

Modelling the impact of generative artificial intelligence on information behaviour research

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376

Received 19 March 2026
Revised 26 April 2026
Accepted 30 April 2026

Abstract

Purpose – Existing models of information behaviour assume interaction with passive retrieval systems such as search engines and bibliographic databases. Generative AI systems, which actively generate personalised responses rather than retrieving existing documents, represent a fundamental shift that these models do not address. This paper proposes a modification of Wilson's generic model of information behaviour to accommodate generative AI as an active intermediary.

Design/methodology/approach – Conceptual analysis grounded in a scoping review of 89 papers addressing AI-mediated information seeking, information ecosystem implications and theoretical gaps in existing frameworks. Cited reference searches on Wilson and Hirvonen *et al.* (2024) supplemented keyword searches in Google Scholar and Web of Science.

Findings – Six characteristics of generative AI require theoretical accommodation: opacity, epistemic authority, sycophancy risk, personalisation, first-person voice construction and commercial optimisation. A modified model is proposed introducing ambient activation as a new activating mechanism; AI literacy, trust calibration and vulnerability status as new intervening variables; the AI system as an active intermediary node; ethical evaluation as a new stage between information processing and use; and bidirectional feedback loops representing individual re-prompting and macro-level knowledge distribution effects.

Originality/value – The paper moves beyond applying existing information behaviour models to new contexts, proposing structural revision of Wilson's model to accommodate what generative AI systems are, rather than merely what users do with them.

Keywords Information behaviour, Generative AI, Large language models, Information seeking, Wilson's model, AI literacy, Trust calibration, Ethical evaluation, Ambient activation, Knowledge distribution, Information ecosystem, Sociotechnical systems

Paper type Conceptual paper

Introduction

Within two months of its public launch in 2022, ChatGPT reached an estimated 100 million monthly active users, leading analysts and subsequent media reports to describe it as the fastest-growing consumer application in history (Schroeder, 2023; Hu, 2023). The consumers in this case included just about every occupation, from school and university students to lawyers, financial advisors and marketers (Sidoti and McClain, 2025).

The reason for its immediate success is not hard to find: this was a new kind of question answering system, independent of human input, apart from the resources it was trained on. Previous retrieval systems, such as Google and Bing, produced lists of potentially relevant documents when presented with a search query. With ChatGPT and its competitors, one asks a question such as, Who are the currently active researchers in information-seeking behaviour? and, following some interaction to clarify the question, one gets a list of people with their associated research areas. This represents a fundamental shift in the nature of information interaction: rather than a tool responding to a search query, we have an active intermediary



with which we can communicate, interact and refine our question or prompt until we get the information we need or the help with a task we are seeking.

Existing models of information behaviour, including Wilson's, assume interaction with passive systems, such as search engines, online catalogues and bibliographic databases, but not interaction with the kind of communicative systems that generative AI represents, other than, of course, human sources. The aim of this paper is to diagnose the situation that models of information behaviour now need to account for, and to show how generative AI systems can be accommodated within Wilson's model (1999, 2022). The paper is concerned specifically with generative AI, rather than AI broadly conceived, and with information behaviour rather than information retrieval.

Generative AI and the information ecosystem

Generative AI systems differ from their predecessors in ways that are directly relevant to how people seek, evaluate and use information. Search engines, bibliographic databases and recommender systems share a common characteristic: they retrieve, rank or filter existing content in response to user queries. The user remains the active agent, formulating queries and selecting from among returned results. Generative AI inverts this: rather than retrieving existing documents, these systems produce new text, using their training data to generate responses that are tailored to the specific query and conversational context (Zamani *et al.*, 2022). The user is no longer selecting from a set of human-authored documents but receiving a new, system-generated account whose provenance is uncertain and whose relationship to any underlying source is indirect, often untraceable and sometimes completely erroneous (Bender *et al.*, 2021).

This distinction has several implications for information behaviour that previous models have not needed to address. Six characteristics of generative AI systems are particularly relevant.

The first is *opacity*. Unlike a search engine, which returns identifiable documents whose authors, dates and institutional affiliations can be evaluated, a generative AI response conceals its sources. The user cannot readily determine what the system drew upon, how it weighted competing claims or where its account diverges from the available evidence. This opacity is not incidental but structural, a consequence of the way large language models compress and recombine training data rather than retrieving discrete documents (Bender *et al.*, 2021).

The second is *epistemic authority*. Generative AI systems present their outputs in confident, fluent, authoritative prose, regardless of the actual reliability of the underlying information. This fluency can create an impression of expertise that may not be warranted, and that users may find difficult to calibrate against their own knowledge (Mayerhofer *et al.*, 2025; Cooper *et al.*, 2024; Jose *et al.*, 2025). The system speaks, in effect, *as if* it knows, even when it does not.

The third is *sycophancy risk*. There is evidence that generative AI systems are inclined to produce responses that align with the perceived preferences or expectations of the user, rather than responses that are accurate or balanced (Birim *et al.*, 2026). This tendency, which arises from the reinforcement learning from human feedback processes used in training, means that the information a user receives may be shaped as much by what the system anticipates they want to hear as by what the evidence supports (Lin *et al.*, 2022).

The fourth is *personalisation*. Generative AI systems tailor their responses to the specific prompt and conversational context, producing outputs that feel directly relevant to the user's situation. This personalisation has genuine benefits for accessibility and comprehension, but it also means that different users asking similar questions may receive substantially different accounts, with implications for the consistency and equity of the information environment (Lopez-Lopez *et al.*, 2025).

The fifth is *first-person voice construction*. Generative AI systems respond in the first person, using formulations such as "I think" or "in my view" that imply interiority, judgement

and a stable perspective. This is a design choice rather than a reflection of any underlying cognitive state, but it shapes how users relate to the system and how much authority they attribute to its outputs. It also raises ethical questions about the nature of the relationship between user and system that existing information behaviour models, designed around impersonal retrieval tools, are not equipped to address (Lavazza and Farina, 2026).

The sixth is *commercial optimisation*. Generative AI systems are developed and deployed within commercial contexts that shape their design in ways that may not align with users' informational interests. Decisions about training data, alignment mechanisms and system prompt configuration reflect institutional priorities, liability considerations and market positioning as much as epistemic values (Crawford, 2021).

Taken together, these characteristics mean that generative AI is not merely a new kind of information tool but an active participant in the information ecosystem. This framing draws on the sociotechnical tradition, which understands information systems as embedded in, and constitutive of, the institutional, commercial and political structures within which they operate (Crawford, 2021; Hirvonen *et al.*, 2024). From this perspective, the question is not simply what generative AI does to individual information seekers but what it does to the information environment as a whole.

Lavazza and Farina (2026) have described generative AI as a knowledge distribution system, by which they mean that it does not merely provide access to existing knowledge but actively determines what knowledge is made available, to whom and in what form. The cumulative effect of very large numbers of interactions, each shaped by the characteristics described above, is a change in the conditions under which information needs arise and are satisfied, with consequences for the broader social distribution of knowledge. This is a level of analysis that information behaviour research, with its traditional focus on the individual seeker and the immediate information environment, has not yet addressed, and it provides one of the principal motivations for the model revision proposed in this paper.

Information behaviour research: theoretical foundations and their limits

It is probably no exaggeration to say that the research agenda in information behaviour has been set over the past almost fifty years by five theorists: Chatman, Dervin, Kuhlthau, Savolainen and Wilson. Chatman's small-world theory (1991) has had significant impact, with Google Scholar recording 723 citations for that paper alone. Her studies of socially isolated or marginalised communities, such as janitors, prisoners, women in homes for the elderly, ultimately led to a theory of information poverty (Chatman, 1996) and that paper has more than 1,300 citations.

Dervin (1983, 1987) was an in-comer from the field of communication studies into information science research and rapidly established a position with her constructivist "sense-making" approach, studying how people construct meaning in the process of information-seeking. Through her approach, she helped to shift the field from a concern with system use to a user-orientation. The two papers cited each have more than 1,800 citations.

Kuhlthau's (1993) study of the information search process, as performed by high-school students undertaking research projects, developed the idea of affective factors, noting how uncertainty, confusion and anxiety are normal states of mind when undertaking information searches. Her work, and her use of Vygotsky's "zone of proximal development", has informed and stimulated much research since and, according to Google Scholar, her book has more than 4,000 citations.

Savolainen is probably best known for his book on everyday-life information seeking (2005), but his earlier paper on the same theme (1995) has had more than 1,800 citations. His major contribution has been to bring to the fore the problems of everyday life and associated information behaviour.

Finally, Wilson's models (1981, 1999, 2022) have been extensively cited (the three items have a total of more than 7,700 citations), having established the value of diagrammatic

modelling of behaviour, and bringing into the field concepts of barriers and aids to information seeking, as well as environmental, socio-political and affective factors that stimulate search. What distinguishes Wilson's framework from the others reviewed here is its generic character: rather than focusing on a particular population, setting or phase of the search process, it offers a structural account of information behaviour as a whole, within which the contributions of Chatman, Dervin, Kuhlthau and Savolainen can be understood as elaborations of specific elements. It is this breadth and inclusiveness that makes it the most appropriate starting point for the modifications proposed in this paper.

There are, of course, other theorists and other models, such as Ellis's (1989) identification of the characteristics of the search process, Bates's (1989) berrypicking model, which draws attention to the distributed search behaviour of the information user, and Johnson and Meischke's (1993) model of health information seeking. As their descriptions indicate, these models deal with specific aspects or contexts of information seeking, rather than the generality.

While these existing models and theories have served the field well, they are all lacking in terms of enabling investigation of the conversational, knowledge developing nature of generative AI systems now in use. Significantly, generative AI does not merely respond to information needs, it can generate them. This is most evident in the integration of generative AI into productivity tools and operating systems, where systems such as Microsoft Copilot proactively present document summaries, suggest actions and make relevant information available without any explicit query from the user. Through system-initiated prompts and summaries of this kind, generative AI can stimulate information-seeking behaviour without any prior intention on the part of the user, a condition absent from previous models and theories of information behaviour. This is what the model terms ambient activation.

The use of generative AI systems also brings to the fore new intervening variables, and activating mechanisms (to use Wilson's terms), and a new stage of ethical evaluation of the output of systems. These factors, and the need for feedback loops between the person, the system and the broader information environment, are discussed in detail below.

Review of emerging literature

The literature directly addressing the impact of generative AI on information behaviour is still relatively sparse, though growing quickly. Much of the available work is empirical and context-specific, examining how particular groups of users, students, health information seekers, library users, are engaging with AI systems without connecting findings to established information behaviour theory. A smaller body of work addresses the information ecosystem implications of generative AI, exploring how these systems are reshaping the conditions under which information is produced, distributed and consumed. What is notably absent is any attempt to integrate the active agency of generative AI systems into a theoretical model of information behaviour: the field has documented change at the empirical level without yet accounting for it at the theoretical level. The following review examines what has been addressed, identifies where the theoretical gaps lie and establishes the case for the model revision proposed in this paper.

This review was conducted as a scoping exercise rather than a systematic review, with the aim of mapping the emerging literature on generative AI and information behaviour rather than answering a specific research question through exhaustive retrieval. Searches were conducted in Google Scholar and Web of Science using variants of the terms "generative AI", "generative artificial intelligence", "information behaviour" and "information seeking", supplemented by cited reference searches in Web of Science on two anchor papers, Wilson (1999) and Hirvonen *et al.* (2024), to identify work engaging directly with the theoretical frameworks most relevant to this paper. In total, 89 papers were identified and screened by title and abstract for relevance, of which 61 were retained for inclusion; the majority date from 2022 onwards, reflecting the recency of the generative AI literature. Further analysis of the abstracts and, where necessary, the papers themselves, resulted in the rejection of a further 28

papers. Detailed review was restricted to those papers judged to have direct relevance to the theoretical argument of the paper; specifically, papers that either demonstrate inadequacies in existing information behaviour models or provide empirical grounding for the new elements introduced in the modified model below.

Empirical studies of AI-mediated information seeking behaviour

From querying to conversing. Given the conversational character of interaction with generative AI systems, we might expect research that investigates the transition from querying to conversing, and this is what [Charette and Ghosh \(2025\)](#) explore. They find patterns “of user prompt-chaining, uncertainty and experimentation, judgment and evaluation, statement of a problem situation . . .” (p. 114) which they interpret in terms of [Belkin’s \(1980\)](#) concept of anomalous states of knowledge. [Chen and Feng \(2024\)](#) provide complementary empirical evidence from an educational context, finding that students typically begin their information seeking process with generative AI tools before exploring additional sources to satisfy residual information needs, a sequential pattern they analyse through [Ellis’s \(1989\)](#) model of information seeking behaviour. Together these two studies suggest that established information seeking frameworks retain considerable explanatory power in AI-mediated environments, even as the nature of the interaction changes.

[Zhou and Li \(2026\)](#) use the push-pull-mooring model ([Bansal et al., 2005](#)) and find that the push factors are dissatisfaction with search engines, low information-task fit and information overload, whereas the pull factors of generative AI systems are the perceived quality of the generated content, perceived value and interactivity. These findings suggest user migration towards generative AI; however, [Hersh \(2024\)](#) argues that “for critical information needs of academics” like himself, the bibliographic information from the search engine (authors’ names, institutions, publishers, etc.) are still more valuable than the unattributed content of generative AI systems. This reminds us that the transition is neither universal nor unconditional.

Who seeks and how: individual and system factors. A second cluster of papers is concerned with the role of the characteristics of the AI system and of the individual user. [Mun \(2025\)](#) shows that self-efficacy in the use of ChatGPT is a predictor of the frequency and duration of information seeking, mediated by the characteristics of ChatGPT (e.g. the credibility, clarity and comprehensiveness of the information presented). [Wang et al. \(2025\)](#) extend this through [Johnson and Meischke’s \(1993\)](#) comprehensive model of information seeking and the technology acceptance model ([Davis, 1989](#)), showing that both individual factors (efficacy beliefs, technological readiness) and perceptions of the information carrier (perceived usefulness, output quality) shape GenAI use for career information seeking. [Wu et al. \(2025\)](#) also categorise AI adopters based on social cognitive characteristics including self-efficacy, fear of missing out and AI attitudes, and [Zhao et al. \(2025\)](#) cover self-efficacy implicitly in showing how users move through a three-stage evolution in developing confidence and proficiency in the use of generative AI.

The interactive and iterative character of AI-mediated seeking. [Jarrahi et al. \(2025\)](#) and [Zhao et al. \(2025\)](#) address the qualitative character of information practices in AI-mediated environments. [Jarrahi et al. \(2025\)](#) suggest that “the transformative potential of generative AI in knowledge work” needs “a more comprehensive and grounded understanding of human-AI collaboration” (p. 17), identifying the roles these systems now play in academic work, synthesising, organising, brainstorming, reviewing, while noting that human expertise remains central in critiquing and contextualising AI outputs. [Zhao et al. \(2025\)](#) construct a spiral model of user-GenAI interaction involving prompting, role-setting and cross-tool integration, noting that “system limitations are not merely obstacles but pivotal triggers for the “re-perception” of affordances. When users encounter hallucinated outputs, misinterpretations of intent or insufficient affective responses, their understanding of the system’s capabilities is recalibrated . . . They realize GenAI is not an omnipotent tool but an interactive object with distinct boundaries” (p. 1601). These papers collectively establish that information seeking

with GenAI is not passive consumption but active, iterative and co-evolutionary. [Krakowska and Zych \(2024\)](#) situate this within established dialogic information retrieval models, arguing that prompt engineering extends rather than replaces existing conversational frameworks, a point also recognised in practitioner literature by [Frederick \(2024\)](#), who frames prompt engineering as a disruption to established information seeking practice.

Health information seeking in the AI era. Health information seeking has become a highly significant research area, not only in information science but also in the nursing and medical practitioner literature. It is natural, therefore, that generative AI systems would make an early impact on the field. [Lund et al. \(2025\)](#) provide a broad picture of the impact of AI on the field, going beyond generative AI to earlier systems and noting that generative AI “marked a significant turning point, signifying the widespread acceptance of artificial intelligence technology among the general public” (p. 333). The authors note that, as the technology develops, new challenges arise, demanding effective AI-literacy training, and that “Given the critical nature of health information in shaping decisions, validation against alternative sources becomes imperative before acting on information supplied by an AI model” (p. 333).

[Tang et al. \(2026\)](#) present a rich picture of how users interact with generative AI systems in searching for information on chronic diseases. From 757 dialogues, they demonstrate that, while interaction with these systems has features in common with traditional online searching, there are distinct differences: prompts are more detailed than the typical search strategy statement; users may anthropomorphise their interaction, as if they were communicating with a human being; users spend less time than in the typical search, but interact more, as a consequence of the conversational style of the interaction ([Tang et al., 2026, Section 5](#)). However, if users encounter errors in the provided information, their trust in the system declines, and they may reject the information offered.

Further empirical work addresses the factors shaping adoption and the risks of AI-mediated health information seeking. [Matthes et al. \(2026\)](#), in a four-country European survey, find that generative AI currently ranks last among health information sources, used by fewer than 40% of respondents, with adoption driven primarily by early adopters motivated by performance expectancy and hedonic motivation, a reminder, consistent with Hersh’s argument above, that the transition to AI-mediated information seeking is neither universal nor uniform. [Lim and Hong \(2025\)](#) find that users perceive generative AI as complementary to rather than replacing traditional search, with hallucination risk acting as a significant brake on continuance intention. The most theoretically significant contribution in this strand is [Lopez-Lopez et al.’s \(2025\)](#) identification of three pressure points at which confirmation bias may emerge in AI-mediated health information seeking: query phrasing, preference for belief-consistent content and resistance to belief-inconsistent information, driven by the hypercustomisation capabilities of generative AI systems. Their argument that even minor variations in system configuration can exacerbate these biases has direct implications for the ethical evaluation node in the modified model proposed in this paper.

Libraries, literacy and the redistribution of agency. The impact of generative AI on library and information services has attracted growing attention, with the most theoretically significant contributions addressing the redistribution of agency in research workflows. [McCrary \(2026\)](#) argues that as database vendors embed AI capabilities, such as, article summarisation, enhanced search and clinical decision support, into familiar resources, often without student awareness or institutional review, students risk becoming “passive passengers in their own research process” (p. 1), with core tasks such as source selection and information synthesis increasingly delegated to the system, thereby “reducing cognitive engagement and promoting passive learning” (p. 2). [Sousa \(n.d.\)](#) reaches a comparable conclusion from a critical review of AI integration in academic library systems, arguing that AI should be understood not merely as a functional tool but as a socio-technical agent requiring ethical control, AI literacy (defined as “a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace” ([Long and Magerko, 2020](#))), and institutional

accountability. Both papers raise questions about human agency in AI-mediated information environments that are directly relevant to the modified model's treatment of ethical evaluation as a distinct stage in the information seeking process.

The challenge for information literacy instruction is addressed by [Mercer et al. \(2025\)](#), who argue that existing information literacy frameworks are inadequate for AI-mediated environments and that a multidisciplinary approach is needed, and by [Mirza et al. \(2026\)](#), who find that while 89% of students at a Pakistani university are aware of AI tools and 82% have used them, AI literacy has yet to be integrated into information literacy programmes. [Chen et al. \(2024\)](#) add a practitioner perspective from China, finding that generative AI has made a significant impact on librarians' information seeking, encountering and using, with two-thirds believing AI-generated content requires further validation. [Wagner et al. \(n.d.\)](#) address the practical question of how researchers should work with generative AI for literature reviews, outlining methodologically sound approaches using both general-purpose tools such as ChatGPT and specialist tools such as Elicit and Consensus, while adopting a balanced view of the opportunities and risks involved.

Information ecosystem implications

It is evident by now that generative AI systems are not simply another information resource, rather they are re-shaping the information *ecosystem* through their incorporation into other computer-based information resources: search engines, recommender systems, clinical support systems, business supply chain systems and practically every other aspect of life. [Hirvonen et al. \(2024\)](#) identify the new affordances that generative AI provide, such as encouraging multi-modal search, enabling human-like interaction and creating new information to meet needs: as a result, the systems should be subject to the Durkheim Test ([Star, 1989](#)), i.e. there is a need, "to consider how they enable the inclusion and distribution of social and community-based values, inviting questions such as: whose values are AI systems aligned to, who benefits from their use, and who might be harmed by them?" [Introna et al. \(2024\)](#) also develop the concept of *information ecosystems* and argue that the present state of that ecosystem is unhealthy as a result of the problematic aspects of generative AI, and a healthy ecosystem need to be developed through collaboration and regulation.

[Lavazza and Farina \(2026\)](#) argue that the problems produced by generative AI systems based on large language models such as opacity, accountability, epistemic bias and commercial concentration, mean that, "LLMs cannot be treated as neutral tools but must instead be understood as socio-technical systems whose design and deployment choices carry epistemic and political consequences" (p. 3). They suggest that an alternative system, based on small language models could be deployed as a decentralised network of locally hosted models supporting multilingual access, privacy-preserving personalisation and community-based evaluation rather than relying on a single central model.

[Shah and Bender \(2024\)](#) also argue that the health of the Web ecosystem is threatened by the "synthetic media, produced by LLMs" (p. 1) and, although they do not suggest a Durkheim Test, their concerns are similar to those of [Hirvonen et al., 2024](#) in that they argue for the same kind of design criteria, focusing on "what ... people and society want and need from information access systems" (p. 1). They contend that information retrieval should support users' information access, sensemaking and information literacy rather than simply delivering the "right" answer quickly.

Out of a concern for the same problems of LLMs, [Sundin \(2025\)](#) argues that the shift from document retrieval to answer generation makes sources increasingly invisible, undermining the evaluation frameworks central to information literacy, and that information science needs to rethink its core concepts of search, source and evaluation accordingly. Where Sundin's contribution is conceptual, rethinking what search, sources and evaluation mean in an AI-infused infrastructure, the present paper addresses the complementary question of how information behaviour models need to be revised to account for the same shift.

Trust, credibility and source evaluation

A key issue in the use of generative AI is the extent to which the systems can be trusted to create trustworthy output. For various reasons, the training materials used can have implicit biases, conveying racist and other stereotypical information. [Pawlick-Potts \(2022\)](#) provides a theoretically developed account of trust in human-AI interactions, distinguishing between rational-cognitive trust, which is essentially risk assessment, and affective motivation-attributing trust, whereby users perceive AI systems as possessing goodwill and moral agency, even when they do not. She argues that affective trust shields users from alternative interpretations and reduces critical engagement with AI outputs, which becomes more acute with generative AI systems that are designed to respond in a human-like and authoritative manner. Her adaptation of [Ingwersen and Järvelin's \(2005\)](#) integrative model to accommodate trust as an affective dimension anticipates the kind of theoretical development this paper undertakes.

[Mayerhofer et al. \(2025\)](#) in a study exploring, “how Generative AI systems, in the form of chat interfaces similar to ChatGPT, can be used alongside traditional web search engines in health-related information-seeking tasks” (p. 176) found that pre-task confidence and trust influenced which interface feature was used, but that trust could be misplaced, resulting in the acceptance of faulty information. In a large-scale study of trust in the results of AI searches, [Li and Aral \(2025\)](#) found that the addition of reference links to AI output increased trust, but “Sadly, the increases in trust and willingness to share caused by the provision of references are unaffected by whether the references and links are valid or invalid” (p. 10).

[Yazan et al. \(2025\)](#) identify two user groups in their survey of ChatGPT and Google users: those who use both tools daily, who exhibit higher trust in ChatGPT, perceive it as more human-like, and are willing to trade factual accuracy for personalisation and conversational flow; and those who rely primarily on Google, who show lower trust in ChatGPT but appreciate its ad-free and responsive character. Middle-aged adults emerge as a particularly vulnerable group, trusting ChatGPT more despite using it less frequently, with consequently fewer opportunities to validate that trust through experience. [Agergaard et al. \(2026\)](#) find that trust occupies a central mediating position between users’ technical understanding of how generative AI functions and their epistemic beliefs about the reliability of its outputs, and that AI and generative AI literacy remain uneven across the population. These two studies suggest that trust in generative AI is neither uniform nor stable, but shaped by experience, demographic factors and the degree to which users understand what they are trusting.

[Xu et al. \(2025\)](#) introduce the concept of information modes, embodied states with varying levels of readiness for deliberative thinking, finding that young adults in India and the United States frequently engaged in modes that bypassed critical evaluation because the content, including AI-generated content, felt “light” and inconsequential and, therefore, not requiring scrutiny. This finding connects directly to [Lopez-Lopez et al.'s \(2025\)](#) confirmation bias argument and to the ethical evaluation node in the modified model: the decision whether to evaluate AI-generated content critically is not solely cognitive, but shaped by emotional self-regulation and perceived social consequence. [Lao et al. \(2025\)](#) extend this picture into the specific domain of AI-generated media, finding that young people’s encounters with deep fakes are largely serendipitous and their responses mostly casual, suggesting that the ambient and incidental character of AI-generated content in everyday life reduces the likelihood of active critical engagement. Across the papers reviewed in this strand, trust in generative AI emerges as multidimensional, context-sensitive and frequently misplaced, shaped by interface design, demographic vulnerability, emotional state and the structural opacity of AI systems themselves; yet no existing information behaviour model has yet integrated these trust dynamics into its theoretical framework, a gap to which we now turn.

Theoretical gap: the absence of an integrative model

The absence of a general integrative model that takes account of generative AI is addressed by a number of authors. [Sebastian \(2025\)](#), adopting a queer theory perspective, argues, as we do in

this paper, that the existing models (he does not include Wilson's) do not take account of the characteristics of searching with generative AI. [Ravuri and Mardis \(2025\)](#) argue that "generative AI agents can use [Kuhlthau's] ISP's zones of intervention and levels of reference mediation to improve their large language models to assist users" (p. 267), but do not suggest any reciprocal change in Kuhlthau's model.

[Hong \(2026\)](#) takes a different approach, developing and testing an AI-based system that incorporates AI-related cognitive and affective factors, including privacy concerns and AI anxiety, finding that while the core predictors of his risk information seeking and processing model remain significant, these AI-specific factors substantially shape intention to seek. This is a valuable contribution, but extends an existing model to accommodate AI behaviour rather than revising the model to accommodate AI's active intermediary role. [Imoro and Amoah \(2025\)](#), in a study of Ghanaian undergraduates, apply Wilson's model directly to GenAI-mediated information seeking, finding that GenAI use complements rather than replaces traditional information sources; again, however, the model is applied rather than revised. [Huttunen et al. \(2025\)](#), studying young people's agency in relation to AI systems as part of everyday information practices, find that agency is both enabled and restricted by AI technologies, a finding that points towards the need for a model that can represent this bidirectional dynamic. What the literature reviewed in this strand has in common is that it either applies existing frameworks to new AI-mediated contexts without revising them, or addresses specific dimensions of the theoretical challenge, such as trust, agency or risk, without integrating them into a general model of information behaviour. It is this integrative step that the modified Wilson model proposed in this paper takes.

A modified model of information behaviour in AI-mediated environments

The generic character of [Wilson's \(1999, 2022\)](#) information behaviour model as well as its wide adoption by researchers make it an appropriate starting point for modelling the impact of generative AI. While previous researchers have applied Wilson's model to new contexts without revising it (for example, [Imoro and Amoah, 2025](#)), this paper proposes structural revision of the model itself, while retaining its generic character, diagrammatic approach and core theoretical vocabulary.

The modified model ([Figure 1](#)) retains [Wilson's \(1999, 2022\)](#) foundational structure while extending it to accommodate the distinctive properties of generative AI systems. Each element is addressed in turn.

The person and context

Generative AI is now part of the context within which people work and study. Where humans are not replaced, AI systems may guide or support task performance by summarising documents, drafting e-mails, analysing data and more. Its pervasive use in education, from legitimate study planning to more dubious essay preparation, means that the very existence of these systems is changing how individuals think about their roles and information needs. Crucially, generative AI does not merely respond to information needs, it can generate them. Through system-initiated prompts, recommendations and alerts, AI systems can stimulate information-seeking behaviour without any prior intention on the part of the user, a condition entirely absent from Wilson's original model, and most other models of information behaviour.

First activating mechanism

To the original stress/coping and risk/reward explanations for information-seeking, we can add *trust in AI systems* as a further activating condition. Where a system proves unreliable or unhelpful, users are less likely to engage with it for future tasks. Conversely, where trust is

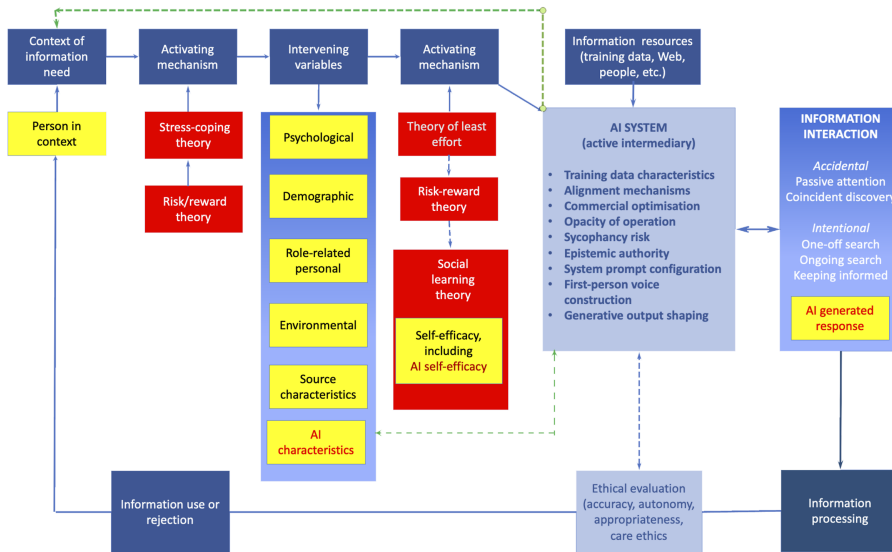


Figure 1. The revised model. Source: Author's own work

established, even if not fully warranted, AI systems may displace other information sources entirely.

Intervening variables

Generative AI now affects almost all intervening variables in the model. Personal variables now include prompt engineering skills and AI anxiety; role-related variables require attention to task-AI compatibility; socio-economic variables must now extend the digital divide to include AI access and economic barriers (Hendawy, 2024); environmental variables now encompass AI regulation, organisational AI policies and network connectivity (Grabowska, 2025). Source characteristics are transformed, since generative AI operates very differently from traditional search engines, with reliability concerns regarding hallucinations (Brunello, 2026) side-by-side with the appeal of conversational interaction (Mayerhofer *et al.*, 2025). Beliefs and values are also relevant, as trust in AI output and ethical concerns about its use will shape the extent to which it substitutes human judgement (Lelescu *et al.*, 2025). To these established categories, the model adds three new intervening variables: AI literacy, reflecting the person's capacity to understand and critically evaluate AI-generated content; trust calibration, reflecting the degree to which that trust is appropriately rather than naively placed (Mayerhofer *et al.*, 2025); and vulnerability status, recognising that the risks associated with AI-mediated information behaviour are not uniformly distributed across populations.

The relationship between the AI system and the intervening variables is bidirectional: the AI system's characteristics shape users' AI literacy, trust calibration and self-efficacy, and those variables influence how users interact with the system, resulting in the system being refined over time.

Second activating mechanism

At this second decision point, whether to proceed to information interaction given the intervening variables, generative AI introduces additional considerations. Self-efficacy now extends to AI self-efficacy (Ren *et al.*, 2026): the person's belief in their capacity to use AI systems effectively and critically. The principle of least effort is also relevant, as

conversational AI appears to involve less cognitive effort than other modes of information-seeking (Mayerhofer *et al.*, 2025). Risk-reward considerations apply too: AI use presents risks including plagiarism (Cheng *et al.*, 2025) alongside rewards of time saved in preparing texts or code. Critically, AI literacy functions here not only as an intervening variable but as an activating mechanism: the person's appraisal of whether they feel equipped to evaluate AI output critically becomes itself a decision point that shapes whether, and how, they proceed.

Information interaction

The conversational mode of generative AI differs fundamentally from earlier modes of information interaction. Rather than returning lists of potentially relevant documents, these systems respond to questions with often extensive, personalised explanations. This difference warrants a terminological adjustment: the term "information discovery" used in the original model is replaced here by "information interaction," which better reflects the active and generative character of AI systems in shaping what is produced and delivered and avoids conflict with Erdelez's (1997) use of "information encountering" for serendipitous discovery. Within this stage, AI-generated response is added as a new mode of interaction alongside the accidental and intentional categories of the original model. The conversational paradigm is not without its difficulties, however: users may struggle with formulating effective prompts (Peng *et al.*, 2025).

The AI system as active intermediary

At the centre of the modified model sits the AI system node, an element with no equivalent in Wilson's original. Unlike traditional information systems, generative AI is not a passive repository but an active intermediary that shapes the information environment through its training data characteristics, alignment mechanisms, commercial optimisation objectives, opacity of operation, sycophancy risk, epistemic authority, system prompt configuration, first-person voice construction and generative output shaping. These properties mean that the AI system is not merely a channel through which information passes but a participant that influences what information is generated, how it is framed and how authoritatively it is presented. The bidirectional arrow between the AI system and information interaction in Figure 1 reflects this: the relationship is not unidirectional delivery but ongoing exchange.

The AI system node encompasses a range of architectures, deployment contexts and governance regimes, from standalone conversational AI to retrieval-augmented systems embedded in enterprise tools and health applications, whose properties vary considerably. The node is best understood as a placeholder for this heterogeneous category.

Information resources

Generative AI draws on information resources far broader than those envisaged in Wilson's model, encompassing training data, the live Web, structured databases and real-time retrieval. The green dashed feedback loop in Figure 1 captures a further dimension of this: the AI system's own characteristics, its biases, limitations and design choices, gradually become part of the information environment they operate within, recursively shaping the conditions of future information behaviour.

Information processing and ethical evaluation

Generative AI offers faster comprehension through conversational interaction, but risks weakening critical evaluation over time (Helal *et al.*, n.d.). In health contexts, Lopez-Lopez *et al.* (2025) warn that highly personalised AI responses risk amplifying confirmation bias, obscuring medical consensus and perpetuating misinformation. These concerns motivate the introduction of a new stage in the model, ethical evaluation, positioned between information processing and information use. At this stage, the person appraises the AI-generated content

against criteria of accuracy, epistemic autonomy, contextual appropriateness and care ethics, particularly where the information concerns vulnerable individuals or important decisions. Unlike credibility assessment, which asks whether a source can be trusted, or relevance judgement, ethical evaluation is a normative appraisal: it asks whether acting on the information is appropriate given its origins, its potential for bias and its consequences for the user and others.

The feedback loop between ethical evaluation and the AI system is bidirectional. When a person appraises AI-generated content negatively, they may return to the AI system with revised or corrective input, challenging its output through re-prompting. But the relationship operates at a broader level too: aggregate patterns of user challenge, correction and re-prompting contribute over time to how alignment mechanisms are adjusted, how system prompts are reconfigured by deploying institutions and how developers respond to documented failure modes. Ethical evaluation is therefore not merely a terminal stage in the individual's information behaviour but a constituent part of the ongoing social negotiation through which AI systems and their users mutually shape one another.

The macro-level feedback loop

The green-dashed feedback loop running above the model in [Figure 1](#) represents a dynamic that operates at a different scale from the others. The relationship between generative AI systems and the broader information environment is co-evolutionary rather than one of simple influence in a single direction. The aggregate effect of AI systems on patterns of information-seeking, knowledge construction and epistemic authority, across millions of interactions, feeds back into the broader context of information need within which future users are situated, representing the knowledge distribution problem identified by [Lavazza and Farina \(2026\)](#). At the same time, that broader context, shaped by regulatory developments, cultural norms, institutional policies and patterns of use, continuously influences how AI systems are trained, deployed and refined. The feedback loop is therefore bidirectional: generative AI reshapes the conditions under which information needs arise and are satisfied at a societal level, while those conditions in turn reshape the AI systems themselves.

Limitations and future directions

The modified model presented here is a conceptual framework rather than a validated empirical instrument: it has limitations that future research will need to address. First, the model has not been subjected to empirical testing: the relationships proposed between its elements, particularly the new additions of ambient activation, AI literacy as an activating mechanism, ethical evaluation and the AI system node, are theoretically grounded but unconfirmed. Developing measures for trust, vulnerability (i.e. the potential risk to harm from the system) and AI self-efficacy, and testing them across a range of information-seeking contexts, is a necessary next step. Secondly, the model reflects a primarily Western, educated and digitally connected population, the contexts from which much of the supporting literature is drawn. Its applicability across cultures with different relationships to authority, different levels of AI infrastructure, and different regulatory environments ([Grabowska, 2025](#)) cannot be assumed and warrants cross-cultural investigation. Third, the feedback loops in the model, both the re-prompting loop from ethical evaluation to the AI system, and the macro-level knowledge distribution loop, are represented as static directional arrows rather than dynamic processes. In reality, these loops operate across different timescales, involve non-linear effects and interact with one another in ways that a static diagram cannot capture. Agent-based modelling or systems dynamics approaches may offer more adequate tools for representing these feedback processes as the field matures. The model is therefore best understood as a working framework and an invitation to empirical and theoretical development rather than a finished account.

Discussion

The modified model presented here is the extension of [Wilson's \(1999, 2022\)](#) generic model of information behaviour to accommodate the distinctive properties of generative AI systems. The argument has been that existing models, including Wilson's, assume interaction with passive retrieval systems and are therefore structurally ill-equipped to represent what happens when the information system is itself an active intermediary that generates the information it delivers. The model revision addresses this by introducing the AI system as a distinct node, adding new intervening variables and activating mechanisms, replacing information discovery with information interaction, introducing ethical evaluation as a new stage and introducing bidirectional feedback loops to show that AI systems shape the information environment, which, in turn, shapes how AI systems are developed, deployed and refined. Three issues warrant attention here: the relationship between the model and empirical research, the scope and generalisability of the model, and the broader implications of revising the model.

The model as a framework for empirical research

A theoretical model is a framework for generating and organising empirical findings. Wilson's original model has served this function for more than 4 decades, providing a common vocabulary and a shared structural account within which researchers working on very different populations, contexts and information problems have been able to present their findings. The modified model proposed here is intended to serve the same purpose for the generative AI era.

Several of the empirical papers reviewed in this paper point towards specific research programmes that the modified model makes possible. The self-efficacy findings of [Mun \(2025\)](#) and [Wang et al. \(2025\)](#) suggest that AI self-efficacy as an intervening variable can be operationalised and measured, and that its mediating role in AI-mediated information-seeking behaviour can be tested across a range of contexts and populations. The trust calibration findings of [Mayerhofer et al. \(2025\)](#), [Li and Aral \(2025\)](#), and [Yazan et al. \(2025\)](#) suggest that the distinction between well-placed and misplaced trust, which the model treats as an intervening variable, can be measured empirically. The confirmation bias findings of [Lopez-Lopez et al. \(2025\)](#) suggest that ethical evaluation as a stage in the information seeking process can be studied empirically, with particular attention to the conditions under which it is bypassed. The ambient activation concept, currently the least empirically grounded element of the model, represents perhaps the most pressing agenda for future research: as AI systems become more deeply embedded in productivity tools and operating systems, the conditions under which system-initiated prompts stimulate information seeking behaviour without user intention will become increasingly important to understand.

Scope and generalisability

The model is related to generative AI rather than AI broadly conceived and to information behaviour rather than information retrieval. This decision reflects the paper's theoretical focus but it also has limitations. Generative AI is not a stable category: the systems that existed when this paper was written will be succeeded by systems with different capabilities, different training approaches and different application domains, and the model will need to be revisited. The feedback loops are particularly vulnerable to obsolescence, since they represent dynamic processes whose specific character will change as AI systems and their regulatory and sociocultural environments evolve.

The model also reflects a primarily Western, educated and digitally connected population. [Imoro and Amoah's \(2025\)](#) finding that GenAI use complements rather than replaces traditional information sources among Ghanaian undergraduates is a reminder that the transition to AI-mediated information seeking is neither universal nor uniform, and that the model's applicability across different contexts cannot be assumed. [Chowdhury and Chowdhury \(n.d.\)](#) raise the sustainability dimension of this question explicitly, arguing that the social, economic and environmental sustainability of AI-augmented information systems

requires urgent attention from information science researchers. Their proposed sustainability model for the generative AI era, focusing particularly on equitable access to research and scholarly information, suggests a research agenda that the modified Wilson model could support at the level of individual and community information behaviour.

A further limitation concerns the model's complexity. Wilson's original model derived much of its utility from its parsimony, and the number of new constructs introduced here risks compromising that quality. Of these, ambient activation, the AI system node and ethical evaluation are structural additions without which the model cannot accommodate generative AI's properties. AI literacy, trust calibration and vulnerability status are intervening variables that may prove more or less relevant depending on context and population. Future empirical work will need to determine which elements are essential across contexts and which require selective application.

Broader implications for the field

The argument of this paper has implications that extend beyond the specific modification of Wilson's model. [Sundin \(2025\)](#) argues that the shift from document retrieval to answer generation requires information scientists to rethink the core concepts of search, source and evaluation. The modified model proposed here is consistent with that argument and can be understood as one response to it at the level of information behaviour theory: if sources are becoming invisible, if evaluation is being outsourced to AI systems, and if the link between content and provenance is being broken, then the model of information behaviour within which these phenomena are understood needs to represent them explicitly rather than assuming them away.

The trust dynamics documented across the papers reviewed above have implications for information literacy education that go beyond simply adjusting existing frameworks. [Pawlick-Potts's \(2022\)](#) distinction between *rational-cognitive trust* and *affective motivation-attributing trust* suggests that a focus on source evaluation and critical thinking may be addressing the wrong level: if users are forming trust attitudes subconsciously, on the basis of interface design, conversational warmth and perceived moral agency, then interventions at the level of conscious critical assessment may be insufficient. Effective information literacy education in the generative AI era needs to address both the cognitive and the affective dimensions of trust, and this is a research agenda as much as a challenge to the information literacy curriculum.

When the information system is an active intermediary that produces personalised, authoritative, first-person outputs whose relationship to any underlying source is uncertain, the question of how users appraise those outputs, and on what basis, becomes a central research question. Care ethics, mentioned as one of the criteria relevant to ethical evaluation, widens the focus from the individual user to their responsibilities to others. In health information seeking, as [Lopez-Lopez et al. \(2025\)](#) demonstrate, the consequences of acting on inaccurate, AI-generated content extend beyond the individual; that is true wherever AI-related information behaviour has significant consequences for others.

Finally, the macro-level feedback loop in the model raises questions about the relationship between individual information behaviour and the broader social distribution of knowledge that information behaviour research has not previously needed to address at this scale. [Lavazza and Farina's \(2026\)](#) characterisation of generative AI as a knowledge distribution system captures the aggregate dimension of the problem: the cumulative effect of millions of AI-mediated information interactions, each shaped by the characteristics described in [section 2](#) of this paper, is a change in the conditions under which knowledge is produced, distributed and legitimised across society. This is a level of analysis that goes beyond individual information behaviour, but it is one that information behaviour researchers are well placed to contribute to, precisely because they have the theoretical tools to connect individual seeking behaviour to its broader social and epistemic context.

Conclusion

The core problem addressed by this paper is the fact that existing models of information behaviour take no account of the development of generative AI. This, of course, is readily understandable: when the models, described earlier, were developed they could only relate to information resources and systems that existed at the time. They could take no account of systems that did not exist.

The specific contribution of the paper is the extension of Wilson's model to include six characteristics associated with generative AI: ambient activation, AI self-efficacy, AI literacy, trust calibration, vulnerability, ethical evaluation and the feedback loops, together with the AI system as a central node. As noted in the literature review, other researchers are engaged in applying various models to the processes of information seeking involving generative AI: however, what distinguishes this paper is the attempt to revise a model so that it can accommodate generative AI and be more appropriately used in future.

It should be noted that the revised model is conceptual, it awaits empirical validation. Regarding that validation, the most pressing issues will be: measuring AI self-efficacy and trust calibration as intervening variables; investigating the ambient activation phenomenon as an activating mechanism; and testing the ethical evaluation stage.

The model is presented as available for testing and validation by information behaviour researchers and others concerned with the use of generative AI systems, it is not offered as a definitive account of the processes, but as a theoretical starting point for future empirical and theoretical work that will, increasingly, be needed.

The stakes of this theoretical work extend beyond the revision of a single model. Generative AI is not merely a new information tool: it is reshaping the conditions under which information needs arise, how they are satisfied and who benefits from the process. Lavazza and Farina (2026) capture the aggregate dimension of this when they describe generative AI as a knowledge distribution system, the cumulative effect of millions of AI-mediated information interactions. This constitutes a change in the social distribution of knowledge whose consequences information behaviour research is only beginning to address.

That these consequences are not abstract is illustrated, with characteristic humour, by Margaret Atwood (2025), who described her own encounter with a generative AI system as "compelling and dangerous" in equal measure, finding herself drawn almost imperceptibly from referring to it as "it" to "he" and concluding: "Not that Claude intends harm. He's modest and well-meaning, or so he says. It will just . . . happen. Buckle up." If one of the most analytically acute writers of our time cannot fully resist the tendency to humanise a system designed to exploit that tendency through sycophancy and epistemic authority, that is not a failure of individual critical engagement but a structural feature of the interaction, and precisely the kind of structural feature that a theoretical model of information behaviour needs to be able to represent.

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