Study on the Impact of Large Language Models on Information Retrieval Systems and User Search Behavior: Postprint

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Abstract

[目的/ 意义]This study explores the impact of Large Language Models (LLMs) and other artificial intelligence generation technologies on user information retrieval behavior, offering recommendations for the development of information retrieval systems and information resource construction.[方法/ 过程]Against the backdrop of the vigorous development of ChatGPT and other LLMs, and combining the technical characteristics of large language models with features of existing products, this paper analyzes—from the perspective of user information behavior and through reviewing existing literature and large language models—the impact of the growing popularization of this technology on information retrieval systems and user retrieval behavior.[结果/ 结论]When used as information retrieval systems, LLMs offer advantages unmatched by traditional products, influencing the underlying logic, action priorities, and retrieval expectations of user information retrieval behavior. However, current limitations in reliability and accuracy make it difficult for LLMs to immediately replace traditional information retrieval methods. It is recommended that information retrieval systems and information resource construction prioritize this technology, explore the intelligent integration of LLMs with information services, to address evolving user information needs and further maximize the value of existing information resources.

Full Text

Research on the Impact of Large Language Models on Information Retrieval Systems and User Retrieval Behavior

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Abstract:
[**Purpose/Significance**] This study explores the impact of artificial intelligence generation technologies such as Large Language Models (LLMs) on users' information retrieval behavior, offering recommendations for information retrieval systems and information resource construction.
[**Method/Process**] Against the backdrop of the rapid development of LLMs like ChatGPT, and considering their technical characteristics alongside existing product features, this paper analyzes how the growing adoption of this technology influences information retrieval systems and user retrieval behavior from the perspective of user information behavior, through examination of existing literature and large language models.
[**Results/Conclusions**] When used as information retrieval systems, LLMs offer unparalleled advantages over traditional products, affecting the underlying logic, action priorities, and retrieval expectations of user information retrieval behavior. However, current limitations in reliability and accuracy prevent LLMs from immediately replacing traditional information retrieval methods. It is recommended that information retrieval systems and resource construction prioritize this technology, exploring intelligent integration of LLMs with information services to address evolving user information needs and fully leverage the value of existing information resources.

Keywords: Large Language Models; ChatGPT; Information Retrieval System; Information Behavior; Artificial Intelligence Generated Content (AIGC)
Classification Number: G350

Since its launch, ChatGPT surpassed 100 million active users in less than two months, attracting widespread attention in the library and information science community. It can interact with humans through conversation, refusing inappropriate requests while generating engaging and creative content such as poetry and lyrics. The application of LLMs represents a milestone in artificial intelligence. In the field of library and information science, LLMs have become a hot topic, with applications in intelligent library services, intelligence analysis, and other areas. These include obtaining historical data through natural language Q&A, automated classification, keyword extraction, and providing personalized literature recommendations and Q&A services through natural language generation technology to build AIGC-era smart libraries.

From the perspective of user information behavior, LLMs have also become a focus across industries. Research has found that some users are actively leveraging such tools to meet their work needs. With the emergence of GPT-4 and competitors like Midjourney, AI tools show potential for industrial revolution. Standing at the intersection of user information behavior, it is necessary to study not only the impact of LLMs on literature and intelligence work but also their influence on user information behavior, providing insights for establishing a Chinese-characteristic AIGC information platform and information literacy education system.

1 Literature Review

Information retrieval behavior has long been a key research focus for scholars worldwide. Since the 1990s, the Internet has broadened public information access channels, making computers and the Internet the fundamental context for academic information retrieval research. As computer technology and algorithms advanced, research evolved from initial text retrieval optimization and multimedia information retrieval to deep learning and natural language processing applications that improved retrieval efficiency and precision. Information recommendation based on user profiles and behavior became a new research hotspot.

The progress in information retrieval technology has also shifted research focuses on user information retrieval behavior. Scholars initially aimed to provide improvement suggestions for information retrieval systems by studying user behavior. With interdisciplinary integration of computer science and medical informatics, research content diversified into multiple themes and hotspots.

Different User Groups: Information retrieval behavior research involves various user groups, with numerous studies analyzing characteristics of different populations. College students have been extensively studied, such as research on their online health information retrieval behavior characteristics and patterns. Gender differences significantly influence health information retrieval behavior patterns throughout the entire process. Differences between junior high school students and graduate students in information retrieval behavior have been compared, revealing variations in cognitive, emotional, and physiological aspects. Discussions on children' s information retrieval behavior have integrated cognitive science and information science.

Different Scenarios: Scenarios primarily refer to places where users access information, such as libraries and social media, or backgrounds/environments like tourism contexts and task situations. For instance, a collaborative tourism information search system was designed and compared with Tripadvisor.com, revealing that collaborative systems can promote tourists' collaborative information retrieval behavior and outperform comparison websites in usability and cooperation support.

Different Information Types: Health information retrieval behavior constitutes a significant portion of research content in medical informatics, with scholars supplementing studies on other information types. Online health information retrieval behavior has been systematically reviewed and evaluated, with experimental research expansion suggestions proposed. Log mining methods have revealed that health information users tend not to modify query terms and prefer clicking on higher-ranked webpages.

Additionally, research has explored influencing factors of user information retrieval behavior and model construction. With continuous LLMs implementation causing tremendous impact on the information management field, the library and information science community is extensively discussing AI' s influence on information retrieval. Studies have compared traditional information retrieval research paradigms with intelligent information retrieval, indicating that intelligent information retrieval represents the future direction. Adaptive literature retrieval frameworks combining large language models have demonstrated superior reliability and flexibility compared to existing methods, showing considerable application potential. Therefore, it is necessary to consider the impact of large language models when studying user information retrieval behavior.

2 Impact of LLMs on Information Retrieval Systems

2.1 LLMs' Language Understanding Capability Enables True Natural Language Retrieval

The essence of information retrieval is matching users' information needs with corresponding information sets. When using current retrieval tools, users generally need to spend time and effort considering keywords and their combinations. In contrast, LLMs enable more natural information retrieval, allowing users to directly describe their information needs in natural language and request answers from the model. For example, with ChatGPT, users can directly pose information needs through natural language in the interface. The model converts instructions into machine-readable formats and automatically retrieves relevant information from the knowledge base to generate answers or results it deems most appropriate, outputting them in coherent, understandable natural language.

Due to their semantic understanding characteristics, LLMs break down barriers between different languages in traditional information retrieval. In multilingual literature retrieval, ChatGPT can directly analyze and process information. Moreover, LLMs can not only search for information but also immediately perform intelligence preprocessing tasks, such as extracting research methods and ideas from scientific literature, clustering different online news by specified themes, and generating tables of contents.

2.2 LLMs Penetrate the Semantic Level of Information Organization, Reducing Costs and Increasing Efficiency for Information Retrieval Systems

Traditional keyword-matching and metadata-matching information retrieval systems mostly remain at the level of lexical understanding, whereas LLMs can conduct deeper information organization based on text understanding and content analysis. When LLMs are used in knowledge base retrieval, the entire retrieval process can be completed through natural language. During knowledge base construction, traditional information organization is no longer necessary, significantly reducing the time and cost of information resource construction.

Embedding LLMs into search engines can accelerate response speed and optimize search results through semantic recognition of texts, improving resource allocation efficiency and accuracy. Microsoft has already integrated its Bing search engine with GPT models for public use. Using language models for knowledge graph construction can enhance entity recognition and relationship extraction, enriching knowledge graph content and connectivity. This can expand the functional boundaries of information retrieval systems.

2.3 LLMs' Instant Task Processing Capability Revolutionizes User Experience in Information Retrieval

The text datasets used for LLMs training typically include social media, news, and other content. Through Reinforcement Learning from Human Feedback (RLHF), LLMs can mimic human language expression and thinking patterns, enabling human-like dialogue and communication. This retrieval method offers users unprecedented experiences, integrating information collection, retrieval, and utilization.

Traditional information retrieval models cannot quickly respond to users' information needs in real-time. In contrast, interactive interfaces like ChatGPT that generate responses word-by-word not only respond promptly but also create psychological intimacy and presence for users. The instant generation feature allows immediate information feedback. If unsatisfied with output results, users can directly point this out in the interface, command the model to improve results, or provide feedback through downvoting, thereby contributing to language model training. These represent unmatched advantages over traditional retrieval methods.

Users can also leverage LLMs' semantic understanding characteristics to establish three-dimensional retrieval results. Most LLMs currently present user interfaces in the form of intelligent Q&A or chatbot conversations, directly outputting semantically coherent and highly readable answers. Users can input research papers into the model, and after automatic text analysis and relationship extraction, perform various tasks based on the input content, including text translation, finding specific content, automatic indexing, summarizing paragraph main ideas, and simple visual presentations. This retrieval method enables users to quickly 梳理 and analyze content structure and logic, improving information granularity and allowing users to achieve three-dimensional cognition of information needs.

2.5 Challenges LLMs Pose to Information Retrieval Systems

Traditional information retrieval systems primarily rely on keyword matching and rule-based algorithms. LLMs, through deep learning and natural language processing, can understand users' semantic intentions and contextual information, providing more accurate and relevant results. However, this poses higher demands on information retrieval systems.

LLMs require substantial computing power to meet user information needs, and continuous algorithm improvement and technological updates are necessary.

These factors increase system operational costs, potentially creating enormous pressure for current information retrieval system operators who may need to seek partnerships with large tech companies or find other technical solutions to reduce costs and pressure.

Most LLMs tend to provide appropriately detailed answers to improve precision. However, since LLMs construct large-scale knowledge networks based on deep learning, they require vast amounts of data for training and optimization. This data often contains users' personal and sensitive information. Ensuring data privacy and security requires comprehensive measures including data anonymization, third-party auditing, and continuous revision of user privacy protection policies to effectively protect user data privacy and database security.

3 Impact of LLMs on User Information Retrieval Behavior

3.1 Change in User Information Retrieval Behavior Logic: From "Subtraction" to "Addition"

When using traditional search engines, users need to refine their information needs into several keywords to improve recall and precision, then adjust retrieval strategies based on results. With LLMs, the entire process occurs through natural language, eliminating controlled language. Users can directly input rough ideas into the model to generate preliminary results and continuously refine them through questioning and range limitation to obtain optimal retrieval results.

This change means that the focus of user retrieval shifts from constructing retrieval strategies to asking questions correctly and efficiently. Natural language retrieval better aligns with human intuition. As users gradually become accustomed to expressing questions in natural language, keyword-based search status may decline. Information retrieval courses traditionally aimed at teaching retrieval strategy construction will face certain impacts.

3.2 Change in User Information Retrieval Behavior Focus: From "Finding" to "Verifying"

As a one-stop retrieval platform, LLMs possess unique advantages. However, LLMs are trained to provide complete natural language processing services, with information retrieval being only a derivative function. This determines that LLMs have creative characteristics, and their information output does not completely follow the narrow information retrieval logic of comparison-matching. Therefore, even though LLMs generally have massive knowledge bases, the accuracy and completeness of generated content cannot be fully guaranteed.

Thus, when using LLMs for retrieval, verifying information authenticity and reliability may become a new focus for users. Since most current LLMs are trained on open-source data from the Internet, including Wikipedia and social media, they appear inadequate when answering professional questions. Research by WAGNER et al. shows that ChatGPT-3 achieved only 67% accuracy when facing 88 random questions across different radiology fields, and only 36.2% of cited references could be found on the Internet. Therefore, LLMs' value for scientific research work is limited, and retrieval results require careful verification when used for professional research.

As LLMs continue to permeate work and life, AIGC content will increasingly proliferate. AIGC content generally has logical coherence and clear structure, which may be misused by users with low discrimination ability. Users must consider the authenticity of information provided by LLMs, and identifying AIGC-generated false information in information streams will become an important aspect of information retrieval work.

3.3 Change in User Information Retrieval Behavior Expectations: From "Accurate and Complete Clues" to "Good and Fast Products"

Since LLMs can directly draft for users and provide immediately usable information products, user demands for direct usability of retrieval results may rival the importance of recall and precision. The instant response and personalized characteristics of LLMs will also make users more demanding regarding response time and personalized customization. However, current LLMs face issues in data reliability, intellectual property attribution, and technical ethics construction, resulting in polarized user attitudes toward LLMs popularization.

4 Recommendations

4.1 Information Retrieval Services in the New Era Must Emphasize AIGC Technologies Like LLMs

Currently, ChatGPT and other LLM models are still in their infancy, with issues like low reliability preventing immediate replacement of traditional search engines. However, their powerful functionality has already influenced related industries and social development directions. Leaders in AI have begun investing massive resources in training and developing similar products. Multimodal and cross-modal AIGC products integrating text, images, and video continue to emerge. As Nvidia founder and CEO Jensen Huang stated, "This is the iPhone moment of AI." Just as Apple popularized mobile Internet through smartphones, ushering in the full Web2.0 era, LLMs will likely reshape industry ecosystems and even change human daily life in the future.

LLMs have demonstrated considerable strength in automatic summarization, knowledge services, and other areas, holding constructive value for information resource construction in libraries and intelligence institutions. As future AIGC technologies continue to be implemented and AI-generated content increases, intelligence agencies can provide rich, high-quality corpora for AI training while simultaneously screening and providing credible, high-quality information resources for users in an era of information explosion. Information retrieval service departments should fully pay attention to the potential and application of

AIGC technology in the library and information field, giving full play to AI' s advantages.

4.2 Information Retrieval System Construction Can Fully Utilize LLMs to Promote Refined and Intelligent Retrieval Services

Information retrieval service platforms can use large language models to provide fine-grained knowledge services, such as knowledge Q&A services and writing assistance services. The instant interactive characteristics of LLMs can also promote information retrieval services toward more intelligent and ubiquitous directions. For example, libraries can integrate language models into virtual librarians to directly help users solve problems, scientific databases can automatically generate literature content briefs after retrieval, and information retrieval service platforms can implement functions like automatic generation of retrieval result reports.

4.3 Timely Revision of Information Literacy Education Content to Help Users Rationally Understand and Use AI Tools

The widespread application of LLMs will inevitably change public information behavior. If AIGC platforms become mainstream for retrieval and the public uses AI extensively to obtain information, existing information literacy courses centered on information screening, recall, and precision will become outdated. Cultivating skills and awareness in verifying reliable information and respecting intellectual property will become important content for information literacy education in the AIGC era.

Although AI tools can surpass humans in mechanical production steps, the value of intelligence ultimately lies in how humans mine and use information. Behind information may lie implicit humanistic and social backgrounds or profound emotions. Simply feeding corpora does not mean AIGC content can fully reflect human advanced intelligent activities. Future information literacy education should emphasize critical thinking cultivation and intellectual property awareness education on the original basis, enhancing public reasoning and judgment abilities to maintain the balance between utilization and rationality when using AI tools.

5 Conclusion

From the perspective of services provided by information institutions like libraries and intelligence agencies, although concepts of knowledge services and intelligent services have existed for some time, knowledge retrieval services directly facing knowledge units remain rare. Current retrieval services mainly provide users with access to literature resources or literature content.

As China welcomes the peak development period of AIGC technology and industry, large language models marked by GPT technology will reshape users' information behavior with their powerful semantic understanding capabilities and intelligence. This study stands from the perspectives of information resource constructors and information users to explore the potential impacts of LLMs and other AI tools on information search behavior. With continuous LLMs application, it becomes possible for information retrieval service platforms to provide fine-grained knowledge services. Meanwhile, the instant interactive characteristics of LLMs can promote information retrieval services toward more intelligent and ubiquitous directions.

Although LLMs currently have issues in usability and credibility, preventing complete implementation in professional and important fields, their demonstrated strength in information retrieval and intelligent Q&A is already sufficient to change users' information-seeking habits and exert considerable influence. Currently, tools like LLMs have made people feel the convenience of AI in work and life with their excellent semantic understanding capabilities. Information resource construction institutions should strive to promote the integration of AI technology and resource construction, applying LLMs gradually to search engine construction, education and teaching assistance, and literature intelligence mining projects to provide users with stronger intelligence services and lay a foundation for providing efficient and high-quality information resource services in the future.

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Note: Figure translations are in progress. See original paper for figures.