Journal of Social Sciences

Review Article

A Multidimensional Framework for Understanding Internet Information Behavior: Influencing Factors and Progression in the Digital Age

Jinyan Liao, Sameer Kumar and Fumitaka Furuoka

Asia-Europe Institute, Universiti Malaya, Kuala Lumpur, Malaysia

Article history
Received: 10-12-2024
Revised: 08-03-2025
Accepted: 25-03-2025

Corresponding Author:
Jinyan Liao
Asia-Europe Institute, Universiti Malaya, Kuala Lumpur, Malaysia
Email:
s2000152@siswa.um.edu.my

Abstract: This study explores the multidimensional characteristics and influencing factors of Internet information behavior and constructs a theoretical framework to explain user behaviors in information acquisition, dissemination, and sharing. The paper defined the core concepts of Internet information behavior and examined its evolution in the digital era. It categorized information acquisition behaviors based on processing methods, emphasizing the roles of search engines and social media in fulfilling users' information needs. Our paper identifies two primary factors shaping users' information behavior: Individual and social factors. Individual factors affect search strategies and channel preferences, while social networks and cultural contexts drive group-level trends in information sharing and dissemination. We also explore the applications of Internet information behavior in education, business, and public services. It analyzes opportunities and challenges posed by technologies such as AI and big data, alongside related ethical and social responsibilities. These findings suggest potential directions for future research.

Keywords: Internet Information Behavior, Information Acquisition, Internet Applications, Public Services

Introduction

Internet Information Behaviour (IIB) has grown to be a major area of research in the information society due to the fast expansion of social media and information technologies (Jia et al., 2021). The continuous changes in user behavior in the search, acquisition, and dissemination of knowledge on digital platforms, which have a significant impact on the economy and society, are influencing personal decision-making especially (Miraj et al., 2021). Thus, a methodical study of IIB's several characteristics, together with an analysis of its underlying influential factors and evolutionary trends, is necessary to grasp the mechanisms of information distribution in the digital age (Wilson, 2024b).

We separate the "social media" from "social networks" to avoid conceptual uncertainty. Facebook, Twitter, WeChat, and TikHub (Kaplan and Haenlein, 2010) are among the social media sites that let users create, distribute, and interact with the material. Social media mostly serves as a tool for information delivery and content development, therefore stressing user-generated content and interactive involvement. On the other hand, social networks represent the framework of social interactions created by technological mediation, which could start with actual contacts (e.g., family and colleagues) or interest-driven communities (Boyd and Ellison, 2007). Social networks stress the structural links among people instead of the specific media outlets. Social media so reflects social networks, but it is not exactly like them. In the study of information behavior, researchers have to clearly separate social interactions (social networks) from platform features (social media) to offer conceptual clarity and avoid misinterpretation.

The absence of integrated multidisciplinary approaches in current theoretical models constrains the systematic elucidation of the interactive mechanisms of information behavior at the individual, group, and societal levels (Chen et al., 2022). Current research predominantly emphasizes disparate perspectives, such as network interactions in sociology or cognitive processes in psychology, while failing to integrate these concepts into a coherent framework. Analyzing the interplay between group-level dynamics, such as social network effects, and individual-level variables, including cognitive biases, uncovers a significant knowledge gap regarding the broader social implications of information behavior. Despite the application of big data and artificial intelligence technologies in this domain, the majority of studies conducted to date have been superficial and have

SCIENCE Publications

© 2025 Jinyan Liao, Sameer Kumar and Fumitaka Furuoka. This open-access article is distributed under a Creative Commons Attribution (CC-BY) 4.0 license.

not thoroughly examined the dynamic aspects of user behavior and their underlying motivations (Liu et al., 2020). Furthermore, there is a dearth of methodical research on the mechanisms and impact routes of IIB in sectors including public services, business, and education (Fedushko and Benova, 2019). Using IIB in these domains sometimes ignores generalizable mechanisms, thus limiting its ability to address broader issues such as information overload or unequal resource distribution. This study aims to construct a varied theoretical framework, incorporating perspectives from information science, psychology, and sociology, thereby addressing these shortcomings and providing a comprehensive understanding of the factors influencing IIB and its consequences across multiple disciplines.

Two aims of this study are to investigate the identified research gaps by means of two objectives: (1) to build a thorough theoretical framework synthesizing insights from psychology, sociology, and information science, and to clarify the basic mechanisms and impact paths of IIB within the digitalization environment; and (2) to investigate the prospective applications of IIB in education, business, and public services, together with the related ethical dilemmas. This study aims to advance theoretical innovation and offer useful advice in the field of IIB, encouraging its methodical growth.

Theory and Methods

IIB refers to the whole spectrum of information-related activities carried out by people or groups inside the Internet environment to meet specific information needs, including information searching, browsing, evaluation, distribution, sharing, and use (Choo, 2005). These actions not only clarify users' cognitive processes and decision-making mechanisms but also greatly affect the effectiveness of information distribution, the evolution of social structures, and the preservation of cultural legacy (Wilson, 2024a). Two main areas of current research are the study of individuals' information acquisition and decision-making processes using conventional information behavior models and the analysis of the dynamic evolutionary characteristics of information behavior in the digital sphere, integrating insights from social networks and technological developments.

Contributions and Limitations of Traditional Models

Ellis's Cognitive-Affective Behaviour Model (1993) and Wilson's Information Behaviour Model (1996) together provide necessary frameworks for understanding information behavior through the prism of information needs and cognitive-affective processes, in line with other basic models of information behavior. Carefully considering significant influencing factors, including psychological states and environmental variables, these models systematically define the main phases of information behavior: Need identification, information searching, evaluation, and use. These initiatives have created a strong foundation for theoretical growth in this field. The rapid expansion of social networks and Internet technologies have made users' information behavior more complex, exposing specific shortcomings in conventional models when addressing new conditions. First, lacking dynamic adaptability (Ruotsalo et al., 2020), these models are limited in their ability to accurately document users' real-time interaction patterns on digital platforms. Second, they do not sufficiently incorporate the major impact of technological environments and sociocultural contexts. Expanding and innovating classic theories while integrating new perspectives will help address these challenges and provide a more precise representation of the complexity of modern information behavior.

Innovative Integration of Theoretical Frameworks

This study develops a multidimensional theoretical framework (Figure 1) integrating psychology, sociology, and information science to systematically analyze user information behavior patterns in the digital age, so addressing the limits of conventional models regarding dynamism and diversity while exploring their fundamental mechanisms and impact paths. Three fundamental dimensions—individual, group, and environment—are included in this framework to examine the dynamic elements of information behavior fully and highlight the interactions among these elements. Individual cognitive and emotional aspects include the evolution of information needs, the optimization of search strategies, and the development of the decision-making process. Those with advanced information literacy are more likely to create more exact search plans and apply more exact criteria for evaluating information dependability. Furthermore, influencing individual behavior is environmental context, including algorithmic recommendations controlling information exposure in addition to knowledge and experience. Group-level social network analysis helps clarify information distribution patterns and identify important propagation variables. With opinion leaders playing a key role, user involvement—including likes, comments, and shares—affects the scope and dependability of information distribution. Their impact follows group size, frequency of interaction, and social network strength. The environmental dimension consists of the effect on information behavior of sociocultural and technological developments. Recommendation systems driven by artificial intelligence adapt information distribution based on user behavior data, affecting cognitive scope and decision-making processes. Furthermore, affecting users' view, interpretation, and information distribution are cultural elements. The three dimensions dynamically interact to form a feedback mechanism rather than operating separately. Recommendation algorithms affect personal search habits; user-sharing activities affect the information spreading on social networks. Furthermore, group interactions support personal cognitive patterns and affect the learning processes of recommendation systems, so producing a dynamic feedback effect on information spread. While highly interactive materials achieves wider social distribution, so improving their impact and visibility, user click behaviors affect personalized recommendations in news distribution. This mechanism clarifies events including information cocoons and viral spread as well as helps one to better understand the nuances of information behavior. Moreover, while concurrently addressing ethical conundrums in information behavior research, it improves the predictive efficacy of behavioral models and provides theoretical support for applications in education, commerce, and public services.

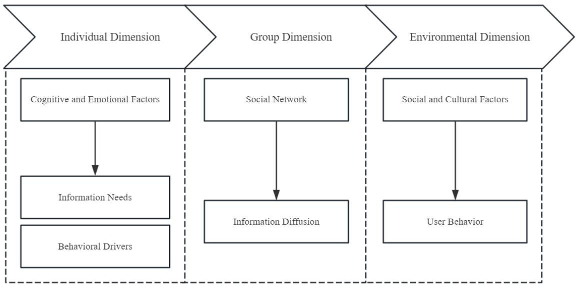

Fig. 1: Multidimensional theoretical framework of IIB

Research Methods

By means of a literature review and theoretical integration approach, this study methodically synthesizes current research on Internet information behavior, so building a multidimensional theoretical framework. Academic papers, policy documents, and industry reports released in the past five years are methodically examined using a text analysis approach to guarantee scientific quality and application of the findings. Four main steps define the research approach. Initially, during the phase of literature collecting and selection, keywords such as "Internet Information Behavior" and "Social Media Information Acquisition" are used to search the Web of Science, Google Scholar, and other academic databases for pertinent papers. Then, relevant information is chosen to provide a thorough and authoritative basis for the study. Second, classical theories such as Wilson's Information Behavior Model and the Technology Acceptance Model (TAM) are investigated to evaluate their relevance and constraints inside the framework of developing an Internet information behavior framework, so offering a theoretical basis during the phase of the theoretical model analysis. Third, during the data analysis stage, a case study approach is used to investigate the expression of Internet information behavior in public services, corporate, and educational spheres, among other spheres. By means of the identification of important contributing elements, this study seeks to clarify the mechanics of information acquisition, processing, and application over many settings. In order to present a methodical, multidimensional theoretical model that fully clarifies the evolution and determinants of Internet information behavior, psychological, sociological, and information science ideas are finally combined during the framework-building phase. This methodical methodology aims to produce essentially accurate and practically useful results, enhancing research on Internet information behavior and offering a theoretical and empirical basis for the next studies in this developing topic.

Classification of Internet Information Behavior

IIB can be classified into two fundamental dimensions: Information acquisition behavior and information dissemination and sharing behavior. This study examines user behaviours in two main contexts, search engines and social media, to identify the similarities and differences, as well as the underlying influencing factors.

Information Retrieval Based on Search Engines

User engagement and knowledge discovery depend on information acquisition. Thus, search engine use is the most common activity (Drivas et al., 2021). Through sophisticated algorithms and indexing systems, search engines—as representations of information retrieval technologies—much improve information accessibility (Sharma et al., 2017). Constantly traversing the Internet, basic web crawler technology independently gathers analyses and stores large volumes of web content, creating significant databases (Suryasa et al., 2023). This operation greatly lowers the time needed for users to get the required information and increases the scope of easily available knowledge (Gupta et al., 2023).

Search engine use patterns expose users' cognitive strategies and decision-making processes across large amounts of information. Entering keywords helps users not only indicate their informational needs and interest preferences but also show their understanding of information structures and their anticipations for retrieval efficacy (Zhang et al., 2020). Recent studies revealed that analysis of search engine logs allowed researchers to get great insights into users' query behavior, click patterns, and page dwell times, so revealing the basic patterns of information acquisition behavior (Xie et al., 2012). Many elements influence the use of search engines: Users' information literacy, the complexity of query tasks, search engine algorithm optimization, and user interface accessibility. While complex query tasks may necessitate multiple searches and result filtering, complicating the information retrieval process, individuals with advanced information literacy can formulate more precise query strategies and swiftly locate the needed information (Lombardo et al., 2019). The personalized recommendation feature of search engines, based on user's previous searches and browsing behaviors, delivers information tailored to individual preferences, thereby enhancing the efficacy and satisfaction of information retrieval. Therefore, using search engines not only shows users' search for knowledge but also emphasises the development of digital era information organisation and retrieval technologies. By means of a thorough investigation of search engine use patterns and influencing elements, information retrieval systems can be improved, user experience can be raised, and the constructive development of the information society can be promoted (Matthews and Glitre, 2021).

Information Behavior in Social Media: Acquisition and Dissemination

In internet information behavior, social media serves both as a main platform for information distribution and sharing and as a necessary source for information acquisition. While their interaction behaviors—such as likes, comments, and shares—determine the channels and effects of information distribution, users learn information via social recommendations, active subscriptions, and algorithmic content suggestions (Moreno-García, 2020). This interactive model suggests that linking the general information spread with individual information behavior depends on social media. Traditional information retrieval techniques are hampered by the scattered character of social media. Instead of depending just on search engines, users are progressively depending on tailored content delivered through recommendations, subscriptions, and personalized algorithmic feeds on social networks (Abdelmalek et al., 2013). To provide highly tailored information streams, social media platforms use browsing history, user preferences, and social contacts to enhance the accuracy of information retrieval (Mishra et al., 2022). Furthermore, people often show more trust in knowledge supported by friends, colleagues, or industry experts from their social networks. This mechanism of "social trust" increases the validity of acquired data (Stathopoulos et al., 2023).

Concurrently, the fundamental network topology shapes the information distribution on social media by exhibiting characteristics of hierarchical diffusion and viral propagation (Liou et al., 2016). With different social relationships and network nodes assuming different roles in the spread of information, users engage in content sharing, commenting, and various interactive behaviors influencing information dissemination (Riaz and Sherani, 2021). While social trust systems and platform recommendation algorithms jointly influence the extent and intensity of information distribution, the content of great quality that resonates with user interests is more likely to be extensively shared (Lee et al., 2020). Moreover, the ways in which knowledge is acquired and shared are closely entwined within the social media terrain, so producing a closed-loop effect. Users actively contribute to content creation and distribution, so influencing how others access and understand knowledge; they are not only passive consumers of it. This interactive model highlights the social aspect of information distribution, so social media is defined as a central hub in the digital information ecosystem (Miller, 2013). Still, the systems that allow information to be shared could also result in echo chambers and information silos, limiting users' exposure to different points of view and so affecting cognitive diversity (Galliera et al., 2025). Therefore, improving information flow systems in social media is a top priority for the next studies since it balances customized recommendations with exposure to different content.

Factors Influencing Internet Information Behavior

Individual Factors

Our findings indicate that users' Information Interaction Behavior (IIB) is significantly influenced by their educational background; thus, information distribution and acquisition behaviors are closely linked to educational attainment. While individuals with higher education typically exhibit superior information literacy, enabling them to efficiently acquire, assess, and utilize knowledge, those with lower educational attainment may experience impaired information behavior due to information overload and the digital divide. Individuals are increasingly inclined to share content on short video platforms as their educational attainment rises. Data from iMedia Research's China Short Video Industry User Behaviour Survey indicates that individuals with undergraduate or higher education shared content an average of 235 times daily in 2023, while those with a high school education or less shared content an average of 78 times. By 2024, the sharing frequency for individuals with undergraduate or higher education levels increased to 276 times daily, whereas it decreased to 75 times for those with lower education levels.

Likewise, data on social media user activity underscores the influence of educational background on user behavior. Users with higher education levels are more inclined to post and comment on platforms such as Weibo while favoring the consumption and liking of content on Douyin. User behavior on WeChat demonstrates a fairly balanced distribution among different educational levels. This trend demonstrates the relationship between social media user engagement and educational attainment, likely stemming from differences in social needs and behavioral patterns among individuals with varying educational levels. Thus, the significant influence of educational background on IIB offers a promising avenue for future research. Understanding the motivations behind user behavior can provide valuable insights for the development and improvement of IIB strategies.

Social Environmental Factors

Social Networks and Information Diffusion

Social networks are a necessary forum for interaction and communication, which greatly shapes opinion expression and knowledge gain. Users can quickly pick up broad knowledge and interact with others from many backgrounds, therefore changing their perspectives and actions. Information diffusion models are essential analytical tools for comprehending the routes, velocity, and node-to-node implications of information flow in examining the influence of social networks on knowledge distribution. The dynamic process of information distribution and its impact on user behavior is investigated in this study using the Independent Cascade Model (ICM). The Independent Cascade Model has many benefits in comparison to other social network diffusion models, such as the Linear Threshold Model. It first matches more precisely with real viral transmission patterns by first simulating the probabilistic paths of information flow inside social networks. Second, it skillfully runs large networks, which makes it particularly relevant for looking at social media environments for information distribution. In the end, ICM clarifies the cascade effect of information spreading and provides important analysis for dynamic network environments to foresee user behavior.

Focusing on the diffusion characteristics of information shared by authoritative institutions such as the World Health Organization (WHO), this study assesses the effectiveness of ICM by analyzing the dispersion of health information during the COVID-19 epidemic. The results show that high-credibility material is more likely to be shared inside the ICM framework, therefore highlighting the critical role authoritative sources play in the distribution of knowledge. A public health messaging simulation on Twitter shows that, via many retweet cycles, health-related information shared by medical professionals reached over a million people. This finding emphasizes how much high-credibility nodes improve the broad information distribution throughout extensive transmission networks. These results show that ICM not only provides a scientific basis for optimizing information distribution strategies, thereby increasing the efficacy of public health communication inside social networks but also precisely forecasts the degree and consequences of information diffusion.

The broad use of information diffusion models provides theoretical bases and insightful analysis to improve information distribution in many spheres. These models enable the exact identification of high-impact nodes, such Key Opinion Leaders (KOLs), and effective distribution channels, so providing important insights for public opinion analysis and marketing. Companies use diffusion models in useful applications to analyze KOL distribution channels on platforms like Weibo, identifying key opinion leaders in particular fields. This improves brand results and helps to maximize methods of resource allocation. Diffusion models were used by government agencies to identify important social media spreading hubs for pandemic control projects. By meticulously orchestrating the distribution of public health information, they tripled the efficiency of conventional methods, significantly enhancing public awareness and engagement. These illustrations demonstrate the significant value and wide applicability of information diffusion models across various contexts, including crisis management, public governance, and commercial promotion.

Sociocultural Context

A great and complex element influencing IIB is the sociocultural context, which greatly shapes people's actions in information acquisition, processing, distribution, and use inside digital environments. Comparative studies and literature reviews expose that sociocultural context acts as an implicit mediator influencing the traits and expressions of information behavior. The sociocultural setting consists of several aspects: Values, belief systems, educational level, language style, and social conventions. These closely related elements help to shape people's information behaviour decision-making process, so generating distinctive cultural patterns. Individualistic and collectivistic communities produce different sociocultural information practices. In collectivist societies, information conduct is consistent and collective; people help one another to meet their information needs. In individualistic civilizations, information behavior stresses autonomous research and self-expression, hence accentuating invention and personalism. Underlying quantitative research on cultural differences in information behavior is Hofstede's cultural features theory. As the power distance theory suggests, high power distance societies distribute knowledge through authoritative structures. As such, conservative information practices are promoted, and the autonomy of information choosing is limited. Low power-distance societies improve transparency and diversity, therefore enabling personal choice and understanding of information.

As a result, people in low power-distance cultures are more likely to open information flow while individuals in high power-distance cultures usually show more resistance to share knowledge. These results emphasise the need of sociocultural background as a major determinant of IIB. Its diversity and complexity require researchers to maintain a high level of sensitivity and adaptability in analysis and practice. By thoroughly understanding information behavior patterns in different cultural contexts, more precise strategies can be developed to optimize cross-cultural information services, promote information equity, and enhance information sharing.

Applications and Challenges

Education

In the field of education, the application of IIB has not only reshaped the methods of knowledge acquisition and delivery but also significantly expanded the breadth and depth of education (Dong et al., 2022). The quick development of flipped classrooms and blended learning emphasizes the indispensable role of the Internet in the distribution of instructional materials and the improvement of personalized learning (Figure 2). Reflecting the growing worldwide need for open-access, high-quality educational resources, Massive Open Online Courses (MOOCs), a key model in online education, have exhibited amazing increase from 50 million in 2015 to 454 million in 2023, indicating participant numbers surge from MOOCs dramatically increase educational access by offering flexible and large-scale online learning choices (Figure 3). Adoption of them depends on societal influences, learning motivation, and personal knowledge level. This study carefully examines these components, applying a multidimensional perspective of Internet information activity. Individual-level information literacy, learning motivation, and technology acceptability are critical determinants of MOOC adoption. Studies show that while those with low information literacy may run across technological challenges or cognitive overload, reducing their inclination to participate in MOOCs, those with high information literacy are more likely to actively seek and use online learning resources. According to the Technology Acceptance Model (TAM), a user's acceptance and continuous usage of MOOCs depend much on their perceived ease of use and perceived usefulness.

Different countries see different social acceptance of MOOCs. Hofstede's Cultural Dimensions show that low power distance societies—Western countries included—usually select open online learning, giving independent discovery and involvement a top priority. On the other hand, high-power remote civilizations—East Asia, for example—give instructor authority top priority, therefore perhaps limiting the MOOC participatory learning experience. Despite the great use of MOOCs in China, the educational model mostly stresses tests, and students prefer course certification over intensive, interactive learning.

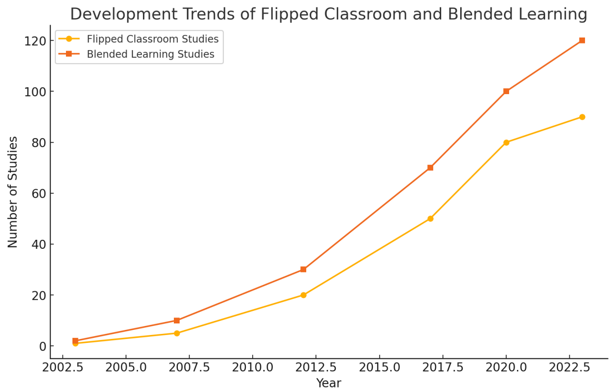

Fig. 2: Development trends of flipped classroom and blended learning

Data Source: Jin, L. (2024) and Huainan, Z. (2019)

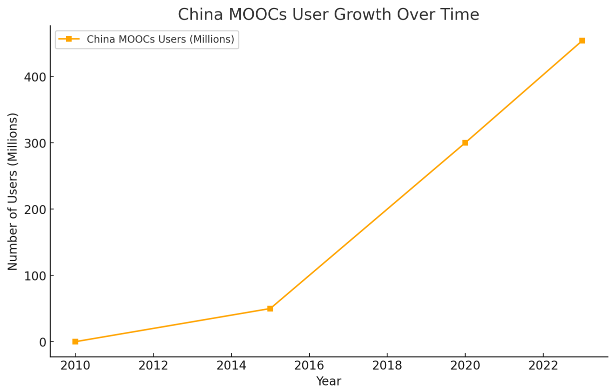

Fig. 3: MOOC users over time

Data Source: Ministry of Education of the People's Republic of China (2023)

New approaches in educational strategies have been motivated by the change in Internet information behavior. Online learning environments use big data analytics to track student learning activities, including study length, learning paths, and performance variances, therefore giving teachers reliable instructional feedback. Incorporating flipped classrooms and blended learning approaches into this data-driven approach has enhanced student involvement and outcomes of individualized learning. Data-driven feedback systems, using a targeted approach, help teachers enhance their instructional design and thereby increase teaching efficacy. Furthermore, by giving rural students access to better educational materials via online learning, educational inequalities both regional and urban have been lessened.

This study provides a multidimensional paradigm for Internet information behavior, stressing that human variables (information literacy), group features (social learning), and environmental factors (technology aid) influence educational information behavior. Information literacy affects students' abilities to effectively search for and use digital information, so enabling those with higher degrees of literacy to create effective learning strategies and raise educational results. Social learning systems are crucial at the group level for online learning environments such as MOOCs and flipped classrooms, so improving information flow and cooperative knowledge generation and so increasing the learning efficacy. Moreover, at the contextual level, technology support—particularly powered by artificial intelligence-based recommendation systems—enhances learning opportunities by means of tailored paths. Nevertheless, given these advances, the application of Internet information behavior in education faces significant challenges. The rapid growth of online learning resources has aggravated information overload and made it more difficult for students to recognize and extract useful knowledge, hence increasing their information literacy needs. Online learning environments' openness and complexity create problems for educational management in terms of guaranteeing the quality of learning, verifying resource legitimacy, and protecting cybersecurity. Resolving these problems calls for students to become more information literate, strengthen social learning systems, and increase technological support systems, optimizing the use of Internet information behavior to reach higher learning efficiency and improved educational quality.

Later research on Internet information behavior in education should then focus on several important spheres. First, thorough studies are needed to investigate the relationship between information behavior and learning results, thereby exposing basic processes to link theoretical results with useful applications. Second, more attention should be paid to helping students become more information literate by means of organized courses, enhancing their ability to filter, evaluate, and use knowledge effectively. Implementing a comprehensive online learning assessment system would help to ensure continuous improvement of the quality of education. In order to promote educational fairness, Internet technologies have to be used to help underprivileged groups, thereby lowering educational differences. These initiatives can realize the whole possibilities of Internet information behavior in education, so enabling revolutions in pedagogical approaches and models and so support educational equity and better growth.

Commerce

The application of Internet information behavior has changed consumer contacts, market tactics, and company operations. By tracking and evaluating users' search, browsing, buying, and reviewing behavior using advanced data analytics, businesses may maximize marketing efforts and increase user involvement. Amazon's personalized recommendation system, driven by big data algorithms, greatly increases customer retention and raises the average order value since roughly 35% of its sales in 2019 were connected to tailored recommendations. This is essentially a basic competitive edge. By way of consumer behavior research, analyzing users' watching histories, ratings, and watch times enables Netflix to generate exact user-profiles and support highly tailored content recommendations (Gomez-Uribe and Hunt, 2016). This approach guarantees a continuous rise in subscription numbers in the very competitive streaming industry by reducing turnover rates and increasing user happiness. Businesses are also increasing the spectrum of Internet information use strategies. Using its Nike Run Club membership program and mobile app, Nike investigates consumer fitness trends and purchase preferences. By personalizing each other, customized product recommendations and individualized workout advice generated by this research raise user engagement and sales conversion rates. Alibaba reduces inventory costs and improves market responsiveness by using artificial intelligence and cloud computing to govern massive volumes of e-commerce data; this helps to improve supply chain management and sales forecasting. Alibaba's Cainiao Network maximizes delivery routes by means of big data analytics, therefore considerably improving logistics efficiency. China's Credit Reference Consortium and other cross-industry data-sharing programs help to demolish data silos and support multi-party cooperation. This will so raise commercial value and inspire innovation.

Although Internet information activity is somewhat common in business, its use has raised major ethical and data privacy problems. More stringent legislation, including the General Data Protection Regulation (GDPR), aimed to protect user privacy, followed the 2018 Facebook-Cambridge Analytica debacle, which exposed the dangers of data exploitation. Corporate applications driven by artificial intelligence might raise moral issues around algorithmic bias and data openness. When Amazon's AI-driven hiring practice revealed gender inequality, critics responded adversely. This bias resulted from the underlying presumptions of the training data, which favored male candidates over female ones. Moreover, underlining the problems with user privacy violations and data usage enabled by personalized advertising and content curation by artificial intelligence is the Cambridge Analytica incident, in which personal data obtained without permission of 87 million Facebook users was targeted for political advertising. This event underscored the need of more strict privacy protection laws, which resulted in global legislative projects including the development of GDPR guidelines. Although legislators should impose rigorous data governance standards, such as the GDPR in the EU and China's Personal Information Protection Law (PIPL), to manage corporate data usage practices, companies should deploy justice-aware machine learning algorithms to lower artificial intelligence bias. As artificial intelligence technologies propel commercial development, striking a balance between ethical obligation and data value will assist in building a transparent, fair, and privacy-aware digital economy.

Public Services

Although it causes many issues, the application of IIB in public services has become clear as a necessary tool for raising service responsiveness and efficiency. By means of the great integration of Internet technology, IIB is changing public expectations and experiences related to public services as well as delivery paradigms. Improving the distribution of public service resources and raising the effectiveness of decisions depend on government data analysis. Using health code and travel code data, the Chinese authorities successfully tracked the contact history and movement trajectories of confirmed patients by means of machine learning classification algorithms and clustering analytic approaches across the COVID-19 epidemic. This approach reduced the transmission rate to thirty percent of the originally expected level. Moreover, local governments effectively predicted peak infection times two weeks ahead by using time-series predictive modeling and big data analysis, therefore enabling the strategic deployment of medical resources and ensuring enough supply for crucial areas. Real-time data analysis helped authorities to precisely assess bed demand and maximize resource allocation using linear programming models, hence enhancing emergency response efficiency during the building of Wuhan's temporary hospitals.

In community service management, big data analysis facilitates the enhancement of public services. Beijing's 'JingTong' platform employs a semantic analysis-driven community demand mining technique to reveal notable disparities in citizens' acceptability of waste sorting among districts. In light of these findings, focused educational and promotional efforts were executed, enhancing the accuracy of waste sorting from 65% to 85% within two months. Research on social media underscores the importance of disseminating information in public services. In response to natural disaster alerts, the Japanese government employed the Social Amplification of Risk Framework (SARF) to assess the dissemination pathways of information via social media, thereby ensuring that warning messages reached 80% of the impacted population within one hour. In response to the proliferation of rumors during the 2011 Fukushima nuclear crisis, the Japanese government employed advanced recommendation algorithms and robust platform-based technologies to counter incorrect information and limit the detrimental impacts of disinformation. This strategy significantly alleviated public concern and impeded the spread of misinformation.

Technological and Ethical Challenges

Technology-Driven Analysis of Information Behavior

Artificial Intelligence and Dynamic Information Interaction

In recent years, the rapid development of AI technology has significantly enhanced the efficiency and depth of research into information interaction and behavior (Pal et al., 2023). By leveraging big data analytics, researchers can capture and uncover user behavior patterns. For instance, by integrating features such as clickstream data, search history, and dwell time, they can construct precise user profiles (Alswiti et al., 2016). Personalized recommendation systems on Netflix and Amazon help to increase user involvement and content relevance. These systems project user needs and preferences by using user profiles. Deep learning and reinforcement learning models are two achievements in artificial intelligence. These tools help to enhance the IIB dynamic analysis. Reinforcement learning lets real-time changes depending on user input help to improve interaction results. Our approach more closely forecasts dynamic behaviors and reflects user interactions in real-world conditions than past models.

Research combining graph analysis methods with deep learning is driving IIB studies now to improve the discipline beyond individual activities to complex group dynamics. Graph Neural Networks (GNNs) provide new tools for analyzing network dynamics since they are used in methods to predict information distribution in social networks. Two areas where knowledge sharing via social media has been investigated are public opinion appraisal and pandemic spread prediction. During the COVID-19 epidemic, AI-driven models were used to monitor the dissemination of false information and project the geographic distribution of the virus, therefore providing vital support for focused public health projects. Future research could look at the inclusion of multimodal data, comprising text, images, and videos, thereby clarifying the parallels and differences in information activity across many social and cultural contexts (Zheng et al., 2019).

Methods of machine learning offer significant tools for the study of IIB. By means of substantial data analysis, machine learning models can effectively identify users' informative behaviour patterns and preferences, therefore enabling advanced functionalities such sentiment analysis and tailored information recommendations. This extensive study of past conduct improves the quality of user-information interaction and the accuracy and efficiency of information retrieval. Concurrent with this development in Natural Language Processing (NLP) technology, IIB research has expanded its scope. Natural Language Processing (NLP) helps

DOI: 10.3844/jssp.2025.76.88

machines to analyze and understand human language, hence improving complex information exchange systems. Currently used extensively in intelligent question-answering systems and dialogue generation technologies, NLP offers users more natural and seamless information services. NLP has great power to progress the development of cross-linguistic translation tools and more intelligent information search systems, thereby changing user access to and engagement with information. These advances will enable more inclusive and effective information ecosystems, therefore enabling people to move across the ever more complicated digital surroundings with more ease.

Recommendation systems, a vital application of artificial intelligence in IIB, are perpetually advancing in complexity and personalization. Spotify's adaptive recommendation system produces precise music suggestions by integrating context-aware collaborative filtering algorithms with deep learning models, including Neural Collaborative Filtering (NCF). Data shows that the tailored recommendation tool has raised user click-through rates by 25%, so increasing user involvement and hence platform income. Future recommendation systems are expected to stress the integration and knowledge of users' contextual information. This will give consumers a more consistent and integrated service experience and allow correct recommendations across platforms and sectors. These developments could change user interaction with knowledge, encouraging creativity in the distribution of tailored content and raising user satisfaction.

While AI technology possesses significant potential for IIB research, its application prompts privacy and ethical dilemmas. Individuals who obtain customized recommendations that restrict their exposure to diverse perspectives may encounter the "filter bubble" phenomenon, wherein they are solely presented with information that corroborates their preexisting beliefs. This may intensify social inequality, suppress creativity, and markedly diminish participation. Platforms can alleviate this effect by employing diversity-enhancing algorithms that align user preferences with a broad spectrum of content. Transparent recommendation systems enable users to regulate the degree of personalization, thereby enhancing information retrieval. Furthermore, algorithmic bias presents significant challenges. In artificial intelligence systems, bias typically arises from biased training datasets or design deficiencies, leading to inequitable recommendations or discriminatory outcomes. Biassed datasets disproportionately represent specific demographic populations, potentially adversely affecting under-represented groups. Tackling this issue depends on methods for justice optimization, including explainable artificial intelligence tools and dataset de-biassing. Frequent audits and the application of ethical standards contribute to greater justice and accountability in government algorithmic decision-making. Addressing these issues will ensure that future studies enable the responsible and sustainable integration of artificial intelligence into IIB, thereby promoting innovation and protecting user rights and trust.

Big Data Analytics and Behavioral Patterns

Comprehensive profiles of users' information behavior are developed from big data analytics—that is, the study of users' online activities, including search records, browsing histories, and social media interactions. Algorithmic models, clustering analysis, and association rule mining help one to identify user preferences, changing needs, and basic ideas controlling information consumption. "Big data analytics" refers to Google's techniques for looking at user search histories and click activity. Using machine learning methods, this data is examined to improve characteristics, including autocomplete and search result ranking. This guarantees that the outcomes quite match the expectations of the user. User input is shown in Figure (4), the first phase of the process. The following stages of data collecting and algorithmic processing produce relevant and exact search results.

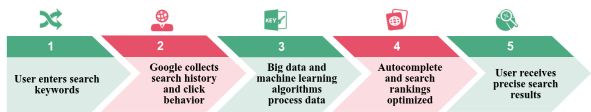

Fig. 4: Google search engine optimization

Fig. 5: Amazon recommendation system

Based on data-driven customized recommendations, Amazon's recommendation system (Figure 5) shows how consumer information behavior has changed and how the market competitiveness of the company has risen. Amazon generates quite accurate recommendations by combining user search history, browsing behavior, and purchase records. By means of deep learning and collaborative filtering approaches, this system assesses consumer preferences, so enhancing user retention and purchase conversion rates. This study presents three fundamental levels of operation of the recommendation system in a multidimensional framework. Suggested content is directly affected by individual user browsing patterns and purchase behavior, so guiding consumers in making decisions based on customized recommendations. Ratings, reviews, and comments among User-Generated Content (UGC) help to influence group-level buying decisions of other consumers. These interactions boost community confidence and help to promote a cooperative approach to decision-making. Amazon enhances its recommendation system using artificial intelligence, enabling a more accurate information distribution. Furthermore, data mining techniques allow one to find market trends, allowing exact adjustments to corporate policies. By means of this dynamic interaction among individual, group, and environmental elements, Amazon can meet specific consumer needs by means of social signals and technological innovations influencing more general market trends. This model shows the great integration of information behavior in corporate environments and stresses the essential component of data-driven decision-making in modern corporate strategy.

One tool used in the investigation of large amounts of data is data visualization. It does this by turning abstract data into understandable charts and images, improving communication and the general understanding of intricate information flow patterns. This helps to efficiently spread ideas and discoveries between legislators and scientists. Using time series charts—which clearly show public opinion trends—helps to improve public event planning. On websites, heat maps, on the other hand, improve user experience by graphically showing user click patterns. A basic feature of artificial intelligence, deep learning has created fresh chances for studying information dynamics in big data analytics. Deep learning models enable independent extraction of high-level features, thus improving the accuracy and efficiency of data analysis. Deep learning models help Netflix to examine user viewing patterns and offer highly tailored content recommendations, thus improving user satisfaction. In the financial industry, deep learning is used to find transaction anomalies, spot possible frauds, and enhance risk-management capacities. By means of multimodal data and real-time analysis, these technologies could be coupled to increase their relevance. Integration of traffic flow analysis and social media data analysis improves traffic scheduling in smart city management, thus increasing urban efficiency. Big data analytics will surely bring in a new phase of development for the study of information behavior as technology develops and its uses get ever more complicated.

Ethical Challenges and Responses in Information Behavior

Given that the ubiquitous collecting, storage, and use of personal data in online information activities present significant privacy concerns, data protection is an ethical issue of great relevance. The Facebook-Cambridge Analytica controversy of 2018 brought global privacy consciousness by revealing the dangers of improper data use. Future studies should concentrate on improving homomorphic encryption and federated learning, building privacy-preserving technology, using blockchain to increase data transparency, and passing thorough privacy laws to build a strong data protection system. Apart from privacy issues, the dissemination of false information in the digital world presents a major ethical difficulty. The COVID-19 epidemic shows how quickly false information travels in an era of information overload, endangering public confidence in preventative actions and hence compromising public decision-making and societal stability. While public education platforms should help to increase information literacy and critical thinking skills, future research should concentrate on deep learning algorithms for fake news identification, especially BERT-based models. Governments, businesses, governments, and the general public have to create a cooperative information governance system to lessen the effects of disinformation on society, governments, companies, and the general public. Online fraud should cause great worry since it immediately causes financial losses and compromises the integrity of the digital terrain. Phishing and telecommunication frauds are expected by the International Telecommunication Union (ITU) to affect around 100 million people and result in worldwide economic losses of $5.5 billion in 2022. Dealing with this challenge calls for early warning systems and real-time monitoring as well as integration of AI-driven cybersecurity solutions to increase law enforcement efficacy and public awareness campaigns to raise users' cybersecurity awareness, thus producing a safer digital environment.

Thanks to developments in data security and privacy, artificial intelligence has become an indispensable technological instrument for addressing ethical conundrums. Strict user data safety has been guaranteed by several AI-driven solutions. Using differential privacy—which combines noise into datasets to anonymize user voice data, prevent individual data identification, and enhance voice recognition algorithms—Apple's Siri by means of Google's Gboard keyboard, federated learning allows local training of AI models on users' devices without involving the transfer of personal data to a central server, therefore preserving user privacy. Leading technology companies have included AI-powered privacy protection technologies in their products; Google's use of differential privacy in Google Maps anonymizes user location data while improving traffic predictions, and Apple's App Tracking Transparency (ATT) framework in iOS lets users control app tracking of their data, so reinforcing user autonomy in data privacy management. Notwithstanding the huge potential of AI-driven privacy solutions to balance data security and accessibility, there are still difficulties, especially in reaching an ideal balance of privacy and data value. Future studies should concentrate on establishing privacy-enhancing strategies to support ethical AI implementation, algorithmic transparency, and improved data security, thus safeguarding the responsible and sustainable development of digital ecosystems.

Conclusion

This study methodically investigates its uses in public services, business, and education and builds a complete paradigm for Internet information behavior. The results show that by combining views from psychology, sociology, and information science, personal information literacy greatly influences information behavior. This emphasizes the need to improve public information evaluation and filtering capacities to maximize information acquisition and use. Information literacy education should be given top priority in future initiatives in order to handle the rising problems of information overload and false information distribution. Furthermore, the spread of information depends on the channels of distribution of social networks; consequently, improving recommendation systems helps to reduce filter bubble effects and increases the equity and width of information distribution. Apart from this changing technical scene, there are benefits and drawbacks; while artificial intelligence-driven algorithms improve information access and retrieval efficiency, they also generate ethical questions and violate data privacy. Thus, improving data privacy protections and ethical government helps to guarantee the long-term viability and integrity of the information ecosystem.

A vital area of research in the digital age, internet information behavior is defined by its complexity and multidimensionality, which both theoretically and practically provide difficulties. This study constructs a three-dimensional theoretical framework methodically investigating the fundamental processes and dynamic flow of diffusion, sharing, and knowledge acquisition. While internet information behavior helps to enable tailored learning and fair resource allocation in school, big data and AI-driven technologies greatly improve learning outcomes and feedback systems. Precision marketing and personalized recommendations are changing the dynamics of the market; data-driven decision-making is increasing company efficiency and competitiveness, therefore enhancing general corporate competitiveness. Demand-driven information behavior analytics enable public service resource allocation more precisely and faster response times. Along with these developments, studies on Internet information behavior now have to address urgent issues of data privacy protection, the spread of false information, and cybersecurity risks, calling for greater research.

This study examines the interplay among individual, group, and environmental factors, establishing a multidimensional theoretical framework for Internet information behavior, notwithstanding certain limitations. The research predominantly employs case analysis and a literature review owing to insufficient empirical validation. Additional research across diverse sociocultural contexts is essential to ascertain the framework's applicability. Second, despite the complex and erratic character of information behavior elements, this study does not quantitatively assess the relative relevance of interpersonal relationships, cognitive processes, and technological surroundings. Integration of social network analysis with machine learning could improve model accuracy in the next studies. Although emerging technologies such as blockchain and artificial intelligence are progressively altering information behavior, the existing framework inadequately addresses the ethical and long-term ramifications. Future studies must tackle essential issues such as algorithmic transparency, privacy protection, and social responsibility while also incorporating multi-source data, experimental methodologies, and comprehensive behavioral monitoring to enhance applicability and predictive accuracy.

Acknowledgment

We would like to express our gratitude to our colleagues at the Asia-Europe Institute, Universiti Malaya, for their valuable advice and support during the course of this study. We also appreciate the constructive feedback from anonymous reviewers, which helped improve the quality of this manuscript.

Funding Information

This research did not receive any funding from external sources.

Author’s Contributions

Jinyan Liao: Contributed to the research design, data collection, and analysis, and played a major role in writing and revising the manuscript.

Sameer Kumar: Coordinated the research, contributed to the methodology, data analysis, and wrote substantial sections of the manuscript. He is the corresponding author for this manuscript.

Fumitaka Furuoka: Contributed to the research design, data analysis, and assisted in the revision of the manuscript.

Ethics

This research does not involve human or animal subjects. The authors declare that there are no conflicts of interest related to this manuscript. Ethical issues that may arise after the publication of this manuscript will be addressed promptly.

References

Abdelmalek, A., Ait Mohamed , O., & Ladjel, B. (2013). *Modeling Approaches and Algorithms for Advanced Computer Applications*. *488*. https://doi.org/10.1007/978-3-319-00560-7

Alswiti, W., Alqatawna, J., Al-Shboul, B., Faris, H., & Hakh, H. (2016). Users Profiling Using Clickstream Data Analysis and Classification. *2016 Cybersecurity and Cyberforensics Conference (CCC)*, 96-99. https://doi.org/10.1109/ccc.2016.27

Boyd, D. M., & Ellison, N. B. (2007). Social Network Sites: Definition, History and Scholarship. *Journal of Computer-Mediated Communication*, *13*(1), 210-230. https://doi.org/10.1111/j.1083-6101.2007.00393.x

Chen, X., Lu, J., & Dai, Y. (2022). Multi-Fusion Analysis of College Education Information System based on High Robust QoS Optimization Computer Technology. *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 1274-1277. https://doi.org/10.1109/icesc54411.2022.9885421

Choo, C. W. (2005). How We Come to Know: Understanding Information-Seeking Behavior. *The Knowing Organization: How Organizations Use Information to Construct Meaning, Create Knowledge, and Make Decisions*, 29-74. https://doi.org/10.1093/acprof:oso/9780195176780.003.0002

Dong, J., Wang, Z., & Li, S. (2022). Analysis of Online Learning Behavior Based on Clustering Algorithm. *2022 IEEE 2nd International Conference on Power, Electronics and Computer Applications (ICPECA)*, 364-368. https://doi.org/10.1109/icpeca53709.2022.9718935

Drivas, I. C., Sakas, D. P., Giannakopoulos, G. A., & Kyriaki-Manessi, D. (2021). Search Engines' Visits and Users' Behavior in Websites: Optimization of Users Engagement with the Content. *Business Intelligence and Modelling*, 31-45. https://doi.org/10.1007/978-3-030-57065-1_3

Fedushko, S., & Benova, E. (2019). Semantic Analysis for Information and Communication Threats Detection of Online Service Users. *Procedia Computer Science*, *160*, 254-259. https://doi.org/10.1016/j.procs.2019.09.465

Galliera, R., Venable, K. B., Bassani, M., & Suri, N. (2025). Collaborative Information Dissemination with Graph-Based Multi-Agent Reinforcement Learning. *Algorithmic Decision Theory*, 160-173. https://doi.org/10.1007/978-3-031-73903-3_11

Gomez-Uribe, C. A., & Hunt, N. (2016). The Netflix Recommender System: Algorithms, Business Value and Innovation. *ACM Transactions on Management Information Systems (TMIS)*, *6*(4), 1-19. https://doi.org/10.1145/2843948

Gupta, A., Tyagi, L. K., & Sisodia, V. S. (2023). Optimization Techniques for Focused Web Crawlers. *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 1500-1507. https://doi.org/10.1109/ictacs59847.2023.10390228

Huainan, Z. (2019). The Current Status and Development Trend of Blended Learning Research in My Country. *Chinese Medical Education Technology*, *33*(1), 12-18.

Jia, X., Pang, Y., & Liu, L. S. (2021). Online Health Information Seeking Behavior: A Systematic Review. *Healthcare*, *9*(12), 1740. https://doi.org/10.3390/healthcare9121740

Jin, L. (2024). Summary of Flipped Classroom Research in China in Recent Ten Years. *Creative Education Studies*, *12*(6), 504-515. https://doi.org/10.12677/ces.2024.126416

Kaplan, A. M., & Haenlein, M. (2010). Users of the World, Unite! The Challenges and Opportunities of Social Media. *Business Horizons*, *53*(1), 59-68. https://doi.org/10.1016/j.bushor.2009.09.003

Lee, S.-H., Jang, W.-D., & Kim, C.-S. (2020). Superpixels for Image and Video Processing Based on Proximity-Weighted Patch Matching. *Multimedia Tools and Applications*, *79*(19-20), 13811-13839. https://doi.org/10.1007/s11042-019-08438-8

Liou, D.-K., Chih, W.-H., Hsu, L.-C., & Huang, C.-Y. (2016). Investigating Information Sharing Behavior: The Mediating Roles of the Desire to Share Information in Irtual Communities. *Information Systems and E-Business Management*, *14*(2), 187-216. https://doi.org/10.1007/s10257-015-0279-2

Liu, Y., Zhou, X., Zhang, Z., & Xu, X. (2020). Analysis of Multi-Element Blended Course Teaching and Learning Mode Based on Student-Centered Concept under the Perspective of "Internet+". *Journal of Business Theory and Practice*, *8*(1), p13. https://doi.org/10.22158/jbtp.v8n1p13

Lombardo, G., Fornacciari, P., Mordonini, M., Sani, L., & Tomaiuolo, M. (2019). A Combined Approach for the Analysis of Support Groups on Facebook - The Case of Patients of Hidradenitis Suppurativa. *Multimedia Tools and Applications*, *78*(3), 3321-3339. https://doi.org/10.1007/s11042-018-6512-5

Matthews, P., & Glitre, K. (2021). Genre Analysis of Movies Using a Topic Model of Plot Summaries. *Journal of the Association for Information Science and Technology*, *72*(12), 1511-1527. https://doi.org/10.1002/asi.24525

Miller, B. (2013). When is Consensus knowledge Based? Distinguishing Shared knowledge from mere Agreement. *Synthese*, *190*(7), 1293-1316. https://doi.org/10.1007/s11229-012-0225-5

Ministry of Education of the People's Republic of China. (2023). *National Education Development Statistical Bulletin*. http://www.moe.gov.cn/jyb_sjzl/sjzl_fztjgb/202410/t20241024_1159002.html

Miraj, M., Chuntian, L., Mohd Said, R., Osei-Bonsu, R., & Rehman, R. ur. (2021). How Information-Seeking Behavior, Essential Technologies and Resilience Enhance the Academic Performance of Students. *Frontiers in Psychology*, *12*, 1-13. https://doi.org/10.3389/fpsyg.2021.651550

Mishra, S., Rezapour, R., & Diesner, J. (2022). Information Extraction from Social Media: A Hands-on Tutorial on Tasks, Data, and Open Source Tools. *CIKM '22: Proceedings of the 31st ACM International Conference on Information & Knowledge Management*, 5148-5151. https://doi.org/10.1145/3511808.3557503

Moreno-García, M. N. (2020). Information Retrieval and Social Media Mining. *Information*, *11*(12), 578. https://doi.org/10.3390/info11120578

Pal, G., Atkinson, K., & Li, G. (2023). Real-Time User Clickstream Behavior Analysis Based on Apache Storm Streaming. *Electronic Commerce Research*, *23*(3), 1829-1859. https://doi.org/10.1007/s10660-021-09518-4

Riaz, M., & Sherani. (2021). Investigation of Information Sharing Via Multiple Social Media Platforms: A Comparison of Facebook and WeChat Adoption. *Quality & Quantity*, *55*(5), 1751-1773. https://doi.org/10.1007/s11135-020-01079-2

Ruotsalo, T., Jacucci, G., & Kaski, S. (2020). Interactive Faceted Query Suggestion for Exploratory Search: Whole-Session Effectiveness and Interaction Engagement. *Journal of the Association for Information Science and Technology*, *71*(7), 742-756. https://doi.org/10.1002/asi.24304

Sharma, P., Kaur, J., Arora, V., & Rana, P. S. (2017). Information Retrieval in Web Crawling Using Population Based, and Local Search Based Meta-heuristics: A Review. *Proceedings of Sixth International Conference on Soft Computing for Problem Solving*, 87-104. https://doi.org/10.1007/978-981-10-3325-4_10

Stathopoulos, E. A., Karageorgiadis, A. I., Kokkalas, A., Diplaris, S., Vrochidis, S., & Kompatsiaris, I. (2023). A Query Expansion Benchmark on Social Media Information Retrieval: Which Methodology Performs Best and Aligns with Semantics? *Computers*, *12*(6), 119. https://doi.org/10.3390/computers12060119

Suryasa, I. W., Chere-Quiñónez, B. F., Pastariya, R., Vanaja, T., & Saravanan, T. (2023). Analysis of Focused Web Crawlers: A Comparative Study. *2023 3rd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 772-778. https://doi.org/10.1109/ictacs59847.2023.10390388

Wilson, T. D. (2024a). Approaches to Information-Seeking Behaviour in Psychology: A Comparison of Early and Contemporary Studies. *Information Research an International Electronic Journal*, *29*(1), 34-53. https://doi.org/10.47989/ir291694

Wilson, T. D. (2024b). Curiosity and Information-Seeking Behaviour: A Review of Psychological Research and a Comparison with the Information Science Literature. *Journal of Documentation*, *80*(7), 43-59. https://doi.org/10.1108/jd-09-2023-0173

Xie, K., Yu, H., & Cen, R. (2012). Using Log Mining to Analyze User Behavior on Search Engine. *Frontiers of Electrical and Electronic Engineering in China*, *7*, 254-260. https://doi.org/10.1007/s11460-011-0177-4

Zhang, F., Liu, Y., Mao, J., Zhang, M., & Ma, S. (2020). User Behavior Modeling for Web Search Evaluation. *AI Open*, *1*, 40-56. https://doi.org/10.1016/j.aiopen.2021.02.003

Zheng, J., Tong, Z., Wu, G., & Liang, R. (2019). Code Confusion Confrontation Method Based on Feature Comparison. *2019 International Conference on Intelligent Computing, Automation and Systems (ICICAS)*, 61-65. https://doi.org/10.1109/icicas48597.2019.00021