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(Un)conventional ways of dialogic information retrieval using prompt engineering and the role of AI literacy

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Abstract

Introduction. This study examines students' use of ChatGPT for information retrieval and creative tasks, integrating AI literacy into library and information science (LIS) models and addressing gaps in AI-mediated processes and ethics.

Method. A literature review and case study of 84 Jagiellonian University students, submitting 72 tasks, analysed transcripts, evaluations and authorship attributions.

Analysis. Thematic analysis revealed eleven themes, including motivations, ethical issues, iterative strategies and AI literacy gaps. Strategies aligned with LIS models like berrypicking but exposed training deficiencies.

Results. Most students (78%) claimed sole authorship; 18% cited co-authorship. Key strategies included iterative refinement (69%) and exploratory dialogues (67%). Outputs highlighted usefulness (82%), confidence (54%) and concerns over biases and authorship.

Conclusions. Curricula must incorporate AI-specific competencies, such as prompt engineering, to promote ethical AI engagement. Future research should adapt frameworks like AUTOMAT and assess long-term AI literacy outcomes.

Introduction

Integrating established information behaviour models with prompt engineering represents a convergence of traditional library and information science (LIS) paradigms with emerging AI applications. This article demonstrates how LIS concepts such as dialogical information seeking underpin the development of AI-driven retrieval systems. While often viewed as a novel technique, prompt engineering is an extension of LIS principles established since the 1980s.

Dialogical information seeking is central to LIS, reflecting the complexity of human-system interactions. Foundational models, including Belkin's Anomalous State of Knowledge (ASK) (Belkin, 1980, 2005), Bates's berrypicking model (Bates, 1989; 2002), and Marchionini's exploratory search paradigm (Marchionini, 1995, 2006), highlight the iterative, nonlinear and context-dependent nature of information behaviours. Belkin's ASK framework emphasises dialogue and feedback in addressing knowledge gaps. Bates's model illustrates how users adapt their strategies dynamically as they engage with new contexts and resources. Marchionini further focuses on cognitive learning, serendipitous discovery and evolving queries.

Together with Savolainen's sociocognitive approach (2002) and Ingwersen and Järvelin's Interactive Information Retrieval (IIR) model (2005), these theories form a comprehensive framework for understanding user engagement, emphasising context, intent and iterative dialogue. Prompt engineering in generative AI (GenAI) extends these principles, reflecting the dialogical, adaptive dynamics central to LIS models. Designing prompts for precise, contextually relevant outputs mirrors Bates's and Marchionini's models, where iterative refinement and contextual adaptation are key. Feedback loops between users and AI align with Ingwersen and Järvelin's principles, focusing on user intent and interaction. Frameworks like CLEAR and AUTOMAT formalise this process, integrating theoretical LIS insights with AI's practical demands.

This study explores the integration of LIS frameworks with prompt engineering in education. As conversational AI gains prominence, information professionals, such as librarians and innovation managers, require a strong foundation in LIS principles and advanced AI literacy. The ACRL Framework for Information Literacy provides a solid base but must expand to include AI-specific competencies, such as evaluating AI-generated outputs, identifying biases and optimising queries for dynamic, user-centred environments.

This study challenges the assumption that information management and electronic information processing students have heightened awareness of AI limitations, such as bias, hallucinations and ethical concerns. Many did not demonstrate advanced AI literacy or a critical approach to generative AI, and their familiarity with LIS models did not translate into effective prompt engineering. This reveals gaps in AI-related competencies, even among information science students. To address these deficiencies, the study examined their motivations, dialogue structuring, evaluation methods and ethical reflections. The findings provide insights into how LIS frameworks influence AI use and emphasise the need for targeted educational interventions. Future research should explore factors shaping AI literacy across disciplines and develop strategies to enhance students' critical engagement with AI-driven systems.

Research objectives and questions

This study examines the integration of LIS models and AI systems through four key objectives. First, it demonstrates how foundational LIS frameworks, such as Belkin's Anomalous State of Knowledge (ASK) (1980), Bates's berrypicking (1989), and Ingwersen and Järvelin's Interactive Information Retrieval (IIR) (2005), can enhance dialogical information retrieval in AI-mediated systems. This is achieved through a critical literature review that examines the adaptability and utility of these models in the context of AI technologies.

Secondly, it investigates the correlations between traditional LIS frameworks and prompt engineering practices. Using case studies, it analyses students' prompt-writing strategies and compares these with established LIS typologies. This analysis explores whether students with prior training in LIS principles recognise parallels between these frameworks and prompt engineering, particularly in iterative feedback and adaptation processes.

Thirdly, the study proposes integrating prompt engineering into AI literacy education, aligned with the ACRL Framework for Information Literacy in Higher Education (2016). The proposal focuses on key competencies such as source evaluation, ethical awareness and authorship considerations, highlighting the need to extend traditional information literacy (IL) practices to encompass skills for engaging effectively with AI systems.

Finally, it contributes to the broader discourse on human-computer interaction by addressing ethical challenges, including bias, reliability and the implications of AI-generated content. The study evaluates how students assess the outputs of both AI systems and their own interactions, emphasising the critical and technical skills required for responsible engagement with these technologies.

The research is guided by the following questions:

RQ1. To what extent can established LIS models of dialogical information seeking be applied to AI-mediated information retrieval processes?

RQ2. Are there identifiable correlations between LIS frameworks and prompt engineering, particularly in iterative feedback and adaptation?

RQ3. How do students' strategies for writing and evaluating prompts align with information literacy competencies as defined by the ACRL Framework?

RQ4. What ethical considerations arise in the application of AI to information-seeking tasks, and how do students address these in their interactions with AI systems?

Conceptual background

This article examines the integration of LIS models of information-seeking behaviour with prompt engineering in generative AI (GenAI), exploring their alignment in dialogical and AI-mediated retrieval. While often seen as novel, prompt engineering extends established LIS frameworks. Information-seeking research has evolved alongside technological advancements and theoretical shifts, influenced by disciplinary perspectives, researcher generations and geographical differences. Recent studies highlight the asynchronous development of LIS models shaped by cognitive and practical changes (Wang and Zhu, 2025; Onyancha, 2025). Emerging technologies, including digital libraries and intelligent search systems, continue to reshape LIS theory, requiring ongoing adaptation. LIS research identifies three core processes – seeking, searching and retrieving – as the foundation for AI integration. Since the 1980s, dialogical information seeking has been central to LIS, providing a theoretical basis for AI-driven systems and reaffirming the relevance of LIS principles in modern technological developments.

Information seeking, searching and retrieving

The processes of information seeking, searching and retrieval are fundamental to understanding human interactions with information systems. These interconnected activities address the dynamic nature of information needs, forming a spectrum of behaviours that encompass recording, seeking, interpreting, and utilising information (Fidel, 2011; Ford, 2015). Information seeking is a cognitive, iterative effort to bridge knowledge gaps, often defined as an anomalous state of knowledge (ASK) (Belkin, 1980). Case and Given (2016) describe seeking as deliberate and intuitive, aligning information pragmatically and semantically with user needs. Bates's berrypicking model (1989) further illustrates how users adapt queries dynamically, making seeking a dialogical activity shaped by contexts, interfaces, and social structures (Savolainen, 2017; Krakowska, 2022).

Information searching is a subset of seeking, involving systematic, targeted activities like query formulation and strategy refinement based on feedback (Bawden and Robinson, 2011). Marchionini's (1995) eight-stage search cycle highlights collaboration between human cognition and system design in refining search trajectories.

Information retrieval, distinct from seeking and searching, focuses on algorithmic data extraction. Lin (2017) characterises retrieval as query matching with system representations, often lacking user-specific context. However, Próchnicka (2004) offers a more dialogical view, framing retrieval as iterative exchanges that transform raw data into actionable insights. Ingwersen's (1992) interactive retrieval frameworks underscore the value of such human-system interactions, demonstrating their critical role in adaptive information processes.

Dialogic and conversational information-seeking schemes in LIS

The concept of dialogical and conversational information seeking has been a cornerstone of LIS since the 1980s, emphasising the interactive and iterative nature of human-system interactions. Belkin's Anomalous State of Knowledge (ASK) model highlights information seeking as arising from knowledge gaps, resolved through iterative dialogue with systems (Belkin, 1980). This framework underscores the dynamic interplay between user intent and system feedback, defining information-seeking behaviour as problem-solving and exploratory. Marchionini's exploratory information-seeking framework (1995) extends this perspective, outlining iterative stages of search, discovery and sensemaking. Driven by a desire to learn, users refine queries and explore iteratively to navigate complex information landscapes. Bates's berrypicking model (1989) complements this by illustrating the nonlinear, adaptive nature of seeking, where users dynamically modify queries across diverse sources. These models challenge linear retrieval assumptions and reflect the fragmented nature of real-world seeking behaviour.

Other LIS models further enrich this dialogical understanding. Krikelas (1983) emphasises the influence of context, motivation and user intent in shaping behaviours within personal and organisational settings. Ingwersen and Järvelin's (2005) interactive retrieval framework integrates cognitive and system-oriented perspectives, focusing on feedback loops mediating user-system exchanges. McKenzie (2003) highlights user-centred practices, underscoring the active role individuals play in shaping search strategies, while Savolainen's sociocognitive approach situates information-seeking behaviours within cultural and habitual contexts (Savolainen, 1995; 2016).

Dialogical approaches to information seeking are central to LIS, with established models providing structured frameworks for understanding diverse information behaviours. These models describe both observable actions and cognitive processes, which can be algorithmic and logical but also creative and emotionally driven (O'Brien, 2011). These information behaviour models, which serve as simplified representations of reality and are used to describe and interpret user interactions (Niedźwiedzka, 2003; Saracevic, 2016, p. 32), traditionally focus on structured systems where queries are refined in deterministic environments. However, generative AI tools like ChatGPT introduce interactive, nondeterministic elements into search processes, requiring a reassessment of LIS frameworks (Tibau et al., 2024). The methodological challenges posed by AI-driven search, where responses evolve iteratively rather than within stable information landscapes, raise concerns about the applicability of existing LIS models (Roy and Mukhopadhyay, 2023).

The unpredictability of generative AI prompts questions about whether LIS models can fully account for these dynamic interactions (Maurya and Sinha, 2024). Addressing these challenges requires methodological adaptations, integrating system modelling approaches to analyse and refine complex user-system interactions (Aldoihi et al., 2023). A shift from model-centric to data-centric AI methodologies could further enhance understanding of LIS frameworks in evolving digital environments (Majeed and Hwang, 2024).

Rather than validating or revising LIS models, this study examines whether LIS students exhibit behaviours consistent with classical frameworks. By identifying user interaction patterns with GenAI, it provides an initial assessment of LIS model relevance in AI-mediated environments, supporting future research on adapting or developing frameworks for generative AI interactions. While the study does not address broader regulatory or technological aspects of the GenAI market, its findings contribute to discussions on ethical and responsible AI engagement in LIS education.

Human information seeking and prompt engineering (or Large Language Models)

The growing prevalence of prompt engineering in GenAI systems underscores the lasting influence of LIS principles in human-computer interaction. This paper argues that prompt engineering extends dialogic information-seeking traditions, with its iterative design process reflecting established principles of interactive and exploratory information retrieval.

Prompt engineering frameworks like CLEAR and AUTOMAT, crucial for systems such as ChatGPT, emphasise clarity, adaptability and user intent, aligning with LIS principles of feedback, contextuality and iterative refinement. Dialogical AI interactions resemble anthropomorphic systems, embodying principles of serendipitous seeking and intuitive exploration, as seen in Ingwersen's IIR framework.

LLMs like ChatGPT shift user engagement by enabling dialogues that integrate Bates' berrypicking and Belkin's ASK frameworks. Prompt engineering optimises AI interactions through linguistic precision, task specificity and contextual adaptability (Mudadla, 2024; Srinivasan, 2024). Structured prompts, guided by frameworks like AUTOMAT or CO-STAR, enhance clarity, context and intent, improving AI accuracy and responsiveness (Vogel, 2024).

AI literacy and ethical considerations and the ACRL Framework

The convergence of information literacy and AI literacy marks a critical evolution in the roles of information professionals, educators and users navigating modern information landscapes. The ACRL Framework for Information Literacy provides a foundation for critical evaluation, ethical use, and strategic engagement with information systems (Case and Given, 2016; ACRL, 2016). AI literacy extends these principles, addressing generative AI (GenAI) systems, challenges like AI hallucinations and optimising the accuracy of AI-generated outputs (Ruksha, 2024; Srinivasan, 2024).

However, while these principles influence AI interactions, research suggests that even those trained in information disciplines may lack critical AI literacy skills (Nicholas et al., 2024). This raises questions about the effectiveness of LIS frameworks in preparing users for AI-driven search environments and highlights the need for further exploration of AI-specific information behaviours. Recent studies show that LIS students struggle to use AI-powered systems efficiently, pointing to deficiencies in current educational approaches to AI literacy (Petrović et al., 2024).

Ethical considerations are central to integrating AI literacy, especially for roles such as prompt engineers and information scientists, who must ensure query structures and prompts do not perpetuate biases or stereotypes (Hall and McKee, 2024; Bates, 2024). This aligns with the ACRL Framework's emphasis on contextual authority, which promotes interrogation of information sources, including AI systems. Transparency about algorithmic processes and biases within training data is essential, resonating with the framework's '*information has value*' principle, which advocates equitable and ethical access to information.

Prompt engineering's iterative process – refining queries, interpreting feedback and adjusting interactions – mirrors the ACRL Framework's recursive '*research as inquiry*' approach, emphasising critical thinking and adaptability. Ethical AI use requires addressing biases and algorithmic transparency, equipping users to interact responsibly with GenAI systems (Lund, 2023). By embedding the ethical dimensions of the ACRL Framework into AI literacy education, information professionals can bridge traditional LIS competencies with AI-driven demands, shaping user-centred, ethical AI systems and ensuring technology aligns with societal values.

Methods

Procedures

The literature review analysed sources from Semantic Scholar, Medium, and the LISTA database to explore prompt engineering (PE) and information behaviour. Conducted in September 2024, the search yielded 59 publications (40 from LISTA and 19 from Medium, post-duplicates). Keywords included '*information-seeking behaviour*', '*information needs*', '*prompt engineering*', and related terms, focusing on PE definitions, principles, competencies and applications. Additional literature was gathered through ResearchGate topic alerts.

The case study analysed how participants used ChatGPT in problem-solving and evaluated their outcomes. Data was collected from 18 November to 1 December 2024, involving students from the Information Management and Electronic Information Processing programmes at Jagiellonian University. The tasks aimed to explore real-world interactions with GenAI. Participants received three tasks (see Figure 1), each containing an implicit ethical dimension to observe whether they addressed it independently. They were not required to complete tasks solely with ChatGPT but chose which subtasks to handle using AI. To reduce academic pressure, tasks included background stories – short narratives providing fictional users' context and motivation (Bailey et al., 2015, p. 3). Allowing participants to adopt a fictional persona aimed to encourage engagement and facilitate demonstrating ChatGPT communication skills.

This study focused on predefined assignments rather than real-world AI use. While structured tasks enable controlled analysis, they may not reflect natural interactions. Future research should consider longitudinal or ethnographic approaches to examine spontaneous AI engagement. Additionally, as an exploratory study, it identifies patterns and behaviours rather than causal relationships. Findings should be interpreted cautiously, and future studies should employ diverse methodologies to validate results across different user groups and settings.

introduction to the exercise	This exercise provides an introduction to selected elements in the application of artificial intelligence in information retrieval and AI literacy. Some of you will complete the assignment during class and then the initial results will be discussed in subsequent meetings. For others of you, this will be an additional assignment to complete and submit to the designated course on the Pegasus platform.
main instructions in points	A. Download the task file to your computer. B. Use this template for your work. C. Choose one of the three tasks below. Briefly explain why you are choosing this task (1,2 or 3). All tasks are linked to ChatGPT. However, you do not need to create an account with OpenAI. You can use the version that is available without logging in at https://chatgpt.com/. D. Once you have completed the conversation, select the entire conversation (both the answers given by the AI and your messages), copy and paste into this file. You have space prepared for this in the template. E. Then evaluate the resulting work with AI. You can complete the task individually or in a group of up to three people. F. When you have finished, upload the assignment to the Pegasus platform.
scheme of tasks to be selected (not available to participants)	**User Persona:** You are... **Task:** You are interested in... Your task is to... You want to do... **Output:** You want to obtain information from sources.... and develop a short note with a synthesis of the most important information (1 page A4). **Final instruction:** Think about what specifically you might use ChatGPT for in this situation. Then conduct a conversation with ChatGPT, submit a transcript of this conversation and evaluate the result you have obtained.

task 1.	**task 2.**	**task 3.**
You are a writer of science fiction novels. You need to gather material and ideas for a new book. You are interested in scientific concepts in the field of the possibility of transferring human consciousness to a computer. You were inspired to this topic by information about a recent new radio interview with Wisława Szymborska, which was generated using artificial intelligence. You want to obtain information from valuable scientific sources and develop a short note with a synthesis of the most important information (for 1 page of A4). Think about what specifically ChatGPT could be useful for in this situation. Then carry out a conversation with ChatGPT, submit a transcript of this conversation and evaluate the result you have obtained.	You are an infobroker, a specialist in obtaining information and presenting it in a way that is relevant to a specific problem situation. Your friend asked you to help him with such a case: he/she is a student at the Academy of Fine Arts and wants to go to Portugal as part of the Erasmus programme. It's just a loose idea, but your friend wants to do some research and find out what conditions he/she has to meet, what the procedure is, what the deadlines are and where he/she can go. Your task is to get information from valuable, up-to-date sources and produce a short note with a synthesis of the most important information (1 page of A4). Think about what specifically ChatGPT could be useful for in this situation. Then carry out a conversation with ChatGPT, submit a transcript of this conversation and evaluate the result you have obtained.	You are a podcast creator. You are developing an episode about the use of AI in computer games. You are interested in the practical, technological and legal considerations and the impact of the possible use of AI on the quality of designed games. You want to develop a script for the episode with a synthesis of the most important information (for 1 page of A4) based on your discernment of the topic from reliable and up-to-date sources. Think about what specifically ChatGPT could be useful for in this situation. Then carry out a conversation with ChatGPT, submit a transcript of this conversation and evaluate the result you have obtained.

Figure 1. Outline of the procedure used in the case study.

The tasks aimed to assess students' AI literacy and promote responsible use of tools like ChatGPT. While some had used GenAI informally, this study provided official academic guidance and feedback on proper use. The didactic goal was to highlight both opportunities and risks, improving competencies in ethical and legal prompt engineering. Assignments were completed in AI literacy-related classes, with instructions given via email or in person. Students worked individually or in teams of up to three, with voluntary participation with no consequences for opting out. A total of 112 students consented, resulting in 72 completed papers.

The papers followed a template consisting of five elements: (1) selected task, (2) justification for the selection, (3) full transcription of the ChatGPT conversation, (4) evaluation of outcomes, and (5) authorship identification. The task instructions, work template, study information and consent form were provided in Polish, the language of the classes.

The study employed an inductive-deductive thematic analysis with the following stages: 1) exploration to familiarise the researchers with the material; 2) development of a preliminary code book aligned with research objectives and questions; 3) independent coding by two researchers, allowing for new codes; 4) merging coded material into a cohesive unit; and 5) verifying and standardising the code book. MAXQDA software was used for analysis, with Excel assisting in code book development. The final code book contained eleven top-level codes with subcodes (see Fig. 2).

No	Codes	Subcodes
1	TLDR	-
2	Authorship	Co-authorship, ChatGPT, Student/s
3	Template elements	Task selection, Justification of task selection, Conversation record, Outcome evaluation, Authorship declaration, Additional elements: Link to the conversation - Personal remarks - Notes
4	Ethics	Role of reliability, Absence
5	Evaluation of results	Starting point for further research, Useful, Criticism of results: Worthless – Biased - Unreliable, Evaluation criteria, Assessment of response style, Confidence in the response
6	Conversation Language	English, Polish
7	AI literacy	Awareness of hallucinations
8	Motivation for Task Selection	Knowledge of the topic, Personal experiences, Probability of the situation, Lack of trust, Ease of the task, Similarity to other tasks, Practical dimension, Similarity to other tasks, Practical dimension, Social dimension, Interests, Curiosity about AI-generated results
9	Information seeking & retrieval method	Content copying: uploading files with tasks, Iterative approach: asking questions, Correlation with information S&R models, Task execution methods: monitoring ChatGPT's actions - in-depth searching: requesting extended responses - requesting concise responses, single response - exploration, Prompt engineering methods: step-by-step approach - providing/uploading specific sources - using a defined prompt structure
10	Perception of ChatGPT	Anthropomorphisation,Tool
11	Tasks	1 writer, 2 Erasmus, 3 podcast

Figure 2. Code book.

Participants

The study analysed 72 works from 84 students who gave informed consent, including 61 individual submissions. Participants comprised 34 first-degree and 19 second-degree information management students, and 31 from electronic information processing. Ethics followed Jagiellonian

University's procedures, ensuring voluntary participation, informed consent, anonymisation and feedback on AI literacy and responsible ChatGPT use.

Findings and analysis

This section examines task selection, information-seeking methods, result evaluation, AI literacy, ethics, reliability, hallucination awareness, authorship and perceptions of ChatGPT. Numbers in parentheses indicate student papers with applied codes or subcodes, while the S&R methods section includes coded segments to illustrate dynamic ChatGPT-based retrieval processes.

Tasks

As part of the study, students selected one of three thematic tasks involving generative AI, revealing their preferences and perceptions of educational challenges. The most popular task, '1 *Writer*', chosen by 28 students, required using ChatGPT creatively to explore an ethical dilemma inspired by a fictional AI-generated interview with Nobel laureate Wisława Szymborska (PolskieRadio.pl, 2024), addressing ethical issues in information sourcing.

The second task, '2 Erasmus', chosen by 22 students, involved analysing the Erasmus programme using ChatGPT, emphasising organised, analytical approaches. It also tested students' ability to identify ethical and quality issues in AI-assisted information brokering, aligned with established ethical standards (e.g., Waligórska-Kotfas, 2019).

The third task, '3 Podcast', also selected by 22 students, required creating scripts or inspiration for audio content with ChatGPT, blending creativity with media adaptation. Ethical challenges included AI's effects on game creators (job displacement, reduced creative autonomy) and players (behaviour manipulation, data protection), alongside ensuring oversight to prevent harmful content.

Motivation for task selection

The analysis of motivation for task selection revealed a multitude of factors that influence students' decisions, as illustrated in Figure 3. The number of subcodes and assignments indicates the complexity of the decision-making process, in which students were guided by personal preferences as well as practical and cognitive aspects of the tasks. The analysis of these data permits the formulation of conclusions regarding the principal motivations.

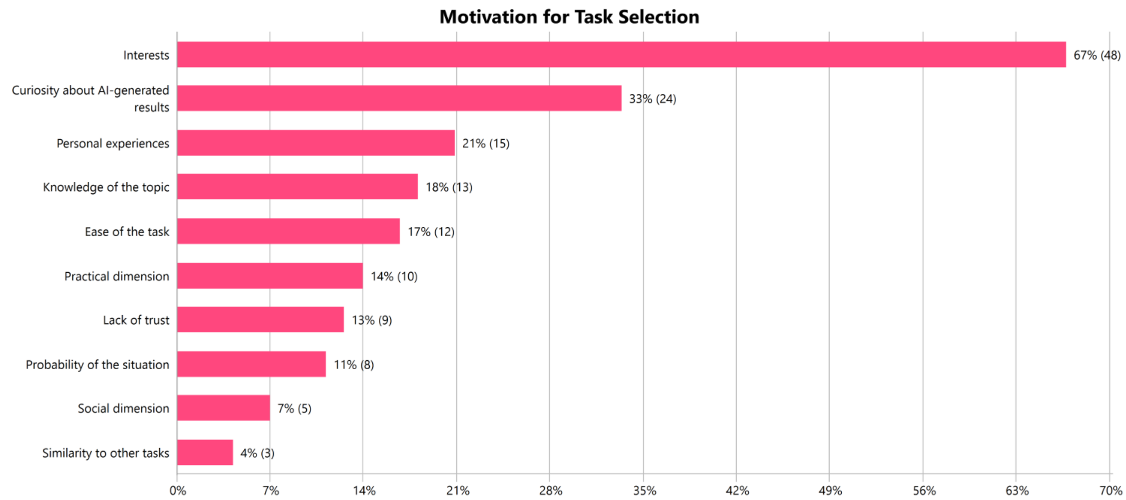

Figure 3. Motivations for task selection (n = 72 papers, it was possible to indicate more than one category per paper).

The most frequently cited motivation for task selection was personal interest, significantly influencing students' choices. Students preferred topics aligning with their interests and passions, such as science fiction, Erasmus aspirations, or other personally resonant themes (e.g., ZI1st3_1: 19; ZI1st1_16: 18). This highlights the value of engaging students through interest-driven tasks.

Curiosity about ChatGPT's outputs was the second most frequent motivation, appearing in 24 cases. Students were eager to explore how generative AI handled complex questions, reflecting a cognitive desire to understand its potential and limitations. For instance, one student noted their interest in how AI could support podcast preparation (ZI1st1_6: 18).

Personal experiences influenced task selection in fifteen cases, enhancing identification with the problem and contextual understanding. Familiarity with a topic increased confidence and reduced challenges. Pragmatic motivations, noted in twelve cases, led students to choose easier tasks to save time or effort. Practical outcomes motivated students in ten cases, especially those working on real-world applications like Erasmus+ analysis or creative writing.

Scepticism about ChatGPT's reliability influenced task avoidance in nine cases, with students expressing concerns over errors or ethical issues. Real-life relevance motivated eight subcodes, underlining the practical applicability of tasks. Social motivations, linked to five subcodes, indicated interest in themes with societal or collaborative implications.

The least cited motivation, similarity to previous tasks, appeared in only three cases, suggesting a limited preference for predictable or familiar tasks. These findings demonstrate diverse motivational factors shaping student engagement with ChatGPT-based assignments.

Information seeking and retrieval method

A study of students' information-seeking methods and prompt engineering strategies with ChatGPT revealed diverse practices in dialogic information retrieval. An iterative approach was most common, with students refining queries and asking follow-up questions (169 segments in 47 documents) to clarify responses, reflecting Bates's berrypicking model's dynamic and flexible nature, albeit unconsciously. Students emphasised monitoring and evaluating ChatGPT's outputs to ensure relevance and quality.

Exploration, noted in 114 segments across 45 documents, emerged as a key strategy, with ChatGPT results often serving as starting points for further research. A smaller group used a single-response strategy (46 segments in 20 documents), prioritising efficiency or reflecting limited AI literacy. Additional methods included response expansion (50 segments in 26 documents) and condensation (thirteen segments in twelve documents). Expansion sought detailed answers for complex tasks, while condensation aimed to simplify responses, reducing cognitive load (e.g., Bawden and Robinson, 2009; Zhou and Li, 2024).

The step-by-step strategy dominated prompt engineering (118 segments in 47 documents), with students breaking queries into smaller, precise steps to improve accuracy and detail. Advanced practices like incorporating specific sources (ten segments in eight instances) were less common, requiring sophisticated integration techniques.

Predefined prompt structures, such as defining personas, tasks or output parameters, appeared only in seven cases across five documents. These incomplete frameworks highlight students' developing skills in advanced query formulation. Structured strategies like AUTOMAT or CLEAR could enhance precision and efficiency in generating outputs, suggesting a need for stronger integration of theoretical frameworks into curricula.

Evaluation of results

The assessment of ChatGPT's outputs was a key focus of the study, enabling an analysis of students' methods for evaluating generative AI content. Various evaluation strategies were identified, offering insights into the tool's practical applications and its limitations. Quantitative and qualitative analysis of the subcodes in the Evaluation of Results category (see Fig. 4) highlights the complexity of students' approaches to content evaluation.

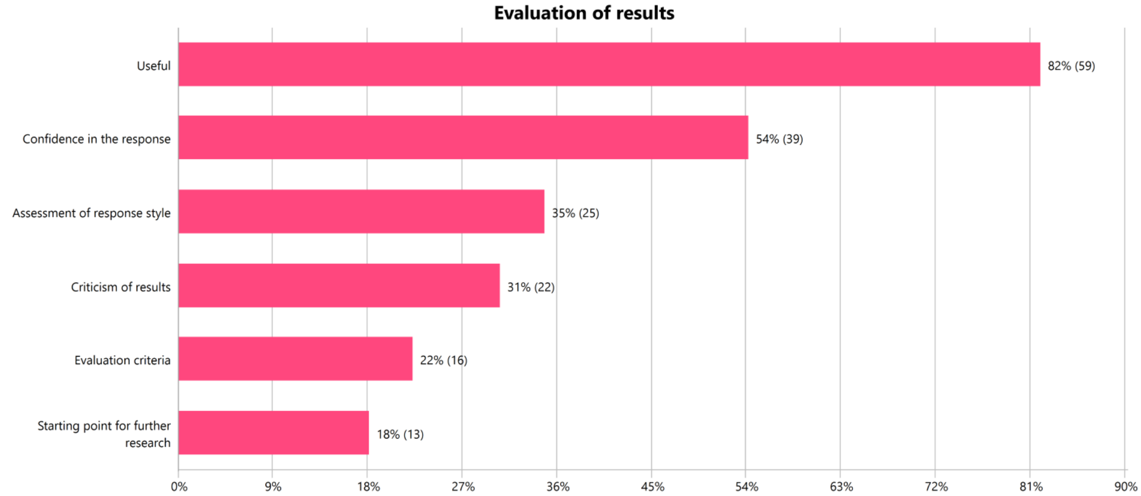

Figure 4. Respondents' evaluation of the work results achieved using ChatGPT (n = 72 papers, it was possible to indicate more than one category per paper).

The most frequently assigned subcode in the analysis was usefulness, appearing 59 times. Students generally evaluated ChatGPT's content as practical and immediately applicable, viewing it as a tool to facilitate task completion by tailoring responses to their needs. Many also regarded ChatGPT as a source of inspiration for further research or deeper exploration, highlighting its role in guiding information-seeking pathways. The subcode critical analysis of results reflected students' reflexivity in evaluating content, with three sub-subcodes identified: a) worthless (five), for responses deemed irrelevant or lacking value; b) biased (four), indicating student recognition of potential model biases; and c) unreliable (twelve), the most frequent, where students noted inaccuracies or factual errors, emphasising the importance of critical verification of generated content.

Some students applied clear criteria to evaluate ChatGPT's outputs, focusing on precision, relevance, completeness and task utility, reflecting growing critical assessment skills. The subcode for stylistic assessment indicates they also considered presentation, noting clarity, errors, hallucinations and the role of structure and language in their evaluations.

The role of credibility

The study among students at the Jagiellonian University's Institute of Information Studies explored their perceptions of the credibility of information generated by ChatGPT during dialogic information retrieval. Students highlighted the benefits of ChatGPT's flexibility, coherence, linguistic fluency and ability to maintain awareness of preceding dialogue. Thematic divisions were noted as effective (ZI1st1_9, Pos. 182). However, limitations arose when questions lacked detail, occasionally leading to irrelevant content. Despite these shortcomings, the information was generally regarded as valuable and useful for the broader research process.

It is worth emphasising that ChatGPT enabled students to reduce the time required for gathering basic information:

> *It allowed me to skip the tedious process of reading through numerous lengthy articles, instead providing me with a handful of necessary information and inspiration on which I could begin my own research.* (ZI2st1_3, Pos. 379)

At the same time, students recognised limitations in the provision of complete sources of information, necessitating additional refinements to queries to obtain more comprehensive results.

Awareness of hallucinations

Hallucinations, or the perception of erroneous or fabricated information as credible, pose a significant challenge in using generative language models like ChatGPT for dialogic information retrieval. The study among students at the Jagiellonian University's Institute of Information Studies explored their experiences with ChatGPT and perceptions of the credibility of its generated content.

A key issue identified was the verbosity and repetitiveness of ChatGPT's responses. Students noted that initial outputs were often overly lengthy, lacking concision and focus, with repetitive and sometimes non-objective or low-value information (EPI1st2_2). Despite these shortcomings, some content was beneficial for users less familiar with a subject. Another significant issue was the generation of erroneous or non-existent links and references, with ChatGPT frequently providing outdated or inaccurate citations:

> *The chat did not assist in locating any particular studies; the links were either non-functional or directed to erroneous websites. In some cases, the studies themselves were flawed, with incorrect authors being provided or studies that did not exist at all.* (EPI1st3_6)

Such instances have an adverse effect on the evaluation of ChatGPT as a reliable source of academic information.

Hallucinations in ChatGPT responses often took the form of fabricated or outdated data, with sources that were obsolete or inconsistent with reality, limiting the usefulness of its outputs (EPI1st2_4). Some participants also noted that prior interactions influenced responses, leading to erroneous assumptions and complicating the achievement of precise results (EPI1st2_2).

Despite these challenges, ChatGPT was widely regarded as both inspiring and helpful. Many students appreciated its ability to offer insights and inspire further investigation:

> *Even in instances where the responses were not entirely precise, ChatGPT was regarded as an inspiring tool that prompted further searches.* (ZI2st2_5)

Students valued its educational role, particularly as a catalyst for deeper research:

> *I believe that ChatGPT provided sufficient information to stimulate further research and investigation into the suggested topics.* (EPI1st2_8)

The content often served as a starting point for more comprehensive inquiries, guiding users in their subsequent searches:

> *Such sources would likely not be regarded as 100% verified information, but they would undoubtedly serve as a guide on where and how to search for such information.* (EPI1st3_2)

Additionally, the tool's capacity for iterative refinement enabled users to adapt results effectively to their specific needs.

Ethical considerations in the use of ChatGPT

The utilisation of generative AI has prompted ethical concerns among students and has demonstrated the practical limitations of such technology. The key issues that emerged included the necessity of attributing authorship to AI-generated responses and ensuring their compliance with current academic standards. As one student observed,

> *For those unacquainted with the process, this information may provide insight into what to look for and what might be important in the application process. However, it would be erroneous to follow the steps offered by ChatGPT without first verifying the accuracy of this information.* (EPI1st3_5, Pos. 262)

Considerations were made regarding AI's limitations in handling morally ambiguous or outdated data. Students noted that using ChatGPT for tasks requiring meticulous verification, such as legal analysis or academic writing, poses risks and demands advanced critical skills (EPI1st3_6, Pos. 18-20). Despite these concerns, assessing AI-generated content was thought-provoking and underscored the need for AI literacy education. While most respondents found the outputs useful and expressed high confidence in them, this raises questions about their ability to reliably assess content, particularly in task 1. This highlights the necessity of equipping users with critical competencies to effectively evaluate AI-generated information.

Authorship

The use of generative language models like ChatGPT in creative processes raises questions about authorship and the user-technology relationship. Analysis of 72 student responses reveals that 78 per cent (56 responses) attributed authorship solely to the students, suggesting AI was viewed as a supplementary tool rather than a substitute for intellectual input. Students commonly used AI-generated content as inspiration or a starting point, subjecting it to refinement and verification.

Co-authorship, identified in 18 per cent (13 responses), involved integrating AI outputs into student work, tailoring content to task-specific requirements. This collaborative approach highlights students' growing awareness of responsible AI use and their ability to merge generative tools with creative efforts. Sole attribution to ChatGPT was rare, occurring in just 4 per cent (3 responses), reflecting students' critical perspective towards AI outputs, often requiring verification for accuracy and relevance.

The findings underscore students' discernment and responsibility in the creative process. The dominance of student-authored responses and the significant co-authorship proportion suggest a reflective approach to AI integration. The low rate of sole attribution to ChatGPT further indicates an understanding of its limitations, such as hallucinations, factual inaccuracies and contextual deficiencies. Students appear to regard AI as a supplementary aid rather than a central element in their creative efforts.

Discussion

As AI-driven tools shape information retrieval, this study examines how students' search strategies align with core LIS principles. While students grasp iterative search concepts, their interactions remain largely superficial, with minimal verification, revealing a gap between LIS curricula and practical AI-driven search strategies (Petrović et al., 2024). Limited critical analysis of AI-generated results highlights the need for stronger AI literacy in education. Integrating exploratory search strategies, prompt engineering and critical evaluation is crucial. Students' reliance on default AI outputs suggests traditional LIS models may not fully address modern information environments (Nicholas et al., 2024). This study contributes to discussions on adapting LIS curricula, emphasising structured pedagogical interventions to enhance students' critical engagement with AI and equip them to use it responsibly.

The iterative, feedback-driven processes in prompt engineering closely align with LIS frameworks, highlighting AI-mediated systems' potential to enhance information retrieval. This section examines iterative refinement, information literacy competencies and ethical considerations, exploring their implications for adapting educational strategies to the challenges and opportunities of generative AI. To contextualise the findings within the research questions, the main results are presented below.

The iterative and exploratory approaches align with foundational LIS models like Bates's berrypicking and Ingwersen's interactive retrieval (RQ1). Frameworks such as AUTOMAT structure user-system interactions, clarify needs and improve retrieval. While traditional LIS models help explain AI-mediated retrieval, their applicability to generative AI is uncertain. Models like Bates's berrypicking and Belkin's ASK were designed for structured environments, whereas AI-driven retrieval relies on probabilistic responses rather than explicit query refinement. These broad models are difficult to falsify, as nearly any search behaviour can be retroactively fitted into an LIS framework. Future research should develop AI-specific models incorporating machine learning dynamics to better understand user-AI interactions. The gap between awareness and application underscores the need for training, as even LIS experts struggle in AI search environments, often relying on surface-level interactions without iterative refinement (Petrović et al., 2024). While LIS models offer conceptual clarity, their effective use in AI systems requires structured teaching to strengthen user competency.

The iterative, feedback-driven nature of prompt engineering closely aligns with LIS principles (RQ2). Techniques like AUTOMAT and CoT reflect similarities in iterative refinement, reasoning clarification and managing complex information needs. Students demonstrated an emerging ability to intuitively adopt these strategies. Case studies highlight the potential for integrating LIS frameworks with prompt engineering to enhance users' ability to regulate and refine AI interactions. Explicit training in these strategies could address gaps in user competency.

Students demonstrated proficiency in core information literacy (IL) competencies, including source evaluation, ethical awareness and query refinement. However, deficiencies in advanced query formulation and reliance on surface-level outputs suggest opportunities for integrating AI literacy into IL curricula (RQ3). Incorporating ACRL Framework competencies – such as ethical information use and iterative inquiry – alongside AI-specific skills would better equip students to engage responsibly with generative AI. Nicholas et al. (2024) similarly note that while iterative query clarification aligns with IL practices, structured pedagogical interventions are needed to strengthen critical analysis and ethical AI application.

Ethical challenges, including hallucinations, biases and authorship attribution, emerged as significant concerns (RQ4). Students' reluctance to attribute full authorship to AI suggests a mature understanding of accountability. However, beyond authorship, AI systems pose broader ethical dilemmas, such as reinforcing biases, opaque decision-making and challenges in evaluating AI-generated content. While students recognised some risks, their reliance on AI outputs without thorough verification underscores the need for further instruction in ethical AI literacy and critical evaluation (Nicholas et al., 2024). The iterative refinement of queries and awareness of limitations, such as outdated or fabricated data, further highlight the importance of fostering ethical practices. Other studies corroborate these concerns, emphasising the risks of over-reliance on AI without rigorous assessment. Integrating discussions on these challenges into educational frameworks could better equip students to identify biases, critically engage with AI-generated content and use AI responsibly and ethically.

Research limitations

This study offers insights into students' AI-driven searches but has limitations. First, the sample – Information Management and Electronic Information Processing students – may not represent broader users due to their LIS and digital tool familiarity. Their background likely shaped their structured search strategies, differing from general AI users. Future research should include diverse disciplines or nonacademic users to examine AI literacy and retrieval variations.

Second, this study does not assess LIS models in the AI context but examines student behaviours aligned with traditional frameworks. Traditional LIS models assume structured environments, while generative AI is dynamic and probabilistic, posing methodological challenges. Future research should explore adapting LIS models for AI-driven retrieval.

Another limitation concerns self-reported data. While structured tasks captured AI interactions, students' reflections on search strategies and ethics were subjective. Future studies should use longitudinal observations or real-world scenarios to better understand AI interactions. Additionally, this study does not examine external factors such as institutional policies, prior AI training or AI ethics education. Investigating these influences would offer a more comprehensive perspective on AI literacy and information-seeking strategies.

Conclusions

This study examines the evolving relationship between traditional LIS models, contemporary AI frameworks and pedagogical strategies, offering insights into students' interactions with generative AI in information retrieval and creative tasks. Key themes include iterative refinement, ethical awareness, AI literacy integration and collaborative AI engagement. While students showed a natural affinity for iterative strategies similar to LIS models like berrypicking, their applicability in AI-driven environments remains uncertain. Traditional LIS frameworks, designed for structured, deterministic spaces, may not fully capture the probabilistic nature of AI-mediated retrieval (Roy and Mukhopadhyay, 2023). This highlights the need for further research into AI-specific models of information behaviour and retrieval.

Beyond this study's findings, broader socioeconomic and ethical concerns surrounding AI require further exploration. The monopolisation of AI-driven knowledge production raises issues of user autonomy and equitable access (Verdegem, 2022). Similarly, the environmental impact, including high energy consumption, warrants investigation (Wang et al., 2024). Though not the focus of this study or noted by students, these remain critical considerations for LIS researchers as AI continues to shape information behaviours and retrieval practices.

To address these challenges, the ACRL Framework should expand to include AI-specific competencies such as prompt engineering, iterative query refinement and critical assessment of AI-generated content. While AI enhances efficiency and creativity, structured educational interventions are essential to foster responsible AI use, ensuring ethical oversight and accountability. Future research should further refine the integration of LIS principles and AI literacy, equipping students with the skills needed to critically navigate the evolving landscape of generative AI technologies.

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