's transition from the Medical Text Indexer-Auto (MTIA) to the Medical Text Indexer-Next Generation (MTIX) in 2024, we wanted to assess whether that was still the case. Using the same approach as our previous study, we reviewed a set of MTIX-indexed records that were excluded by the HSSS. Only 1.1% turned out to be human studies that were inappropriately excluded – a major improvement over not only MTIA but also human indexers in our previous comparison. However, problems remain with automated indexing and search filters. This commentary outlines our findings and our ongoing concerns.

Keywords: Automated MeSH indexing; filter; commentary

INTRODUCTION

Medical Subject Headings (MeSH) are a key controlled vocabulary for health librarians. They are used extensively in knowledge synthesis searching both to discover relevant records and to exclude those which are irrelevant, as exemplified by the Cochrane Highly Sensitive Search Strategies (HSSS), which use the string 'exp animals/ not humans.sh' combined with NOT against the rest of the search to limit to human studies ("NOT-NOT" logic) [1]. Traditionally MeSH have been applied to records in PubMed/Medline by human indexers; however, more recently the National Library of Medicine (NLM) has moved to automatically applying algorithmically determined headings to its records. The current algorithm in use, Medical Text Indexer-NeXt Generation (MTIX), uses a machine-learning model for MeSH term assignment. It replaced the previous Medical Text Indexer-Auto (MTIA) algorithm in April 2024 [2].

We previously evaluated the impact of MTIA on inappropriate exclusion of human records through use of the Cochrane HSSS [3]. At that time, we concluded that the HSSS would inappropriately exclude human studies automatically indexed via MTIA at nearly seven times the rate of those indexed by human indexers. We sought to update our previous study to evaluate the implementation of MTIX, to see if our conclusions would change.

REPEATING OUR METHODS

As reported at CHLA 2025 [4], we sought to assess the potential impact of MTIX on the assignment of human indexing terms and the resulting inappropriate exclusion

of human studies from knowledge synthesis searches. To accomplish this, we adopted the methodology of our previous study [3]: we first conducted a search in Ovid Medline using the Cochrane HSSS [1] as our search strategy. We then limited our results to those which were specifically excluded by the non-human-studies string in the period since the implementation of MTIX and which used an automated indexing method.

1. randomized controlled trial.pt.
2. controlled clinical trial.pt.
3. randomized.ab.
4. placebo.ab.
5. clinical trials as topic.sh.
6. randomly.ab.
7. trial.ti.
8. 1 or 2 or 3 or 4 or 5 or 6 or 7
9. exp animals/ not humans.sh.
10. 8 not 9
11. 8 not 10
12. medline.st.
13. 11 and 12
14. and (202405* or 202406* or 202407* or 202408* or 202409* or 202410* or 202411* or 202412*).da.
15. and automated*.ig.

A total of 2,285 unique results were imported into Covidence for screening. The results were screened independently by two team members at the title-abstract and full-text stages. Records were included if they described a human study, according to the definition adopted in our previous paper: (a) the study was interventional and the intervention was performed on a human or human product (human cells, tissues, etc.); (b) the study was comparative and involved a comparison between groups of humans; or (c) a significant outcome of interest was focused on humans. Twenty-five studies meeting this definition were ultimately included and were analyzed using the custom data extraction form developed for our previous study.

As part of the extraction process, we considered potential reasons why papers might be misidentified as non-human studies. The most frequent cause was a single record which described multiple studies, at least one of which was a human study – for example, combining an observational study in humans with an experimental study on animal subjects, which is then indexed only using animal terms. This cause is consistent with the performance of both MTIA and human indexers in our previous paper.

Our previous study found that 4.2% of articles excluded by the non-human-studies string and indexed via MTIA were in fact human studies, compared to 2.2% in the set of studies indexed by human indexers. In this update, 25 of 2,285 studies screened, or 1.1%, were inappropriately excluded human studies. Thus, according to our analysis, MTIX outperformed not only MTIA but also the human indexers in our previous study.

This is consistent with expectations from NLM. As they reported in their launch of MTIX, they found that F1 scores (combining recall and precision) in MTIX-indexed records were 96% for the MeSH term “humans” and 92% for “animals” [5]. However, terms that were used less consistently by human indexers (which was the indexing method for the algorithm’s training set) perform less well [6].

SO, WE’RE ALL GOOD NOW?

At first glance, our repeated study has a positive outcome, and we do not wish to downplay the benefit of having better indexing moving forward. However, there continues to be a major stumbling block in using this filter for knowledge synthesis: while some individual records have been curated by human indexers – a few even before our previous study was published – others remain

uncorrected even years after publication and continue to be inappropriately excluded by the filter. Moreover, hundreds of knowledge synthesis projects published while MTIA indexing was in effect used the Cochrane Highly Sensitive Search Strategy.* It is unknown what impact potentially missing human studies may have had on their findings.

Although curation addressed the misindexing of some of the records in our study, this practice is limited: as reported on the expertsearching listserv, curation is targeted only to high-impact publication types and population groups, does not generally add missing headings outside a narrow set, and “curators are instructed to leave terms in place unless they are sure they are wrong” [7]. NLM has reported that they are considering using MTIX to update old records, but that such a project would be limited in scope [2]. As noted by Amar-Zifkin and colleagues, it would also impact replicability of prior searches [8].

UH OH

There is also evidence to suggest that the problem extends beyond human studies filtering to encompass other purely MeSH-based approaches to study inclusion or exclusion. For example, a MeSH string is often used to limit results by age group or by sex/gender. As one author presented at CHLA 2025 [9], there was a sharp decline in use of major age-related MeSH terms like “adult” and “newborn”, as well as “female” and “male”, in Medline records during the period in which MTIA was in use. This is consistent with the pilot study by Chen and colleagues using the Interactive MTI tool [10]. While to our knowledge no study has yet evaluated the practical effect of these indexing deficiencies, it seems very likely that they would impact MeSH-based filtering of records by age or sex/gender.

Other authors have described further problems with MTIA indexing which may impact discoverability of records. For example, Amar-Zifkin and colleagues found cases of both inappropriately assigned and inappropriately omitted MeSH terms [11]. Philippopoulos found that no MTIA-indexed records included the MeSH for “intersex persons”, despite the presence of around 100 records that should have included it [12]. Wilson found that MTIA often misunderstood figurative language in applying the MeSH term “Malus” (apple tree) to records in which the term “apple” was used metaphorically [13]; while this example resulted in overbroad rather than overspecific search results, it suggests the possibility of studies using more figurative terms being missed due to

* While inexact, a search of Google Scholar for (“exp animals not” intitle:review) limited to publications between 2021 and 2024 returns 367 results.

literal interpretation. Again, it is unclear what impact these have had on already published reviews, or ongoing or future reviews that will search records from this period.

It is also possible that problems with MeSH indexing may impact searches in other databases. For example, Embase uses MeSH terms for “articles from other MEDLINE titles (with a focus on basic biomedicine, Allied Health and other topics that are peripheral to the core topics of Embase)” [14]. Searches on these topics in Embase would thus also be affected by problems with MeSH indexing, particularly given that these are areas that already tend towards ambiguous terminology, as explored by Amar-Zifkin and colleagues [8]. Additionally, while EBSCO reports only using human indexers [15], our informal investigation of indexing problems has led to the incidental finding that the Human heading is often absent from CINAHL records of human studies, despite the records being otherwise well-indexed. It is unclear why this is the case, but it does suggest that limiting to human studies in CINAHL could be of questionable validity for knowledge synthesis searching.

WHAT NOW?

MTIX represents a significant improvement over MTIA in terms of accuracy of human/animal indexing. However, records which were indexed by MTIA still exist, and are still potentially relevant to knowledge synthesis searches. Therefore, we echo our previous conclusions: we urge information specialists conducting knowledge synthesis projects in Medline or PubMed to exercise caution in using pure-MeSH filters for searches that will encompass the period in which MTIA was in use. In fact, given the findings of colleagues, we would extend that caution to any use of exclusively MeSH-based approaches for records from this period.

It is also advisable to consider other methods to ensuring the discoverability of research, such as through author-supplied keywords or an amended approach to abstract writing. This is particularly important given that MTIX does not have access to the full text of the article, whereas human indexers did [6]. Allen and colleagues have proposed an author checklist to mitigate indexing problems [16].

Indexing concerns in databases other than PubMed/Medline are relatively understudied. There have been some studies of indexing discrepancies in Embase's Emtree [17], but more work is needed to understand if and how indexing algorithms and practices may impact searches in other databases.

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Appendix A was not included with the originally published manuscript. The appendix has since been added and is now available with the article.



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