AI and Open Science: Implications and Library Practice Recommendations

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Nicole Helregel

Abstract
With the increasing proliferation of artificial intelligence (AI) in higher education and science, technology, engineering, and mathematics research, what are the implications for open science? As the open science movement advocates for increased transparency and openness in the research process, where do AI and machine learning fit in? And where does that leave library and information science professionals in roles related to open science? This article explores several approaches and considerations for how AI impacts open science, including whether AI has sufficient openness and transparency to align with the goals of open science, whether AI can be used to further open science goals, and the effects of AI use on researcher and public attitudes and actions. The article provides recommendations for library practice, including knowledge-building, connections and advocacy, consultations and liaison work, licensing, and science communication and engagement.

Keywords
artificial intelligence, open science, open scholarship, open knowledge, transparency, replicability, reproducibility, public trust

Introduction and Definitions
Artificial intelligence (AI) and its applications across science, technology, engineering, and mathematics (STEM) research disciplines have many important implications for the open science movement and, by extension, those in the library and information science world who support open science practices, infrastructure, and community. This article engages with artificial intelligence as a broad category that contains several

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subcategories, including machine learning, neural networks, and generative AI. This article addresses the ways that AI creation and use across STEM impact and interact with open science, as well as recommendations for librarianship practice.

Open science is an umbrella term that encompasses and engages with a variety of open movements. Open science usually refers to making various elements of the research process publicly available and transparent—including the research methodology used, any code created (for analysis, visualization, etc.), data collected or generated, publications produced, peer review reports written, and metrics generated—in an effort to expand access to scientific knowledge both within and outside of academia. While some definitions and conceptions of open science are limited to making parts of the research process publicly and freely available, largely with access for other academics in mind, a large part of open science is concerned with making science more comprehensible and participatory for those outside of academia via efforts such as science communication, citizen/participatory science, and science democratization. Silveira et al. (2023) and UNESCO (2021) propose useful taxonomies and visualizations of the many components of open science. Openness thus tends to operate on a spectrum, with stricter definitions that necessitate open licenses at one end and looser definitions that advocate for more transparency in general on the other end.

One helpful way to parse the different components and motivations across open science is presented in Fecher and Friesike's "Open Science: One Term, Five Schools of Thought" (2014). They outline the assumptions, worldviews, and goals of open science practitioners and advocates across five different schools of open science:

- The infrastructure school, which focuses on building the tools and platforms needed to make open science more doable;
- The democratic school, which focuses on ensuring the free access of knowledge for all via projects such as open access publication and open data sharing;
- The pragmatic school, which focuses on the benefits to science outcomes gained from open collaboration;
- The public school, which focuses on making science understandable for all via projects such as science communication, citizen/participatory science, and public engagement; and
- The measurement school, which focuses on changing the incentive structures that currently drive much of the current scholarly communication enterprise, via projects such as open peer review, preprints, and registered reports.

The Five Schools of Thought framework offers a helpful lens through which to view the different goals, priorities, and projects associated with open science.

Libraries and library and information science (LIS) workers have engaged with the open science movement in a variety of ways, including through supporting repositories, open workflow software, and other infrastructure; providing instruction on research data management and related tools; and building community via hosting reproducibility discussion groups and supporting citizen/participatory science projects. Libraries are well positioned to participate in and shape the open science movement, as they already contribute to many of the projects and initiatives of open science, including open data, open access, and research data management. LIS workers are often driven by many of the principles that ground the different open science schools of thought, including democratizing access to knowledge, focusing on engagement and outreach, and building accessible tools and infrastructure for large institutional projects and goals.

Libraries are similarly well positioned to contribute to conversations about AI in STEM research and higher education. The recent fervor around generative AI and its implications for higher education has led to extensive conversation in the LIS world on how libraries should be engaging with generative AI in several areas, including evaluating generative AI tools for relevance, trustworthiness, accuracy, bias, privacy, and so on; using generative AI for literature searching and topic building; and conceptualizing algorithmic literacy, as either part of or distinct from information literacy and data literacy. LIS workers should broaden and expand this conversation beyond generative AI to include different types of AI, how AI is being used in STEM research, and how AI use impacts open science.

AI Implications for Open Science

Increased creation and use of AI applications affects open science in three different major ways: (1) the potential openness and transparency, or lack thereof, of AI use in STEM research; (2) the potential for using AI to further the projects and goals of open science; and (3) the effects of AI use on the attitudes and actions of those within and outside of the scientific research community.

AI Use, Openness, and Transparency: Problems and Potential

AI models and tools are increasingly being used across several STEM disciplines in a variety of different research projects, from protein structure prediction to agricultural pest identification to space weather prediction (National Artificial Intelligence Research Resource Pilot, n.d.). Consequently, how AI use in STEM research will affect openness and transparency is of great concern. Potential problems with AI and openness are abundant, but so are the emerging proposed solutions.

One overarching problem is the lack of standardization for preserving AI models and making them more transparent. Without adequate documentation of the component parts of a model as well as indicators of how it makes decisions, reproducibility and replication are hindered.

Reproducibility and replication are key parts of the modern scientific method, as they help to validate and solidify conclusions from existing studies. If researchers use a preexisting AI tool in the course of their research, whether a generative AI tool for writing and/or literature searching or an existing AI model within a subject or research area, they need to evaluate whether the tool is sufficiently transparent to support the goals of open science. If a tool lacks transparency or its creators are engaged in "open-washing," wherein they claim that the tool is open but in effect it is not (Kessler 2024), the outcomes of a study based on use of the tool are not as replicable or reproducible as they could be. If the AI tool is closed or proprietary, then often the best that researchers can do to foster openness is to cite their use of the tool, include the date it was used or accessed, and give an indication of the version. However, many AI tools are updated nearly continuously and do not have discrete versions.

If researchers create their own AI models, then the tasks of preservation and transparency fall to them. Unfortunately, a variety of different stakeholders are still very much in the process of creating, codifying, and agreeing on the guidance for AI preservation and transparency. Many efforts toward creating guidance have come out of the concern that AI use within STEM is causing its own reproducibility crisis (Ball 2023; Gibney 2022). Also, there is concern that science will end up relying on AI models that are not sufficiently sound, which is hard to determine without enough transparency. For example, a common problem in the creation of an AI model is data leakage, which is when errors occur in the construction of a model, often because the training dataset and the testing dataset were not distinct enough, leading to misleadingly positive assessments of the model's performance (Kapoor and Narayanan 2023). If an AI model is insufficiently documented, then peer reviewers and readers will have trouble identifying such problems.

These documentation issues are compounded by disagreements about how much transparency is enough for AI models, often playing out at the disciplinary level, due to the absence of strict, clear, or even extant guidelines from the journal or publisher. For example, in 2020 a group of researchers published an AI system in *Nature* that they claimed was better than human experts at detecting breast cancer from mammography imagery (McKinney, Sieniek, et al. 2020). Another group of researchers published a response stating that the initial group had not included sufficient documentation, explaining that even if the full datasets could not be shared due to privacy concerns, much more information about the development of the model, including the hyperparameter definitions, model predictions, and data labels, should have been shared (Haibe-Kains et al. 2020). The initial researchers responded by adding an addendum to the article that addressed some of the omissions and also publishing a response that pushed back on several assertions, explaining that some of the data was not from an open dataset and thus could only be used in a closed manner (McKinney, Karthikesalingam, et al. 2020). Thus, the lack of set guidelines and policies continues to present a problem, as researchers are often caught between the desire to open up more of their work and the logistics and legalities of doing so.

Even when researchers commit to a high level of openness in the documentation of their AI models, translating that into something comprehensible can be a challenge. As ever more complex black box machine learning models have emerged, the concepts of AI explainability and interpretability have become increasingly important. Some equate the two concepts, whereas others make a distinction; the International Organization for Standardization defines explainability as the “level of understanding how the AI system came up with a given result” and interpretability as the “level of understanding how the underlying (AI) technology works” (2020). So explainability is slightly narrower, as it refers to specific decisions or results, whereas interpretability is a broader understanding of how the whole system functions. Both are important ways of understanding complex deep learning and neural networks and are important for transparency and accountability.

There are many techniques for addressing explainability and interpretability, including feature importance, which highlights which factors most affected the decision or outcome (Dirgová Luptáková et al. 2024); saliency maps for image-based machine learning, which show the parts of the image that contributed most to the decision or outcome (Rudner and Toner 2021); model visualization, where an AI model attempts to make a visualization of how it works and makes its decisions (Rudner and Toner 2021); text explanations, where an AI model explains in words how it came to a decision (Barredo Arrieta et al. 2020); and explanations by example, where an AI model gives specific data points as examples of how it came to a specific decision or outcome (Barredo Arrieta et al. 2020). None of these techniques are a silver bullet for making an AI model as transparent as possible but, rather, serve as individual tools toward increasing AI transparency.

Increasing demands for AI explainability and interpretability are part of broader calls for AI accountability, particularly when AI applications are used to make decisions that directly affect people and their lives. This points to the desire for AI to be more open not only technically and infrastructurally but also publicly and democratically. Increased transparency and openness will enhance the potential for reproducibility and replication, as other researchers will have the information needed to reproduce and replicate studies based on AI models. But greater transparency and, when applicable, a focus on explainability and interpretability could also result in greater accountability for those who deploy AI-based decision-making applications and, potentially, greater trust in AI-based research. Interpretability is key to enabling individuals to be critical of AI use by large institutions and governments and to challenge AI-based decisions (Busuioc 2021). Thus, working toward greater transparency, openness, and explainability/interpretability for research that uses AI can have effects that go beyond academia.

While there are many pitfalls and deficiencies in the current landscape of AI transparency and openness, many individuals and organizations are stepping up to propose solutions and develop regulations, guidelines, protocols, and metrics for making AI more open. Many of the guiding principles that already exist within the open methods, open code, and open data areas of open science can be applied toward efforts to open up AI. For example, the Open Source Initiative, which is a nonprofit organization that spearheads the open-source software movement, is currently working on a definition of what "open-source AI" would look like. The April 2024 draft of the definition specifies that open-source AI systems grant permissions to freely use, study, modify, and share the system and includes several required components: data information (including training methodologies and techniques, training data scope and characteristics, training data provenance, training data labeling procedures, and training data cleaning methodology), code (including that for data preprocessing, training, validation, testing, and inference and supporting libraries and tools), and the model (including the model architecture and the model parameters) (Open Source Initiative 2024). A variety of other elements are considered optional, including the training, testing, validation, and benchmarking datasets; sample model outputs; and model metadata. This definition, once codified into a stable form, will have an impact on behavior, in terms of what some individuals and institutions will do to make sure that their AI is classified as open source; many will not be able to get away with the open-washing that they have been operating under so far. Fully open AI cannot be the expectation for all, as privacy concerns and protections against misuse are still important considerations. But specifying what defines an AI system as open source will be a helpful step toward more openness and transparency in AI use in STEM research.

Another example of a proposed solution for increased AI transparency involves the FAIR principles and their adaptations for AI. The FAIR principles are guidelines for making data more transparent, though not necessarily or strictly open, and they focus on four areas: findability, accessibility, interoperability, and reusability (Wilkinson et al. 2016). These areas all specify details for the data itself as well as the metadata in order to ensure ease of access and reuse. These principles have been adapted for research software in the FAIR Principles for Research Software (Barker et al. 2022). Barker et al.'s definition of research software, citing Gruenpeter et al. (2021), includes "source code files, algorithms, scripts, computational workflows and executables that were created during the research process or for a research purpose" (Barker et al. 2022). While descriptive in terms of software, this definition and the accompanying list of FAIR research software principles do not include the level of specificity needed for replicable and reproducible AI models, as things such as operating systems and hardware specifics also play a large role in achieving AI-based outcomes.

Thus, some have gone further and more specifically toward calling for and starting to outline FAIR principles for AI applications. Huerta et al. (2023) offer a comprehensive overview of the need for and efforts around FAIR principles for AI applications across a variety of science, engineering, and medical disciplines and propose FAIR AI principles. These FAIR AI principles offer more specificity regarding the elements that make up an AI model and for which documentation is needed to achieve FAIRness. Adoption of FAIR AI principles and practices by individual researchers, or even at a larger scale by journals, publishers, and/or funders, would have a significant impact on the openness, reproducibility, and replicability of AI-based science research. Giving researchers clearer guidelines and instructions would begin to address the relative lack of openness of AI in STEM and would set transparency expectations for researchers going forward.

With broad, cross-discipline models still being developed, much of the progress on making AI in STEM more open and transparent is happening within specific disciplines. As exemplified by the McKinney, Sieniek, et al. breast cancer imaging example given earlier, the details are often dependent on field-specific concerns, such as the privacy of health data. Models have been suggested for AI and machine learning transparency and documentation in a variety of subject areas, including the life sciences (Heil et al. 2021), chemistry (Artrith et al. 2021), and medicine (Kolbinger et al. 2024). And some models have emerged from researchers across many disciplines being brought together by computer scientists, such as that of Kapoor et al. (2024). Common elements of these suggested models include access to or, at a minimum, citation of dataset sources; documentation of steps for data cleaning, processing, or transformation; clarification of data labels; documentation of model validation measures; documentation of model training datasets and processes (some include explicit measures to prevent data leakage); inclusion of necessary code/scripts; and documentation of computing infrastructure. The suggested models also represent various levels of computational reproducibility, with some having flexibility across different levels of compliance and others requiring full single-command reproducibility. As with the open-source AI and FAIR AI models, adopting or even promoting these models at the individual researcher, journal, publisher, or funder level would have a large impact on the transparency, reproducibility, and replicability of AI-based science research. Conversations at the discipline level can also helpfully inform broader, cross-disciplinary frameworks.

Regulation and policy for AI are also increasingly happening at the federal level. Given the recent mandates from the US federal government and large funding agencies regarding the openness and availability of research publications and, in some cases, research data, it seems prudent to expect that such mandates will also eventually specify details regarding the openness or transparency of AI applications created with federal funding. In the October 2023 Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence, the White House called for a variety of actions from several government agencies and actors regarding AI use, including encouraging independent regulatory agencies to "emphasiz[e] or clarif[y] requirements and expectations related to the transparency of AI models and regulated entities' ability to explain their use of AI models" (2023). This emphasis on transparency is shared by the National Institute of Standards and Technology, which is under the Department of Commerce. The National Institute of Standards and Technology (n.d.) has been working for years on developing AI-related standards, fundamental research, and testing and evaluation methods. Some of its fundamental AI research areas are explainability, interpretability, accountability, and transparency, with a goal of increasing public trust in AI. Along with the National Science Foundation, it is sponsoring the work of the Institute for Trustworthy AI in Law and Society at the University of Maryland and George Washington University, which aims to address, among other topics, "how people make sense of AI systems, and the degree to which [the systems'] levels of reliability, fairness, transparency and accountability can lead to appropriate levels of trust" (Institute for Trustworthy AI in Law and Society, n.d.). Government focus on transparency is encouraging and will hopefully lead to greater transparency in STEM research that uses AI, both government-sponsored and otherwise.

Using AI to Further Open Science Goals

There is a great deal of potential for using AI to further several open science goals, both within and outside of the research community. Bourg et al. (2024) suggest that AI tools could be used to expand access to open data via projects such as automating data description and access processes and checking for open or transparent practice compliance. AI tools could also be used during the editorial process to help screen for submissions that meet journal requirements or after publication to track and measure the open science outputs of a journal, publisher, or institution.

Several examples of these kinds of tools and processes already exist: ODDPub, which screens for open data and open code within publications (Riedel et al. 2020); rtransparent, which screens for open data, open code, conflict of interest statements, funding statements, and protocol registrations (Serghiou et al. 2021); and DataSeer, which is being used by the Public Library of Science (PLOS) (2024) to measure rates of open data, open code, preprint posting, protocol sharing, and preregistration. These tools can help lower the administrative burden of tracking, measuring, and screening for open science in both editorial and assessment contexts, which helps institutions more efficiently implement open science policies.

Another way AI could be used to further open science goals is via translating science outputs, particularly scholarly articles, across different languages. The English language currently dominates indexed scientific scholarly publishing; for example, 97 percent of science articles indexed in Web of Science through 2015 were in English (Liu 2017). Open science must go beyond making things free and available online to think about linguistic openness as well. This should not entail using AI to convert everything into English for publication, which would just further the linguistic homogenization of the scientific literature. Rather, AI could be used to enable translation into whatever language is needed in the context of access. Bourg et al. (2024) argue for the use of AI to translate English-language publications into languages used in countries with developing and transitional economies. Chan et al. argue for research funders to support translation and open access publication of science from Indigenous knowledge holders and researchers from the Global South, particularly non-English-speaking countries, in order to create a "truly plurilingual scientific commons" (2020). AI translation tools have the power to contribute toward increased access to scientific knowledge; it will largely be up to journals, publishers, funders, and large platforms to decide what the funded practices and established norms will be as we move forward.

AI could be used to further the public-focused goals within the open science movement of increased science communication, outreach, and engagement with everyday people. One example is using AI to write summaries of scientific publications that are more comprehensible to nontechnical, public audiences. These summaries have the potential to make scientific research more understandable to the public, reducing barriers to scientific knowledge. Several such lay-summary tools already exist and purport to expand access to scholarly knowledge. Critics of the current tools warn of potential pitfalls, including that fact that using AI-created summaries can introduce inaccuracies (Nahas 2024); using the tools could lower public trust in science, whether due to errors or the perceptions of generative AI as untrustworthy (Alvarez et al. 2024); and using the AI summary tools could disincentivize scientists to learn the fundamentals of science communication and engagement, thus widening the personal gap between researchers and the public (Alvarez et al. 2024). Thus, it is probably best to consider AI as simply one more tool in the science communication toolbox, but one that should be used with judicious caution.

Finally, AI has the potential to advance the goals of participatory/citizen science projects, making them more efficient and wide-reaching. Participatory science projects can make scientific research more understandable and accessible to the public through direct engagement in the process of doing science work. Ceccaroni et al. (2019) outline several possible ways to use AI in participatory science projects: classifying or validating participant-collected data, using AI systems to maintain connections with participants and encourage their participation via customized rewards, and using AI systems to provide participant training and educational support in different contexts and languages. Ceccaroni et al. do warn of potential risks and pitfalls: that for some tasks AI will not prove to be better than humans; that participants could become disengaged from participatory science projects because they are uncomfortable interacting with an AI system; and that some AI systems lack mechanisms for accountability when they make mistakes, making them a liability in the context of publicly engaged science. Thus, researchers employing AI in participatory science projects should weigh the benefits and risks of doing so for their specific project, because while AI has the potential to further the goal of enhancing participation in science, it could also end up backfiring.

Effects of AI Use on Researcher and Public Attitudes

The increasing use of AI, both within STEM research and more broadly, impacts the actions and attitudes of individual researchers and the public. Some researchers' willingness to publish open access and make other parts of their research output publicly available will be affected by the practices of generative AI companies, which are known to harvest data from the open web to train their models. Researchers who do not want their work being used to train AI may be more hesitant to publish open access, share their data openly, or contribute to open science communication projects, including open resources such as Wikipedia. But choosing to share their outputs through more "closed" methods may not be the solution that AI-wary researchers imagine it to be, as several academic publishers have made or are exploring licensing deals with generative AI companies, including Taylor & Francis, Wiley, Oxford University Press, and Cambridge University Press (Wood 2024). In many of these cases authors were not asked for permission for their content to be licensed—something the publishers were not obligated to do under many publishing agreements—and the issue of royalties or other remuneration for authors looks to be largely undetermined as of yet (Hansen 2024). Conversely, some researchers may actively pursue open access publication in an effort to make their research more available to generative AI tools, with the goal of potentially broadening their impact. Thus, we may see changes in publisher agreements and types of licenses for publications, data, code, and other research outputs as authors consider degrees of openness and how their work could be used in the era of generative AI.

Another implication of the increasing use of AI is its effect on public attitudes toward science. In a 2023 Pew survey, 73 percent of respondents said that they had a great deal or fair amount of confidence in scientists to act in the public's best interest; this was down from 86 percent in 2019 (Kennedy and Tyson 2023). While public awareness of AI has increased in the last few years due to the proliferation of generative AI tools such as ChatGPT, this has not led to an increase in public trust. A 2023 survey of 17,000 people across seventeen countries conducted by researchers at the University of Queensland in collaboration with KPMG Australia found that 61 percent of respondents were either ambivalent or distrustful of AI and that their knowledge of AI was mixed: "Most people (82%) have heard of AI, yet about half (49%) are unclear about how and when it is being used. However, most (82%) want to learn more" (Gillespie et al. 2023). With the public being more trustful of science than of AI, increased use of AI in scientific research has the potential to further decrease trust in science.

One way to increase public trust in science, including, possibly, research that uses AI, is to increase public participation in and understanding of scientific research. In a 2024 report on "public perceptions, awareness, and information sources," the National Science Board and the National Science Foundation found that "U.S. adults who demonstrate greater understanding of scientific logic tend to express more trust in scientists to act in the best interests of society than those who express less understanding" (Southwell and Schneider 2024). Thus, working to increase public participation in and understanding of science research will likely have a positive impact on public trust in science. Multiple areas within the open science movement focus on this kind of work, including science communication, participatory science projects, and public engagement in scientific research and policy. The methods used in these areas of open science could prove to be effective when engaging the public on AI to increase their understanding of AI technologies and how they are used.

Calls to make research that uses AI more explainable and interpretable within the scientific community are also now being joined by calls to make AI more understandable to the public, to increase public rights to AI openness and transparency, and to engage the public in the cocreation of policy that governs AI applications by governments and the private sector. Some have advocated for the use of deliberative democracy groups to make recommendations on AI-related policy and governmental usage. One example is the People's Panel on AI, an event that brought together a small group of people, sampled representatively from across the United Kingdom, over the course of four days to learn about AI, confer with AI experts, engage in discussion, and create recommendations for AI policy (Davies 2024). Their recommendations included assertions that a global governing body for AI should be created, citizens should be central to AI governance in the United Kingdom, efforts to raise public awareness about AI across society should be increased, transitional workplace training for jobs that will use AI going forward should be created, conversation about AI that includes a group like the People's Panel should continue, and inclusive collaboration and transparency should be central to AI. By the end of the panel the participants had also developed a vision for public engagement with AI: "a model of informed citizens as decision makers, supported by evidence from diverse expert stakeholders. … They envisage similar panels providing guidance, recommendations or judgements about AI to industry, government, new institutions, elected officials and public media" (Davies 2024, 8). Engaging the public directly on issues around AI, including governance and policy development, can increase people's understanding of AI and possibly address the impact of trust in AI on overall trust in science.

Recommendations for Librarianship

The intersections of AI and open science have a variety of implications for LIS workers who support or otherwise engage with open science. As a preface to these recommendations: LIS workers should consider how much of this work relates to their core duties and principles and then consider what they will do less of to make room for this new work. Libraries and LIS workers cannot and should not be expected to take on and be all things. Julia Glassman (2017) and Meredith Farkas (2021) explore "slow librarianship," avoiding burnout, and resisting the calls to latch onto the latest new thing. LIS workers should consider the advice of Glassman and Farkas as they evaluate their own scope and bandwidth for open science and AI.

LIS workers should also be mindful of the variety of working definitions and frameworks related to both AI and open science presented at the beginning of this article. Tailoring efforts and messaging to individual collaborators and stakeholders is necessary for successful communication. LIS workers should be mindful of preexisting knowledge in these areas, especially that which has been cultivated by for-profit entities. The Five Schools of Thought framework can be a helpful way to understand a collaborator's top priorities and methods (Fecher and Friesike 2014).

Knowledge-Building

An introductory step to engaging with the crossover between open science and AI is to build knowledge and become more conversant in the emerging issues and debates. This article and its references have hopefully provided a good starting point, but AI and open science are evolving topics where policy, best practices, and new technologies are ever changing. Liaison librarians should consider searching for frameworks for AI documentation, transparency, FAIRness, and/or openness in their subject area(s). They should also become familiar with the AI policies of major journals in their subject area(s), particularly those that their researchers publish in frequently. This can be another facet of the work that liaison librarians do to keep up with their discipline(s), and being conversant can contribute to their efforts to build rapport with their department(s).

Connections and Advocacy

LIS workers should build and strengthen connections with others who are engaging in AI work across their institutions. This will help with referrals when needed and can also be important for engaging in advocacy work. LIS workers sit at the nexus of a variety of activities, principles, and values that are relevant to both AI and open science, including scholarly communication, publishing rights and licenses, intellectual property, intellectual freedom, privacy rights and literacy, and information and data literacies. LIS workers can bring a great deal of experience and expertise to any type of committee or group that provides oversight or input on the use of AI—LIS workers can advocate for library representation on such groups at their institutions. Offices of Research and Innovation are also prime candidates for connection and conversations on AI and transparency and openness. LIS workers can engage with these offices about AI policy creation and implementation and the transparency of AI use. Information technology departments are also critical partners in conversations about support for AI in STEM research, as the use or creation of AI systems often requires large and complex computing resources.

Consultations and Liaison Work

Conversations about openness and AI easily fit into existing consultations and communications with researchers regarding data management, open data, and open access publication. Discussing AI issues can also be a way to start a new conversation about open practices, given that AI is so prevalent in the popular discourse right now, especially in academia. As in more general conversations about reproducibility, replicability, and openness, LIS workers should emphasize that there is a spectrum of possibility when it comes to openness and AI, as opposed to a binary of open/good versus closed/bad. LIS workers should explain that small steps, such as reading about a proposed AI documentation model in their field or evaluating the openness of AI tools referred to in class, can be a great place to start. It can be overwhelming for researchers to encounter new or different expectations and practices around openness, so LIS workers should try to ground their conversations in the researcher's values and principles and how they can relate to open practices. Some researchers are motivated by complying with relevant policies or requirements for funding or publication, so that can also be a good starting place. LIS workers can utilize the Five Schools of Thought framework to consider what motivations and goals are most relevant in a given conversation (Fecher and Friesike 2014).

LIS workers should be able to point to practical models and tools for evaluating and opening up AI, especially models that are discipline-specific.

One example of a framework LIS workers can use is the ROBOT Test, created by Sandy Hervieux and Amanda Wheatley (2020). The ROBOT Test walks users through a series of questions related to a tool's reliability, objective, bias, owner, and type and poses questions such as "Are bias or ethical issues acknowledged by the party responsible for the AI?" and "Does [the tool] rely on any human intervention?" The test is not a checklist that ends in a "use or do not use" determination; rather, it is a starting place for critical reflection on aspects of an AI tool beyond its utility, especially if it is being covered by the media, as many generative AI tools are. The test can be used by researchers when considering a particular tool or could be recommended to instructors for use in contexts where students ask about AI tool use.

Models for making AI more open and transparent are also helpful to have on hand for liaison conversations; the models mentioned earlier, both general (Huerta et al. 2023; Kapoor et al. 2024) and subject-specific (Artrith et al. 2021; Heil et al. 2021; Kolbinger et al. 2024), are good starting places. For more in other subject areas LIS workers can try searching for AI and model (or framework) and documentation (or transparency or open or FAIR) and whichever subject area, subdiscipline, or research area they are interested in.

It will also be important to keep track of policies related to AI use, documentation, transparency, and licensing at journal, funding agency, and government levels, most of which are still evolving regularly. These policies will vary in terms of content and scope: Some pertain to the use of generative AI for writing, reviewing, and analysis; some cover publishing agreements and publisher licensing of author content; and others cover transparency and openness of data and code and sometimes specifically AI tools. It can be helpful to know the specifics of the relevant policies and be able to help researchers meet requirements, advocate for their author rights, and follow best practices. This will fit into preexisting workflows for consultations on data management plans for grant applications or conversations about publishing or licensing. A good starting place for liaison librarians is to search for AI-related policies in the journals that their liaison-area researchers publish in most often, as well as the most relevant funders for their subject area(s).

Licensing AI Tools

Many libraries likely already subscribe to more than one tool or database with AI features or elements and may choose to investigate or initiate licenses for new AI-based tools. Advocating for openness and transparency is one of the guiding principles for artificial intelligence outlined by the Association of Research Libraries (2024). LIS workers should collaborate with collection development colleagues to evaluate the openness and transparency of AI-based tools and contribute to licensing and renewal conversations. Sample questions and lines of inquiry include Where can users go for documentation about how an AI tool or feature works? How extensive and transparent is the documentation about how an AI tool or feature makes decisions or creates outputs? Is a given AI tool Health Insurance Portability and Accountability Act (HIPAA) compliant, or does it meet any other privacy or data protection standards that could be needed for Institutional Review Board approval? Does a given tool integrate with common open science tools such as Open Science Framework or electronic lab notebooks? LIS workers should advocate for user privacy, author rights, and transparency as they investigate these tools and negotiate with vendors.

Science Communication and Engagement

There are many ways that LIS workers can increase public knowledge about AI and engagement around AI use and policy. An introductory step is to connect with other groups at their institutions that practice science communication or public engagement and discuss the topic of AI. What programming or initiatives about AI are in planning stages or already happening, and does it make sense for the library to contribute? The library can collaborate with partners to sponsor programming or can spearhead such efforts. Programming can be instructive, for example, "how to protect your privacy when using generative AI tools," or more discussion-based and open-ended. Possible ideas for programming include programming on AI transparency aimed at a general public audience, programming that engages the public with research done at a local institution that uses AI and explores how the AI is used, discussion-based programming that encourages open dialogue and discovery around AI topics, and participatory democracy events that develop public-created AI policy recommendations (see the People's Panel on AI example given earlier).

Examples of AI engagement that could be replicated and implemented include

- A discussion event on AI, modeled after the ongoing Dibner Discussions at New York University (Emara 2024). The discussions feature prompting questions and resource documents with books, news and media, scholarly articles, and other places to read and learn more about the discussion topic. The series has featured several discussions on topics related to AI, including "ChatGPT," "Algorithmic Bias," "Generative AI," and "Will Tech Save Us?" The discussions encourage participants to think critically about the topics, engage in dialogue with each other and the facilitators, and go forth to learn more. This open-ended engagement is a model to emulate when thinking about how to engage the public with AI, as it moves beyond the basics of information literacy, such as introductions to AI tools and when and how to use generative AI in scholarly writing.

This model incorporates algorithmic literacy and critical approaches into AI-related programming and encourages a mindset-based approach that will work across different tools. This model could easily be used for single events or as a series.

- A series of workshops, modeled after Keeping Up with Artificial Intelligence, a series originally created and run at McGill University (Wheatley and Hervieux 2022). The three workshops were titled "AI Literacy," "AI Ethics and Bias," and "AI in Research." This model features definitions, a framework for evaluating AI tools, an exploration of multiple AI case studies, an overview of relevant legislation and policies, and large-group discussions as well as multiple small-group activities. This model is a good way to cover basic introductory information as well as dive into critical discussions that are based in real-world scenarios and policy. The three-part length of the series is optimal for trying to attract repeat attendees, as the time commitment is moderate. Attendees can also get something out of each workshop individually and will not be at a disadvantage if they did not attend the preceding session(s).
- A structured learning circle, modeled after We Are AI: Taking Control of Technology, a course developed by the Center for Responsible AI (n.d.) at New York University, in collaboration with P2PU, a public education nonprofit, and the Queens Public Library. The course consists of five ninety-minute sessions over five weeks and comes complete with instruction guides, readings, discussion questions, and activities; it does not require any participant or organizer to have preexisting knowledge of AI topics. The goal of the course is "to introduce the basics of AI, discuss some of the social and ethical dimensions of the use of AI in modern life, and empower individuals to engage with how AI is used and governed" (Center for Responsible AI, n.d.). This model is grounded in real-world examples of AI implementation and policy and encourages participants to become advocates for their ideas about responsible AI use. This model goes beyond providing information and encouraging discussion toward calling participants to action and engagement outside of the course itself.

These programs are all examples of AI-related programming that could be implemented at a variety of institutions in order to increase understanding of and critical engagement with AI. By endeavoring to increase public awareness of and engagement with AI, LIS workers can contribute to the greater project of increasing public understanding of and engagement with the sciences.

Conclusion

Open science, AI, and librarianship are all ever-evolving areas. As new AI tools debut and evolve, so will best practices, policies, regulation, and legislation. At present there are few studies that meet the limited existing guidelines and frameworks for openness and transparency, which has a negative impact on the reproducibility and replicability of AI-based research. While there is potential for AI to contribute to furthering open science goals, there are also potential downsides to its use that should be considered. And the effects of AI use on researcher and public attitudes and actions are myriad, both positive and negative. LIS workers should seek to bring critical awareness and engagement to the intersection of open science and AI, across a variety of LIS services and support areas. They should seek to challenge notions of neutrality, eschew utopic assumptions about the future of both AI and the open science movement, and engage these topics with nuance and care, both for themselves and with library users.

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References

Alvarez, Amanda, Aylin Caliskan, M. J. Crockett, Shirley S. Ho, Lisa Messeri, and Jevin West. 2024. "Science Communication with Generative AI." *Nature Human Behaviour* 8 (4): 625–27. https://doi.org/10.1038/s41562-024-01846-3.

Artrith, Nongnuch, Keith T. Butler, François-Xavier Coudert, et al. 2021. "Best Practices in Machine Learning for Chemistry." *Nature Chemistry* 13 (6): 505–8. https://doi.org/10.1038/s41557-021-00716-z.

Association of Research Libraries. 2024. "Research Libraries Guiding Principles for Artificial Intelligence." Last modified April. https://www.arl.org/resources/research-libraries-guiding-principles-for-artificial-intelligence/.

Ball, Philip. 2023. "Is AI Leading to a Reproducibility Crisis in Science?" *Nature* 624 (7990): 22–25. https://doi.org/10.1038/d41586-023-03817-6.

Barker, Michelle, Neil P. Chue Hong, Daniel S. Katz, et al. 2022. "Introducing the FAIR Principles for Research Software." *Scientific Data* 9 (1): 622. https://doi.org/10.1038/s41597-022-01710-x.

Barredo Arrieta, Alejandro, Natalia Díaz-Rodríguez, Javier Del Ser, et al. 2020. "Explainable Artificial Intelligence (XAI): Concepts, Taxonomies, Opportunities and Challenges Toward Responsible AI." *Information Fusion* 58:82–115. https://doi.org/10.1016/j.inffus.2019.12.012.

Bourg, Chris, Sue Kriegsman, Nick Lindsay, Heather Sardis, Erin Stalberg, and Micah Altman. 2024. "Generative AI for Trustworthy, Open, and Equitable Scholarship." *An MIT Exploration of Generative AI.* Last modified March 26. https://doi.org/10.21428/e4baedd9.567bfd15.

Busuioc, Madalina. 2021. "Accountable Artificial Intelligence: Holding Algorithms to Account." *Public Administration Review* 81 (5): 825–36. https://doi.org/10.1111/puar.13293.

Ceccaroni, Luigi, James Bibby, Erin Roger, et al. 2019. "Opportunities and Risks for Citizen Science in the Age of Artificial Intelligence." *Citizen Science: Theory and Practice* 4 (1). https://doi.org/10.5334/cstp.241.

Center for Responsible AI. n.d. "We Are AI." Accessed October 11, 2024. https://dataresponsibly.github.io/we-are-ai.

Chan, Leslie, Budd Hall, Florence Piron, Rajesh Tandon, and Lorna Williams. 2020. "Open Science Beyond Open Access: For and with Communities, a Step Towards the Decolonization of Knowledge." Zenodo. https://doi.org/10.5281/ZENODO.3946773.

Davies, Tim. 2024. "Involving the Public in AI Policymaking: Experience from the People's Panel on AI." Connected by Data. Last modified February 12. https://connectedbydata.org/projects/2023-peoples-panel-on-ai.

Dirgová Luptáková, Iveta, Jiří Pospíchal, and Ladislav Huraj. 2024. "Beyond Code and Algorithms: Navigating Ethical Complexities in Artificial Intelligence." In *Software Engineering Methods in Systems and Network Systems*, edited by Radek Silhavy and Petr Silhavy. Springer. https://doi.org/10.1007/978-3-031-54813-0_30.

Emara, Hebah. 2024. "Dibner Discussions: Creating Space for Critical Discussions in STEM." Presentation at the STEM Library and Information Professionals Mini Conference, Barnard College, New York, March 15.

Farkas, Meredith Gorran. 2021. "What Is Slow Librarianship?" *Information Wants to Be Free* (blog), October 18. https://meredith.wolfwater.com/wordpress/2021/10/18/what-is-slow-librarianship/.

Fecher, Benedikt, and Sascha Friesike. 2014. "Open Science: One Term, Five Schools of Thought." In *Opening Science: The Evolving Guide on How the Internet Is Changing Research, Collaboration and Scholarly Publishing*, edited by Sönke Bartling and Sascha Friesike. Springer International. https://doi.org/10.1007/978-3-319-00026-8_2.

Gibney, Elizabeth. 2022. "Could Machine Learning Fuel a Reproducibility Crisis in Science?" *Nature* 608 (7922): 250–51. https://doi.org/10.1038/d41586-022-02035-w.

Gillespie, Nicole, Steve Lockey, Caitlin Curtis, Javad Pool, and Ali Akbari. 2023. *Trust in Artificial Intelligence: A Global Study*. University of Queensland and KPMG Australia. https://doi.org/10.14264/00d3c94.

Glassman, Julia. 2017. "The Innovation Fetish and Slow Librarianship: What Librarians Can Learn from the Juicero." *In the Library with the Lead Pipe*, October 18. https://www.inthelibrarywiththeleadpipe.org/2017/the-innovation-fetish-and-slow-librarianship-what-librarians-can-learn-from-the-juicero/.

Gruenpeter, Morane, Daniel S. Katz, Anna-Lena Lamprecht, et al. 2021. "Defining Research Software: A Controversial Discussion." Zenodo. https://doi.org/10.5281/zenodo.5504016.

Haibe-Kains, Benjamin, George Alexandru Adam, Ahmed Hosny, et al. 2020. "Transparency and Reproducibility in Artificial Intelligence." *Nature* 586 (7829): E14–16. https://doi.org/10.1038/s41586-020-2766-y.

Hansen, Dave. 2024. "What Happens When Your Publisher Licenses Your Work for AI Training?" *Authors Alliance* (blog), July 30. https://www.authorsalliance.org/2024/07/30/what-happens-when-your-publisher-licenses-your-work-for-ai-training/.

Heil, Benjamin J., Michael M. Hoffman, Florian Markowetz, Su-In Lee, Casey S. Greene, and Stephanie C. Hicks. 2021. "Reproducibility Standards for Machine Learning in the Life Sciences." *Nature Methods* 18 (10): 1132–35. https://doi.org/10.1038/s41592-021-01256-7.

Hervieux, Sandy, and Amanda Wheatley. 2020. "The ROBOT Test [Evaluation Tool]." *The LibrAIry* (blog), March 11. https://thelibrairy.wordpress.com/2020/03/11/the-robot-test/.

Huerta, E. A., Ben Blaiszik, L. Catherine Brinson, et al. 2023. "FAIR for AI: An Interdisciplinary and International Community Building Perspective." *Scientific Data* 10 (1): 487. https://doi.org/10.1038/s41597-023-02298-6.

Institute for Trustworthy AI in Law and Society. n.d. "Research." Accessed August 7, 2024. https://www.trails.umd.edu/research.

International Organization for Standardization. 2020. "Software and Systems Engineering—Software Testing, Part 11: Guidelines on the Testing of AI-Based Systems." ISO/IEC TR 29119-11:2020. https://www.iso.org/standard/79016.html.

Kapoor, Sayash, Emily M. Cantrell, Kenny Peng, et al. 2024. "REFORMS: Consensus-Based Recommendations for Machine-Learning-Based Science." *Science Advances* 10 (18). https://doi.org/10.1126/sciadv.adk3452.

Kapoor, Sayash, and Arvind Narayanan. 2023. "Leakage and the Reproducibility Crisis in Machine-Learning-Based Science." *Patterns* 4 (9): 100804. https://doi.org/10.1016/j.patter.2023.100804.

Kennedy, Brian, and Alec Tyson. 2023. "Americans' Trust in Scientists, Positive Views of Science Continue to Decline." Pew Research Center, November 14. https://www.pewresearch.org/wp-content/uploads/sites/20/2023/11/PS_2023.11.14_trust-in-scientists_REPORT.pdf.

Kessler, Sarah. 2024. "Openwashing." *The New York Times*, May 17. https://www.nytimes.com/2024/05/17/business/what-is-openwashing-ai.html.

Kolbinger, Fiona R., Gregory P. Veldhuizen, Jiefu Zhu, Daniel Truhn, and Jakob Nikolas Kather. 2024. "Reporting Guidelines in Medical Artificial Intelligence: A Systematic Review and Meta-analysis." *Communications Medicine* 4 (1): 1–10. https://doi.org/10.1038/s43856-024-00492-0.

Liu, Weishu. 2017. "The Changing Role of Non-English Papers in Scholarly Communication: Evidence from Web of Science's Three Journal Citation Indexes." *Learned Publishing* 30 (2): 115–23. https://doi.org/10.1002/leap.1089.

McKinney, Scott Mayer, Alan Karthikesalingam, Daniel Tse, et al. 2020. "Reply to: Transparency and Reproducibility in Artificial Intelligence." *Nature* 586 (7829): E17–18. https://doi.org/10.1038/s41586-020-2767-x.

McKinney, Scott Mayer, Marcin Sieniek, Varun Godbole, et al. 2020. "International Evaluation of an AI System for Breast Cancer Screening." *Nature* 577 (7788): 89–94. https://doi.org/10.1038/s41586-019-1799-6.

Nahas, Kamal. 2024. "Is AI Ready to Mass-Produce Lay Summaries of Research Articles?" *Nature Index*, March 20. https://doi.org/10.1038/d41586-024-00865-4.

National Artificial Intelligence Research Resource Pilot. n.d. "Resource Allocations." Accessed August 6, 2024. https://nairrpilot.org/awarded-projects.

National Institute of Standards and Technology. n.d. "Artificial Intelligence." Accessed May 31, 2024. https://www.nist.gov/artificial-intelligence.

Open Source Initiative. 2024. "The Open Source AI Definition—Version 0.0.8." Last modified April 24. https://hackmd.io/@opensourceinitiative/osaid-0-0-8.

Public Library of Science. 2024. "PLOS Open Science Indicators." FigShare. https://doi.org/10.6084/M9.FIGSHARE.21687686.V7.

Riedel, Nico, Miriam Kip, and Evgeny Bobrov. 2020. "ODDPub—a Text-Mining Algorithm to Detect Data Sharing in Biomedical Publications." *Data Science Journal* 19 (1). https://doi.org/10.5334/dsj-2020-042.

Rudner, Tim G. J., and Helen Toner. 2021. "Key Concepts in AI Safety: Interpretability in Machine Learning." CSET Issue Brief. Center for Security and Emerging Technology. https://cset.georgetown.edu/publication/key-concepts-in-ai-safety-interpretability-in-machine-learning/.

Serghiou, Stylianos, Despina G. Contopoulos-Ioannidis, Kevin W. Boyack, Nico Riedel, Joshua D. Wallach, and John P. A. Ioannidis. 2021. "Assessment of Transparency Indicators Across the Biomedical Literature: How Open Is Open?" *PLOS Biology* 19 (3): e3001107. https://doi.org/10.1371/journal.pbio.3001107.

Silveira, Lúcia da, Nivaldo Calixto Ribeiro, Remedios Melero, et al. 2023. "Open Science Taxonomy: Revised and Expanded." Zenodo. https://doi.org/10.5281/zenodo.7940641.

Southwell, Brian G., and Benjamin Schneider. 2024. "Science and Technology: Public Perceptions, Awareness, and Information Sources." NSB-2024-4, February 14. Science and Engineering Indicators 2024. National Science Foundation and National Science Board. https://ncses.nsf.gov/pubs/nsb20244.

UNESCO. 2021. "UNESCO Recommendation on Open Science." https://doi.org/10.54677/MNMH8546.

Wheatley, Amanda, and Sandy Hervieux. 2022. "Separating Artificial Intelligence from Science Fiction: Creating an Academic Library Workshop Series on AI Literacy." In *The Rise of AI: Implications and Applications of Artificial Intelligence in Academic Libraries*, edited by Sandy Hervieux and Amanda Wheatley. Association of College & Research Libraries.

White House. 2023. "Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence." Last modified October 30. https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence/.

Wilkinson, Mark D., Michel Dumontier, IJsbrand Jan Aalbersberg, et al. 2016. "The FAIR Guiding Principles for Scientific Data Management and Stewardship." *Scientific Data* 3 (1): 160018. https://doi.org/10.1038/sdata.2016.18.

Wood, Heloise. 2024. "Wiley and Oxford University Press Confirm AI Partnerships as Cambridge University Press Offers 'Opt-In.'" *The Bookseller*, August 1. https://www.thebookseller.com/news/wiley-cambridge-university-press-and-oxford-university-press-confirm-ai-partnerships.

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