ADVANCES IN KNOWLEDGE ORGANIZATION
Proceedings of International ISKO Conference - ISSN: 0938-5495 - 2026 - São Paulo

AI-Assisted Reading vs. Traditional Screen Reading: An Empirical Study on Cognitive Load and Reading Comprehension from a Knowledge Organization Perspective

Yue Gong

School of Information Management, Wuhan University, China

Jinbin Zhang

School of Information Management, Wuhan University, China

Xiaoguang Wang

School of Information Management, Wuhan University, China

Abstract

This study investigates the differences between AI-assisted reading and traditional screen reading in terms of cognitive load and reading comprehension from the perspective of knowledge organization. A controlled experiment was conducted based on cognitive load theory. The results showed that the AI-assisted reading group experienced significantly higher cognitive load. Although no significant difference was found in overall reading comprehension, the traditional screen reading group performed better in information extraction and logical reasoning, while the AI-assisted reading group excelled in divergent thinking. The findings suggest that AI, as a medium for knowledge reorganization, promotes divergent thinking by constructing networked knowledge representations, but it also increases cognitive load and interferes with information extraction and logical reasoning. This study provides theoretical insights for the balanced design of AI reading tools between efficient information retrieval and knowledge discovery.

Keywords: AI-assisted reading; cognitive load; reading comprehension; knowledge organization

1.0 Introduction

The landscape of academic reading has undergone a profound transformation, shifting from traditional paper-based reading to reading on digital screens, and now, to reading augmented by artificial intelligence (Mullis et al. 2017; Picton 2014; Shenoy and Aithal 2016). The emergence of AI-powered conversational agents, such as ChatGPT and Kimi Chat, represents a new epoch in human-information interaction. These AI assistants are increasingly integrated into the learning environment, playing roles as partners, tutors, or mentors (Fidan and Gencel 2022; Wollny et al. 2021). By providing personalized content, real-time feedback, and one-to-one guidance, they hold the potential to fundamentally reshape how readers engage with and comprehend texts (Fidan and Gencel 2022). Prior research has demonstrated that AI assistants can enhance academic performance

(Vázquez-Cano et al. 2021), stimulate learning interest (Wambsganss et al. 2021), boost motivation and engagement (Chien et al. 2022; Ruan et al. 2021), and improve learning self-efficacy (Yin et al. 2021). They facilitate the integration of new and prior knowledge through dynamic interaction (Lee et al. 2022). As AI technology becomes a new and powerful reading medium, it is crucial to understand its impact on the fundamental cognitive processes underlying reading.

From a knowledge organization perspective, reading is not merely the passive reception of information but an active process of knowledge construction and reorganization. Traditional reading media—whether paper or screen—preserve the linear structure of the text as originally authored. In contrast, AI-assisted reading introduces a fundamentally different mode of knowledge organization. Through semantic understanding, concept extraction, and cross-textual linking, AI tools dynamically restructure the original text into a multidimensional knowledge network (Han and Choi 2025). This AI-driven knowledge reorganization can manifest in various forms: summarization, contextual explanation, conceptual mapping, and even the generation of new questions and connections. Such transformations raise important questions about how the reorganization of knowledge influences readers' cognitive load and comprehension outcomes.

The influence of media on reading comprehension has been a long-standing area of inquiry. A substantial body of research comparing paper and screen reading has yielded mixed results. While some studies have found screen reading to be superior (Aydemir et al. 2013), others have found no significant difference between media (Hermena et al. 2017; Margolin et al. 2013; Porion et al. 2016; Rockinson-Szapkiw et al. 2013). Conversely, a significant number of studies have documented a "screen inferiority effect," where paper reading leads to better comprehension (Golan et al. 2018; Halamish and Elbaz 2020; Mangen et al. 2013; Singer and Alexander 2017). Researchers have explored these differences through various lenses, including metacognition. For instance, Ackerman and Goldsmith (2011) found that digital reading is associated with less stable time allocation, while Ackerman and Lauterman (2012) identified time pressure as a key moderator, revealing that the "screen disadvantage" is linked to overconfidence and lower performance under time constraints. However, despite the wealth of research on paper versus screens, there is a notable paucity of empirical studies examining the effects of AI-assisted reading—a gap this study aims to fill.

To understand the mechanisms behind these media effects, Cognitive Load Theory (CLT) offers a powerful framework (Paas et al. 2016; Sweller 1994). CLT posits that learning and comprehension are constrained by the limited capacity of working memory. It distinguishes between three types of cognitive load: intrinsic load (inherent to the task's complexity), extraneous load (imposed by the instructional material's design), and germane load (devoted to constructing schemas). Prior research has established a strong link between cognitive load and reading comprehension performance (Hsu et al. 2013; Kong et al. 2018). Studies comparing paper and screen have often found that digital reading imposes a higher cognitive load. Factors such as scrolling, which disrupts visual continuity, add to the reader's mental burden (Noyes et al. 2004; Wästlund et al. 2005), potentially impairing

learning efficiency (Noyes and Garland 2003). Although advancements in display technology have mitigated some of these disadvantages (Porion et al. 2016), challenges persist, especially with demanding texts (Delgado et al. 2018; Rosenfield et al. 2015).

The introduction of AI into the reading process presents a new set of questions regarding cognitive load and knowledge organization. According to CLT, AI-assisted reading could potentially reduce extraneous load by summarizing information, providing contextual explanations, and guiding attention to key points. However, it could also increase intrinsic or extraneous load through novel interface interactions, the cognitive effort of evaluating AI-generated insights, or by encouraging a more superficial engagement with the text. Moreover, from a knowledge organization perspective, AI tools act as knowledge reorganizers: they restructure linear text into associative networks, thereby altering the fundamental representation of information. This reorganization may have dual effects: it may facilitate exploratory knowledge discovery (supporting divergent thinking) while simultaneously complicating targeted information retrieval (hindering precise extraction). The net effect on cognitive load and its subsequent impact on different facets of reading comprehension-such as extracting specific facts, logical reasoning, and generating new ideas—remains an open empirical question.

Therefore, this study aims to investigate the cognitive consequences of AI-assisted reading from a knowledge organization perspective. Specifically, we designed a controlled experiment to compare AI-assisted reading with traditional screen reading. Our research questions are as follows:

RQ1: Does AI-assisted reading lead to a different level of cognitive load compared to traditional screen reading?

RQ2: Is there a difference in overall reading comprehension performance between AI-assisted reading and traditional screen reading?

RQ3: Are there differential effects of AI-assisted reading on specific sub-dimensions of reading comprehension, namely information extraction, logical reasoning, and divergent thinking?

2.0 Literature Review

2.1 Media and Reading Comprehension

Research on paper versus screen reading has yielded mixed findings. While some studies report screen advantages (Aydemir et al. 2013) or no difference (Hermena et al. 2017; Porion et al. 2016), many document a "screen inferiority effect" where paper reading leads to better comprehension (Delgado et al. 2018; Kong et al. 2018). Ackerman and Lauterman (2012) identified time pressure as a key moderator: under time constraints, screen readers exhibit greater overconfidence and lower performance. Ackerman and Goldsmith (2011) further found digital reading associated with unstable time allocation. Despite extensive research on paper versus screens, studies on AI-assisted reading remain scarce.

2.2 Cognitive Load and Reading

Cognitive Load Theory (CLT) distinguishes intrinsic, extraneous, and germane load in learning (Sweller 1988; Paas and van Merriënboer 1994). Screen reading typically imposes higher extraneous load than paper due to scrolling and interface demands (Noyes et al. 2004; Wästlund et al. 2005), potentially impairing learning efficiency (Noyes and Garland 2003). Although display improvements have mitigated some disadvantages (Porion et al. 2016), digital reading continues to challenge comprehension, particularly for demanding texts (Delgado et al. 2018).

2.3 AI-Assisted Reading and Knowledge Organization

Knowledge organization research examines how structuring information enhances accessibility and comprehension (Hjørland 2016). Recent advances demonstrate AI's knowledge reorganization capabilities: Han and Choi (2025) found AI-generated concept maps reduced cognitive load by 31.5%. While AI-generated questions promoted complex thinking, they also led to fragmented integration of information. White et al. (2025) showed that combining LLMs with knowledge graph visualization reduces cognitive load during exploratory search. Zhang et al. (2025) offers hierarchical decomposition of academic papers, balancing overview with detail.

From a knowledge organization perspective, AI-assisted reading tools function as "dynamic knowledge reorganizers," transforming linear texts into networked representations through: (a) semantic extraction—identifying key concepts and relationships; (b) contextual linking—connecting to external knowledge sources; (c) generative elaboration—producing explanations and analogies. Understanding these trade-offs is essential for designing AI tools that optimally support human cognition.

3.0 Method

3.1 Reading Material

The reading material was a 6000-word scientific article from New Scientist ("Digital Damage"), selected for its professional content, moderate difficulty, and estimated 20-minute reading time suitable for experimental sessions.

3.2 Test Materials

Reading comprehension test. A 10-item questionnaire was developed based on the PISA reading literacy framework (OECD 2009), assessing three sub-dimensions: information extraction, logical reasoning, and divergent thinking. A pre-test with six graduate students informed subsequent adjustments.

Cognitive load questionnaire. The NASA-TLX scale (Hart and Staveland 1988) was administered following established practices (Shadiev and Huang 2020). The raw NASA-TLX score (unweighted average of six subscales: mental demand, physical demand, temporal demand, performance, effort, frustration) served as the global cognitive load measure.

3.3 AI-Assisted Reading Condition

Participants in the AI-assisted group used a custom interface integrating the article with a ChatGPT-based assistant capable of providing real-time summaries, answering content-related questions, and suggesting conceptual connections. Participants could interact with the assistant freely during the 20-minute session; all interactions were logged.

3.4 Participants

Undergraduate and graduate students from Wuhan University were recruited and randomly assigned to either the AI-assisted group (n = 15) or the traditional screen reading group (n=15). All participants confirmed no prior knowledge of the article. Sample size calculation (Cohen's d=0.8, α=0.05, power=0.80) indicated a target of 26 per group; the current sample provides preliminary results, with data collection ongoing.

4.0 Results

Table 1 presents the results of independent samples t-tests comparing the effects of AI-assisted reading and traditional screen reading on cognitive load and reading performance.

Table 1 Comparison of cognitive load and reading comprehension between groups. Values are mean ± SD. *p < 0.05.

Measure	AI-Assisted Reading (n=15)	Traditional Screen Reading (n=15)	t	p
Cognitive Load	68.4 ± 8.1	60.9 ± 9.6	2.38	0.024*
Reading Performance (Total Score)	77.2 ± 6.5	76.1 ± 7.3	0.45	0.654
Subscale Scores				
Information Extraction (/35)	26.5 ± 3.3	29.0 ± 2.5	-2.42	0.022*
Logical Reasoning (/35)	26.0 ± 3.8	28.8 ± 3.2	-2.28	0.030*
Divergent Thinking (/30)	24.7 ± 2.8	18.3 ± 4.5	4.92	<.001*

Cognitive Load: A statistically significant difference in cognitive load was observed between the two groups, *t*(28) = 2.38, *p* = .024. The mean score for the AI-assisted reading group (M = 68.4, SD = 8.1) was significantly higher than that of the traditional screen reading group (M = 60.9, SD = 9.6). This indicates that engaging with the AI-assisted reading interface imposed a greater cognitive burden on participants.

Overall Reading Performance: No statistically significant difference was found in the total reading comprehension score between the AI-assisted reading group (M = 77.2, SD = 6.5) and the traditional screen reading group (M = 76.1, SD = 7.3), *t*(28) = 0.45, *p* = .654. This suggests that both reading methods were equally effective for knowledge acquisition from the text.

Reading Performance Subscales: Despite the lack of difference in overall score, clear dissociations emerged across subscales:

Information Extraction: A significant difference was found for the Information Extraction subscale, *t*(28) = -2.42, *p* = .022. The traditional screen reading group (M = 29.0, SD = 2.5) outperformed the AI-assisted reading group (M = 26.5, SD = 3.3).

Logical Reasoning: Similarly, for the Logical Reasoning subscale, a significant difference was observed, *t*(28) = -2.28, *p* = .030. Again, the traditional screen reading group (M = 28.8, SD = 3.2) scored higher than the AI-assisted reading group (M = 26.0, SD = 3.8).

Divergent Thinking: A highly significant difference was identified for the Divergent Thinking subscale, *t*(28) = 4.92, *p* < .001. In a reversal of the previous pattern, the AI-assisted reading group (M = 24.7, SD = 2.8) demonstrated markedly superior performance compared to the traditional screen reading group (M = 18.3, SD = 4.5).

5.0 Discussion

The experiment identifies a clear cognitive trade-off induced by generative AI during reading. Compared with conventional screen reading, AI assistance produced a statistically significant increase in readers' overall cognitive load without bringing comprehensive gains in reading comprehension. In particular, AI support weakened performance on tasks demanding concentrated information retrieval and rigorous logical reasoning, the strengths of unaided traditional reading. By contrast, the same AI tool substantially improved participants' divergent thinking performance. These outcomes indicate that AI redistributes limited cognitive resources: mental effort is diverted from streamlined factual processing to developing creative associative ideas.

5.1 Cognitive Mechanisms and Empirical Explanations of AI-Assisted Reading

Knowledge is not static material transmitted unilaterally but a cognitive product actively constructed by readers. Traditional screen reading relies on the original linear narrative structure of texts. Through continuous and coherent engagement with the text, readers systematically integrate external textual information into their pre-existing cognitive schemas to realize personalized meaning construction. This process is highly subjective: readers develop unique textual interpretations based on their prior knowledge reserves, inherent cognitive processing styles, and thinking perspectives. Such autonomous and coherent meaning construction constitutes the core of in-depth reading, and lays the foundation for accurately locating textual information and sorting out progressive logic.

This perfectly accounts for the experimental finding that participants in the traditional screen reading group achieved significantly better performance in information extraction and logical reasoning in this study.

Based on the logic of knowledge construction, this study adopts Cognitive Load Theory (CLT) as the core analytical framework to clarify the internal mechanism linking cognitive load and reading performance when AI is introduced into reading scenarios. Under the AI-assisted reading condition, readers are required to process multiple information sources simultaneously, including the original text, AI-generated summaries, conceptual explanations, and cross-textual connections. They must independently undertake multiple processing tasks such as information retrieval, cross-source content comparison, and integration of fragmented knowledge.

Although readers can delegate shallow semantic processing tasks such as summarization and contextual paraphrasing to generative AI, they still need to allocate substantial cognitive resources to verify AI outputs, identify model hallucinations, align AI-generated content with core arguments of the original text, and rectify logical biases produced by AI. A large proportion of mental resources are consumed on content monitoring and authenticity verification, which consequently crowds out germane cognitive load dedicated to internalizing knowledge and developing deep cognitive schemas.

5.2 Knowledge Organization Implications

The differential effects on comprehension subscales can be interpreted through the lens of knowledge organization. Traditional screen reading preserves the linear, author-structured knowledge representation, which supports sequential processing—essential for extracting specific facts and tracing logical arguments. In contrast, AI-assisted reading imposes a networked knowledge representation: the AI reorganizes the text into associative links, summaries, and external references. This reorganization appears to benefit divergent thinking, as users can more easily traverse conceptual spaces and generate novel connections. However, the networked representation may come at the cost of precise information retrieval and logical coherence, as the original argumentative structure is overlaid with associative pathways.

These results contribute to knowledge organization theory by empirically demonstrating the cognitive consequences of different knowledge representations. They suggest that AI tools function as dynamic knowledge organizers, with their organizational schemes having measurable effects on users' cognitive strategies. The trade-off between linear and networked representations echoes foundational debates in knowledge organization about the optimal balance between hierarchical classification and associative linking (Hjørland 2016). More broadly, our findings underscore a critical design tension for AI reading tools: supporting exploratory knowledge discovery—which benefits from networked, associative representations—may inherently conflict with supporting efficient, accurate information retrieval—which is better served by linear, structurally transparent representations.

Navigating this tension will be a central challenge for the next generation of AI-assisted reading technologies.

AI Use Statement

Generative AI tools were used only for language polishing and grammatical improvement.

References

Ackerman, Rakefet, and Morris Goldsmith. 2011. "Metacognitive Regulation of Text Learning: On Screen versus on Paper." Journal of Experimental Psychology: Applied 17: 18–32. doi: 10.1037/a0022086.

Ackerman, R., and T. Lauterman. 2012. "Taking Reading Comprehension Exams on Screen or on Paper? A Metacognitive Analysis of Learning Texts under Time Pressure." Computers in Human Behavior 28: 1816–1828.

Aydemir, Z., E. Öztürk, and M. B. Horzum. 2013. "The Effect of Reading from Screen on the 5th Grade Elementary Students' Level of Reading Comprehension on Informative and Narrative Type of Texts." Educational Sciences: Theory and Practice 13: 2272–2276.

Chien, Yu-Cheng, Ting-Ting Wu, Chia-Hung Lai, and Yueh-Min Huang. 2022. "Investigation of the Influence of Artificial Intelligence Markup Language-Based LINE ChatBot in Contextual English Learning." Frontiers in Psychology 13: 785752. doi: 10.3389/fpsyg.2022.785752.

Delgado, Pablo, Cristina Vargas, Rakefet Ackerman, and Ladislao Salmerón. 2018. "Don't Throw Away Your Printed Books: A Meta-Analysis on the Effects of Reading Media on Reading Comprehension." Educational Research Review 25: 23–38. doi: 10.1016/j.edurev.2018.09.003.

Fidan, M., and N. Gencel. 2022. "Supporting the Instructional Videos with Chatbot and Peer Feedback Mechanisms in Online Learning: The Effects on Learning Performance and Intrinsic Motivation." Journal of Educational Computing Research 60: 1716–1741.

Golan, D. D., M. Barzillai, and T. Katzir. 2018. "The Effect of Presentation Mode on Children's Reading Preferences, Performance, and Self-Evaluations." Computers & Education 126: 346–358.

Halamish, Vered, and Elisya Elbaz. 2020. "Children's Reading Comprehension and Metacomprehension on Screen versus on Paper." Computers & Education 145: 103737. doi: 10.1016/j.compedu.2019.103737.

Han, Junzhi, and Jinho D. Choi. 2025. "Beyond Linear Digital Reading: An LLM-Powered Concept Mapping Approach for Reducing Cognitive Load." In Proceedings of the 20th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2025), edited by Ekaterina Kochmar, Bashar Alhafni, Marie Bexte, Jill Burstein, Andrea Horbach,

Ronja Laarmann-Quante, Anaïs Tack, Victoria Yaneva, and Zheng Yuan, 805–817. Vienna: Association for Computational Linguistics. doi: 10.18653/v1/2025.bea-1.58.

Hart, Sandra G., and Lowell E. Staveland. 1988. "Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research." In Human Mental Workload, edited by Peter A. Hancock and Najmedin Meshkati, 139–183. Advances in Psychology 52. Amsterdam: North-Holland. doi: 10.1016/S0166-4115(08)62386-9.

Hermena, Ehab W., Mercedes Sheen, Maryam AlJassmi, Khulood AlFalasi, Maha AlMatroushi, and Timothy R. Jordan. 2017. "Reading Rate and Comprehension for Text Presented on Tablet and Paper: Evidence from Arabic." Frontiers in Psychology 8: 257. doi: 10.3389/fpsyg.2017.00257.

Hjørland, Birger. 2016. "Knowledge Organization (KO)." Knowledge Organization 43: 475–484. doi: 10.5771/0943-7444-2016-6-475.

Hsu, C. K., G. J. Hwang, and C. K. Chang. 2013. "A Personalized Recommendation-Based Mobile Learning Approach to Improving the Reading Performance of EFL Students." Computers & Education 63: 327–336.

Kong, Y., Y. S. Seo, and L. Zhai. 2018. "Comparison of Reading Performance on Screen and on Paper: A Meta-Analysis." Computers & Education 123: 138–149.

Lee, Y. F., G. J. Hwang, and P. Y. Chen. 2022. "Impacts of an AI-Based Chatbot on College Students' After-Class Review, Academic Performance, Self-Efficacy, Learning Attitude, and Motivation." Educational Technology Research and Development 70: 1843–1865.

Mangen, A., B. R. Walgermo, and K. Brønnick. 2013. "Reading Linear Texts on Paper versus Computer Screen: Effects on Reading Comprehension." International Journal of Educational Research 58: 61–68.

Margolin, S. J., C. Driscoll, M. J. Toland, and J. L. Kegler. 2013. "E-Readers, Computer Screens, or Paper: Does Reading Comprehension Change across Media Platforms?" Applied Cognitive Psychology 27: 512–519.

Mullis, I. V., M. O. Martin, P. Foy, and M. Hooper. 2017. ePIRLS 2016: International Results in Online Informational Reading. International Association for the Evaluation of Educational Achievement.

Noyes, J. M., and K. J. Garland. 2003. "VDT versus Paper-Based Text: Reply to Mayes, Sims and Koonce." International Journal of Industrial Ergonomics 31: 411–423.

Noyes, J., K. Garland, and L. Robbins. 2004. "Paper-Based versus Computer-Based Assessment: Is Workload Another Test Mode Effect?" British Journal of Educational Technology 35: 111–113.

OECD. 2009. PISA 2009 Assessment Framework: Key Competencies in Reading, Mathematics and Science. Paris: OECD Publishing.

Paas, Fred G. W. C., and Jeroen J. G. van Merriënboer. 1994. “Instructional Control of Cognitive Load in the Training of Complex Cognitive Tasks.” Educational Psychology Review 6: 351–371. doi: 10.1007/BF02213420.

Paas, Fred, Juhani E. Tuovinen, Huib Tabbers, and Pascal W. M. van Gerven. 2016. “Cognitive Load Measurement as a Means to Advance Cognitive Load Theory.” In Cognitive Load Theory: A Special Issue of Educational Psychologist, edited by Fred Paas, Alexander Renkl, and John Sweller, 63–71. Routledge.

Picton, Irene, and Christina Clark. 2015. The Impact of Ebooks on the Reading Motivation and Reading Skills of Children and Young People: A Study of Schools Using RM Books. Final report. London: National Literacy Trust.

Porion, A., X. Aparicio, O. Megalakaki, A. Robert, and T. Baccino. 2016. “The Impact of Paper-Based versus Computerized Presentation on Text Comprehension and Memorization.” Computers in Human Behavior 54: 569–576.

Rockinson-Szapkiw, A. J., J. Courduff, K. Carter, and D. Bennett. 2013. “Electronic versus Traditional Print Textbooks: A Comparison Study on the Influence of University Students’ Learning.” Computers & Education 63: 259–266.

Rosenfield, Mark, Shadika Jahan, Kiara Nunez, and Kahei Chan. 2015. “Cognitive Demand, Digital Screens and Blink Rate.” Computers in Human Behavior 51: 403–406. doi: 10.1016/j.chb.2015.04.073.

Ruan, Sherry, Liwei Jiang, Qianyao Xu, Zhiyuan Liu, Glenn M. Davis, Emma Brunskill, and James A. Landay. 2021. “EnglishBot: An AI-Powered Conversational System for Second Language Learning.” In Proceedings of the 26th International Conference on Intelligent User Interfaces, edited by Tracy Hammond, Katrien Verbert, Dennis Parra, Bart Knijnenburg, John O’Donovan, and Paul Teale, 434–444. New York: Association for Computing Machinery. doi: 10.1145/3397481.3450648.

Shadiev, R., and Y. M. Huang. 2020. “Investigating Student Attention, Meditation, Cognitive Load, and Satisfaction during Lectures in a Foreign Language Supported by Speech-Enabled Language Translation.” Computer Assisted Language Learning 33: 301–326.

Shenoy, Padmanabha, and P. S. Aithal. 2016. “A Study on History of Paper and Possible Paper Free World.” International Journal of Management, IT and Engineering 6: 337–355.

Singer, Lauren M., and Patricia A. Alexander. 2017. “Reading across Mediums: Effects of Reading Digital and Print Texts on Comprehension and Calibration.” The Journal of Experimental Education 85: 155–172.

Sweller, J. 1988. “Cognitive Load during Problem Solving: Effects on Learning.” Cognitive Science 12: 257–285.

Sweller, J. 1994. “Cognitive Load Theory, Learning Difficulty, and Instructional Design.” Learning and Instruction 4: 295–312.

Vázquez-Cano, Esteban, Santiago Mengual-Andrés, and Eloy López-Meneses. 2021. "Chatbot to Improve Learning Punctuation in Spanish and to Enhance Open and Flexible Learning Environments." International Journal of Educational Technology in Higher Education 18: 33. doi: 10.1186/s41239-021-00269-8.

Wambsganss, Thiemo, Tobias Kueng, Matthias Soellner, and Jan Marco Leimeister. 2021. "ArgueTutor: An Adaptive Dialog-Based Learning System for Argumentation Skills." In Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, article 683, 1–13. New York: Association for Computing Machinery. doi: 10.1145/3411764.3445781.

Wästlund, E., H. Reinikka, T. Norlander, and T. Archer. 2005. "Effects of VDT and Paper Presentation on Consumption and Production of Information: Psychological and Physiological Factors." Computers in Human Behavior 21: 377–394.

White, Matt Murtagh, Yunkai Xu, Nicole León, and Frank E. Ritter. 2025. "Athena: A Conversational Book Discovery Interface Combining LLM-Powered Retrieval-Augmented Generation and Interactive Graph Visualization." In UIST Adjunct 2025: Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology, edited by Andrea Bianchi, Elena Glassman, Shengdong Zhao, Jeeeun Kim, Ian Oakley, and Wendy E. Mackay, article 74, 1–3. New York: Association for Computing Machinery. doi: 10.1145/3746058.3758400.

Wollny, Sebastian, Jan Schneider, Daniele Di Mitri, Joshua Weidlich, Marc Rittberger, and Hendrik Drachsler. 2021. "Are We There Yet? A Systematic Literature Review on Chatbots in Education." Frontiers in Artificial Intelligence 4: 654924. doi: 10.3389/frai.2021.654924.

Yin, Jiaqi, Tiong-Thye Goh, Bing Yang, and Yang Xiaobin. 2021. "Conversation Technology with Micro-Learning: The Impact of Chatbot-Based Learning on Students' Learning Motivation and Performance." Journal of Educational Computing Research 59: 154–177. doi: 10.1177/0735633120952067.

Zhang, Zijian, Pan Chen, Fangshi Du, Runlong Ye, Oliver Huang, Michael Liut, and Alán Aspuru-Guzik. 2025. "TreeReader: A Hierarchical Academic Paper Reader Powered by Language Models." In Proceedings of the 2025 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC), 286–292. IEEE. doi: 10.1109/VL-HCC65237.2025.00039.