Understanding and Facilitating Learning with AI in Multi-Source Information Environment for College Students

ANONYMOUS AUTHOR(S)*

College students access information from diverse sources like academic databases, social media, and textbooks. This varied landscape offers more learning opportunities but also challenges, including source credibility asessment and information integration. AI tools have the potential to alleviate these challenges by streamlining information processes for students. However, existing AI tools are not yet optimized for handling multi-source information challenges in academic settings. To address this gap, we conducted a two-phase study. Firstly, we conducted focus group workshops to explore students' multi-source information behaviors in AI-assisted learning environments. Secondly, we held participatory design workshops to gather design considerations to address current challenges. Our analysis revealed a framework of students' multi-source information behaviors comprising four key phases: Search, Read, Extract, and Manage. These insights provide practical guidance for enhancing AI-assisted academic tools, ultimately improving students' multi-source information retrieval and management experiences.

CCS Concepts: • **Human-centered computing → Participatory design**; *Empirical studies in HCI*; **Empirical studies in HCI**.

Additional Key Words and Phrases: Education/Learning, Schools/Educational Setting, Participatory Design, Qualitative Methods

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1 Introduction

College students regularly deal with multi-source knowledge to enhance the breadth, depth, and accuracy of the information they collect for study purposes [62]. For instance, a biology student might refer to a research paper on gene editing, read textbooks for foundational concepts, and watch videos visualizing molecular processes on platforms like Khan Academy [27]. By engaging with diverse sources, students develop a more comprehensive understanding of complex topics [21], fostering critical thinking skills crucial for academic success [13]. However, previous research on college students' information retrieval behaviors primarily focused on single-source information retrieval and management [28, 29, 34, 54, 56, 66, 68]. This limited scope overlooks the complexity of students' current information handling practices [13, 50]. Therefore, we were inspired to have an in-depth understanding of college students' information retrieval and management behaviors with a focus on multi-source information.

Despite the benefits of engaging with diverse information sources, it also brings challenges for college students, including verifying source credibility [36], managing cognitive load [62], and organizing multi-source information [51]. With the emergence of Artificial Intelligence (AI), AI-powered information tools are serving as potential solutions to these challenges [3, 31]. These tools aggregate and summarize information from multiple sources, assist in personalized search and query formulation, and provide intuitive information retrieval [2, 79]. However, despite their benefits,

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current AI tools do not fully address the complex challenges of using information from multiple sources in academic settings due to lack of nuanced credibility evaluation and knowledge synthesis across disciplines [49]. Concerns about AI-generated hallucinations and algorithmic biases further challenge their reliability in academic contexts [38, 40]. These issues highlight the need for specialized AI-powered information tools tailored to the demands of multi-source information retrieval and management.

Therefore, we sought to fill in the gaps by investigating the following research questions (RQs):

- **RQ1.** How do college students perform multi-source information retrieval and management in light of the current trend of generative AI? And what are the challenges in this process?
- **RQ2.** How might AI-powered tools be designed to improve college students' multi-source information retrieval and management experience?

To answer RQ1, we conducted focus group studies with participants from diverse academic backgrounds to understand current practices and challenges of college students' AI-assisted multi-source information behaviors. Through inductive analysis and deductive analysis [6] guided by the Information Foraging Theory (IFT) [63, 65], our analysis revealed a framework comprising four interconnected phases of information behavior: Search, Read, Extract, and Manage (SREM). Within each phase, we identified challenges of students engaging with multi-source information assisted by AI, including AI hallucination in recommendations, information reliability assessment, depth-breath balance in reading, exposure limitation, contextual misclassification, cross-platform extraction difficulties, tool-workflow misalignment, and cognitive load from multiple tool management.

Building on the challenges identified in the focus group studies, we conducted participatory design workshops with college students to answer RQ2. We designed the workshop around five key tasks derived from our SREM framework: improving answer accuracy and relevance, assisting in evaluating information quality, enhancing academic content comprehension, facilitating multi-source information extraction and management across multiple platforms, and personalizing information management. During the workshops, participants produced sketches with verbal explanations and offered feedback on each other's ideas. We collected and analyzed the sketches, transcripts, and observational notes using a combination of inductive and deductive coding methods. Through our analysis, we derived 9 key design considerations for AI-assisted multi-source information tools, covering the four phases of our SREM framework.

This study contributes to the fields of human-computer interaction and educational technology by providing a comprehensive analysis of college students' AI-assisted multi-source information behaviors and offering empirically-grounded design considerations for future tools. Our SREM framework offers a structured approach to understanding how students navigate the complex interplay between traditional academic sources and emerging AI tools, addressing a critical gap in current literature. Through focus group studies and participatory design workshops, we identified key challenges and developed design considerations that align with each phase of the SREM framework to guide the future design of AI-powered tools for multi-source information retrieval. By bridging the gap between theoretical understanding and practical application, our research offers valuable insights for educators, researchers, and designers working to enhance students' information literacy and academic success in the increasingly AI-influenced landscape of higher education.

2 Related Work

2.1 Multi-Source Information Behavior of College Students

In the increasingly complex digital landscape, multi-source information retrieval has become a critical aspect of knowledge acquisition and management, particularly for college students. This process involves gathering, evaluating, and synthesizing information from various sources to enhance the breadth, depth, and accuracy of knowledge [36, 37]. College students exhibit diverse information needs and behaviors, shaped by their academic requirements and personal interests [36]. Research indicates that students rely heavily on a combination of digital and traditional resources for their information needs [34]. While traditional resources remain valuable, the internet has become a primary source for both academic and everyday information seeking, with search engines like Google being ubiquitous in students' research processes [34, 54]. Given this shift towards digital mediums, understanding how students retrieve and manage multiple information sources becomes important as the information ecosystem continues to evolve. However, the specific strategies students employ and the challenges they face remain largely underexplored.

Multi-source information retrieval presents unique challenges that go beyond traditional single-source information seeking [9, 21]. Students often struggle to find context for their research topics and face difficulties in integrating information from diverse sources. The abundance of digital information, while providing extensive resources, can paradoxically make it more challenging to find and access relevant materials [35, 37]. This information overload can lead to what some researchers call "digital deterrence," where the sheer volume of available information discourages thorough research [36]. Moreover, the process of evaluating and synthesizing information from multiple sources poses significant challenges for students, as it requires sophisticated critical thinking and digital literacy skills that many are still developing [28, 29]. This difficulty underscores the need for strong design interventions to facilitate this process, helping students effectively manage and integrate diverse information sources.

To better understand these complex behaviors, researchers have turned to Information Foraging Theory (IFT) as a theoretical framework. Originally proposed by Pirolli and Card [63, 64], IFT adapts concepts from optimal foraging theory in biology to analyze human information-seeking behaviors. The theory posits that individuals adapt their strategies to maximize their rate of valuable information gain within the constraints of the information environment. This adaptive view provides a unique perspective on how students navigate the multi-source information landscape.

IFT introduces several key concepts that are particularly relevant to multi-source information retrieval. Information patches, analogous to patches of food in nature, represent clusters of information that may exist across different sources [64, 65]. In the context of student research, these patches might include academic databases, online encyclopedias, or social media platforms. Information scent refers to the cues that guide foragers to valuable information [65]. For students, this might involve following citations, using keywords, or relying on recommendations from peers or AI systems. The concept of information diet describes the selection of information types to pursue, which is crucial in multi-source environments where students must decide which sources to prioritize [51, 64].

Researchers have applied IFT to various aspects of information behavior, demonstrating its versatility and relevance. Liu et al. [51] proposed an ISE (Information goal, Search strategy, Evaluation threshold) user classification model based on IFT, showing its utility in understanding user behavior in interactive content-based image retrieval systems. This model highlights how IFT can effectively classify and analyze user strategies in complex information environments. Similarly, Fok et al. [25] used IFT as a heuristic model for developing an AI-assisted information retrieval system for business document workflows, finding improvements in efficiency and reduced cognitive load. These studies indicate that IFT provides a robust theoretical framework for modeling user behavior in environments rich with diverse information sources. Given the complexity of multi-source information environments that college students navigate, IFT is particularly well-suited to our research. It offers valuable concepts and models to analyze how students search for, evaluate, and integrate information from various sources. By applying IFT, we can gain deeper insights into the strategies students employ, the challenges they face, and how they adapt their information-seeking behaviors within the constraints of their academic and digital ecosystems. This theoretical foundation not only helps us understand the underlying processes but also informs the design of interventions and tools to facilitate more effective information retrieval and management for students.

However, while IFT has been applied in various contexts, its specific application to college students' multi-source information behaviors remains underexplored. Despite the demonstrated potential of IFT in modeling complex information environments, there is a significant gap in research focusing on how students integrate and manage information from diverse sources cohesively, especially within AI-assisted learning environments. While studies have examined information behaviors across different sources [33, 37], there is limited research on how students integrate and manage information from these diverse sources cohesively. The rapid evolution of AI-powered information tools further complicates this landscape, necessitating investigation into how these technologies are reshaping traditional models of information behavior and cognition [36]. As we move forward, it is crucial to address these gaps by conducting comprehensive studies that examine the entire lifecycle of multi-source information retrieval and management among college students. By leveraging frameworks like IFT and its extensions, we can develop more nuanced understandings of these complex behaviors and design more effective interventions and tools to support students in their information retrieval and management endeavors.

2.2 AI-Assisted Tools for Information Retrieval and Management

AI is rapidly transforming information retrieval and management processes, offering new possibilities for enhancing learning experiences in higher education [85]. For college students, AI-powered tools have the potential to streamline research processes, improve information organization, and facilitate more efficient knowledge acquisition for college students [3, 32]. These advancements are particularly evident in personalized teaching systems, adaptive interfaces, and sophisticated data collection methods about learners [45].

Current AI-assisted tools for information retrieval include intelligent search engines and recommendation systems that can personalize results based on user preferences and behavior [1, 4]. Students utilize LLM-empowered conversational agents like ChatGPT as a channel of information retrieval as well [60]. In information management, AI applications such as automated summarization and content categorization are becoming increasingly sophisticated [46]. These tools offer potential benefits for college students, including more efficient information discovery, improved organization of study materials, and personalized learning experiences. However, current AI-assisted information tools face challenges and limitations. These include potential biases in AI algorithms [7], difficulties in explaining complex AI decisions to users [20] , and concerns about data privacy and security [24]. Additionally, there is a risk of over-reliance on AI tools, potentially hindering the development of critical thinking skills in students [72].

To address these challenges, there is a growing emphasis on user-centered design in AI tools for academic use. Understanding student needs and preferences is crucial for developing effective and trustworthy AI-assisted information tools [15]. Involving students in the design process through co-design and participatory methods can lead to more tailored and user-friendly tools [23] . Despite of these research, there is a significant gap in understanding how students actually use AI tools for multi-source information tasks in academic settings. Limited research exists on the impact of these tools on students' information behavior and cognitive processes [45]. This highlights the need for more

ID	Session	Period of Study	Area of Study
I1	#1	Master	Human-Computer Interaction
I2	#1	Master	Data Centered Artificial Intelligence
I3	#1	Master	Human-Computer Interaction
I4	#2	Master	Educational Inequalities
I5	#2	Master	Robotics
I6	#2	Master	Internet of Things
I7	#3	Doctoral	Machine learning
I8	#3	Master	Optics
I9	#3	Undergraduate	Computer Science and Technology
I10	#4	Master	Materials Science and Engineering
I11	#4	Master	Clinical Medicine
I12	#4	Undergraduate	Media and Communication
I13	#4	Master	Industrial Design Engineering
I14	#5	Undergraduate	Computer Science
I15	#5	Doctoral	Internet of Things
I16	#5	Doctoral	Human-Computer Interaction

Table 1. Demographic of Focus Group Studies participants (N=16)

comprehensive studies examining how AI tools influence students' research strategies, information synthesis, and overall learning outcomes.

3 Methods

We conducted two types of studies: 1) focus group studies to understand current college students' AI-assisted knowledge retrieval and management patterns, and 2) participatory design workshops to reveal students' expected solutions. We chose focus group studies over individual interviews because group interactions can enrich the information generated [74] and help participants recall past experiences [48]. The challenges identified from the focus group studies were used to inform the participatory design in Study 2.

3.1 Study 1: Focus Group Studies

3.1.1 Participants. As information-seeking behaviors differ across disciplinary areas [58, 82], we recruited students from diverse fields to minimize disciplinary bias. Our inclusion criteria need participants to be currently engaged in academic research with experience using AI to assist academic activities. Through personal networks and snowball sampling, we recruited 16 participants from computer science, sociology, design, arts, physics, medicine, and engineering (Table 1).

3.1.2 Study Process. We divided 16 participants into 5 groups, with 3 or 4 people in each group. Each study session lasted about 60 minutes. We first asked participants to describe recent scenarios where they used multiple information sources for academic activities. Next, we asked participants to recall as many information sources as possible from their daily academic life, encouraging them to supplement each other's responses freely. For each type of source mentioned (e.g., academic papers, online databases, AI tools), we followed up with questions about their experiences. Then we discussed how they managed information from different sources and their note-taking patterns. We specifically inquired about how participants integrated AI into their workflow and the challenges of using AI for academic activities. During

ID	Session	Period of Study	Area of Study
P1	1	Master	User Experience Design
P2	1	Master	Information Systems Management
P3	2	Master	Industrial Design
P4	2	Master	Interactive Design
P5	3	Master	Data Science
P6	3	Master	Mathematics
P7	3	Master	Computer Science
P8	4	Master	Industrial Design
P9	4	Master	Industrial Design
P10	5	Undergraduate	Computer Science
P11	5	Master	Digital Media and Arts

Table 2. Demographic of Participatory Workshop participants (N=11)

the study, we used instructional slides that briefly outlined the study goals, listed the topics for discussion, and provided definitions of terms like multi-source knowledge and information management.

3.1.3 Data Analysis. The focus group studies were recorded and transcribed using a commercial automatic speech recognition system - iFlyrec[1] and verified by the research team. We conducted inductive and deductive analyses, allowing us to combine the Information Foraging and Management Framework with new themes emerged from the data. For the inductive analysis, we employed thematic analysis to identify patterns and themes of the transcribed data [70]. Two researchers independently coded the transcripts, focusing on participants' information retrieval and management behaviors, their use of AI tools, and the challenges they encountered. After the initial coding, all coauthors met to discuss and refined the codes, resolving any discrepancies through consensus. These initial themes then informed the subsequent deductive analysis phase. For the deductive analysis, we organized the themes from our inductive analysis using the IFT. All coauthors discussed these themes to ensure they fit the information management framework. This approach gave us a structured understanding of participants' behaviors. We also applied key concepts from IFT to interpret the focus group studies findings in Section 4, offering fresh insights into the motivations behind participants' behaviors.

3.2 Study 2: Participatory Design Workshops

3.2.1 Participants. We recruited 11 participants for the participatory design workshops through online recruitment and snowball sampling. The inclusion criteria for this part were the same as for the focus group studies: 1) currently conducting academic research, and 2) using AI to assist in academic activities. The demographic information is provided in Table 2.

3.2.2 Participatory Design Workshops Process. We conducted the participatory design workshops 2-5 weeks after the focus group studies. We chose the participatory design method and asked participants to sketch their ideal scenarios addressing challenges because it can help us generate implications about the adoption of future technologies [75]. We divided the 11 participants into 5 groups, with 2-3 people in each group lasting about 50 minutes.

[1]https://www.iflyrec.com/zhuanwenzi.html

In preparation for our participatory design workshops, we first summarized the content of the focus group studies, identifying and organizing the key challenges into four stages of information foraging and management framework: Search, Read, Extract, and Manage. To better stimulate participants' thinking and facilitate the sketching process, we color-coded the five identified challenges and printed them out (Figure 1). On each drawing sheet for the challenges, we provided participants with three basic low-fidelity interfaces: a conversational AI interface (such as ChatGPT), a browser search interface, and a mobile social media interface. We selected these interfaces based on the three most common sources of information mentioned by participants in the focus group studies: conversational AI, search engine, and mobile applications . The main co-design activity focused on five challenges: 1) improve the accuracy and relevance of answers. 2) assist users in evaluating the relevance and quality of answers. 3) better understand academic content. 4) extract information from multiple sources and manage it centrally. 5) personalize information management. We introduced our research theme and these five challenges to participants along with the findings from the focus group studies. Then we asked participants to sketch designs for AI artifacts that could help solve these challenges. Throughout the process, we encouraged participants to discuss and communicate with each other.

Fig. 1. Participatory design workshops set up. The photos were taken from three different sessions. Parts of the picture are blurred for privacy. Participants were sketching their ideas on the color-coded challenges sketch paper. We classified the sketching paper into five colors according to the five challenges and printed some low-fidelity interfaces on the paper as the sketching material.

3.2.3 Data Analysis. The participatory workshop was recorded and transcribed using iFlyrec, and then verified by the research team. We collected the sketches from the participatory design workshops and shared them with the research team. Our analysis incorporated both inductive and deductive approaches. For the inductive analysis, two researchers independently conducted thematic analysis on the transcripts and sketches, generating initial design consideration themes. The research team then reviewed and discussed the coding outcomes, refining the codes iteratively to resolve any discrepancies. This inductive analysis helped us generate initial design consideration themes from the participatory workshop, which we then used as a basis for the deductive analysis. In the deductive phase, the research team generalized the design consideration themes in accordance with the framework used in the focus group studies. This alignment of analysis frameworks ensured that our design considerations were grounded in real user needs and challenges while incorporating innovative ideas from the participatory design process. We categorized the design considerations into four main areas: search interactions, read interactions, extract interactions, and management interactions. In addition, we applied some key concepts from IFT to interpret the participatory design workshop findings in Section 5.

4 College Students Information Behaviors and Challenges

With the guidance of IFT concepts [63–65], we developed a comprehensive analytical framework that examines how college students' traditional ways of finding information interact with the new opportunities and challenges brought by AI technologies. Our framework also draws inspiration from prior works in information retrieval, which adopt IFT model as theoretical foundations [25, 67, 76]. Our framewrok consists of four interconnected phases: Search, Read, Extract, and Manage (SREM), see Figure 2. Each phase covers an important part of how students interact with information, from initial discovery to long-term knowledge organization. Throughout these phases, we observe how AI tools both support and disrupt established information foraging patterns.

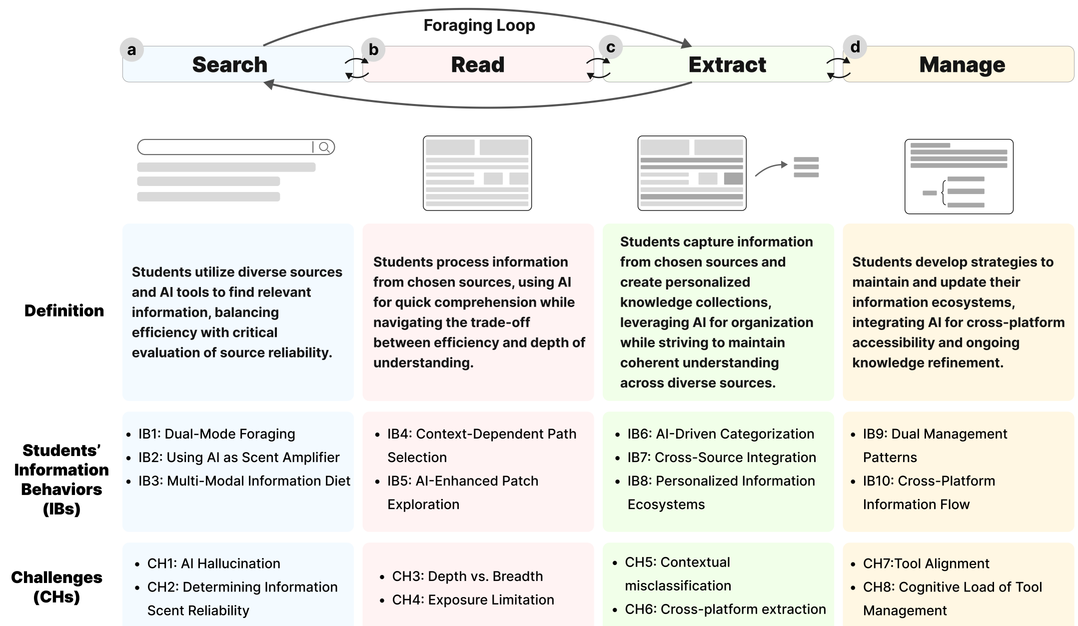

Fig. 2. SREM Model: composed by four phases of (a) Search: students find information via various sources; (b) Read: students process information; (c) Extract: students capture information; (d) Manage: students maintain, update, and utilize the information, and the corresponding students' information behaviors (IBs) and challenges (CHs) identified from each phase.

4.1 Phase 1: Search

Students navigate a complex information landscape, utilizing both traditional and AI-enhanced cues to discover valuable information patches across diverse platforms. In the context of IFT, the *search* phase represents the initial foraging behavior where students seek out information patches, i.e. clusters of information that may exist across different sources [63]. This process is now heavily influenced by AI technologies. AI tools act as scent amplifiers, enabling more efficient between-patch foraging, while also introducing new challenges in assessing source reliability and maintaining a balanced information diet.

4.1.1 Information Behaviors in Search Phase. In the Search phase, we identified three types of **information behaviors (IB)**: dual-mode foraging, using AI as a scent amplifier, and multi-modal information diet.

IB1: Dual-Mode Foraging. Students engage in both targeted and exploratory information foraging across multiple platforms. This dual approach allows them to balance specific academic needs with broader knowledge acquisition.

Mode 1 - Targeted. When students have clear academic goals, they tend to use more specialized and authoritative sources. This behavior aligns with the concept of "information scent" in IFT, where users follow strong scents to locate high-value information patches [18, 64]. For example, *"journals like Nature, Science, or others..." (I8)* and databases for specific academic disciplines like *"Web of Science" (I6)* and *"PubMed, which has many medical papers" (I11)*. When students know exactly what information they need, they would look for trustworthy sources related to their field (*"PubMed and APA PsycNet" -I11*), and general academic search engines (*"Google Scholar" -I10*).

Model 2 - Exploratory. Students also engage in exploratory information gathering, similar to "berry-picking," [8], where they collect information from various sources over time. For instance, *"social media like RED and WeChat Official Accounts" (I8)* and *YouTube (I2)*. This exploratory approach serves several purposes, including staying tuned with current trends: *"many researchers use RED" (I12)*, gaining diverse perspectives: *"I check journals and WeChat Official Accounts." (I1)*, and accessing multimedia content: *"When learning a new skill, I tend to use video" (I12)*.

Integrating the two modes. Interestingly, students are developing sophisticated strategies to integrate the two foraging modes: *"Start with informal channels like some blogs and social media, which often has references that link to professional sources like journals" (I14). "I use a parallel approach, searching from both academic journals and blogs" (I15)*. This approach demonstrates a layered foraging strategy, where students use more accessible informal sources as starting points to identify relevant topics or keywords, before diving into more authoritative academic sources.

IB2: Using AI as Scent Amplifier. Cues in the environment that guide users to valuable information sources are known as Information Scents [63]. AI tools, specifically Generative AI tools such as ChatGPT [2] and Claude [3] are increasingly serving as powerful scent amplifiers, helping students better recognize and follow these cues during their academic information seeking. From the start of an information search, AI tools help students generate more effective keywords: *"I would use ChatGPT to help me generate keywords for the literature I want to search" (I13)*; AI-assisted keyword generation expands search vocabulary and identifies trending topics by suggesting synonyms, related terms, and field-specific jargon that students might not have considered, leading to more thorough search results. By analyzing large amounts of recent data, AI can also highlight current hot topics or emerging trends in a field, guiding students toward the latest research. AI tools also provide quick summaries or previews of content, helping students efficiently assess the relevance and value of information sources: *"I will import the PDF into ChatGPT and let it generate a more comprehensive instruction" (I14)* With AI information scents highlighting key concepts, students can quickly grasp the main ideas of a document and determine if it aligns with their needs. Additionally, for non-native speakers or when dealing with highly technical texts, AI summaries can provide a more accessible starting point.

IB3: Multi-Modal Information Diet. College students are increasingly building a diverse "information diet" that includes traditional academic resources, social media platforms, and AI-generated content. This multi-modal approach to information gathering enables them to draw from a variety of perspectives, formats, and levels of formality. Each type of information source serves a different purpose in their academic journey: **(1) Traditional Academic Sources**: *"Google Scholar and Web of Science" (I10)*; *"PubMed, which has collected many medical papers" (I11)*. These sources serve as the foundation of formal academic research, offering peer-reviewed and highly credible information; **(2) Social Media and Informal Online Sources**: *"WeChat Official Accounts, RED, and Weibo" (I8)*. Social media platforms offer more trend-focused information and diverse perspectives, often in more accessible formats; **(3) Video Platforms**: *"For learning courses, I generally use YouTube" (I2)*. Video provides visual and audio learning experiences, making it easier to understand complex ideas or practical skills; **(4) AI-Generated Content**: *"I basically use ChatGPT as a search engine" (I14)* AI tools are being integrated as a new layer in the information ecosystem, offering synthesized knowledge and analytical support. Moreover, participants developed sophisticated strategies to integrate these diverse sources: *"I use a parallel approach, searching both from formal channels like academic journals and from blogs and articles" (I15)*

4.1.2 Challenges presented in Search Phase. We identified two main challenges (CH) in the Search phase: AI hallucination and determining information scent reliability.

CH1: AI Hallucination. AI hallucination is when AI systems generate false or made-up information and present it as if it were true [38, 40]. This poses a significant challenge in academic information foraging, where accuracy and reliability are essential. *"Actually, half of the literature it (ChatGPT) recommended doesn't exist" (I16).* The considerations of this challenge are multifaceted. AI hallucinations can lead students down unproductive research paths, wasting time and resources on made-up or irrelevant information. AI can also generate information that sounds credible but is false, potentially spreading misinformation about academic literature if not verified: *"it might give you a random piece of literature, which is not very reliable." (I7)* AI hallucinations exacerbate this problem by introducing fake citations. Participants suggested AI systems provide source attribution like links for easier verification: *"If it provides links, at least I know the source. I trust it more, and if I want to learn more about it later, it would also be easier" (I9).*

CH2: Determining Information Scent Reliability. The challenge of determining the quality and relevance of information persists in both traditional and AI-assisted search contexts. This challenge is exacerbated by the vast amount of information available and the increasing sophistication of misleading content. The abundance of information can lead to decision fatigue and difficulty in relocating valuable sources: *"when there's a lot of information, searching becomes problematic. It's very difficult to find your way back, there's still a big difficulty in finding that place again." (I5)* Another major problem is keyword mismatch: *"Sometimes you search with some keywords, and the results may not be suitable." (I8)* Translating user intentions into effective keywords is a problem that persists even with AI assistance. Participants are also struggling to assess the credibility of sources, especially when AI-generated content seems authoritative but contains errors: "It may be different from what I learned." (I8)

4.2 Phase 2: Read

The *read* phase represents within-patch foraging, where students extract information from chosen sources. AI changes this process by enabling quick evaluation and switching between sources, which can affect how deeply or widely students explore information. Students need to balance the reduced mental effort provided by AI tools with the risk of only gaining a surface-level understanding, constantly adjusting their approach based on their specific academic goals.

4.2.1 Information Behaviors in Read Phase. We identified two information behaviors in the Read phase: context-dependent path selection and AI-enhanced patch exploration.

IB4: Context-Dependent Path Selection. The evaluation of information patches (sources) is a complex process heavily influenced by specific academic contexts, goals, and educational stages. This behavior aligns closely with the IFT's concept of patch assessment [63, 65], where information seekers continuously evaluate the potential value of information sources relative to their current needs and the cost of accessing them. Different fields have unique "information ecologies" with varying patch values [26, 59]: *"I think this may be closely related to the discipline, and also related to the educational stage" (I16). "economics articles don't value citations that much." (I4)* Traditional metrics like citation counts may not be as valuable in economics as in other fields, necessitating a different approach to source evaluation. Modern academic research often requires students to explore multiple disciplines, necessitating a more diverse and adaptable approach to choosing information patches. *"Some articles are not easy to subdivide, because of interdisciplinary content." (I8)* Students independently develop a strategy where they use less formal sources as starting points to identify relevant topics before moving to more authoritative ones. For instance, *"I generally start with informal channels like blogs and social media" (I14)*, and *"In those blogs, it often has some references that can link to more professional sources such as books or journals" (I14)*. This demonstrates a context-dependent, multi-stage approach to patch selection.

IB5: AI-Enhanced Patch Exploration. The integration of AI tools in academic information foraging is fundamentally changing how students approach and interact with complex information patches, particularly academic papers and specialized literature. This trend aligns with the IFT's concepts of information scent and patch assessment [63, 65], where AI acts as both a scent amplifier and a patch evaluator. AI tools are increasingly serving as cognitive scaffolds, helping students quickly understand complex academic materials. The support can reduce the mental effort required to read challenging texts by using AI-provided initial structure and simplified explanations: *"let ChatGPT explain in simple terms" (I15)*; *"It helps you quickly organize the structure of the entire literature" (I13)*. This scaffolding can be particularly beneficial for interdisciplinary research and non-native language materials. Additionally, AI is used for preliminary analyses of academic materials, helping students to identify critical concepts and potential areas for further exploration within a paper or across the literature (*"AI can help you extract some common search keywords" -I15*).

4.2.2 Challenges presented in Read Phase. Challenges in Read Phase include balancing depth and breadth, and exposure limitation.

CH3: Depth vs. Breadth. The challenge of balancing depth and breadth in AI-assisted reading is a critical issue that reflects the fundamental tension between the efficiency offered by AI tools and the comprehensive understanding required in academic contexts: *"The challenge is that sometimes it's not comprehensive enough, and sometimes it's quite superficial" (I14)*. However, this challenge is more nuanced and multifaceted than it might initially appear, including oversimplification of complex concepts (*"sometimes it can be superficial. " -I15*), neglect of contextual nuances (*"Because some articles, their content... is not easy to subdivide, because it has a lot of interdisciplinary content." -I8*), and reduction of critical engagement (*"At the beginning, yes. Later, I stopped... Because there's too much to read... Feeling that taking too much time is not very meaningful." -I8*).

CH4: Exposure Limitation. The challenge of exposure limitation stems from the potential for AI recommendations to create an echo chamber effect, restricting students' exposure to diverse, non-AI-suggested sources. Participants mentioned: *"The biggest difference between humans and AI is that when we discuss an idea with different students, we'll definitely have many points that you couldn't think of yourself" (I16)*; *"Also, I would ask classmates. Ask some more experienced seniors and the like. If they know, they will share some information." (I8)*. These examples highlight the value of human interaction in academic information seeking. However, the challenge of exposure limitation extends beyond this: AI recommendations may inadvertently reflect biases present in their training data, potentially skewing students' exposure to certain perspectives or bodies of literature. *"AI-generated content may sometimes be inaccurate or hallucinated, potentially misleading users." (I16)*

4.3 Phase 3: Extract

The *extract* phase involves creating enriched, personalized information habitats through AI-assisted categorization and cross-source integration of harvested knowledge. While AI is enhancing efficiency in information organization, students continue to face challenges in creating coherent knowledge structures from diverse sources. The ongoing evolution of this phase suggests a need for more integrated, AI-enhanced tools that can better handle the nuances of academic information while still allowing for the high degree of personalization that students value.

4.3.1 *Information Behaviors in Extract Phase.*
Information behaviors in the Extract phase include AI-driven categorization, cross-source integration, and personalized information ecosystems.

IB6: AI-Driven Categorization. Students are increasingly leveraging AI to streamline the organization of their academic information. This trend aligns with the IFT concept of "enrichment," where foragers modify their environment to enhance future foraging efficiency [63]. One student reported using AI to *"help me polish and organize my informal, colloquial notes into a more readable, standardized form" (I14).* This demonstrates how AI is serving as a cognitive assistant, transforming raw, unstructured notes into more usable, structured information. The application of AI extends beyond individual note organization to broader literature synthesis. As one participant noted, AI *"helps you quickly organize the structure of the entire literature" (I13).* This capability suggests a significant shift in how students approach large-scale information processing, potentially reducing the cognitive load associated with literature reviews and enhancing overall academic productivity.

IB7: Cross-Source Integration. In response to the fragmented nature of academic information across multiple platforms, students are developing sophisticated strategies for information integration. A common approach involves creating centralized repositories for diverse information. One student described having "*a dedicated Word document where I copy various useful information" (I11)*, while another used a collaborative platform, stating, *"I'll collect the good or useful ones into a Feishu document, because I'm afraid if the information is too scattered, I won't remember it, so I manage everything in one place" (I5).* These strategies reflect an adaptive response to information overload and the challenge of maintaining coherence across diverse sources. By centralizing information, students are creating their own information patches that are rich in relevant content, aligning with the patch model in IFT.

IB8: Personalized Information Ecosystems. Students are crafting highly individualized systems for information extraction and organization, tailored to their specific cognitive styles and academic needs. One participant described a personal system where *"I will have a configuration, and on that configuration are all the papers I've read. Those papers are categorized by area" (I14).* This approach demonstrates the creation of personalized taxonomies that reflect individual mental models of their field of study. The use of flexible, user-friendly tools is central to this personalization. As one student mentioned, *"I actually use Notion, then build something like a knowledge base" (I10).* Tools like Notion allow for the creation of highly customized knowledge management systems, enabling students to structure information in ways that best suit their cognitive processes and academic workflows.

4.3.2 *Challenges presented in extract phase.*
Challenges in extract phase include Contextual misclassification and Cross-platform extraction.

CH5: Contextual misclassification. Despite the benefits of AI and personalized systems, students face significant challenges in information extraction and organization. The issue of contextual misclassification is particularly salient for interdisciplinary content. As one student noted, *"Because some articles, their content... is not easy to subdivide, because it has a lot of interdisciplinary content. Not very good, you use a field... a title to restrict it" (I8).* This highlights the limitations of rigid categorization systems, whether AI-driven or manual, in handling the nuanced intersections of academic fields.

CH6: Cross-platform extraction. Cross-platform extraction remains a persistent challenge. Students often resort to basic methods like bookmarking or copying links, with one participant stating, *"Sometimes if I think it's more important, I might bookmark it in the browser or even copy the link" (I9).* More comprehensive approaches involve combining multiple elements, as another student described: *"I'll put those... important links, for example, put important links in the notes, including some screenshots of websites" (I8).* These manual methods, while functional, suggest a lack of seamless tools for integrating information across diverse platforms.

4.4 Phase 4: Manage

Information habitat maintenance strategies evolve to incorporate AI-powered updates and cross-platform fluidity, optimizing future foraging through effective scent trail preservation and patch refreshment. The *manage* phase encapsulates the ongoing challenge of balancing the complexity of accumulated information and tools against the future benefits of a well-maintained, easily navigable personal information ecosystem.

4.4.1 Information Behavior in manage phase. We identified two information behaviors in the Manage phase, including dual management patterns and cross-platform information flow.

IB9: Dual Management Patterns. Students adopt either distributed or centralized approaches to multi-source information management, reflecting diverse strategies for organizing and accessing information from various sources. Some students prefer a distributed approach, keeping information in its original platforms or using multiple tools for different types of content. As one participant noted, *"I now mostly keep the links open and leave them in the browser. Sometimes if I think it's more important, I might bookmark it in the browser or even copy the link." (I9)* This strategy leverages the native features of different platforms, with students using platform-specific tools like bookmarks or favorites. Another student mentioned, *"Or it would be in Zhihu or CSDN or... It may have an account on its own website, and then I click to favorite things inside." (I9)* This distributed approach offers advantages of contextual preservation and reduced transfer cost. Information remains in its original environment, maintaining associated context and related content, with no need to manually move information between systems. However, it also presents challenges of difficulties in searching across multiple platforms simultaneously and platform dependence, bearing with risk of losing access to information if a platform changes or shuts down.

In contrast, other students prefer to consolidate information from various sources into a single, centralized platform or document. One student explained, *"I'll also save them, and then I'll collect the good or useful ones into a Feishu document, because I'm afraid if the information is too scattered, I won't remember it, so I manage everything in one place." (I5)* This centralized approach often involves using comprehensive note-taking or knowledge management tools. Another participant mentioned, *"I actually use Notion, then build something like a knowledge base." (I14)*. The centralized approach offers benefits of unified search, consistent organization, and reduced risk of losing access due to changes in original sources. However, it also has drawbacks of information transfer effort, requiring manual effort to move and organize information. It also relies on a single tool may create vulnerability if the tool becomes unavailable.

IB10: Cross-Platform Information Flow. There's a growing need for seamless information flow between different platforms. Students are increasingly using multiple platforms and seeking ways to integrate information across them. This trend is evident in students' tool choices, with one participant noting about their reference management software, *"Because these can be used across multiple platforms" (I13)*, and another stating, *"I can use it on multiple platforms" (I14)*. This desire for cross-platform fluidity is driven by device diversity and collaborative requirements. Students work across multiple devices (smartphones, tablets, laptops) and need consistent access to their information. Moreover, academic work often involves collaboration, necessitating easy information sharing across platforms.

4.4.2 Challenges presented in manage phase. While students are developing sophisticated strategies for information management, they face significant challenges in this process.

CH7:Tool Alignment. AI tools and other information management systems may not perfectly align with individual students' unique habits and workflows. This misalignment can lead to increased effort and frustration. As one student candidly expressed, *"I feel that the cost of management is actually quite high" (I13)*. This sentiment suggests that current tools may not fully meet students' needs, resulting in a gap between tool capabilities and user requirements. The challenge lies in developing tools that are flexible enough to accommodate diverse management styles while still providing powerful organizational features.

CH8: Cognitive Load of Tool Management. Students face the challenge of balancing the benefits of multiple tools against the cognitive cost of managing them. The learning curve associated with new tools can be steep, as illustrated by one participant's comment: *"If you want to cite correctly, you actually need to learn. You need to specifically watch videos to learn how to use it." (I3)* This learning process contributes significantly to the cognitive load of information management. Students must weigh the potential long-term benefits of a new tool against the immediate time and effort required to master it.

5 Design Considerations for College Students Information Retrieval and Management

Stage	**Challenges from Focus Group Studies**	**Design Challenges in Participatory Design Workshop**	**Design Considerations**
Search	CH1: AI Hallucination CH2: Information Scent Reliability	1. How to improve the accuracy and relevance of answers 2. How to assist users in evaluating the relevance and quality of answers	*5.1.1* Facilitate users' verification of AI answers' credibility *5.1.2* Facilitate users to provide context information *5.1.3* Facilitate user's information assessment before diving into it
Read	CH3: Depth vs. Breadth CH4: Exposure Limitation	3. How to better understand academic content	*5.2.1* Facilitate user's quick query in the document *5.2.2* Facilitate adjustment of AI answer's level of detail
Extract	CH5: Contextual misclassification CH6: Cross-platform extraction	4. How to extract information from multiple sources and manage it centrally	*5.3.1* Facilitate customized structured extraction *5.3.2* Facilitate extraction across multiple information sources and sending to one place
Manage	CH7: Tool Alignment CH8: Cognitive Load of Tool Management	5. How to personalize information management	*5.4.1* Facilitate interactions with AI based on the notes' context *5.4.2* Facilitate revisiting historical notes through contextual recommendation

Table 3. Challenges and Design Considerations in the SREM model

We summarize the findings from the participatory design workshops primarily to address RQ3. Table 3 shows the design considerations addressed to the challenges. Through participants' feedback, we confirmed the challenges highlighted in the focus group studies and gained design considerations for AI-assisted information retrieval and management tools. Based on the information foraging and management framework, we present our findings in four areas: **search interactions, read interactions, extract interactions, and management interactions.** For the design considerations that indicate specific functions, we redraw the participants' sketches into figures to demonstrate the functions they proposed in the workshop. Note that we do not claim these design considerations to be comprehensive given that our participatory design participants skew towards a limited number of disciplines and backgrounds of academic students. However, they offer valuable insights into potential design features that can enhance the functionality of AI-assisted tools for academic research.

5.1 Design Considerations for Search Interactions

5.1.1 Facilitate users' verification of AI answers' credibility. Most participants mentioned adding references to improve the credibility of AI responses. *"References provide a way for me to delve deeper into the content. It enhances the interpretability of AI-generated answers." (P1)* Participants (P2, P8, P9) mentioned that accessing references should not require too much effort. *"The most frustrating part is navigating away from the main page. This process can be cumbersome, especially when you've opened numerous pages." (P9)* For the solution, P9 suggested, *"It would be helpful if we could see a preview of the references directly in the AI's response. "*(Figure 3a) This suggestion aligns with one of the environment enrichment strategies in Information Foraging Theory - to reduce the average cost of getting from one information patch to another [65]. In our example, checking the reference to verify the credibility and acquire more knowledge is a switch between "AI information patch" and "reference information patch", and previewing the reference could reduce the effort of switching between different information patches. Additionally, AI could enhance the corresponding relationship between the AI's answer and the references. P8 said, *"It's difficult for us to determine which content is directly quoted and which is AI's own interpretation."* For the design considerations, P6 suggested AI give out structured results with each opinion along with its reference apart to facilitate user verification. P8 and P10 both suggested using color to highlight the quoted part of the response which has a reference (Figure 3b).

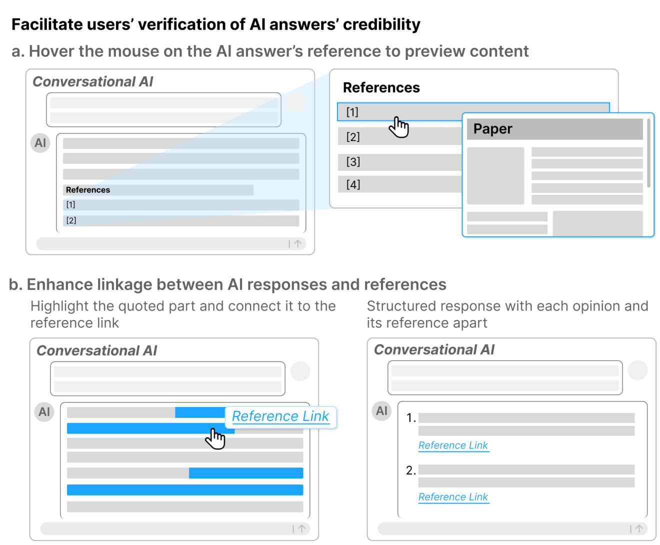

Fig. 3. Search Consideration 1: Facilitate users' verification of AI answers' credibility. We show two examples: a. Hover the mouse on the reference to preview the information content b. Two methods to enhance the linkage between AI responses and references

5.1.2 Facilitate users to provide context information. Semantic relevance refers to how well AI-generated answers align with the user's intention and context. Participants mentioned the challenge that AI sometimes provides irrelevant or off-topic responses. To address this issue, P4 and P10 suggested adding context information to user prompts. For instance, using customized tags to describe context information (Figure 4a). *"if you chat with AI about HCI research a lot,* *you can add an HCI research tag. Next time when you start a new chat, you could directly choose this tag to set the context for your conversation. This way, you don't have to repeatedly explain every time you start a new chat." (P4)* Additionally, AI can guide users to provide more semantic information when the question is not well-structured. P1 and P3 mentioned that AI could suggest some possible further questions for users to choose from (Figure 4b). *"The system could offer buttons with more specific domains. Clicking these buttons would filter and refine the results, allowing me to quickly find relevant information without rephrasing the question many times." (P1)*

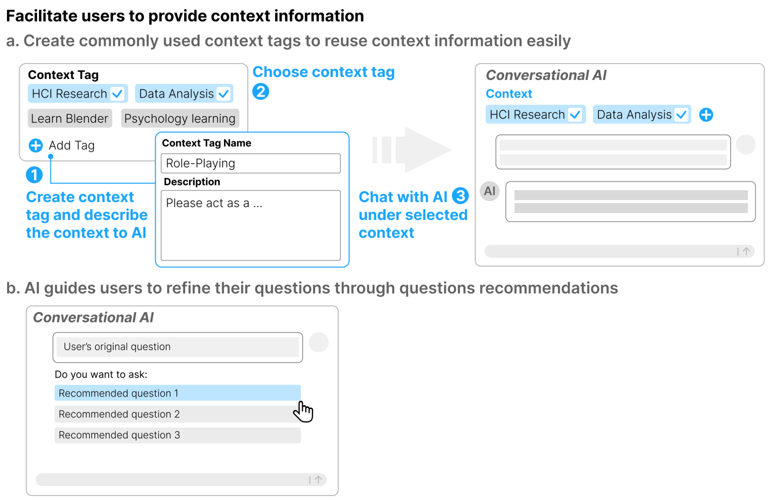

Fig. 4. Search Consideration 2: Facilitate users to provide context information. We show two examples: a. Customize context tags for the conversation to enhance the answer's relevance, which includes three steps: 1. Users create context tags and describe the context to AI; 2. Users choose the context tag before starting a new conversation with AI; 3. Users chat with AI under the selected context b. AI guides users to refine their questions through question recommendations. Users can select to refine the questions

5.1.3 Facilitate user's information assessment before diving into it. In the Information Foraging Theory, information scent is the (imperfect) perception of the value, cost, or access path of information sources obtained from proximal cues. If the scent is sufficiently strong, the forager will be able to make the correct choice at each decision point [65]. A good information scent could help users choose the relevant information sources among information sources efficiently. The information scent is crucial for users especially in the AI-powered search engine, as the search engine always returns denser information sources for the user to choose from.

P11 proposed using tags to show information features for assessing quality before delving into the information sources (Figure 5a). These tag's content could be customized by users according to their needs. P2 shows one of the products he used which can tag the academic article with some core index to assist the user's assessment, such as the journal ranking, indexing databases, research institute, etc. Despite the objective index of the information sources, participants (P4-8) showed their need for customized contextual information: *"Everyone has their own judgment on the quality. Even the same person will focus on different aspects of the article according to the context changes." (P5)* P8 suggested that the features that users want to amplify may also differ among different disciplines. For example, *In the area of design, we will also look for design websites where we focus on the competition award that one design has won. If AI* *could help me extract these features, it would benefit in quality assessment of the design.* Some participants also proposed using AI summaries to help people know the content briefly before they delve into the information source (Figure 5b).

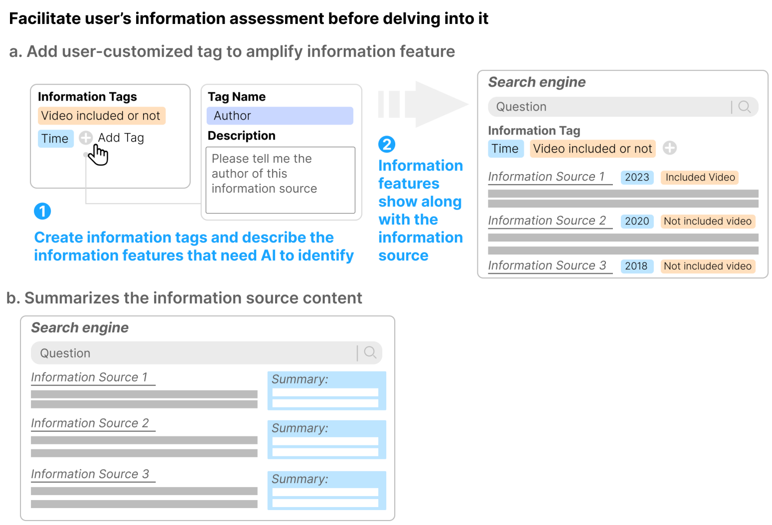

Fig. 5. Search Consideration 3: Facilitate user's information assessment before delving into it. We show two examples: a. Add user-customized tags shown with information sources, which include two steps: 1. Create information tags and describe the information features that need AI to identify; 2. Then the information features will show along with the information source in search engines' results b. Summarize the information source content

5.2 Design Considerations for Read Interactions

5.2.1 Facilitate user's quick query in the document. For AI-assisted reading interaction, participants proposed a quick inquiry feature to enhance the reading experience based on the repetitive questioning challenges. P1, P10 and showed their need for the term explanation when they were reading articles. P10 said, *"When I'm reading the paper, I often encounter unfamiliar terms and have to ask 'What does ... mean ?' repeatedly. I hoped AI would provide explanations or the hyperlink for the unfamiliar term in the document automatically, similar to how Wikipedia works."* Despite the term explanation query, P1 also proposed using users' feedback to optimize the question recommendation algorithm and provide more types of query recommendations for users, *"AI could learn which part of the article that users asked most and what questions users ask. Then insert the questions in these places. When I'm reading a new article, AI can generate similar questions for me to choose."* Combining the participants' ideas, the design consideration is using AI to predict potential question points in the document and insert inquiry buttons at these locations (Figure 6). These buttons would allow users to quickly access explanations or ask relevant questions about the document without typing repeated questions to ask AI for additional information.

5.2.2 Facilitate adjustment of AI answer's level of detail. Participants mentioned they would use AI to summarize or retell the article to help them understand the content of the article. However, the AI answer's level of detail didn't meet their requirements sometimes For example, P8 said, *"Sometimes I want to quickly go through a research paper and ask AI to summarize. But the answer it gives me is nearly the same as the paper's abstract, which is too brief for me."* To help users

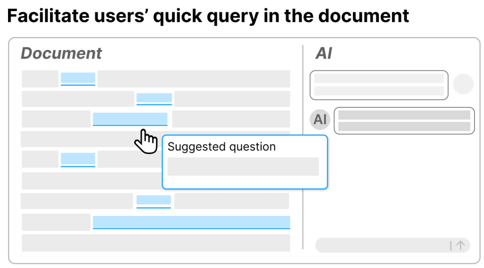

Fig. 6. Read Consideration 1: Facilitate users' quick query in the document. AI inserts recommended queries into the document, users can quickly ask AI these questions by clicking it.

have better control of the answer's level of detail, P8 and P9 proposed using a slider to control the answer's level of detail (Figure 7). When the detail level is low, AI provides a brief answer. When the detail is high, AI provides an answer that is as detailed as the paper itself. P9 further illustrated the example usage scenario, *If I ask AI what experiments this article did, with the slider set to "brief" it might only mention what experiments were conducted. When I wanted to know more details about these experiments, I could then move the slider a little to the "detailed" end, and the AI would tell me specifically what experimental methods were used, what conclusions were drawn, and how many samples were collected.*

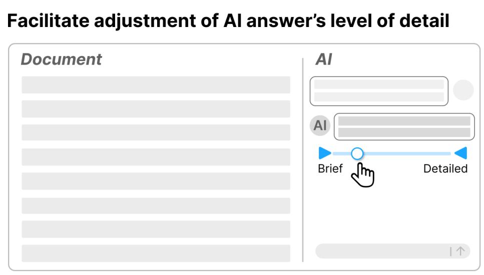

Fig. 7. Read Consideration 2: Facilitate adjustment of AI answer's level of detail. Users can adjust the AI answer's level of detail through a slider under AI answer.

5.3 Design Considerations for Extract Interactions

5.3.1 Facilitate customized structured extraction. When taking notes, Participants mentioned they would process the raw information before they put the piece of information into their notes, which is the process of extracting information. For example, P4 said, *"I use tables to manage the papers I read. I will extract specific information from each paper, such as the research question, methodology, and key findings, and organize them into a structured table format that I customized. However, this process is cumbersome and time-consuming. Having AI assistance for this extraction process could significantly improve my efficiency in maintaining my research notes."* To solve this problem, P4 and P11 proposed the use of AI to assist with this customized structured extraction process (Figure 8). The proposed feature would allow users to define their own extraction templates, specifying the types and content of information they want to extract from various sources. P11 proposed her expected usage scenario, *"When I'm finding program references, I prefer to extract the link of* *the source material, the summary of the program, and the program's picture in the table. In an ideal scenario, AI could automatically extract and fill these elements in the table as soon as I input a program reference link."*

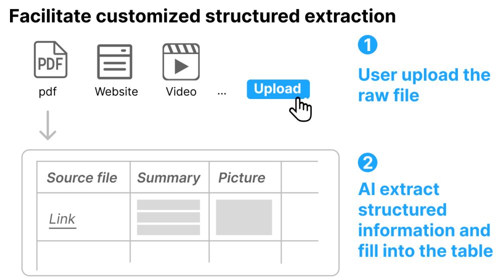

Fig. 8. Extract Consideration 1: Facilitate customized structured extraction, which includes two steps: 1. Users upload different types of raw files to the AI tool; 2. AI automatically extracts structured information to fill in user-created tables.

5.3.2 *Facilitate extraction across multiple information sources and converge them in one place.* In the focus group studies, participants mentioned they always acquire knowledge from multiple information sources such as websites, journals, social media, etc. However, participants (P1, P3, P4, p9) mentioned extracting and organizing information from these diverse sources can be challenging. For example, P9 said, *"When collecting design reference pictures, I sometimes encounter problems downloading and managing images in different formats. An application called "Eagle" helps me download and save the pictures in one place with the same format quickly, so I don't need to manually download and change the format of each picture every time."* To address the extracting problem, participants proposed using a floating window plugin that can extract and send different information sources to one place (Figure 9). For example, P1 proposed, *"Imagine having a small, floating window that you can call on your screen across different platforms and devices. As you browse different information sources such as websites, PDFs, or even watch videos, you can drag the information to this floating window to save it. The plugin would automatically categorize and store this information in a centralized location, making it easy to access later."* P3 also described a plugin with a similar function, *"It's like inserting link of the academic paper or pdfs in our digital note. We could have a plugin that can help us extract and insert more types of information sources in our note, such as the posts from Xiaohongshu (a Chinese photo sharing social media), so that I could manage them in one place."*

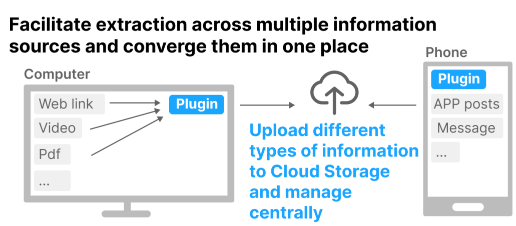

Fig. 9. Extract Consideration 2: Facilitate extraction across multiple information sources and converge them in one place. Users can use the plugin to upload different types of information from different devices and converge them to Cloud Storage to manage centrally

5.4 Design Considerations for Manage Interactions

5.4.1 Facilitate interactions with AI based on the notes' context. Participants suggested that when managing their notes, they need an AI assistant to interact with them under the context of their notes (Figure 10). The types of questions vary based on users' needs, including fuzzy searching of past notes, organizing note structures, reflecting on note content, etc. For example, P11 wished AI could help her *"search for the notes which are approximately in a specific time period."* P5 said, *"I hope AI can help me sort out the logic of my notes with mind maps".* P6 hoped AI could give him some suggestions for his knowledge and help him reflect on his current knowledge structure. For example, P6 said, *" AI could provide me some suggestions of the depth and scope of my notes, thus inspiring me of which part of the knowledge should I learn more."*

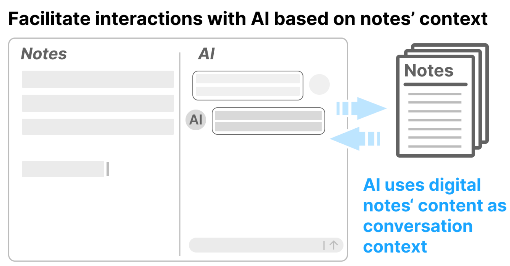

Fig. 10. Manage Consideration 1: Facilitate interactions with AI based on notes' context. While users are taking notes and interacting with AI, AI could use digital notes' content as the conversation context.

5.4.2 Facilitate revisiting historical notes through contextual recommendation. When discussing the challenges in the information management process, participants mentioned they have problems revisiting their notes. Sometimes they forget to visit the notes for a long time and cannot make full use of their notes. To address the challenges, P1 proposed a proactive interaction design that can recommend relevant historical notes based on the user's current context. She gave an example (Figure 11), *"When I'm scrolling on my phone and see an article related to 'Unity', or mentioned 'Unity' in a chat, or see another Unity-related post on social media, etc., AI could pop up a notification and send me a message to trigger me reading some relevant content about 'Unity' in my previous note."* P10 also suggested notifying users with relevant historical notes when they are doing new notes, *"When new information is related to existing knowledge in my notes, AI could suggest links for me to revisit the previous notes."*

6 Discussion

In this study, we explored college students' information retrieval and management behaviors in the context of the information explosion and the AI era. Through focus group studies and participatory design workshops, we gained a comprehensive understanding of students' information behaviors and identified key design considerations for AI tools to better support these behaviors. In Section 6.1, we align our findings with past research and compare the identified design considerations with current AI tools. In Section 6.2, we discuss actionable insights for HCI and education researchers and directions for future work. In Section 6.3, we acknowledge the limitations in our research and reflect on the scope and generalizability of our findings.

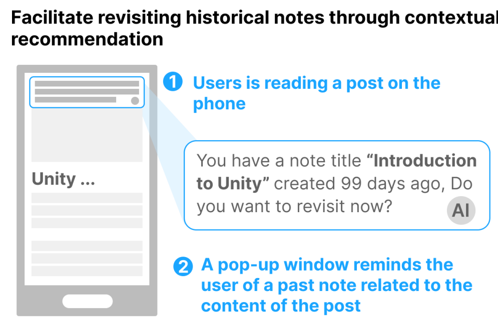

Fig. 11. Manage Consideration 2: Facilitate revisiting historical notes through contextual recommendation. For example, when the user is reading a post about Unity on the phone, AI will search through the user's past notes and pop up a window to remind the user to revisit the notes about Unity.

6.1 Designing AI Tools to Support College Students' Information Retrieval and Management

While some insights and challenges align with prior research, such as distractions caused by switching between different tasks [41, 52, 71], deficiency of short queries [11], and poor information scent's negative impact in user's retrieval task performance [55], our findings highlight new complexities introduced by the combination of multi-source information environments and AI technologies. A key innovation in our work is the identification of the Search, Read, Extract, and Manage (SREM) framework, which provides a comprehensive lens for understanding students' evolving information behaviors. We further identified unique challenges such as AI hallucination, contextual misclassification in interdisciplinary content, and the need for dynamic adjustment of AI-generated content detail. To address these challenges, existing solutions include providing interruption time feedback to help users focus on the main task [14], asking for more information to refine the query [10, 44], using visual salience for high information scent target [77], utilizing AI for structured information extraction in different areas [22, 25, 30]. Our work builds upon these approaches while introducing novel design considerations tailored to the AI-assisted multi-source information environment. By integrating AI capabilities, our design considerations not only supplement prior solutions to existing challenges but also address new challenges and solutions arising from AI technology. Table 4 demonstrates how our design considerations align with previous empirical works or systems design. In previous work, we discovered that many studies have researched AI's capability for query improvement and structured information extraction in different areas addressing design considerations 5.1.2 and 5.3.1. However, our work goes further by proposing solutions for AI-specific challenges, such as cross-platform information extraction (5.3.2) and context-aware AI interactions with notes (5.4.1). For the design consideration 5.1.1, while previous empirical studies verify users' needs for sourcing in AI's responses, some studies also reveal the problems in generating references in AI's responses, such as fabricated and inaccurate references [12, 53].

6.2 Future Work on College Students' Information Behaviors

The information landscape for college students has dramatically evolved, characterized by an explosion of available sources and the integration of AI technologies. Students now navigate a complex ecosystem of traditional academic databases, informal sources like social media, and AI-powered tools [29, 36]. This shift has led to both opportunities and challenges in information retrieval and management [50]. Our findings align with previous research highlighting the potential benefits of diverse information sources [27], while also revealing new challenges specific to AI integration.

Design Considerations	Empirical study that aligned with or systems that exemplified the design considerations
5.1.1 Verify the credibility of AI answer through references	User trust the answers when Jennifer (AI chatbox) provides links to a credible source [84], User's trust improves when information source is provided [42, 43], Users show need for preview information source before dive into it [42], A system shows references for user to check fact without leaving current pages [57], A system show evidence from external knowledge for the LLM to generate responses grounded in evidence [61]
5.1.2 Improve the user's query by adding context information or recommended questions	An AI system that clarifies users' unmatched questions and provides follow-up questions [84], A system framework that uses LLM to evaluate the context to enhance the relevance of generated queries [81], A system that uses LLM for query rewriting for better image retrieval [88] A system that leverages top search results of the query to help generate better description [87]
5.1.3 Amplify the information scent to help the user better assess the information source	Users show the need for descriptions accompanying the search results [42], A system uses the checkmark or cross to show users' assessment of the information [39]
5.2.1 AI predicts the user's question points and inserts quick inquiry in the document	AI generates questions to guide users' reflection during the reading process [17], AI generates and co-locates comprehension and analysis questions in an academic paper to facilitate deeper understanding, and developing critical reading skills [69]
5.2.2 Set the level of detail when using AI to summarize the document	A system that can generate a personalized human-AI summary [17], A web-based tool tailored for humanities students to effectively summarize their lecture transcripts and to personalize the summaries to their specific needs [47]
5.3.1 Customized structured extraction	An AI system that extracts keywords for designer's reference image [19], A LLM system that can collect multi-modal data extracted from PDF-format catalogs [78], A system that can extract structured information from business documents [25], A system that helps create design cards from academic papers using an LLM and text-to-image model [73]
5.3.2 Plugin for extraction across multiple information sources	A LLM system that can perceive inputs and generate outputs in arbitrary combinations of text, images, videos, and audio [83]
5.4.1 Interact with AI based on the notes' contextual information	A LLM system that allows end-users to construct personalized context rules through natural language and simple interactions on the GUI [16], Use contextual information for text entry interface suggestions [5]
5.4.2 Contextual recommendation for revisiting historical notes	A system that uses context information for learning recommendation [80]

Table 4. Empirical study that aligned with or systems that exemplified the design considerations

Our findings offer actionable insights for HCI and education researchers. The challenges revealed in verifying AI-generated content and managing information across multiple sources underscore the need for advanced AI-enhanced information literacy tools. These tools should focus on improving students' ability to critically evaluate AI outputs and integrate information from diverse sources, potentially incorporating real-time credibility checks and cross-platform information visualization. Additionally, our study highlights the importance of developing adaptive AI interfaces that can adjust to students' varying needs for detail and context, suggesting an opportunity to explore dynamically adaptive interfaces that respond to students' expertise levels and learning contexts. Furthermore, the personalized information ecosystems created by students, as observed in our study, point to the need for AI tools that can learn from and adapt to individual information management styles. This aligns with ongoing research in recommend systems [86] and personalized learning environments [45], but with a specific focus on academic information retrieval and management.

Looking ahead, several new directions emerge for future research. While our study focused on college students, future work could explore how evolving information landscapes influence professionals across various fields, potentially revealing broader trends in information behavior. There's also a need to investigate discipline-specific AI assistance, as different academic fields may require tailored approaches to information retrieval and management. Furthermore, the long-term impact of AI-assisted information practices on students' cognitive development and critical thinking skills remains an important area for longitudinal studies. Finally, the design considerations identified in our study should be implemented and evaluated quantitatively to ensure their effectiveness in real-world academic environments. By addressing these areas, researchers can work towards creating more effective, ethical, and user-centered AI-assisted information tools that enhance students' learning experiences and outcomes in the evolving digital landscape.

6.3 Limitations

While our study provides valuable insights into college students' information behaviors in the AI era, the research has several limitations. Given the complexity of multi-source information behaviors among college students, our relatively small sample size may not have captured all facets of these behaviors. The intricate nature of information retrieval and management practices, combined with the rapidly evolving landscape of AI tools, means that our findings, while informative, may not be exhaustive. Nonetheless, our work provides a crucial first step toward understanding these complex behaviors in the context of AI-assisted learning. Moreover, our study aimed to reveal common needs, challenges, and expectations across various disciplines. However, individual factors such as academic background, knowledge requirements, and personal preferences can significantly influence information behaviors. While we included students from diverse disciplines to enhance the representativeness of our findings, discipline-specific challenges and how AI could address them were not fully explored. The nuances of information needs and behaviors across different academic fields warrant further investigation.

Furthermore, our research focused primarily on college students' academic activities, which may limit the generalizability of our findings to other populations and contexts. Nonetheless, many of the insights gained are potentially applicable beyond the academic setting. The evolving information landscape affects information behaviors across various professions and daily activities, and some strategies and challenges identified in our study may resonate with a broader audience engaging in complex information retrieval tasks. Although we did not specifically investigate other populations, the fundamental aspects of multi-source information retrieval and management could extend to different contexts. Lastly, while our participatory design workshops yielded valuable design considerations for AI tools, these ideas have not been implemented or quantitatively evaluated in real-world settings. The effectiveness and practicality of these design considerations may vary when applied to specific tasks or contexts, and further research is needed to validate and refine these proposals.

7 Conclusion

This study offers valuable insights into the complex landscape of college students' multi-source information retrieval and management behaviors in the AI era. By conducting focus group studies, we identified current students' multi-source information retrieval and management patterns and challenges in light of the generative AI background. Based on these challenges, we conducted participatory design workshops and gathered design considerations for AI-assisted academic information tools from users' perspectives. During the data analysis process, we innovatively incorporated Information Foraging Theory to comprehend our findings and reveal students' information behaviors and challenges in four interconnected phases: Search, Read, Extract, and Manage (SREM). Addressing those challenges, we generated nine design considerations through participatory design workshops and redrawn participants' sketches to demonstrate some of the example functions. Through the empirical study, our research provides a foundation for developing more effective, user-centered AI tools for college students' multi-source information retrieval and management in the future.

References

[1] Solmaz Abdi, Hassan Khosravi, Shazia Sadiq, and Dragan Gasevic. 2020. Complementing educational recommender systems with open learner models. In *Proceedings of the tenth international conference on learning analytics & knowledge*. 360–365.

[2] Ibrahim Adeshola and Adeola Praise Adepoju. 2023. The opportunities and challenges of ChatGPT in education. *Interactive Learning Environments* (2023), 1–14.

[3] Adebowale Jeremy Adetayo, Mariam Oyinda Aborisade, and Basheer Abiodun Sanni. 2024. Microsoft Copilot and Anthropic Claude AI in education and library service. *Library Hi Tech News* (2024).

[4] Vincent Aleven, Elizabeth A McLaughlin, R Amos Glenn, and Kenneth R Koedinger. 2016. Instruction based on adaptive learning technologies. *Handbook of research on learning and instruction* 2 (2016), 522–560.

[5] Timothy J Aveni, Armando Fox, and Björn Hartmann. 2023. Bringing context-aware completion suggestions to arbitrary text entry interfaces. In *Adjunct Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–3.

[6] Theophilus Azungah. 2018. Qualitative research: deductive and inductive approaches to data analysis. *Qualitative research journal* 18, 4 (2018), 383–400.

[7] Ryan S Baker and Aaron Hawn. 2022. Algorithmic bias in education. *International Journal of Artificial Intelligence in Education* (2022), 1–41.

[8] Marcia J Bates. 1989. The design of browsing and berrypicking techniques for the online search interface. *Online review* 13, 5 (1989), 407–424.

[9] Svetla Baykoucheva. 2015. 5 - Finding and managing scientific information. In *Managing Scientific Information and Research Data*, Svetla Baykoucheva (Ed.). Chandos Publishing, 33–41. https://doi.org/10.1016/B978-0-08-100195-0.00005-6

[10] Nicholas J Belkin, Diane Kelly, Giyeong Kim, J-Y Kim, H-J Lee, Gheorghe Muresan, M-C Tang, X-J Yuan, and Colleen Cool. 2003. Query length in interactive information retrieval. In *Proceedings of the 26th annual international ACM SIGIR conference on Research and development in informaion retrieval*. 205–212.

[11] Michael Bendersky and W Bruce Croft. 2009. Analysis of long queries in a large scale search log. In *Proceedings of the 2009 workshop on Web Search Click Data*. 8–14.

[12] Mehul Bhattacharyya, Valerie M Miller, Debjani Bhattacharyya, and Larry E Miller. 2023. High rates of fabricated and inaccurate references in ChatGPT-generated medical content. *Cureus* 15, 5 (2023).

[13] ACRL Board. 2016. *Framework for information literacy for higher education*. Technical Report. American Library Association.

[14] Judith Borghouts, Duncan P Brumby, and Anna L Cox. 2020. TimeToFocus: feedback on interruption durations discourages distractions and shortens interruptions. *ACM Transactions on Computer-Human Interaction (TOCHI)* 27, 5 (2020), 1–31.

[15] Simon Buckingham Shum, Rebecca Ferguson, and Roberto Martinez-Maldonado. 2019. Human-centred learning analytics. *Journal of Learning Analytics* 6, 2 (2019), 1–9.

[16] Weihao Chen, Chun Yu, Huadong Wang, Zheng Wang, Lichen Yang, Yukun Wang, Weinan Shi, and Yuanchun Shi. 2023. From Gap to Synergy: Enhancing Contextual Understanding through Human-Machine Collaboration in Personalized Systems. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology*. 1–15.

[17] Xiang "Anthony" Chen, Chien-Sheng Wu, Lidiya Murakhovs' ka, Philippe Laban, Tong Niu, Wenhao Liu, and Caiming Xiong. 2023. Marvista: exploring the design of a human-AI collaborative news reading tool. *ACM Transactions on Computer-Human Interaction* 30, 6 (2023), 1–27.

[18] Ed H Chi, Peter Pirolli, Kim Chen, and James Pitkow. 2001. Using information scent to model user information needs and actions and the Web. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 490–497.

[19] DaEun Choi, Sumin Hong, Jeongeon Park, John Joon Young Chung, and Juho Kim. 2024. CreativeConnect: Supporting Reference Recombination for Graphic Design Ideation with Generative AI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–25.

[20] Cristina Conati, Oswald Barral, Vanessa Putnam, and Lea Rieger. 2021. Toward personalized XAI: A case study in intelligent tutoring systems. *Artificial intelligence* 298 (2021), 103503.

[21] Hilary Coombes. 2001. *Collecting the Data.* Macmillan Education UK, London, 55–93. https://doi.org/10.1007/978-1-137-05029-8_4

[22] John Dagdelen, Alexander Dunn, Sanghoon Lee, Nicholas Walker, Andrew S Rosen, Gerbrand Ceder, Kristin A Persson, and Anubhav Jain. 2024. Structured information extraction from scientific text with large language models. *Nature Communications* 15, 1 (2024), 1418.

[23] Mollie Dollinger, Danny Liu, Natasha Arthars, and Jason M Lodge. 2019. Working together in learning analytics towards the co-creation of value. *Journal of Learning Analytics* 6, 2 (2019), 10–26.

[24] Hendrik Drachsler and Wolfgang Greller. 2016. Privacy and analytics: it's a DELICATE issue a checklist for trusted learning analytics. In *Proceedings of the sixth international conference on learning analytics & knowledge*. 89–98.

[25] Raymond Fok, Nedim Lipka, Tong Sun, and Alexa F Siu. 2024. Marco: Supporting Business Document Workflows via Collection-Centric Information Foraging with Large Language Models. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. ACM, Honolulu HI USA, 1–20. https://doi.org/10.1145/3613904.3641969

[26] Jenny Fry and Sanna Talja. 2007. The intellectual and social organization of academic fields and the shaping of digital resources. *Journal of information Science* 33, 2 (2007), 115–133.

[27] Engida H Gebre and Joseph L Polman. 2016. Developing young adults' representational competence through infographic-based science news reporting. *International Journal of Science Education* 38, 18 (2016), 2667–2687.

[28] Melissa Gross and Don Latham. 2011. Experiences with and Perceptions of Information: A Phenomenographic Study of First-Year College Students. *The Library Quarterly* 81, 2 (April 2011), 161–186. https://doi.org/10.1086/658867

[29] Melissa Gross and Don Latham. 2012. What's Skill Got to Do with It?: Information Literacy Skills and Self-Views of Ability among First-Year College Students. *Journal of the American Society for Information Science and Technology* 63, 3 (2012), 574–583. https://doi.org/10.1002/asi.21681

[30] Bowen Gu, Vivian Shao, Ziqian Liao, Valentina Carducci, Santiago Romero-Brufau, Jie Yang, and Rishi Desai. 2024. Scalable information extraction from free text electronic health records using large language models. *medRxiv* (2024), 2024–08.

[31] Chong Guan, Jian Mou, and Zhiying Jiang. 2020. Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies* 4, 4 (2020), 134–147.

[32] Chong Guan, Jian Mou, and Zhiying Jiang. 2020. Artificial intelligence innovation in education: A twenty-year data-driven historical analysis. *International Journal of Innovation Studies* 4, 4 (2020), 134–147.

[33] Daqing He, Dan Wu, Zhen Yue, and Anna Fu. 2011. Undergraduate Students' Interaction with Online Information Resources in Their Academic Tasks. *Aslib Processdings* (2011). https://doi.org/10.1108/00012531211281715

[34] Alison J Head. 2009. *How College Students Seek Information in the Digital Age.* Technical Report. Project Information Literacy.

[35] Alison J Head. 2009. *What Today's College Students Say about Conducting Research in the Digital Age.* Technical Report. Project Information Literacy.

[36] Alison J Head, Erica DeFrain, Barbara Fister, and Margy MacMillan. 2019. Across the Great Divide: How Today's College Students Engage with News. *First Monday* (Aug. 2019). https://doi.org/10.5210/fm.v24i8.10166

[37] Alison J. Head and Michael B. Eisenberg. 2010. Truth Be Told: How College Students Evaluate and Use Information in the Digital Age. *SSRN Electronic Journal* (2010). https://doi.org/10.2139/ssrn.2281485

[38] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, and Ting Liu. 2023. A Survey on Hallucination in Large Language Models: Principles, Taxonomy, Challenges, and Open Questions. arXiv:2311.05232 [cs]

[39] Farnaz Jahanbakhsh and David R Karger. 2024. A Browser Extension for in-place Signaling and Assessment of Misinformation. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–21.

[40] Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. Survey of Hallucination in Natural Language Generation. *Comput. Surveys* 55, 12 (Dec. 2023), 1–38. https://doi.org/10.1145/3571730

[41] Jing Jin and Laura A Dabbish. 2009. Self-interruption on the computer: a typology of discretionary task interleaving. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1799–1808.

[42] Prerna Juneja, Wenjuan Zhang, Alison Marie Smith-Renner, Hemank Lamba, Joel Tetreault, and Alex Jaimes. 2024. Dissecting users' needs for search result explanations. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–17.

[43] Yongnam Jung, Cheng Chen, Eunchae Jang, and S Shyam Sundar. 2024. Do We Trust ChatGPT as much as Google Search and Wikipedia?. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–9.

[44] Diane Kelly, Vijay Deepak Dollu, and Xin Fu. 2005. The loquacious user: a document-independent source of terms for query expansion. In *Proceedings of the 28th annual international ACM SIGIR conference on Research and development in information retrieval*. 457–464.

[45] Hassan Khosravi, Simon Buckingham Shum, Guanliang Chen, Cristina Conati, Yi-Shan Tsai, Judy Kay, Simon Knight, Roberto Martinez-Maldonado, Shazia Sadiq, and Dragan Gašević. [n. d.]. Explainable Artificial Intelligence in Education. 3 ([n. d.]), 100074. https://doi.org/10.1016/j.caeai.2022.100074

[46] Simon Knight, Antonette Shibani, Sophie Abel, Andrew Gibson, and Philippa Ryan. 2020. AcaWriter: A learning analytics tool for formative feedback on academic writing. *Journal of Writing Research* (2020).

[47] Zahra Kolagar and Alessandra Zarcone. 2024. HumSum: A Personalized Lecture Summarization Tool for Humanities Students Using LLMs. In *Proceedings of the 1st Workshop on Personalization of Generative AI Systems (PERSONALIZE 2024)*. 36–70.

[48] Richard A Krueger. 2014. *Focus groups: A practical guide for applied research.* Sage publications.

[49] Kang Li. 2023. Determinants of college students' actual use of AI-based systems: An extension of the technology acceptance model. *Sustainability* 15, 6 (2023), 5221.

[50] Alexandra List and Patricia A Alexander. 2019. Toward an integrated framework of multiple text use. *Educational Psychologist* 54, 1 (2019), 20–39.

[51] Haiming Liu, Paul Mulholland, Dawei Song, Victoria Uren, and Stefan Rüger. 2010. Applying Information Foraging Theory to Understand User Interaction with Content-Based Image Retrieval. In *Proceedings of the Third Symposium on Information Interaction in Context*. ACM, New Brunswick New Jersey USA, 135–144. https://doi.org/10.1145/1840784.1840805

[52] Gloria Mark, Victor M Gonzalez, and Justin Harris. 2005. No task left behind? Examining the nature of fragmented work. In *Proceedings of the SIGCHI conference on Human factors in computing systems*. 321–330.

[53] Alessia McGowan, Yunlai Gui, Matthew Dobbs, Sophia Shuster, Matthew Cotter, Alexandria Selloni, Marianne Goodman, Agrima Srivastava, Guillermo A Cecchi, and Cheryl M Corcoran. 2023. ChatGPT and Bard exhibit spontaneous citation fabrication during psychiatry literature search. *Psychiatry Research* 326 (2023), 115334.

[54] Miriam J Metzger, Andrew J Flanagin, and Lara Zwarun. 2003. College Student Web Use, Perceptions of Information Credibility, and Verification Behavior. *Computers & Education* 41, 3 (Nov. 2003), 271–290. https://doi.org/10.1016/S0360-1315(03)00049-6

[55] Gregory D Moody and Dennis F Galletta. 2015. Lost in cyberspace: The impact of information scent and time constraints on stress, performance, and attitudes online. *Journal of Management Information Systems* 32, 1 (2015), 192–224.

[56] Kayla Morehead, John Dunlosky, Katherine A. Rawson, Rachael Blasiman, and R. Benjamin Hollis. 2019. Note-Taking Habits of 21st Century College Students: Implications for Student Learning, Memory, and Achievement. *Memory* 27, 6 (July 2019), 807–819. https://doi.org/10.1080/09658211.2019.1569694

[57] An T Nguyen, Aditya Kharosekar, Saumyaa Krishnan, Siddhesh Krishnan, Elizabeth Tate, Byron C Wallace, and Matthew Lease. 2018. Believe it or not: designing a human-ai partnership for mixed-initiative fact-checking. In *Proceedings of the 31st annual ACM symposium on user interface software and technology*. 189–199.

[58] Xi Niu and Bradley M Hemminger. 2012. A study of factors that affect the information-seeking behavior of academic scientists. *Journal of the American Society for Information Science and Technology* 63, 2 (2012), 336–353.

[59] Carole L Palmer, Lauren C Teffeau, and Carrie M Pirmann. 2009. Scholarly information practices in the online environment. *Report commissioned by OCLC Research. Published online at: www. oclc. org/programs/publications/reports/2009-02. pdf* (2009).

[60] Hyanghee Park and Daehwan Ahn. [n. d.]. The Promise and Peril of ChatGPT in Higher Education: Opportunities, Challenges, and Design Implications. In *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Honolulu HI USA, 2024-05-11). ACM, 1–21. https://doi.org/10.1145/3613904.3642785

[61] Baolin Peng, Michel Galley, Pengcheng He, Hao Cheng, Yujia Xie, Yu Hu, Qiuyuan Huang, Lars Liden, Zhou Yu, Weizhu Chen, et al. 2023. Check your facts and try again: Improving large language models with external knowledge and automated feedback. *arXiv preprint arXiv:2302.12813* (2023).

[62] Charles A Perfetti, Jean-François Rouet, and M Anne Britt. 1999. Toward a theory of documents representation. *The construction of mental representations during reading* 88108 (1999).

[63] Peter Pirolli. 2009. An Elementary Social Information Foraging Model. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, Boston MA USA, 605–614. https://doi.org/10.1145/1518701.1518795

[64] Peter Pirolli and Stuart Card. 1995. Information Foraging in Information Access Environments. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems - CHI '95*. ACM Press, Denver, Colorado, United States, 51–58. https://doi.org/10.1145/223904.223911

[65] Peter Pirolli and Stuart Card. 1999. Information foraging. *Psychological review* 106, 4 (1999), 643.

[66] Gayle Prybutok and Sherry Ryan. 2015. Social Media: The Key to Health Information Access for 18- to 30-Year-Old College Students. *CIN: Computers, Informatics, Nursing* 33, 4 (April 2015), 132. https://doi.org/10.1097/CIN.0000000000000147

[67] Gonzalo Ramos, Napol Rachatasumrit, Jina Suh, Rachel Ng, and Christopher Meek. 2022. ForSense: Accelerating Online Research Through Sensemaking Integration and Machine Research Support. *ACM Trans. Interact. Intell. Syst.* 12, 4, Article 30 (nov 2022), 23 pages. https://doi.org/10.1145/3532853

[68] Deborah K. Reed, Hillary Rimel, and Abigail Hallett. 2016. Note-Taking Interventions for College Students: A Synthesis and Meta-Analysis of the Literature. *Journal of Research on Educational Effectiveness* 9, 3 (July 2016), 307–333. https://doi.org/10.1080/19345747.2015.1105894

[69] Liam Richards Maldonado, Azza Abouzied, and Nancy W Gleason. 2023. ReaderQuizzer: Augmenting Research Papers with Just-In-Time Learning Questions to Facilitate Deeper Understanding. In *Companion Publication of the 2023 Conference on Computer Supported Cooperative Work and Social Computing*. 391–394.

[70] Maria Rosala. 2019. How to analyze qualitative data from UX research: Thematic analysis. *NN-Nielsen Norman Group* (2019).

[71] Adam Rule, Karen Boyd, Jim Hollan, and Aurélien Tabard. 2015. Restoring the context of interrupted work with desktop thumbnails. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, Vol. 37.

[72] Neil Selwyn. 2019. *Should robots replace teachers?: AI and the future of education.* John Wiley & Sons.

[73] Donghoon Shin, Lucy Lu Wang, and Gary Hsieh. 2024. From Paper to Card: Transforming Design Implications with Generative AI. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–15.

[74] David W Stewart and Prem N Shamdasani. 2014. *Focus groups: Theory and practice.* Vol. 20. Sage publications.

[75] Miriam Sturdee and Joseph Lindley. 2019. Sketching & drawing as future inquiry in HCI. In *Proceedings of the Halfway to the Future Symposium 2019*. 1–10.

[76] Sangho Suh, Bryan Min, Srishti Palani, and Haijun Xia. 2023. Sensecape: Enabling Multilevel Exploration and Sensemaking with Large Language Models. In *Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology* (San Francisco, CA, USA) *(UIST '23)*. Association for Computing Machinery, New York, NY, USA, Article 1, 18 pages. https://doi.org/10.1145/3586183.3606756

[77] Franklin P Tamborello and Michael D Byrne. 2005. Information search: the intersection of visual and semantic space. In *CHI'05 Extended Abstracts on Human Factors in Computing Systems*. 1821–1824.

[78] Yi Tang, Chia-Ming Chang, and Xi Yang. 2024. PDFChatAnnotator: A Human-LLM Collaborative Multi-Modal Data Annotation Tool for PDF-Format Catalogs. In *Proceedings of the 29th International Conference on Intelligent User Interfaces*. 419–430.

[79] Luke Tredinnick. 2017. Artificial intelligence and professional roles. *Business Information Review* 34, 1 (2017), 37–41.

[80] Katrien Verbert, Nikos Manouselis, Xavier Ochoa, Martin Wolpers, Hendrik Drachsler, Ivana Bosnic, and Erik Duval. 2012. Context-aware recommender systems for learning: a survey and future challenges. *IEEE transactions on learning technologies* 5, 4 (2012), 318–335.

[81] Dung Vo. 2024. IntellectNavigator: Enhancing Search Tools with LLMs-Powered Query Instruction. In *Companion Proceedings of the ACM Web Conference 2024*. 1880–1883.

[82] Ethelene Whitmire. 2002. Disciplinary differences and undergraduates' information-seeking behavior. *Journal of the American society for Information Science and Technology* 53, 8 (2002), 631–638.

[83] Shengqiong Wu, Hao Fei, Leigang Qu, Wei Ji, and Tat-Seng Chua. 2023. Next-gpt: Any-to-any multimodal llm. *arXiv preprint arXiv:2309.05519* (2023).

[84] Ziang Xiao, Q Vera Liao, Michelle Zhou, Tyrone Grandison, and Yunyao Li. 2023. Powering an ai chatbot with expert sourcing to support credible health information access. In *Proceedings of the 28th international conference on intelligent user interfaces*. 2–18.

[85] Olaf Zawacki-Richter, Victoria I Marín, Melissa Bond, and Franziska Gouverneur. 2019. Systematic review of research on artificial intelligence applications in higher education–where are the educators? *International Journal of Educational Technology in Higher Education* 16, 1 (2019), 1–27.

[86] Yu Zhang, Jingwei Sun, Li Feng, Cen Yao, Mingming Fan, Liuxin Zhang, Qianying Wang, Xin Geng, and Yong Rui. 2024. See Widely, Think Wisely: Toward Designing a Generative Multi-agent System to Burst Filter Bubbles. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*. 1–24.

[87] Ziliang Zhao, Zhicheng Dou, Jiaxin Mao, and Ji-Rong Wen. 2022. Generating clarifying questions with web search results. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 234–244.

[88] Hongyi Zhu, Jia-Hong Huang, Stevan Rudinac, and Evangelos Kanoulas. 2024. Enhancing Interactive Image Retrieval With Query Rewriting Using Large Language Models and Vision Language Models. In *Proceedings of the 2024 International Conference on Multimedia Retrieval*. 978–987.

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