Information literacy: A foundational approach to generative AI competence

Cara Olson
Iowa State University
United States
colson6@iastate.edu

Tassia Corcoran
University of Hawaiʻi at Mānoa
United States
tassia@hawaii.edu

Branden Ogata
University of Hawaiʻi at Mānoa
United States
bsogata@hawaii.edu

Michael-Brian Ogawa
University of Hawaiʻi at Mānoa
United States
ogawam@hawaii.edu

Abstract: This study evaluated instructional design for information literacy as a foundational approach to generative AI usage in education and its perceived usefulness. We analyzed the effectiveness of instructional materials through student surveys and semi-structured teaching assistant (TA) interviews. The survey included questions about the perceived confidence level of students in using generative AI effectively after instruction and how it evolved their practices. Student assignments were collected, analyzed, and assessed using a rubric based on the ACRL Framework for Information Literacy for Higher Education. TA interviews and analysis of the assignment revealed that students were able to ask informational questions that paralleled traditional search queries but struggled with content generation and the usage of personas. Survey responses highlighted a strong application of the ARCS Model of Motivation, which included a high level of satisfaction and overall motivation to learn. The instructional design included prominent components to maintain student attention with high viewer retention through relevant examples. Overall, students found information literacy as a framework for generative AI to be useful for homework, resumes, and informational support.

Introduction

Generative artificial intelligence (AI) changed the learning landscape for students and educators by creating many new opportunities for learning. These opportunities come with concerns from educators that include plagiarism, information accuracy, and bias amplification (Lund, et al., 2023). Commonly cited benefits of generative AI in education include usage as an on-demand writing and study tool (Meyer, et al., 2023), idea generation and practice problem creation tool (Kasneci, et al., 2023), and visualization tool (Chen, Zhang, & Hu, 2024). As a writing tool, generative AI can be used to improve the clarity and style of writing (Meyer, et al., 2023). At the elementary level, it can provide sample writing prompts for students to practice their writing skills, while more advanced students can use it to help generate ideas (Kasneci, et al., 2023). Kasneci et al. also found that students can use generative AI as a study tool, where students use generative AI to create additional practice problems and receive step-by-step explanations without the need for a tutor. Students can also creatively use tools such as image creation AI to visualize difficult concepts (Chen, Zhang, & Hu, 2024) to improve their understanding.

Although generative AI has many use cases, there are also user-centric limitations that limit its implementation at high levels. These include effective prompt engineering, difficulty in distinguishing the accuracy of the information, and whether or not a human produced the content (Ogawa & Ogata, 2023). For example, generative AI has difficulty interpreting context in prompts such as cultural context (Frick, 2024). To effectively use generative AI to increase their understanding and to minimize the limitations, Ogawa and Ogata (2023) suggested information literacy as a common frame across disciplines. Information literacy allows students to verify the accuracy of generative outputs, reduce reliance by allowing students to learn from multiple sources, and reduce plagiarism through the intentional usage of generative AI as an information-gathering and generation tool to support their work. In addition to information literacy skills, users need to learn prompt engineering techniques to create outputs that meet information needs (Lo, 2023).

Background

The emergence of large language models (LLMs) and generative AI chatbots, including ChatGPT and Bing Chat, is transforming the educational landscape, creating a need for educational institutions to reevaluate instructional approaches. As generative AI becomes more prevalent in academic spaces, educators are charged with determining how to integrate these tools while maintaining ethical and educational integrity that continues to promote learning outcomes.

The literature illustrates a general consensus that AI needs to be incorporated into educational frameworks rather than prohibit its usage. Integration of AI presents complex challenges. Meyer et al. (2023) emphasized how AI can be a powerful education tool when properly implemented, especially for non-native English speakers who can benefit from its language processing capabilities to help the user understand topics such as grammar. The technology offered a range of benefits across all educational levels, from generating practice problems for elementary students to providing detailed summaries and feedback in higher education (Kasneci, et al., 2023). Instructors also have the ability to leverage AI for efficient lesson planning and the creation of learning materials (Chen, Chen, & Lin, 2020).

Despite the benefits, the utilization of AI in education raises concerns. Plagiarism is a primary concern, with scholars debating the authorship of AI-generated content (Meyer, et al., 2023). Lund et al. (2023) raised important considerations about content ownership, whether the information generated belongs to the user, the AI company, or the data sets the AI drew its information from. Technical limitations also present pressing challenges within AI: chatbots often have low accuracy, particularly in complex fields like medicine, law, and academia. Generative AI often struggles with understanding the context of different situations and queries, where it can perpetuate biases toward marginalized groups on the basis of gender, race, ethnicity, and disability status. These biases can lead to unintentional biases in outputs based on AI if the author does not verify the information (Lund, et al., 2023). Kasneci et al. (2023) noted that most LLMs are predominantly English-based, creating comprehension barriers for non-English speaking students. Kasneci et al. believe that generative AI poses a barrier to non-English speaking learners focusing on the content generated, whereas insights from Meyer et al. regarding English language learners focus on the capability of generative AI as a tutor. Therefore, these perspectives highlight the different use cases and how LLMs can either hinder or support the same group depending on usage.

The effectiveness of AI in instruction involves nuanced factors such as prompt engineering techniques. Lo (2023) emphasized that successful interactions with AI depend heavily on the ability of users to engineer prompts, suggesting that structured approaches such as the CLEAR model (Concise, Logical, Explicit, Adaptive, and Reflective) may greatly enhance AI utilization in academic settings. An additional factor is the varied perspectives of generative AI usage since teachers and students see different opportunities (Waltzer, Cox, & Heyman, 2023). They are often met with different expectations that are generally not met for either party. Therefore, finding common ground for its usage is critical to its usage in education.

In addition to prompt engineering techniques, scholars such as Ogawa and Ogata (2023) discussed the importance of using information literacy as a framework for generative AI usage. This approach accounts for some of the previous issues discussed by making the user the center of information verification. The Association for College and Research Libraries (ACRL) provides a framework for assessing information literacy skills. It is based on six concepts that are foundational for students building their information literacy skills, which can then be applied to many disciplines (Association of College and Research Libraries, 2016). The ACRL framework concepts are as follows:

- *Authority Is Constructed and Contextual*: Authority is not an absolute concept, and it comes from the context and purpose of its use.
- *Information Creation as a Process*: Information is created through a process; however, the process changes based on the format, medium, and purpose of the information.

- *Information Has Value*: All information has value; however, the value changes depending on the context of the use of the information. Students should be able to cite where their information comes from correctly.
- *Research as Inquiry*: Research is an iterative process of asking questions, finding information, and revising understanding.
- *Scholarship as Conversation*: Scholarship is a conversation among researchers and scholars where new ideas build upon and challenge previous ones.
- *Searching as Strategic Exploration*: Searching is a strategic process that evolves over time.

These concepts focus on not only the process of finding information but also the ability to discern credible information and the context in which the information comes from. James and Filgo (2023) discussed how the ACRL framework for information literacy can be applied to generative AI such as ChatGPT. They noted that the six concepts of the ACRL information literacy framework could help students understand how to determine the relevance and accuracy of the information they are gaining from generative AI.

Although there are studies on theoretical frameworks and case studies (Meyer, et al., 2023; Kasneci, et al., 2023; Chen, Zhang, & Hu, 2024), very few articles examine the instructional design of AI education from an information literacy vantage point. This creates an opportunity for the authors to conduct research merging instructional design considerations for generative AI as a learning support tool while incorporating student insights to better match instruction to students and learning outcomes. Our study looks to provide valuable insights for pedagogical consideration in information literacy generative AI instruction to support a cross-disciplinary approach to AI skills development. Based on these areas of need, we posed the following research questions:

1. How well do students use information literacy skills taught to determine the accuracy of generative AI responses?
2. How did the ARCS model of motivation support learning generative AI-based information literacy?
3. What do students see as important uses of generative AI in the future?

Setting

The study was conducted at a Research I public university in the Western United States. We developed and implemented the study with a 100-level large-enrollment introductory computer science course designed for non-Computer Science majors. This course focused on computational thinking concepts and application usage for productivity regardless of major. The course typically enrolls approximately 250 students from over 30 majors per semester. Instruction was delivered in a hybrid format, with a weekly in-person lecture and an asynchronous lecture podcast. Students were also required to attend one in-person lab session each week where they received hands-on instruction from a teaching assistant (TA) in the effective use of applications and completed an asynchronous lab each week. Therefore, half of the class was taught in person, while the other half was taught with asynchronous material.

This course was selected for the study due to its diverse majors and content. The wide range of majors was particularly beneficial to see how well information literacy as a framework was useful across disciplines. The content targets computational thinking, productivity application, and information literacy skills. The productivity application focus of the course focused on the development of application usage skills and automation that complement generative AI use. This includes the creation of content and data sets for analysis with these tools. We implemented the study in the Spring 2024 semester, which included the creation and implementation of a generative AI information literacy module, an assessment of their learning and application of generative AI information literacy skills, a survey on generative AI dispositions, and TA interviews.

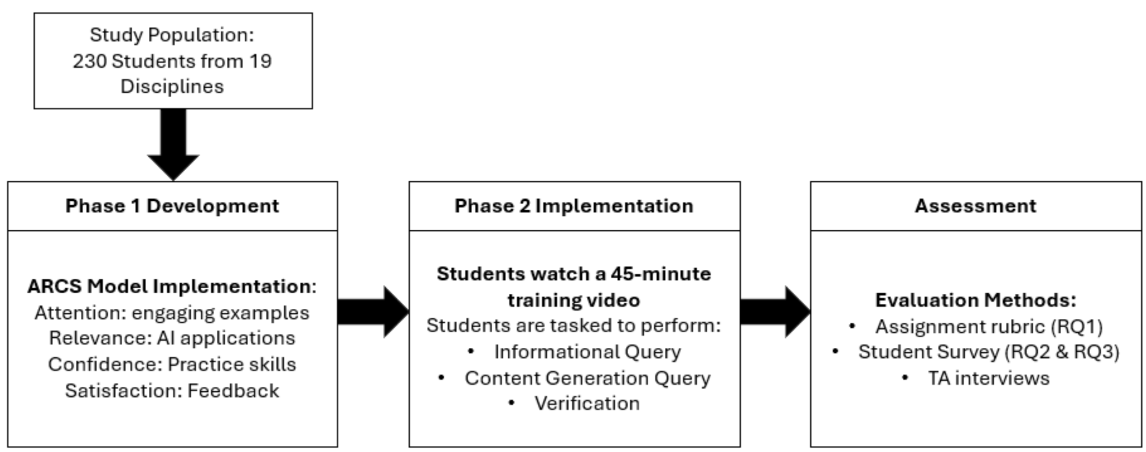
Methods

A total of 230 students participated in the study from 19 disciplines, with a majority of students majoring in a sector of Business Administration. Forty-eight percent of the students were in their first year of college, 35% were in their second year, 16% were in their third year, and 1% were in their fourth year or greater. Twenty-nine percent of the students were 18 years old, 53% were 19, 18% were 20, 10% were 21, 2% were 22, and 6% were 23-30.

The study consisted of two phases (Figure 1). The first phase was the development of the generative AI information literacy module using the ARCS model of motivation as an instructional design framework, while the second phase was focused on implementation and evaluation (Fang, et al. 2023). In the development phase, the research team utilized ARCS as a framework to systematically develop the module to enhance student motivation while learning to use generative AI, in which students had varied experiences. The motivation focus was identified as critical to ensure engagement and application to their daily lives. We implemented the ARCS Model of Motivation as follows:

- *Attention*: Get the attention of students with relatable examples.
- *Relevance*: Maintain attention through relevant usage of generative AI, including information-gathering techniques (prompt engineering), verification techniques (multiple sources, applied checking), examples of when generative AI gives incorrect results, and citation methods.
- *Confidence*: Give students the opportunity to practice prompt engineering skills, output verification, and citation. We also followed up with students on their ability to consistently apply generative AI to their work throughout the class in subsequent assignments.
- *Satisfaction*: The teaching team gave feedback directly to students to demonstrate what worked well and where their skills could be improved to celebrate their success and highlight areas for continued growth.

Figure 1. Study design



Once we developed the module, we implemented it in the first week of class. Students were instructed to view a 45-minute video on generative AI, which included prompt engineering techniques for information-based queries and content generation with personas, verifying outputs, and citing generative AI. Information-based queries are defined as queries that have direct answers with little need for interpretation. An example of an information-based query is “What is the current salary of a marketing executive in the United States?” Content-generation queries with personas are defined as queries where a user asks for an artifact they can use. An example of this would be,” As a marketing manager, create a marketing campaign for a new sunglass line set to be released in the summer.”

To answer the first research question, the research team assessed de-identified student assignments according to a rubric based on the ACRL Framework guidelines (James & Filgo, 2023). The rubric was assessed by multiple trained raters using a standardized evaluation approach. To ensure consistency, the ratings were analyzed using Fleiss's Kappa, resulting in an inter-rater reliability score of 0.84. The rubric uses the following scales of achievement:

- Below benchmark: The student did not show any critical analysis of the generative AI output.
- Benchmark: The student used secondary sources to confirm the accuracy of generative AI output but did not describe the specific sources they used.
- Milestone: The student meets the criteria for the benchmark and describes potential inaccuracies in the generative AI output and differences they found between the output and their secondary sources.
- Capstone: The student meets the criteria for the milestone and shows a strong understanding of inaccuracies in generative AI outputs and where these inaccuracies occur.

The assignment tasked students with identifying a career of interest and utilizing generative AI to learn more about their selection. Students were asked to create one informational and one content-generation query about their career of interest using generative AI. They were then required to explain why the queries were relevant to their chosen career or current major and include how they chose to verify the generative AI output as accurate or useful.

To address RQ2 and RQ3, students were given a survey with questions targeting the different components of ARCS and additional open-ended questions. A set of questions was retrospective to determine how the instruction impacted the perceptions of students of generative AI. We used a 7-point scale for the survey to reduce the likelihood of students choosing a neutral option for every statement. The overall ratings were then compared to the overall performance on the assignment. For example, participants were asked to rate their understanding of the difference between an informational and content-generating question. The average score was then calculated and compared to the overall performance on that section of the accompanying assignment.

Teaching Assistants (TAs) were asked to participate in semi-structured interviews as a triangulation source to confirm the findings from the survey. They were asked to report on their section's overall performance on the assignment, what kind of support they provided to their students, and any additional insights they may have had.

Findings

RQ1: How well do students use information literacy skills taught to determine the accuracy of generative AI responses?

The learning goals targeted the abilities of students to conduct a content generation query, informational query, follow-up questioning, identification of key points, and verification of responses. Overall, students performed well in generating content for their major, with 83.8% of students achieving either the milestone or capstone level (Table 1). However, 53% met or exceeded the milestone for the content-generation follow-up questioning. Forty-five percent of students met or exceeded the milestone for the informational query. Their follow-up questioning on this type of search improved to 69.0%. In comparing these two types of queries and follow-up questioning, it appears that students were able to follow the prompt engineering structure provided for content generation. The informational query included a less structured search, which resulted in varied approaches to creating this type of prompt. The research team reviewed the submissions in more detail to identify themes in the search structure. We found that while students could follow the prompt engineering structure for content generation queries, they were less familiar with reviewing this type of output. With informational queries, students were much more familiar with this type of search due to their prior experiences with search engines. This led to them using their previously acquired search strategies, which were at a wider range of implementation, resulting in a lower achievement level. Students were able to adjust for their varied level by having stronger follow-up questions to get to their targeted information needs. These findings illustrated the abilities of students to implement *Research as inquiry* and the varied levels of understanding as applied to the different types of searches. Thus, there is a need to focus on building follow-up questioning skills for areas that students are less familiar with, such as content-generation-based prompts.

Table 1. Student performance for learning goals.

Learning Goal	No Submission	Approaching	Benchmark	Milestone	Capstone
Generate content related to major	10.6%	1.4%	4.2%	21.8%	62.0%
Content Generation: Follow up questioning	15.5%	25.4%	5.6%	28.9%	24.6%
Informational query related to major	9.9%	11.3%	33.8%	28.2%	16.9%
Informational Query: Follow up questioning	10.6%	14.8%	5.6%	34.5%	34.5%
Identify key points	15.5%	22.5%	26.8%	16.9%	18.3%
Verification	12%	21.8%	38.7%	16.2%	11.3%

Students struggled with identifying key points, with 35.2% at the milestone or capstone levels. The level of performance on this learning objective demonstrated the challenge of extracting critical information from generative AI queries. Verification of information from generative AI queries included low performance, with 27.5% achieving the milestone or capstone level. Upon reviewing the queries of students, it was evident that many accepted generative AI outputs as factual without verifying the accuracy of the information. The ACRL frame, *Authority is constructed and contextual*, is an area that needs additional consideration based on how generative AI provides results. Although information can be cited depending on the LLM used, it is critical to teach how to determine authority and its context with these types of tools, which have varied levels of clarity for the end-user.

RQ2: How did the ARCS model of motivation support learning generative AI-based information literacy?

The components of the ARCS model of motivation helped students improve their understanding of generative AI-based information literacy. Students were instructed to watch a lecture, which maintained steady viewership after the initial drop-off from the video. There was a significant drop in views about one minute and 30 seconds into the video. This could be attributed to students restarting the video and skipping to a relevant part of it for their assignment. There was also a slight spike in viewership immediately before the section of the video instructing students how to cite generative AI correctly. This demonstrated that the lecture was able to capture and maintain the attention of students at critical points, which demonstrates a reasonable application of *Attention* in the design of the module.

When analyzing the open-ended questions, common themes highlighted student *Relevance* and *Satisfaction* with their learning experience. They stated that prior to the lecture, they did not see many uses for generative AI in their personal or educational lives. After watching the video, they found a high level of relevancy due to generative AI having more practical uses than they originally thought. This relevant theme led to high levels of satisfaction from students due to the practicality of their newfound knowledge and their ability to use it. Although they were appreciative of the feedback from teaching assistants, relevancy and practicality were more impactful on their satisfaction levels. Additionally, students indicated that the module sparked curiosity in different applications of generative AI, such as image and sound manipulation, as well as surrounding ethical implications. This suggests that the module fostered an intrinsic motivation to learn about complementary areas, aligning with the *Satisfaction* component of the ARCS model of motivation. Overall, the motivation to use generative AI increased, where many increased their generative AI usage or planned to implement it in their future workflow.

The survey included retrospective questions about *Confidence* in using generative AI. Students reported feeling more *Confidence* in their generative AI usage. The survey asked students to rate their confidence level in using generative AI for various tasks (Table 2). Confidence significantly increased by 1.3 for writing informational question prompts, writing content generation prompts, and determining the accuracy of generative AI responses. It was interesting that the highest increase in confidence was with determining the accuracy of generative AI responses, while the performance on the related task was the lowest of all the skills. The researchers posit that this had the highest confidence increase since many students had minimal prior experience verifying generative AI outputs, making this a new area of learning for them.

Table 2. Paired t-test results for retrospective confidence perception in prompt generation

Item	Significance	Average increase
Creating informational questions	$p<0.05$	1.3 (4.2 → 5.5)
Creating content generation questions	$p<0.05$	1.3 (4.2 → 5.5)
Determining the accuracy of generative AI responses	$p<0.05$	1.4 (3.9 → 5.3)

RQ 3: What do students see as important uses of generative AI in the future?

After learning how to use generative AI from an information literacy viewpoint, the researchers were interested in the perspectives of the students on its future value. We found three major themes based on the insights of students that were confirmed with the TA interviews. Twelve percent of students showed interest in how generative AI responses are formed. This was a newfound interest for some, as they previously took outputs for granted without considering how they are created and potential biases. Thus, we believe that this module helped to bring a critical eye to what and how information is created, which demonstrates a deeper understanding of the *Information Creation as a Process* ACRL frame. Furthermore, 14.1% were interested in the ethical implications of using generative AI in school and the workplace. Seeing this level of interest from students stressed the importance of *Relevance* in the ARCS Model of Motivation. Curiosity about ethics is demonstrative of personal relevance to how they may use these tools in the future. Lastly, 16.3% showed interest in utilizing generative AI outside the scope of the course, such as sound and image generation. As students are exposed to additional types of generative AI, they are becoming increasingly interested in the possibilities for school, work, and their personal lives. Many of them are concerned about how the workforce will evolve throughout their careers. When reviewing these themes together, it was clear that as students learned about generative AI, their curiosity about its use, applications, workforce needs, and ethical considerations increased.

Conclusions

Information literacy serves as a strong foundation for teaching generative AI concepts to students in education. Our study illuminated how areas of the ACRL framework, such as *Authority is constructed and contextual, Information creation as a process, Information has value, and Research as Inquiry,* were at the core of student learning in this module. Although *Scholarship as conversation* and *Searching as Strategic exploration* were not directly linked to student performance and survey data, these areas also support generative AI literacy. *Scholarship as conversation* may become more apparent as learners dig deeper into the sources for generative AI outputs. This will help them to understand the output and the sources of conversation that were used to create the generated output. We see this as a possible area for future research, as it requires a much deeper understanding of outputs and how to conduct a citation analysis. We also see *searching as strategic exploration* as a moving target. As LLMs mature, additional prompt engineering approaches may be needed to get outputs that meet information needs.

Our application of the ARCS Model of Motivation underscored areas for practitioners to consider as they develop instruction to support generative AI usage in education. The study revealed that prior experiences with the traditional search made initial informational generative AI queries more challenging. Content generation prompts were easier to produce with a structure but more difficult to follow up with additional questions for clarity. These findings showcase the importance of audience analysis to determine where and what types of additional practice to include within instruction. The audience analysis can also improve relevance, which was a key component that led to greater attention and satisfaction. Depending on context, it may be beneficial for instructors to expand the lesson and include instruction on different forms of content generation outside of text generation. This is feasible with image manipulation AI, such as generative fill, which adds additional content to an image.

The ARCS model of motivation and the ACRL guidelines for information literacy created a powerful foundation for generative AI instruction. ARCS places emphasis on learner motivation throughout the process. Therefore, an audience analysis plays a critical role in applying these frameworks by targeting information literacy environments for college students. Although they are typically in their late teens to early 20s, accounting for the needs of the adult learner is important. This process is reinforced by ARCS through *Relevance.* In producing relevant learning modules for students, instructors would need to consider their learning needs. In addition to motivation, ACRL emphasizes active learning and improving critical thinking skills, which align well with *Confidence* and *Satisfaction* in ARCS. Students are encouraged to engage in difficult tasks and receive feedback promoting the development of critical mental models. By aligning these frameworks, instruction regarding generative AI can develop knowledge and skills while motivating students to consider the breadth and depth of possibilities and its impact on their future.

The study created many opportunities for future research. We intend to explore a deeper integration of the ACRL framework in generative AI instruction and how to best apply instructional design theories to improve learning. In particular, we are interested in exploring the different ACRL frames in detail to determine how to best meet each of the standards and where they are most applicable. We believe that there may be slight differences based on discipline but are looking to find more evidence to demonstrate how information literacy can be the core of generative AI learning in education. Our research also created opportunities to conduct follow-up studies to determine how well students are able to implement their generative AI skills in subsequent course assignments (same course; short-term) and other courses (long-term). This may illuminate instructional design considerations for long-term learning and the application of generative AI. These best practices could be beneficial for practitioners as educators determine how they want to implement generative AI into their curriculum.

This study included limitations such as a large number of participants having a business-focused major, which limited the generalizability to other disciplines. The data were also collected in a single semester, making it a reasonable initial study. However, we would like to expand the data collection over longer periods of time to strengthen validity. This research was case specific and only examined data collected from a single module.

Our study was a first step toward considering information literacy as a core foundational approach to teaching generative AI usage that is cross-disciplinary. Since information retrieval skills, such as Web searches, serve as a mental structure for many getting started with AI, we need to evolve with the tools to support our students in being information literate in all of their areas of interest. Instructional design is a strong approach to more effectively prepare our students for a world with integrated AI.

Acknowledgments

We would like to express our gratitude to Rondell Torres, D. Kanoa Borromeo, and Herman Ma for their research support. We would also like to acknowledge the University of Hawaii UROP, Iowa State University, and Dr. Randall Minas with the HINT lab for their financial support in the completion of this study.

References

Association of College and Research Libraries. (2016). Framework for Information Literacy for Higher Education. Retrieved from https://www.ala.org/sites/default/files/acrl/content/issues/infolit/Framework_ILHE.pdf.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial Intelligence in Education: A Review. *IEEE Access, 8*, 75264-75278. doi:10.1109/ACCESS.2020.2988510

Chen, Y., Zhang, X., & Hu, L. (2024). A Progressive Prompt-Based Image-Generative AI Approach to Promoting Students' Achievement and Perceptions in Learning Ancient Chinese Poetry. *Educational Technology & Society*. doi:https://doi.org/10.30191/ETS.202404_27(2).TP01

Fang, X., Ng, D. T., Leung, J. K., & Xu, H. (2023). The Applications of the ARCS Model in Instructional Design, Theoretical Framework, and Measurement Tool: A Systematic Review of Empirical Studies. *Interactive Learning Environments*, 1-28. doi:10.1080/10494820.2023.2240867

Frick, T. W. (2024). Are We Dupes? Limitations of AI Systems: What Should Educators Do with Them? *TechTrends: For Leaders in Education & Training, 68*(1), 14-26. doi:10.1007/s11528-023-00893-3

James, A. B., & Filgo, E. H. (2023). Where Does ChatGPT Fit into the Framework for Information Literacy? The Possibilities and Problems of AI in Library Instruction. *College & Research Libraries News, 68*(9), 334.

Kasneci, E., Kathrin, S., Stefan, K., Maria, B., Daryna, D., Frank, F., . . . al, e. (2023). ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education. *Learning and Individual Differences, 103*. doi:10.1016/j.lindif.2023.102274

Lo, L. S. (2023). The Art and Science of Prompt Engineering: A New Literacy in the Information Age. *Internet Reference Services Quarterly, 27*(4), 1-8. doi:10.1080/10875301.2023.2227621

Lund, B. D., Ting, W., Nishith Reddy, M., Bing, N., Somipam, S., & Ziang, W. (2023). ChatGPT and a New Academic Reality: Artificial Intelligence-written Research Papers and the Ethics of the Large Language Models in Scholarly Publishing. *Journal of the Association for Information Science and Technology, 74*(5), 570-81. doi:10.1002/asi.24750

Meyer, J. G., Urbanowicz, R. J., Martin, P. C., O'Connor, K., Li, R., Peng, P.-C., . . . al, e. (2023). ChatGPT and Large Language Models in Academia: Opportunities and Challenges. *BioData Mining, 16*(1), 20. doi:10.1186/s13040-023-00339-9

Ogawa, M., & Ogata, B. (2023). Artificial Intelligence for Educators. Retrieved from https://stempreacademy.hawaii.edu/resource/artificial-intelligence-for-educators/

Waltzer, T., Cox, R., & Heyman, G. (2023). Testing the Ability of Teachers and Students to Differentiate between Essays Generated by ChatGPT and High School Students. *Human Behavior & Emerging Technologies*, 1-9. doi:10.1155/2023/1923981