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Your Information ZODIAC: An Information Evaluation Framework for the Age of Generative AI

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ABSTRACT

Building on information evaluation mnemonics like the CRAAP Test, SIFT, and ACT UP, the authors propose the ZODIAC of information evaluation for a generative AI-dominated information environment: Zooming in, Other opinions, Dataset, Intent, Authenticity, and Consistency. Each letter introduces students to considerations unique to the critical thinking considerations of AI-generated information, such as datasets and their large language models, evaluating the intent of a generative AI prompt, and questioning the authenticity and consistency of generative AI output. As an introductory framework, the ZODIAC method does not fully address all aspects of information literacy, such as environmental considerations and workforce readiness. Therefore, this discussion highlights areas where others can build upon and develop additional generative AI evaluation methods.

KEYWORDS

information literacy, information evaluation, artificial intelligence literacy

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Introduction & Context for ZODIAC: Information Evaluation & AI

Artificial Intelligence (AI) has drastically altered the way educators understand information evaluation and higher education. A 2023 Forbes article describes AI as a "disruption" for which "the educational industry is not prepared" (Silver, para. 1), and academic literature corroborates this claim. Archambault (2024) notes how "postsecondary students are largely unaware of the impact of algorithms on their everyday lives" and that "noncomputer science students are not being taught about algorithms as part of the regular curriculum" (p. 44). Academic librarians, with their expertise in information literacy, can facilitate higher education's AI readiness, with many having already posited various frameworks and dispositions for the AI literate student (see Archambault, 2023; Lo, 2024; Ridley & Pawlick-Potts, 2021; Florida International University, n.d.; Long & Magerko, 2020). Accordingly, librarians play a critical role in allaying Forbes' so-called "AI disruption."

Although there is no one solution to AI's disruptions, librarians can work to mitigate AI's challenges. One solution is to equip educators and students with a method to evaluate AI-generated information. Thus, this paper proposes merely one solution to AI's challenges: The ZODIAC method. Paying close attention to nuanced differences between information literacy and AI literacy, the ZODIAC method – zooming in, other sources, datasets, intent, authenticity, and consistency– asks questions germane to AI. By proposing this method, the authors hope to initiate scholarly dialogues around AI literacy and alleviate higher education's AI-induced nonplus.

To address the quandary, a definition of AI literacy must be established. In this paper, the authors understand AI literacy "as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool on the web, at home, and in the workplace" (Long & Magerko, 2020, p. 2). Like previous information evaluation frameworks, the ZODIAC method aims to be an accessible device, empowering students to analytically question AI-generated information. While ZODIAC does not prescribe dispositions of an AI-literate student, it poses questions students can ask when leveraging AI information, whether in or outside the classroom. Ultimately, in a rapidly changing information environment, ZODIAC is one method librarians and information literacy professionals can use to cultivate AI literacy in higher education and beyond.

Literature Review: Information Evaluation & CRAAP Test

Source evaluation frameworks, particularly those as acronyms, can be useful tools for librarians to teach students information evaluation skills. Acronyms help students to remember the criteria or questions they should use to determine whether a given source is appropriate for their information need. Over the last 20 years, many frameworks and approaches have been developed and utilized to address an ever-evolving information environment. While this literature review could seek to address the various mnemonics and their effectiveness in the classroom, it only seeks to review the mnemonics themselves, ultimately to situate ZODIAC within a larger context.

The CRAAP Test

The CRAAP test was developed by S. Blakeslee and presented at the LOEX 2004 conference. The acronym was developed to help students remember source evaluation criteria, springing from her realization that, “If I couldn’t remember these important criteria [during library instruction] when I worked with them almost daily, how could I expect my students to remember them?” (Blakeslee 2004, p. 6). The acronym, Blakeslee (2004) reports, not only helps students recall Currency, Relevance, Authority, Accuracy, and Purpose of sources, but the mnemonic captures the attention of students for its crass nature. Since 2004, many instruction librarians have adopted this source evaluation method; however, information systems have changed significantly since the inception of CRAAP, and by the 2010s, librarians began seeking alternatives.

RADAR

J. Mandalios’ 2013 RADAR (relevance, authority, date, appearance, and reason for writing) approach to source evaluation builds upon the CRAAP by keeping most of its checklist elements, but instead of “accuracy,” which can be hard for beginners to evaluate, the second A of the test is “appearance: what clues can you get from the appearance of the source?” (as cited in Sye & Thompson 2023, p.86). RADAR is also intended to serve as a metaphor; RADAR helps ships navigate oceans and helps researchers navigate the world wide web (Sye & Thompson 2023, p.86). RADAR does not offer anything novel to the concept of source evaluation that CRAAP does not, but the metaphorical shift may prove to be more helpful for some students.

SIFT

M. Caulfield’s 2017 SIFT method has arguably been the most widely adopted source evaluation acronym among librarians since the CRAAP test. This wide adoption can be attributed to SIFT’s focus on evaluating web sources in an era of rampant misinformation and disinformation.

Rather than criteria to measure against, the letters in SIFT’s acronym describe specific steps or “moves” students should take to evaluate a source they encounter on the internet. First, students are prompted to Stop to consider the reputation of the source in question and consider one’s own emotional response and biases toward the source and topic. This first step is, at its most basic level, asking students to be reflective and mindful before they continue reading. Next, students are prompted to Investigate the source. This step describes several questions students can ask to evaluate the source vertically on face value, whereas the following step, Find better coverage, prompts students to begin evaluating the source laterally within the context of other sources on the same topic with similar or better quality. Finally, the last step of the SIFT method has students Trace claims, quotes, and media back to the original context.

Overall, the SIFT method provides a comprehensive description of what students should do to effectively navigate online information. The four moves of SIFT have even been mapped to ACRL's Framework for Information Literacy (Pausch & Popp, n.d.; Faix and Fyn 2023), making it conducive to library instruction. Although the SIFT method has demonstrated great effectiveness in helping students evaluate online information, AI has engendered opportunities to enhance SIFT.

ACT UP

D. Stahura's ACT UP was shared in *College & research libraries news* in 2018. This framework for source evaluation puts a special emphasis on social justice, asking researchers to critically analyze the systems of oppression that elevate some voices and disenfranchise others, even (and especially) within academic settings. ACT UP asks students to consider the Author, Currency, and Truth of the source, as well as to consider if the source is Unbiased and what kinds of Privilege may be at play. These criteria map back to the criteria of the CRAAP test (author - authority, truth - accuracy, currency - currency), but the method asks students to contextualize one source within a landscape of other sources, challenging students to consider other perspectives, especially those of marginalized communities.

IF I APPLY

K. Phillips, E. Roles, and S. Thomas (2022) developed the source evaluation acronym IF I APPLY and presented it at the LOEX 2019 conference. Since then, many academic librarians have adopted it to teach source evaluation.

The new acronym was developed in response to the CRAAP test; more information is available on the internet beyond simply websites, and the CRAAP test was developed with just websites in mind. The new acronym starts with "IF I," which is described as personal steps for the learner. The learner is prompted by "IF I" to reflect on their feelings and perceptions on the topic at hand, as doing so is "essential in order to identify confirmation bias" (Phillips et al., 2022, p. 125). The letters of "IF I" stand for: Identify emotions attached to the topic; Find unbiased reference sources for proper review of the topic; Intellectual courage to seek authoritative voices on topic that may be outside of the thesis. The following steps, called the "source steps," are more in line with the CRAAP test, in that the word selected for the acronym is central to the idea of the criteria. Authority established; Purpose/Point of view of the source; Publisher; List of sources; Year of publication.

Overall, IF I APPLY tries to supplement the criteria of the CRAAP test with a reflective, metacognitive step. However, the letters selected to create the acronym are not intuitive, which is also a criticism of the SIFT test (example: what am I supposed to “Find” again? - Tardiff, 2022, p. 127). If students must reference a graphic of the acronym when they use it to remember what the steps are, the mnemonic is surely limited in its effectiveness.

CCOW

A.B. Tardiff published the CCOW source evaluation acronym in 2022, responding to criticism and shortcomings of the CRAAP test. The CCOW mnemonic takes the one-word-per-criterion approach of the CRAAP test, making the tool easier for learners to remember; however, CCOW is similar to the SIFT method in that each criterion prompts students to take specific actions for each criterion. CCOW denotes how active investigation, lateral reading, and metacognition are crucial to successfully evaluating sources in today’s information environment.

CCOW stands for Credentials, Claims, Objectives, and Worldview. Most of these steps are remixed criteria from the CRAAP test (for example, CCOW’s Credentials is mapped to CRAAP’s Authority). However, Tardiff removes the Relevance and Currency criteria from this new interaction, aggregating questions related to those criteria into either Credentials, Claims, or Objectives. Specifically, Worldview (W) is novel in the mnemonic because it values metacognition and presents bias in a nonjudgmental way. The idea that everyone has bias is, admittedly, nihilistic for developing learners; however, accepting a worldview that affects our reaction to new information is less challenging for students developing their information literacy skills.

Because each framework has its own strengths and weaknesses, no one framework can be relied upon exclusively for teaching students how to evaluate sources. Indeed, the diversity of literature on source evaluation, including those not dealing with mnemonics, demonstrates this. Although a review on source evaluation literature on non-mnemonic approaches to source evaluation is beyond the scope of this paper, some studies are worth noting, as they are pursuant to the skills ZODIAC tries to teach. Dalal et al. (2025) note how Generation Z students, the predominant student cohort in higher education, “were more attentive and concerned about the quality of internet sources, less inclined to evaluate information, more attentive to the bias of those sources, and were more inclined to search for and use sources as needed for an assignment” (p. 270). Furthermore, recent studies have sought to center – or rather recenter—relevance, confidence, and metacognition in source evaluation (Tardiff, 2024; Graf, 2024; Dawkins & LeGrand, 2024).

With AI complicating the information landscape, information professionals and librarians need to adapt evaluation frameworks to meet the needs of the current information environment. Generative AI poses new problems for library and information science professionals to address, but it concurrently posits opportunities for innovation and engagement. Meakin (2024) maintains that “AI has a great deal of potential to enhance student information discovery and retrieval; offer personalization which can increase engagement; streamline research processes; and serve to improve digital literacy and the information evaluation research capabilities of students” (p. 8). To achieve that vision, nevertheless, students must be equipped to evaluate an AI-dominated landscape.

ZODIAC Method

ZODIAC is ideal for library one-shot sessions that focus on evaluating information. Though not intended to replace methods like SIFT and CCOW, it can be used as an extension of existing information evaluation methods to show students that critically thinking about information applies to anything that generative AI produces. For example, after teaching students how to evaluate a source such as an academic journal article or a blog post, the librarian might follow up with ZODIAC, leveraging active learning activities to show students the nuances of using generative AI in the research process. Alternatively, in courses that rely heavily on generative AI, ZODIAC can be used alone, but it should be contextualized within larger paradigms of information evaluation.

Additionally, ZODIAC is not intended to evaluate a given generative AI. Although some letters of ZODIAC – especially D: Dataset and C: Consistency —ask students to consider technical aspects of a generative AI, ZODIAC itself is not suited for teaching students about a generative AI’s information-producing capabilities. Thus, for instance, a computer science class that covers topics like algorithms, machine learning, and data structures would not use ZODIAC to teach students how to build a generative AI. However, a research methods-oriented computer science class might benefit from ZODIAC if the course learning outcomes necessitate discussions of source or information evaluation. Ultimately, ZODIAC’s intent is for students to think critically about the information a generative AI produces, and while that process entails analytically questioning the AI, ZODIAC is not intended to teach the technical skills associated with programming or building AI.

Z: "Zooming in"

Z stands for “zooming in” on the prompt and asks students to consider the information they have provided to the generative AI. When using generative AI for research, students who are developing their information literacy skills might not use salient keywords or articulate their research questions thoroughly. For instance, someone researching climate change’s impact on the economy might ask a generative AI: “How does climate change impact the economy?” Most generative AIs, especially those freely available, will produce a broad overview of climate change’s impact, which is too broad for a college-level research paper.

When “zooming in” on a prompt, ZODIAC encourages students to consider how much information they have provided and whether they can be more specific. Using the “How does climate change impact the economy?” example again, an instructor teaching the Z of ZODIAC might show students how to focus on a particular phenomenon of climate change, a geographic location, and a specific aspect of the economy. A student who has successfully “zoomed in” on their prompt might change the question to “How does climate change impact National Park tourism in the United States?”

This approach aligns with established information evaluation techniques, particularly keyword development, which is familiar to those who teach research. For example, a generative AI’s response will vary significantly between the prompts “How does climate change impact the economy?” and “How do warming ocean temperatures impact Florida’s economy?” While databases and search engines might yield relevant results for both queries, a generative AI might struggle to provide specific answers that align with the student's research topic. This level of specificity and attention to detail might be new to students, making the concept of “zooming in” a valuable tool for refining their prompts.

O: Other AIs, Opinions, Sources, & Interpretations

The "O" in ZODIAC stands for seeking other opinions, sources, and interpretations. This step is like components in previous information evaluation mnemonics, such as the “A” in the CRAAP Test, the “F” in the SIFT method, and the “T” in ACT UP, which all emphasize looking beyond a single source. In the context of generative AI, instructors have various ways to teach students how to seek diverse opinions and sources. Like traditional information evaluation methods, students can search through databases or the web for different perspectives, but generative AI offers new opportunities. For instance, when guiding students through the ZODIAC method, instructors might encourage them to create a prompt that challenges their stance on a topic. By analyzing the rhetoric in the AI's responses, students can form a more informed opinion. Additionally, when using generative AIs that provide sources, this approach allows students to evaluate individual sources—whether they support or contradict their argument.

One active learning opportunity for ZODIAC's "O" involves asking students for a generative AI to produce a blog post that takes a firm stance on a given topic or social issue, regardless of whether they agree with it or not. Students then seek one that takes the opposite stance on the given subject. From there, students use their analytical skills to see how the generative AI constructed its argument, paying close attention to the sources, if any, the AI consulted in the generation of its argument. Furthermore, this gently introduces students to the ACRL Scholarship as Conversation Frame, as it shows how ideas can be debated (Association of College and Research Libraries, 2016).

D: Dataset

The third letter, “D,” stands for dataset, a step unique to this method. In this step, students are encouraged to consider the dataset on which their LLM—and, by extension, all generative AI—are trained, as well as how that dataset can impact the quality of the information they receive. For example, many free versions of generative AIs have an information cutoff date, meaning their responses might not include current information. In the summer of 2024, specifically, GPT-4 and ChatGPT+ could not access information produced after September 2021 (Griffith, 2023). The currency of generative AI’s information can change rapidly, making it challenging for students and instructors to stay informed about dataset limitations. Students need to be aware that limitations exist, regardless of which generative AI is being used.

Classroom activities for the dataset step can vary, but a practical exercise involves students researching the limitations of their AI’s dataset and comparing notes with others. This think-pair-share method allows students to understand the limitations of their generative AI while learning whether another might be better suited for their research. Also, this step can be extended by having students brainstorm topics that are not suitable for a given generative AI. For instance, if someone is looking for information on recent world news and politics, they can be guided to see that a search engine or a different generative AI might be more appropriate for their needs.

I: Intent

ZODIAC’s “I” involves students examining the intent of their generative AI prompt, which can naturally lead to questioning an information source’s purpose. This aligns with steps in other evaluation methods, such as the “P” in CRAAP, the “I” in SIFT, and the “P” in IF I APPLY. However, ZODIAC’s “I” differs slightly by asking students to investigate why they prompted a generative AI and whether the response aligns with their intent. This encourages students to use metacognitive skills to ensure the information they receive supports the purpose of their writing.

In the classroom, instructors can teach intent by asking students to reflect on why they are prompting a generative AI. This approach is similar to analyzing a source’s intent or purpose, but ZODIAC emphasizes understanding the student's intent with the AI, rather than the intent of the information produced. Although the AI’s intent may or may not align with the student's intent, reflecting on intent can demonstrate how information serves various purposes and highlights the importance of context in understanding intent. Ultimately, by asking students to reflect on their intent with a generative AI, they can learn to use information in a way that aligns with the goals of their project or writing assignment.

A: Authenticity

Authenticity is derived from the values and belief systems that determine genuineness in any society. AI-generated content is disrupting how the element of "genuineness" is determined or ascribed. Students will be guided to examine and rethink the true essence of authenticity, given that generative AI can produce human-like outputs (Lee, 2023). The ZODIAC method encourages students to engage in academic rigor integral to the "guided inquiry" aspect of inquiry-based learning (IBL). "IBL, as an approach instead of a specific method, is a cluster of teaching and learning strategies where students inquire into the nature of a problem(s) or question(s)" (Blessinger & Carfora, 2015, p.5). Consequently, in this work, authenticity refers to checking for bias and how authentically a generative AI represents the people, places, or events described in its response. This step asks how authentic a response is, aiming to deepen understanding beyond the output itself.

There is no single way to best teach authenticity. Nevertheless, when evaluating an information source's authenticity, ZODIAC calls for students to ensure that events, places, and people are represented ethically, checking for implicit or explicit biases. Although checking for authenticity is important for all types of information, it is especially crucial when evaluating AI-generated information. Jfarzadeh (2025) articulately posits why evaluating the authenticity of information is important:

AI algorithms are often designed and developed by a narrow group of people, which can lead to biases in the data and models they create. These biases can then perpetuate harmful stereotypes, leading to gender discrimination in employment, lending, and criminal justice. The lack of diversity in the development of these systems is not intentional, but rather a result of the lack of diverse representation in the datasets used to train them (para. 5).

> Indeed, generative AI exacerbates existing biases, and academic literature denotes that bias in generative AI abounds (see Warr et al., 2024; Hupperich, 2024; and Wei et al., 2025). ZODIAC does not prescribe a specific way of teaching students how to spot bias, but it does call for instructors to use innovative methods to demonstrate how generative AI perpetuates longstanding biases.

C: Consistency

Consistency in generative AI refers to the degree of similarity in responses when the same question is asked in separate sessions or by different individuals. In the distinct parlance of computer systems exhibiting human-like intelligence through machine learning, "consistency" is referred to as the "function calling" operator in large language models (LLMs). It is important to emphasize that LLMs are types of artificial intelligence algorithms that use neural network techniques to recognize, process, and understand human languages or texts

(Neapolitan & Jiang, 2018; Kim et al., 2023). By examining varying responses, students can develop critical skills in identifying weaknesses in AI datasets, understanding the importance of cross-referencing information, and reading critically for discrepancies among sources, particularly in the context of AI. This investigation of consistency reinforces overarching themes in ZODIAC. When checking for consistency among responses, students are encouraged to pay more attention to authenticity, the intent behind the AI's response, and the limitations of the underlying datasets. This process can enhance students' ability to critically evaluate AI-generated content and foster a deeper understanding of the complexities inherent in AI systems.

Limitations

Although ZODIAC addresses some challenges and biases of information evaluation, it is not without limitations. Specifically, it does not address what the authors describe as a second, “hidden” layer of information and AI literacy: the digital divide, the labor practices surrounding the development of AI, and AI’s environmental costs. The AI literacy competencies ZODIAC attempts to instill in students have implications for the workforce. As AI becomes more integrated into workflows, employers will expect college graduates to have a level of AI literacy (Snow, 2025). Though not discussed in ZODIAC, the authors believe these aspects of AI are worth mentioning because they are crucial considerations for educators and higher education institutions.

In 2004, Brendan Luyt articulately posited the dualistic realities that the Internet seemingly promised: “At the highest levels of government and inter–governmental organizations, this newest form of information technology is viewed as a ticket to everlasting peace, progress, and prosperity… However, Internet technology is not evenly distributed around the world and as a result, there is a new issue on the tables of international fora, the problem of the digital divide” (paras. 1-2). Moreover, societal and equity issues associated with the digital divide have not been overcome, and AI is exacerbating extant problems from the early days of the digital divide. Writing two decades after Luyt, Bentley et al. (2024) express approximately the same sentiment: “AI technologies have the potential to solve some of society’s most complex challenges… However, the speed of AI’s recent integration into society has prompted ethical concerns, particularly a fear that this next digital evolution will leave behind significant sections of society” (p. 10). ZODIAC facilitates discussions and an understanding of how some populations are noticeably absent in the datasets of LLMs, but it does not explicitly encourage students to notice that some people are inherently excluded from using AI technologies altogether.

In addition to systemically magnifying the effects of the digital divide, the rise of generative AI has elicited awareness of the labor practices used in dataset training. In a 2023 *TIME* article, Billy Perrigo reported how OpenAI paid Kenyan workers between $1.32 and $2 per hour to label data that “described situations in graphic detail like child sexual abuse, bestiality, murder, suicide, torture, self-harm, and incest” (para. 6). Furthermore, reporting for *The Conversation*, Ben Lee Taylor notes how outsourcing data labeling is commonplace: “Data labeling is often outsourced to labor markets in the Global South where companies can find workers who are fluent in English and willing to work for low wages” (para. 2). While labor practices are not listed in ZODIAC, those tasked with teaching AI literacy can work to ensure students and other educators are aware of the practices used to make generative AI, cultivating a society that is vigilant of AI’s business models.

The ramifications of AI extend beyond labor practices, permeating the climate crisis. Although AI has the potential to attenuate select effects of climate change, it concurrently worsens existing issues, such as water scarcity and overworked power grids. Li et al. (2023) note how “a large AI model can consume a stunning amount of water in the order of millions of liters for training” (p. 9). They further articulate that AI’s water consumption “is very concerning, as freshwater scarcity has become one of the most pressing challenges shared by all of us in the wake of the rapidly growing population, depleting water resources, and aging water infrastructures” (p. 1). In addition to the water costs of generative AI, the amount of energy needed to cool the data centers required for AI is an environmental concern. Justin Scott (2024) notes how “AI requires high-performance processors that generate more thermal power than traditional chips” (p. 12), which, in turn, requires data centers to maintain lower temperatures, increasing their energy demand. Accordingly, as students learn about AI technologies and how to evaluate information, they need to be aware of how AI is simultaneously providing solutions while creating new problems for society, a learning threshold that extends into workforce readiness.

Conclusion

Mnemonic devices have been widely used to help students recall critical questions to ask when evaluating information sources, frequently changing to meet the dynamic needs of the information environment and workforce competencies. AI has significantly transformed the information environment, allowing users to ask a question and receive a direct answer. This transformation warrants revisiting the questions students should ask when they consume AI-generated information, for both academic and professional purposes. AI literacy and current workforce readiness competencies cannot be separated, meaning evaluation techniques such as ZODIAC are timely. According to Drydakis’s (2024) report on AI and employment prospects, students with AI capital, defined as “a vector of knowledge, skills, and capabilities related to AI technologies” (p. 916), are more likely to receive job interviews than those without AI capital. While one might assume AI capital always refers to technical skills, trends show that AI has increased the demand for critical thinking and interpersonal skills, as they underscore “the importance of developing a well-rounded workforce capable of adapting to technological change while maintaining strong interpersonal and analytical capabilities” (Oschinski et al., 2024, p. 1). Higher education, then, must be prepared to educate a workforce that is ready to embrace the duality of possibilities and challenges of an AI-inundated world. To do that, students must learn to examine generative AI from a variety of perspectives, something ZODIAC strives to achieve.

ZODIAC is one tool for information literacy professionals, intended to foster classroom discussions on critically evaluating AI-generated information. Like all devices, however, it has limitations, such as not addressing the social and environmental challenges that AI has recently exacerbated. To address this gap in AI literacy, the discussion provides sources and opportunities for others to develop frameworks that encourage students to be vigilant of AI's social and environmental costs. Future research and educational initiatives should focus on integrating these broader considerations into AI literacy curricula.

References

Association of College and Research Libraires. (2016, January 11). *Framework for information literacy for higher education*. American Library Association. https://www.ala.org/acrl/standards/ilframework

Archambault, S. G. (2023). Expanding on the Frames: Making a case for algorithmic literacy. *Communications in Information Literacy*, *17*(2), 530–553. https://doi.org/10.15760/comminfolit.2023.17.2.11

Archambault, S. G. (2024). Toward a new framework for teaching algorithmic literacy. *Information and Learning Sciences*, *125*(1/2), 44–67. https://doi.org/10.1108/ILS-07-2023-0090

Bentley, S. V., Naughtin, C. K., McGrath, M. J., Irons, J. L., & Cooper, P. S. (2024). The digital divide in action: How experiences of digital technology shape future relationships with artificial intelligence. *AI and Ethics, 4,* 1–15. https://doi.org/10.1007/s43681-024-00452-3

Blakeslee, S. (2004). The CRAAP Test. *LOEX Quarterly, 31*(3), 6–7. https://commons.emich.edu/loexquarterly/vol31/iss3/4

Blessinger, P. & Carfora, J.M. (2015). Innovative approaches in teaching and learning: An introduction to inquiry-based learning for multidisciplinary programs. In P. Blessinger & J.M. Carfora (Eds.), *Inquiry-based learning for multidisciplinary programs: A conceptual and practical resource for educators* (pp. 3–22). Emerald Publishing Limited. https://doi.org/10.1108/S2055-364120153

Caulfield, M. (2019, June 19). SIFT (the four moves). *Hapgood.* https://hapgood.us/2019/06/19/sift-the-four-moves/

Dalal, H. A., Taylor, A., & Whitfield, S. (2025). Assessing students' information literacy: Attitudes and perceptions of college students across generations. *College & Research Libraries, 86*(2), 255–274. https://doi.org/10.5860/crl.86.2.255

Dawkins, V., & LeGrand, S. (2024). Cultivating critical information evaluation through motivational confidence: An exploratory crosswalk analysis. *Journal of Information Literacy, 18*(2), 1–21. https://doi.org/10.11645/18.2.644

Drydakis, N. (2024). Artificial intelligence capital and employment prospects. *Oxford Economic Papers, 76*, 901–929. https://doi.org/10.1093/oep/gpae005

Faix, A. I., & Fyn, A. F. (2023). Six frames, four moves, one habit: Finding ACRL's framework within SIFT. *College & Research Libraries News, 84*(11), 411–416. https://doi.org/10.5860/crln.84.11.411

Florida International University Libraries. (n.d.). Artificial intelligence + ACRL Frameworks: Introduction. https://library.fiu.edu/AI-ACRL/intro

Graf, A.J. (2024). Centering relevance in information literacy teaching and learning. *Communications in Information Literacy, 18*(2), 244–263. https://doi.org/10.15760/comminfolit.2024.18.2.7

Griffith, E. (2023, March 16). GPT-4 vs. ChatGPT-3.5: What's the difference? *PCMAG*. https://www.pcmag.com/news/the-new-chatgpt-what-you-get-with-gpt-4-vs-gpt-35

Hupperich, T. (2024). A perspective on gender bias in generated text data. *Frontiers in Human Dynamics*, *6,* 1–6. https://doi.org/10.3389/fhumd.2024.1495270

Jafarzadeh, A. (2025, 26 February). Gender bias in artificial intelligence. *Ethics in the Built Environment*. https://sites.psu.edu/visionaryarchitecture/2025/02/26/gender-bias-in-artificial-intelligence-ai/

Kim, S., Moon, S., Tabrizi, R., Lee, N., Mahoney, M. W., Keutzer, K., & Gholami, A. (2023). An LLM compiler for parallel function calling. *ArXiv*. https://doi.org/10.48550/arXiv.2312.04511

Lee, V. R. (2023, May 1). A Stanford professor who specializes in A.I. says it's redefining "authenticity" and it could be as revolutionary as the calculator. *Fortune*. https://fortune.com/2023/05/01/ai-redefining-authenticity-revolutionary-calculator-stanford-professor-says/

Li, P., Yang, J., Islam, M. A., & Ren, S. (2023). Making AI Less "thirsty": Uncovering and addressing the secret water footprint of AI models. *ArXiv*. https://doi.org/10.48550/arXiv.2304.03271

Lo, L. S. (2024). The CLEAR path: A framework for enhancing information literacy through prompt engineering. *The Journal of Academic Librarianship*, *49*(4), 1–3. https://doi.org/10.1016/j.acalib.2023.102720

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–16. https://doi.org/10.1145/3313831.3376727

Luyt, B. (2004). Who benefits from the digital divide? *First Monday, 9*(8-2). https://doi.org/10.5210/fm.v9i8.1166

Mandalios, J. (2013). RADAR: An approach for helping students evaluate Internet sources. *Journal of Information Science, 39*(4), 470–478. https://doi.org/10.1177/0165551513478889

Meakin, L. (2024). Exploring the impact of generative artificial intelligence on higher education students' utilization of library resources: A critical examination. *Information Technology & Libraries, 43*(3), 1–13. https://doi.org/10.5860/ital.v43i3.17246

Neapolitan, R. E., & Jiang, X. (2018). *Artificial intelligence : With an introduction to machine learning* (2nd edition). Chapman and Hall/CRC. https://doi.org/10.1201/b22400

Oschinski, M., Crawford, A., & Wi, M. (2024). *AI and the future of workforce training*. Center for Security and Emerging Technology. https://cset.georgetown.edu/publication/ai-and-the-future-of-workforce-training/

Pausch, L.M., & Popp, M.P. (n.d.). *Assessment of information literacy: Lessons from the higher education assessment movement*. Association of College and Research Libraries. https://apastyle.apa.org/style-grammar-guidelines/references/examples/webpage-website-references

Perrigo, B. (2023, January 18). Exclusive: The $2 per hour workers who made ChatGPT safer. *TIME*. https://time.com/6247678/openai-chatgpt-kenya-workers/

Ridley, M., & Pawlick-Potts, D. (2021). Algorithmic literacy and the role for libraries. *Information Technology & Libraries, 40*(2), 1–15. https://doi.org/10.6017/ital.v40i2.12963

Phillips, K., Roles, E., & Thomas, S. (2022). Navigating the information ecosystem: Getting personal with source evaluation IF I APPLY. *LOEX Conference Proceedings 2019, 125*–132. https://commons.emich.edu/loexconf2019/35

Snow, J. (2025, February 12). *Universities, employers, increasingly insist on AI literacy*. Government Technology. https://www.govtech.com/education/higher-ed/universities-employers-increasingly-insist-on-ai-literacy

Stahura, D. (2018). ACT UP for evaluating sources. *College & Research Libraries News, 79*(10), 511–12. https://doi.org/10.5860/crln.79.10.551

Scott, J. (2024). Climate-conscious data Center cooling in an AI era. *ASHRAE Journal, 66*(1), 12–18. https://research.ebsco.com/linkprocessor/plink?id=be80df8d-0ea4-39a3-915c-608c6f8e6de1

Silver, N.S. (2023, June 5). The future of education disruption caused by AI and ChatGPT: artificial intelligence series 3/5. *Forbes*. https://www.forbes.com/sites/nicolesilver/2023/06/05/the-future-of-educationdisruption-caused-by-ai-and-chatgpt-artificial-intelligence-series-3-of-5/

Sye, D. & Thompson, D. S. (2023). Tools, tests, and checklists: the evolution and future of source evaluation frameworks. *Journal of New Librarianship, 8*(1), 76–100. https://doi.org/10.33011/newlibs/13/9

Tardiff, A. (2024). The inclusion of metacognition in source evaluation instruction. *Communications in Information Literacy, 18*(2), 133–157. https://doi.org/10.15760/comminfolit.2024.18.2.2

Tardiff, A.B. (2022). Have a CCOW: A CRAAP alternative for the internet age. *Journal of Information Literacy, 16*(1), 119–130. https://dx.doi.org/10.11645/16.1.3092

Taylor, B. L. (2023, November 15). Long hours and low wages: The human labour powering AI's development. *The Conversation*. http://theconversation.com/long-hours-and-low-wages-the-human-labour-powering-ais-development-217038

Warr, M., Oster, N. J., & Isaac, R. (2024). Implicit bias in large language models: Experimental proof and implications for education. *Journal of Research on Technology in Education*, 1–24. https://doi.org/10.1080/15391523.2024.2395295

Wei, X., Kumar, N., & Zhang, H. (2025). Addressing bias in generative AI: Challenges and research opportunities in information management. *Information & Management, 62*(2), 1–9. https://doi.org/10.1016/j.im.2025.104103