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**Editor's Note:**

# From Retrieval to Mediation: Generative AI and the Reconfiguration of Information-Seeking Behavior Across the Life Course

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## Abstract

**Purpose:** This editorial examines how generative artificial intelligence is reconfiguring information-seeking behavior by shifting users from interaction with predominantly retrieval-oriented systems toward engagement with active and conversational intermediaries that participate in searching, synthesizing, evaluating, and shaping information use across the life course.

**Methodology:** The article draws on an evidence-informed integrative synthesis of selected and credible research on information behavior, AI literacy, trust and verification, cognitive offloading and cognitive delegation, anthropomorphism, the AI divide, and family and institutional mediation. Evidence is examined across five life stages, childhood, adolescence, emerging adulthood, midlife, and later life, and subsequently organized through an evidence-informed SWOT framework and TOWS analysis.

**Findings:** Life stage does not directly determine GenAI-mediated information behavior; rather, its effects emerge through interaction with information and AI literacy, domain knowledge, metacognition, self-efficacy, prior experience, socioeconomic resources, and context of use. In childhood, source recognition and parental mediation are particularly salient; in adolescence, credibility assessment and ethical use; in emerging adulthood, the management of cognitive offloading and delegation; in midlife, efficiency, domain knowledge, and risk-sensitive trust; and in later life, access, self-efficacy, verification, and mediated use.

**Conclusion:** Educational and policy goals should move beyond increasing AI use and instead foster AI literacy, calibrated trust, verification competence, and retained epistemic agency.

**Value:** The editorial proposes a multilevel, life-course framework for understanding GenAI-mediated information behavior while avoiding deterministic generational interpretations.

**Keywords:** ***Generative Artificial Intelligence; Information-seeking Behavior; Life Course; AI Literacy; Epistemic Agency; Calibrated Trust; Cognitive Delegation***

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## 1. Introduction: From Retrieval to Mediation

The emergence of generative artificial intelligence (GenAI), particularly large language models (LLMs), has not simply added another tool to the expanding repertoire of information resources. More fundamentally, it is reshaping the logic through which information is sought, evaluated, interpreted, and used. In conventional information retrieval environments, users typically entered a system with an information need or problem, formulated a query, and received a set of documents, webpages, scholarly articles, or other information objects in response. The tasks of selecting among sources, comparing them, assessing their credibility, and synthesizing their contents remained largely the responsibility of the user. By contrast, LLM-based systems do not merely retrieve or point to information; they generate, synthesize, reframe, and present responses within an interactive conversational exchange. In this sense, generative AI can no longer be understood simply as an extension of information retrieval systems. It increasingly operates as an active information intermediary capable of participating in the articulation of questions, the clarification and reformulation of information needs, the synthesis of information, the suggestion of subsequent lines of inquiry, and even the direction of the interaction itself (Wilson, 2026).

This transformation makes it necessary to distinguish among three related but conceptually different phenomena. Information retrieval is primarily concerned with the matching of queries to information objects and the return of relevant items. Information seeking encompasses a broader range of cognitive, affective, contextual, and behavioral processes through which individuals recognize an information need, seek information, select and evaluate sources, and ultimately use what they have found. Generative AI introduces a further configuration that may be described as AI-mediated conversational information behavior. In this environment, the user is not merely searching for a source but engaging with a system that constructs responses, offers apparently reasoned explanations, adapts the level and language of its output to the user, and develops subsequent responses in light of the preceding exchange. Depending on the context, such a system may be perceived not only as a tool, but also as an information source, adviser, cognitive collaborator, or even an epistemic authority. This shift raises a new set of questions concerning information provenance, credibility, trust, verification, cognitive delegation, and the preservation of human epistemic agency.

The implications of this transformation, however, are unlikely to be uniform across users. A child who is still learning to distinguish reliable from unreliable information does not encounter generative AI under the same conditions as an adolescent who has incorporated such systems into everyday educational and social practices. Nor does a university student who delegates part of the search and synthesis process to AI occupy the same informational position as a middle-aged adult using GenAI for professional, family, financial, or health-related decisions, or an older adult who may simultaneously benefit from simplified conversational access while facing barriers related to digital experience, confidence, or access. The study of information behavior in the age of generative AI therefore requires sensitivity to differences across the life course and to the contexts in which AI-mediated information seeking takes place.

At the same time, analytical categories such as Generation Alpha, Generation Z, Millennials, Generation X, and Baby Boomers should be used with caution. Although such labels may provide approximate historical markers for cohorts that have encountered digital technologies under different social and technological

conditions, they should not be treated as natural, fixed, or intrinsically explanatory categories. Methodological critiques of generational research have repeatedly shown how difficult it is to disentangle the effects of age, historical period, and cohort in cross-sectional designs. Differences attributed to a "generation" may instead reflect life stage, educational background, socioeconomic resources, cultural context, prior technological experience, or some combination of these factors (Costanza et al., 2023; Rudolph et al., 2021). Accordingly, generational labels are used in this editorial only as descriptive reference points where useful, while the primary analytical framework is a life-course perspective.

Within this framework, the editorial is guided by four interrelated questions. First, how does generative AI reconfigure information-seeking behavior across different stages of the life course? Second, what user-level strengths and vulnerabilities, and what environmental opportunities and threats, characterize GenAI-mediated information behavior at these stages? Third, what strategies can be derived from the interaction of these factors at the individual, family and institutional, and governance levels? Fourth, what new research agenda does this transformation create for Knowledge-Research Studies, particularly in relation to information behavior, AI literacy, epistemic trust, verification, and information justice?

To address these questions, this editorial draws on an evidence-informed integrative synthesis of selected peer-reviewed research on information behavior and information seeking, AI literacy, trust and verification, cognitive offloading and delegation, anthropomorphism, digital and AI divides, and family and institutional mediation, supplemented by relevant authoritative policy documents. The resulting evidence is interpreted across different stages of the life course and subsequently organized through an evidence-informed SWOT framework. In this analysis, SWOT is not used to generate evidence; rather, it serves as a means of organizing and interpreting evidence already available in the literature. Because conventional applications of SWOT may devolve into broad, unprioritized, and insufficiently validated lists (Hill & Westbrook, 1997), the analysis is extended through the TOWS matrix, allowing relationships among strengths, vulnerabilities, opportunities, and threats to be translated into more explicit strategies at the individual, institutional, and governance levels (Weihrich, 1982).

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## 2. Generative AI and the Reconfiguration of Information-Seeking Behavior

Classical models of information behavior, despite their theoretical differences, generally assume that individuals experience an information need or a state of uncertainty and subsequently turn to people, documents, databases, or retrieval systems in search of relevant information. In a simplified form, this process may be represented as:

**Information need → Search → Exposure to Sources → Selection → Evaluation → Use.**

Even when search engines play an active role in ranking and facilitating access to information, users typically remain confronted with identifiable and differentiated sources, while the tasks of comparison, interpretation, synthesis, and judgment remain largely their own responsibility.

Generative AI alters this configuration. Large language models do not merely direct users toward sources; they can combine, synthesize, reframe, and contextualize information within a single response and adapt subsequent outputs to the evolving conversational context. Wilson (2026) conceptualizes this shift as

a movement away from interaction with relatively passive retrieval systems toward engagement with generative AI as an active intermediary in information behavior. Such systems do not merely respond to an information need; they may participate in articulating and reformulating that need, shaping the direction of inquiry, suggesting subsequent questions, and even generating new information needs through the interaction itself. From this perspective, the logic of information seeking can be reformulated as:

**Information need or Uncertainty → Conversational Seeking → Synthesized Response → Follow-up Questioning → Trust or Doubt → Verification → Cognitive Delegation or Retention of Judgment → Use or Decision.**

A crucial difference is that evaluation may no longer precede synthesis. Users often encounter an already integrated and apparently coherent response and only subsequently, if sufficiently motivated and equipped to do so, investigate its provenance, credibility, and accuracy.

Understanding this environment requires attention to four interrelated concepts. The first is AI literacy. Long and Magerko (2020) define AI literacy as a set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with them, and use them across different contexts. Ng et al. (2021) further conceptualize AI literacy across four broad domains: knowing and understanding AI, using and applying AI, evaluating and creating with AI, and understanding its ethical implications. AI literacy, therefore, cannot be reduced to the ability to formulate effective prompts. It also involves understanding system capabilities and limitations, critically evaluating generated outputs, and recognizing the ethical implications of AI use.

The second concept is trust calibration. The desirable objective in human-AI interaction is neither maximal trust nor generalized distrust, but rather a level of trust proportionate to the actual capabilities and limitations of the system. Lee and See (2004) demonstrated that trust plays a central role in determining reliance on automated systems and that miscalibrated trust may result either in excessive dependence or in the unjustified rejection of useful technological assistance. This issue becomes particularly salient in generative AI environments, where linguistic fluency, coherence, confidence, and apparent expertise can create an impression of reliability that is not necessarily aligned with factual accuracy.

The third conceptual domain concerns cognitive offloading and cognitive delegation, which are related but not interchangeable. Cognitive offloading refers to shifting part of one's cognitive workload to an external tool in order to reduce cognitive effort, whereas cognitive delegation emphasizes the deliberate transfer of task execution, judgment, or functional responsibility to an AI system. In this editorial, cognitive delegation is used primarily to denote the user's conscious decision about which cognitive activities may be entrusted to AI and which should remain under human responsibility. Generative AI can facilitate both processes, but their consequences depend on the type and complexity of the activity transferred and the degree of critical engagement retained by the user (Jiang & Chen, 2026). The central issue is therefore not offloading or delegation per se, but the boundary between augmenting cognition and substituting for human judgment.

The fourth concept is epistemic agency, which is treated in this editorial as the principal normative outcome of responsible interaction with generative AI.

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Epistemic agency refers to an individual's capacity to recognize and articulate an information need, determine when and how AI should be used, formulate appropriate questions, evaluate and verify generated responses, calibrate trust, and consciously decide which elements of cognition and judgment may be delegated to the system and which should remain under human control. From this perspective, the central issue for the future of information behavior is not whether people use more or less AI, but rather how epistemic responsibility is distributed between the human user and the system. The appropriate balance is likely to vary across the life course as a function of literacy, experience, domain knowledge, context, and user vulnerability.

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**3. Why a Life-Course Perspective Rather Than Fixed Generations?**

Discussions of artificial intelligence and user differences are frequently organized around generational categories such as Generation Alpha, Generation Z, Millennials, Generation X, and Baby Boomers. These labels can be useful as approximate markers of historically situated cohorts whose encounters with digital technologies have unfolded under different social and technological conditions. They should not, however, be treated as natural, fixed, or intrinsically explanatory boundaries. Methodological research on generational differences has repeatedly shown that many studies are unable to disentangle the effects of age, historical period, and cohort. As a result, a difference attributed to "generation" may instead reflect life stage, socioeconomic circumstances, educational background, access to resources, prior technological experience, cultural context, or some combination of these factors (Costanza et al., 2023; Rudolph et al., 2021). This caution is especially important in the study of GenAI-mediated information behavior. Lower rates of generative AI use among older adults, for example, should not automatically be interpreted as a characteristic of belonging to an "older generation." Such differences may be associated with access, digital self-efficacy, prior experience, information needs, health status, perceived usefulness, or opportunities for learning. Similarly, higher levels of use among adolescents and young adults do not necessarily imply higher AI literacy, stronger critical evaluation skills, or better calibrated trust. Considerable variation may exist within the same age group or cohort in domain knowledge, digital competence, motivation, socioeconomic position, and patterns of technology use.

For these reasons, the analytical framework adopted in this editorial is grounded primarily in a life-course perspective. The principal analytical stages are childhood, adolescence, emerging adulthood, midlife, and later life. This classification does not assume that each stage possesses a fixed or universal set of characteristics. Rather, it recognizes that information needs, cognitive and social resources, levels of autonomy, forms of institutional and family mediation, exposure to risk, and contexts of decision-making change over the course of life. Consequently, engagement with generative AI may acquire different meanings and produce different outcomes at different stages.

Generational labels are therefore used only where they are employed in the studies under review or where they provide useful historical orientation. The primary basis for interpretation remains life stage, context of use, and information conditions, rather than an assumed generational essence. This approach reduces the risk of generational stereotyping and provides a more defensible basis for examining the strengths, vulnerabilities, opportunities, and threats associated with generative AI-mediated information behavior.

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## 4. Generative AI-Mediated Information Behavior Across the Life Course

The reconfiguration of information behavior in generative AI environments cannot be adequately understood without considering where users are situated across the life course. Conversational interaction, rapid response generation, personalization, and ease of use may offer advantages to users of all ages, yet the ability to recognize information provenance, assess credibility, calibrate trust, verify outputs, and retain independence of judgment is not constant across life stages. The nature of information needs, the degree of autonomy in decision-making, and the role of human intermediaries also change over time. Children commonly operate within information environments strongly shaped by parents and schools; adolescents acquire greater informational autonomy; young adults and students increasingly integrate AI into academic, professional, and everyday information practices; and in later life, factors such as accumulated experience, accessibility, digital self-efficacy, and support networks may become increasingly salient. The central question, therefore, is not which age group uses AI "better" or "more," but rather how users' capabilities and vulnerabilities interact with the opportunities and risks of AI-mediated information environments at different stages of life.

### 4.1. Childhood: From Curiosity to Source Recognition

In childhood, one of the most fundamental challenges of AI-mediated information behavior is not prompt quality, but the ability to understand where information comes from, who or what produced it, and how much trust it warrants. Langer et al. (2026), in a study of children aged 6 to 10, found that children experienced difficulty distinguishing AI-generated content from human-generated content and showed a particular tendency to classify synthetic faces and texts as human. Greater exposure to technology was not associated with greater accuracy in detecting AI-generated content; indeed, the study observed a negative relationship between technology use and detection accuracy. From an information behavior perspective, this is significant because it demonstrates that greater technological exposure should not be equated with greater competence in source recognition or credibility assessment.

Trust is equally complex in childhood. Lin et al. (2026), in two experimental studies with upper-primary students, found that children's trust in AI recommendations could exceed their trust in teacher recommendations after interaction, while anthropomorphic design features increased the likelihood that children would revise their initial choices. Such design features are therefore not merely aesthetic. Human-like voices, social cues, or conversational styles can influence perceived reliability and willingness to accept recommendations. This suggests that anthropomorphism itself should be treated as an object of information and AI literacy. Children need to learn that fluency, friendliness, human-like presentation, and social presence do not constitute evidence of knowledge, responsibility, or factual accuracy.

At the same time, the conversational characteristics of generative AI may create meaningful educational opportunities. AI systems can simplify explanations, adjust vocabulary to a child's level, provide multiple examples, and support iterative questioning. The appropriate policy response is therefore not necessarily to exclude AI from children's information environments, but to define the conditions under which it can support learning without displacing human interaction, independent judgment, or authoritative sources. UNICEF's guidance on AI and children emphasizes precisely this child-centered orientation,

highlighting safety, privacy and data protection, transparency, accountability, non-discrimination, well-being, and the need to prepare children for informed engagement with AI (UNICEF, 2025).

Family mediation is particularly important at this stage. Güngör and Güngör (2026), in a qualitative study of parents of children aged 4 to 6, found that parents used generative AI to explain difficult concepts in age-appropriate language, design activities, organize routines, and address parenting concerns. More cautious users cross-checked outputs, avoided entering personally identifiable information about their children, and referred higher-risk matters to human experts. From the perspective of information behavior, the parent thus becomes more than a gatekeeper of access; the parent functions as an epistemic intermediary between the child and the AI system. The educational priority in childhood should therefore be the gradual development of three foundational capacities: recognizing information provenance, distinguishing human-like presentation from epistemic credibility, and developing the habit of asking, "How do we know this answer is correct?" These capacities provide an early foundation for calibrated trust and epistemic agency later in life.

**4.2. Adolescence: Digital Fluency and Epistemic Vulnerability**

Adolescence is a stage in which informational autonomy expands rapidly and digital technologies become deeply embedded in educational, social, and everyday life. With the integration of generative AI into this environment, adolescents are no longer merely consumers of information. They can interrogate systems, request revisions, seek explanations, compare alternatives, and delegate parts of their learning or decision-making processes to AI. Yet practical familiarity with technology should not be conflated with AI literacy or epistemic maturity. Evidence indicates substantial heterogeneity among adolescents in the affective, behavioral, cognitive, and ethical dimensions of AI literacy (Sun & Chan, 2025).

One important vulnerability concerns understanding the origins and production of AI-generated information. Bråten et al. (2026) found that many secondary-school students, despite prior experience with ChatGPT, held incomplete or inaccurate conceptions of where ChatGPT obtains information, how its responses are generated, and the quality of the sources underlying those responses. This matters because in generative environments the source may be partially or entirely invisible at the point of interaction. A coherent, fluent, and confident answer may therefore substitute psychologically for source evaluation. Provenance awareness should consequently become a central component of adolescent information literacy: users should understand how a response may have been generated, what kinds of sources may or may not underlie it, and when independent verification is required.

Adolescents are not, however, merely vulnerable users. Research also suggests that critical engagement with AI-generated text can itself become an educational opportunity. Latini et al. (2026) found that students in some conditions evaluated text labeled as ChatGPT-generated more cautiously, even though such texts could still support integrated understanding. Awareness of AI authorship may therefore function as a trigger for more deliberate evaluation, provided that students possess the tools needed to assess credibility, compare sources, and judge evidence.

AI literacy at this stage should consequently extend well beyond operational competence or prompt construction. Cruz et al. (2026) found that higher levels of AI literacy and stronger ethical practices were associated with different patterns of reliance on generative AI. The important implication is that the goal of

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education should not be to maximize AI use, but to cultivate conditional and proportionate reliance. An adolescent who knows when to verify an answer, when to return to a primary source, and when to limit the role of the system is in a stronger informational position than one who merely uses AI frequently and efficiently.

The ethical dimension is equally important. The use of generative AI in assignments, learning, content production, and social communication complicates the boundaries among legitimate assistance, substitution of cognitive effort, undisclosed reuse, and academic misconduct. Education at this stage should therefore integrate AI literacy, provenance awareness, credibility assessment, verification, transparency of use, and ethical responsibility. Digital fluency becomes a genuine strength only when accompanied by questioning, skepticism, verification, and independent judgment. Adolescence is, in this sense, a critical period in the transition from being a technologically capable user to becoming an individual with epistemic agency.

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**4.3. Emerging Adulthood and University Life: From Searcher to Cognitive Collaborator**

In emerging adulthood, and particularly in higher education, generative AI enters an information environment already distributed across search engines, scholarly databases, library collections, social media, instructors, and peers. The addition of AI chatbots does not simply expand this information ecology by introducing another source; it reconfigures the relationships among searching, source selection, evaluation, synthesis, and knowledge production. Lund et al. (2026), in a comparative study of AI chatbots, search engines, and library resources among university students, showed that AI has become part of students' information repertoires for academic and everyday purposes. The significance of this development lies in the ability of AI systems to synthesize, summarize, compare, and reconstruct information into a coherent response, rather than merely directing users toward separate sources.

The key issue at this stage is therefore no longer simply access to AI, but rather how much, and which parts, of cognition and evaluation are delegated to it. Generative AI can reduce the burden of repetitive or lower-level tasks such as preliminary summarization, rewriting, generating examples, or organizing material. In doing so, it may free cognitive resources for more complex tasks. The same affordance, however, can lead users to outsource activities that are central to academic learning, including interpretation of evidence, comparison of perspectives, argumentation, and judgment.

Jiang and Chen (2026) addressed this issue by distinguishing between lower-order and higher-order cognitive offloading. Their study of 667 university students showed that the ability to use AI and the ability to evaluate AI output do not have identical implications. In particular, stronger evaluative competence may constrain some forms of offloading, yet it does not automatically prevent the delegation of more complex cognitive activity. The ability to use AI, therefore, should not be treated as a sufficient marker of competent engagement; evaluative capability, metacognition, and an understanding of the consequences of different forms of cognitive offloading are equally important. At the level of deliberate task allocation, these capacities enable users to define appropriate boundaries of cognitive delegation.

Behavioral evidence reinforces this concern. Misiejuk et al. (2026), using longitudinal analysis of students' actual prompts, demonstrated that prompting

practices reflect how cognitive effort is distributed between user and system. Some students accepted generated output with little revision or critical engagement, while stronger interactions involved greater contextualization, clearer instructions, and more active steering of the system. Quality of use, therefore, cannot be inferred from frequency of use or even apparent sophistication of prompts alone; what matters is the extent to which the user remains cognitively involved in structuring, evaluating, and revising the process.

Similar heterogeneity was identified by Si et al. (2026), who distinguished four patterns of GenAI use ranging from simple question-and-answer users to critical co-thinkers. Importantly, greater depth of AI use did not necessarily correspond to greater cognitive independence. In some cases, more advanced use was accompanied by greater delegation of cognitive autonomy. The shift from searcher to cognitive collaborator is therefore beneficial only when the student retains responsibility for problem definition, evidence selection, response evaluation, and final judgment.

In higher education, the central issue should consequently move beyond the binary question of whether AI use should be permitted. Universities, instructors, and academic libraries should instead focus on transforming students from passive recipients of generated answers into critical collaborators with AI who understand what can be delegated, what requires independent verification, and which dimensions of reasoning and judgment should remain under human responsibility. At this stage of the life course, the boundary between empowering use and cognitive dependency is defined by the extent to which epistemic agency is preserved.

**4.4. Midlife: Efficiency, Domain Knowledge, and Trust**

Midlife remains comparatively underexplored in the literature on generative AI-mediated information behavior. Much of the available evidence derives either from general adult populations or from cross-generational comparisons in which middle-aged adults constitute only one subgroup. Consequently, there is currently insufficient empirical basis for attributing a uniform pattern of GenAI behavior to "midlife users." This lack of direct evidence should itself be regarded as an important research gap.

Nevertheless, available studies suggest that midlife occupies an important position at the intersection of experience, practical information needs, and technology adoption. Information needs at this stage are often closely linked to professional responsibilities, family management, financial decisions, health, and continuing learning. In such settings, rapid response generation, summarization, option comparison, and time-saving can make GenAI particularly attractive. Evidence from broader working-age populations shows that generative AI use is increasing rapidly in both professional and non-professional settings, with users reporting substantial time savings (Bick et al., 2026). These findings, however, concern adults aged 18 to 64 as a whole and should not be interpreted as specific evidence about midlife.

Use of GenAI is also uneven across adult populations. Suárez and García-Mariñoso (2025), drawing on national survey data, found that increasing age, lower educational attainment, and lower levels of digital technology use were associated with reduced likelihood of generative AI adoption. This indicates that non-use cannot be attributed simply to resistance or unwillingness; opportunity structures, digital experience, education, and perceived utility also matter.

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Trust is similarly complex. Cohn et al. (2026), in a study of 1,485 adults, found meaningful differences across age groups in anthropomorphism, trust, and perceived accuracy of LLM responses. Younger participants, contrary to common assumptions, displayed lower trust and lower anthropomorphism than some older groups. Human-like design cues, including voice, increased perceived human-likeness and perceived accuracy across age groups. These findings demonstrate that trust does not vary linearly with age and that design features of the system itself can shape user judgment.

From an information behavior perspective, accumulated professional and domain knowledge may plausibly support more informed evaluation of AI responses in some contexts, but this should not be treated as a universal or empirically established characteristic of all middle-aged users. Expertise may help identify errors within familiar domains, while users remain vulnerable in unfamiliar areas to the same risks of fluent misinformation, anthropomorphic cues, and miscalibrated trust found elsewhere. The central issue at this stage is therefore the relationship among efficiency, domain knowledge, and calibrated trust. The scarcity of direct research on how middle-aged adults verify, interpret, and incorporate GenAI outputs into professional and everyday decisions represents a significant gap in the current literature.

**4.5. Later Life: From the AI Divide to Calibrated Trust**

Later life is one of the most complex stages for examining generative AI-mediated information behavior because two apparently contradictory patterns coexist. On the one hand, evidence on the digital divide and the emerging AI divide suggests that older age, in combination with factors such as educational attainment, digital experience, and social resources, may be associated with lower rates of generative AI use. On the other hand, conversational interfaces may reduce some of the barriers associated with complex information systems by allowing users to ask questions in natural language and receive tailored explanations. Later-life information behavior should therefore not be approached primarily through a deficit model; the key issue is the interaction among access, AI literacy, self-efficacy, trust, verification, and human support networks.

Kaur and Chen (2023), in a study of 207 adults aged 60 and older, found substantial variation in awareness, experience, and understanding of AI. Many participants expressed a desire to learn more about AI in order to make more informed decisions about AI-enabled products and services. This challenges the assumption that older adults are inherently disinterested in, or incapable of learning, emerging technologies. At the same time, such heterogeneity indicates that educational interventions should be tailored not to chronological age alone, but to prior experience, confidence, practical needs, and existing levels of AI literacy.

Trust also does not correspond neatly to use or non-use. Wang et al. (2026), using a mixed-methods design combining a survey of 217 older adults with interviews with 20 participants, found that active AI users and individuals who consciously refrain from direct use may arrive at comparable levels of trust through different pathways. Among users, the authors identify practice-based trust, which develops through repeated use, exposure to errors, adjustment of expectations, and ongoing verification. Among some non-users, they identify delegated trust, whereby assessment or use of AI is intentionally transferred to accountable human intermediaries such as family members or knowledgeable others. Non-use, therefore, should not automatically be interpreted as a lack of literacy or

technological resistance; it may represent an informed strategy for risk management.

This distinction is particularly important for information behavior because it shows that appropriate trust does not necessarily require direct, continuous use. Some older adults may calibrate trust through personal experimentation and cross-checking; others may rely on trusted human networks to verify or interpret AI-generated information. What matters in both cases is the preservation of evaluative capacity and meaningful choice.

AI literacy and self-efficacy in later life should also be understood as developable rather than fixed. Liu and Li (2026), in a case study of an older-adult learning institution in China, examined a Teacher–Learner–AI model of collaboration. Their findings suggest that guided interaction with LLMs, supported by a facilitating instructor, can strengthen practical skills, metacognitive awareness, and self-efficacy. In this model, AI does not replace the teacher; it becomes a cognitive resource embedded within a supportive learning environment.

Later life should therefore be understood simultaneously as a site of AI inequality and a domain of lifelong learning opportunity. The principal risk is not simply low levels of use. Uncritical use, overreliance, weak verification, or dependence on apparently authoritative outputs may be equally problematic. Conversely, life experience, trusted human networks, structured learning, and gradual engagement with AI can support more calibrated forms of trust. The objective should not be to turn all older adults into intensive users of generative AI, but to create conditions in which they can decide when to use AI, when to verify its output, when to seek human mediation, and when not to rely on it at all. Such choice constitutes an important expression of epistemic agency in later life.

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## 5. An Evidence-Informed SWOT Matrix Across the Life Course

To move from descriptive findings toward strategic analysis, the evidence reviewed above can be organized through a SWOT framework. In this editorial, strengths and vulnerabilities/weaknesses refer to user-level characteristics and capacities, including AI literacy, information literacy, domain knowledge, metacognition, self-efficacy, and verification competence. By contrast, opportunities and threats refer to features of the external AI and information environment, such as conversational access, personalization, instructional affordances, source opacity, anthropomorphic design, misinformation, privacy risks, and inequalities in access. This distinction is important because it prevents limitations inherent in AI systems, such as hallucination or lack of source transparency, from being misclassified as user "weaknesses."

Table 1 synthesizes the empirical evidence discussed in the preceding sections. Each cell is grounded in one or more identifiable sources and should therefore be read as a concise representation of current evidence rather than as a fixed description of any age group. This evidence-informed approach also addresses a longstanding criticism of SWOT analysis, namely its tendency to generate broad, weakly validated, and insufficiently prioritized lists (Hill & Westbrook, 1997).

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**Table 1. Evidence-informed SWOT matrix of generative AI-mediated information behavior across the life course**

| Life stage | Strengths | Vulnerabilities / Weaknesses | Opportunities | Threats |
|---|---|---|---|---|
| Childhood | Capacity to learn through structured conversational interaction; potential to acquire vocabulary and knowledge through guided AI-supported learning while continuing to value human and parental interaction (Quan et al., 2026). | Limited ability to distinguish human-generated from AI-generated content; tendency to classify synthetic content as human; greater exposure to technology does not necessarily produce better detection accuracy (Langer et al., 2026). | Age-adapted explanations, interactive and personalized learning, use of AI as a supplement to parental instruction, and parental mediation in interpreting and evaluating AI responses (Güngör & Güngör, 2026; Quan et al., 2026). | Obscured information provenance; anthropomorphic cues that may increase trust and acceptance of recommendations; privacy and data-protection risks; possible inappropriate substitution of AI interaction for human interaction (Langer et al., 2026; Tang et al., 2026; UNICEF, 2025). |
| Adolescence | Emerging capacities in cognitive, ethical, and behavioral dimensions of AI literacy; potential for more critical evaluation when users are aware that content is AI-generated (Latini et al., 2026; Sun & Chan, 2025). | Considerable heterogeneity in AI literacy; misconceptions about where ChatGPT obtains information and how responses are generated; limited understanding of GenAI even in high-access environments (Bråten et al., 2026; Cruz et al., 2026; Sun & Chan, 2025). | Use of AI as a setting for teaching source comparison, credibility assessment, verification, and critical AI literacy; potential to use exposure to AI-generated text to strengthen source evaluation and ethical reasoning (Cruz et al., 2026; Latini et al., 2026). | Reduced visibility of provenance; risk of overreliance on fluent and immediate answers; blurred boundaries between educational assistance and substitution of cognitive effort; academic integrity, privacy, and misinformation risks (Bråten et al., 2026; Cruz et al., 2026). |
| Emerging adulthood / university life | Ability to navigate a diversified information ecology incorporating AI, search engines, and library resources; evidence of critically engaged patterns of AI use and co-thinking; evaluative competence and learning motivation may help preserve cognitive independence (Jiang & Chen, 2026; Lund et al., 2026; Si et al., 2026). | Risk of outsourcing higher-order cognitive activities; acceptance of generated output with limited revision or critical engagement among some users; possibility of "deep use" combined with high cognitive dependence (Misiejuk et al., 2026; Si et al., 2026). | AI-supported preliminary summarization, ideation, comparison, feedback, and learning support; potential to free cognitive resources for more complex work; development of critical co-thinking when combined with appropriate metacognitive instruction (Jiang & Chen, 2026; Si et al., 2026). | Replacement of direct engagement with scholarly sources by synthesized AI responses; source invisibility; hallucinated content and references; reduced cognitive effort and dependency; blurred boundaries of authorship and academic integrity (Misiejuk et al., 2026; Wilson, 2026). |
| Midlife | Available evidence indicates variation in domain-sensitive evaluation and verification across adult age groups; professional and domain knowledge may provide a potential basis for context-sensitive assessment, although direct evidence specific to midlife remains limited (Cohn et al., 2026). | Heterogeneity in GenAI experience and use; lower likelihood of use with increasing age alongside effects of education and digital experience; insufficient evidence to assume a uniform pattern of AI literacy or information behavior in midlife (Suárez & García-Mariñoso, 2025). | Increased efficiency in professional and everyday tasks, summarization, decision support, and lifelong learning; potential to combine AI with professional expertise, provided that verification is retained (Bick et al., 2026). | Trust may be shaped by anthropomorphic design; efficiency may encourage uncritical acceptance; verification behavior varies by domain; persistent inequalities associated with education, digital skills, and resources (Cohn et al., 2026; Suárez & García-Mariñoso, 2025). |
| Later life | Considerable heterogeneity in AI literacy and willingness to learn; capacity to develop trust through experience, error detection, and verification; potential use of trusted human intermediaries to manage uncertainty (Kaur & Chen, 2023; Wang et al., 2026). | Lower access, experience, and digital self-efficacy among some groups; variation in AI knowledge and prior experience; need for support tailored to individual background and needs rather than chronological age alone (Kaur & Chen, 2023; Suárez & García-Mariñoso, 2025). | Natural-language interfaces may reduce the complexity of some information systems; structured Teacher–Learner–AI support can strengthen practical skills, metacognitive awareness, and self-efficacy; potential for lifelong learning and improved information access (Liu & Li, 2026). | Anthropomorphic and voice cues may increase perceived human-likeness and accuracy; misinformation in high-stakes domains such as health; exclusion through the AI divide; risk of miscalibrated trust in the absence of experience and verification (Cohn et al., 2026; Suárez & García-Mariñoso, 2025; Wang et al., 2026). |

Two broader conclusions emerge from this matrix. First, no stage of the life course can be characterized simply as either "capable" or "vulnerable." The same affordance may produce different outcomes depending on the user's capabilities and the context of use. Conversational AI, for example, may facilitate age-appropriate explanation for children while simultaneously obscuring distinctions between an artificial system and a human information source. For university students, cognitive offloading may reduce the burden of repetitive tasks but may also undermine learning when evaluation and reasoning are delegated excessively. In later life, even non-use should not automatically be interpreted as weakness; reliance on a trusted human intermediary may constitute a deliberate and rational strategy for managing uncertainty (Wang et al., 2026).

Second, the evidence base is uneven across life stages. Direct empirical research is expanding rapidly for children, adolescents, university students, and older adults, whereas midlife remains comparatively underexamined and is still represented largely through cross-generational studies and broader adult surveys. The matrix should therefore not be interpreted as a set of fixed or deterministic profiles. Rather, it represents the current state of evidence and provides the analytical foundation for the next step: moving from diagnosis to strategy through TOWS, by examining how strengths can be mobilized to exploit opportunities or counter threats, and how available opportunities can be used to reduce vulnerabilities (Weihrich, 1982).

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## 6. From SWOT to TOWS: Strategies for Responsible Information Behavior

The SWOT matrix provides a structured diagnosis of the current landscape, but diagnosis alone does not indicate how strengths, vulnerabilities, opportunities, and threats should be translated into action. To move from description to intervention, the analysis can be extended through the TOWS matrix. Weihrich (1982) proposed TOWS as a systematic means of linking internal and external factors: SO strategies use strengths to capitalize on opportunities; ST strategies mobilize strengths to mitigate threats; WO strategies use available opportunities to reduce vulnerabilities; and WT strategies aim to minimize vulnerabilities while simultaneously limiting exposure to threats. In the context of generative AI-mediated information behavior, the value of this framework lies in its capacity to derive strategies from the interaction between evidence about users at different life stages and the affordances and risks of the AI information environment.

At the individual level, the central strategic objective should be a transition from mere competence in using AI toward responsible epistemic agency. Technical proficiency or the ability to formulate effective prompts is necessary, but insufficient. Responsible engagement also requires information literacy, AI literacy, awareness of source provenance, verification competence, privacy literacy, metacognitive awareness, and the ability to calibrate trust. The goal is neither maximal reliance nor generalized skepticism, but reliance proportionate to the actual capabilities of the system and the stakes of the situation, consistent with the logic of appropriate reliance developed in the automation literature (Lee & See, 2004). In childhood and adolescence, this begins with source recognition, awareness of the distinction between human-like presentation and epistemic credibility, and the development of habits of verification. In emerging adulthood, the focus shifts toward defining appropriate boundaries for cognitive offloading. In midlife and later life, it increasingly involves domain-sensitive risk assessment,

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contextual verification, and informed decisions about whether to use AI directly, through a trusted intermediary, or not at all.

Within the TOWS logic, these objectives can be expressed through different strategic combinations. An SO strategy for adolescents and university students, for example, would involve using digital familiarity and emerging AI competence to exploit the interactive and explanatory affordances of GenAI for learning, comparison, and idea development, while preserving independent evaluation. An ST strategy would draw on information literacy and domain knowledge to detect hallucinations, misleading claims, and unreliable sources. A WO strategy could use the explanatory and adaptive capabilities of AI itself to strengthen AI literacy and self-efficacy among less experienced users. A WT strategy, particularly in high-stakes domains such as health, finance, or children's use, would prioritize restricted reliance, mandatory verification, and recourse to authoritative human or documentary sources.

The second level concerns family and institutional intermediaries. Information behavior is never entirely individual, and the forms of mediation that matter vary across the life course. In childhood, parents and schools serve as primary epistemic intermediaries and can reduce risk through co-use, verification, and limits on the disclosure of personal data. During adolescence, schools and libraries should connect practical AI use with instruction in source evaluation, credibility assessment, provenance, and ethical responsibility. In higher education, instructors and academic libraries should move beyond a binary emphasis on either prohibiting or permitting AI use and instead focus on the quality of the cognitive process. Students should be encouraged to disclose how AI was used, identify independent sources, recognize the limitations of generated responses, and retain responsibility for final judgments. In midlife, workplaces, professional networks, and health systems can establish norms for responsible AI use in expert and high-stakes decision-making. In later life, families, libraries, lifelong-learning institutions, and health services can provide guided learning and access to trusted human verification.

At this level, intergenerational mediation deserves particular attention. The transfer of AI-related competence is not necessarily unidirectional from older to younger family members. Adolescents and young adults may help parents or older relatives develop practical skills, while older adults may contribute domain knowledge, risk awareness, and evaluative experience. The family can therefore be conceptualized not merely as a site of supervision, but as a shared information ecology in which technological skill, contextual knowledge, and epistemic judgment circulate across generations.

The third level is governance and system design, because responsibility for safe and credible information behavior cannot be placed entirely on users. Children and adolescents, in particular, should not bear the full burden of identifying synthetic content, detecting errors, protecting their own data, or resisting persuasive anthropomorphic design. UNESCO's AI competency framework for students emphasizes a human-centered orientation, ethics, understanding of AI applications, and responsible participation (Miao et al., 2024). UNICEF's guidance on AI and children similarly foregrounds safety, privacy and data protection, non-discrimination, transparency, explainability, accountability, and preparation for informed engagement with AI systems (UNICEF, 2025). These principles can be extended across the life course through age-appropriate design,

privacy by design, source transparency, provenance disclosure, accessibility, multilingual equity, protection of vulnerable users, and platform accountability.
Responsible AI-mediated information behavior therefore cannot be reduced to individual competence. It depends on the simultaneous presence of capable users, supportive human and institutional intermediaries, and accountable AI systems and governance structures. In this sense, TOWS provides a means of converting dispersed empirical findings into a multilevel intervention framework. The ultimate objective is not to maximize the use of generative AI, but to create conditions in which users can make informed decisions about what to ask, when to trust, what to verify, and which forms of judgment should remain under human control.

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## 7. A Life-Course Model of Generative AI-Mediated Information Behavior

Drawing on the evidence reviewed above and the preceding SWOT–TOWS analysis, generative AI-mediated information behavior can be conceptualized as a dynamic, recursive, and multilayered process unfolding across the life course. The process still begins with an information need or a state of uncertainty, but the route from need to use differs substantially from conventional search. Rather than moving directly toward a set of documents or independently identifiable sources, the user engages in a conversational exchange with an AI system, receives a synthesized response, evaluates its quality and credibility, calibrates trust, verifies the response where necessary, decides how much cognitive work to delegate to the system, and subsequently uses the output for knowledge construction, decision-making, or action. The core sequence of the model can therefore be represented as follows:

**Information Need or Uncertainty → Conversational Seeking → Response Evaluation → Trust Calibration → Verification → Cognitive Delegation → Knowledge Construction → Decision/Action.**

This sequence is not strictly linear. Users may return to earlier stages, reformulate their questions, introduce additional sources, or revise the degree of trust and reliance as the interaction unfolds (Lee & See, 2004; Wilson, 2026).
A defining feature of the proposed model is that life stage is treated as a moderating rather than a directly determining factor. Childhood, adolescence, emerging adulthood, midlife, and later life represent contexts in which information needs, cognitive and social resources, levels of autonomy, patterns of mediation, and exposure to risk may differ. The effects of GenAI use, however, emerge from the interaction of life stage with other factors, including information literacy, AI literacy, domain knowledge, metacognitive capacity, prior experience, socioeconomic resources, the type of information need, the sensitivity of the context, and the availability of family or institutional support. This formulation is consistent with a life-course perspective and avoids treating observed differences as fixed or intrinsic characteristics of generations (Costanza et al., 2023; Rudolph et al., 2021).
The model also incorporates three surrounding layers. The first is the individual level, encompassing information and AI literacy, domain knowledge, metacognition, self-efficacy, prior experience, verification competence, and trust calibration. The second consists of family, educational, and institutional intermediaries, whose roles vary across the life course, from parents and schools

to universities, libraries, workplaces, health systems, lifelong-learning institutions, and social or professional networks. The third is the level of governance and AI system design, which shapes the conditions of interaction through source and provenance transparency, privacy protection, accessibility, linguistic equity, age-appropriate design, protection of vulnerable users, and platform accountability.

The normative outcome of the model is not greater AI use, but the preservation and strengthening of epistemic agency. Users should be able to determine when generative AI is functioning primarily as a search or explanatory tool, when it can serve as a cognitive collaborator, when independent verification is required, and when further delegation of judgment may diminish the quality of knowledge or decision-making. Responsible information behavior in generative AI environments should therefore be understood as the product of interaction among user capabilities, social and institutional mediation, and the quality of technological design and governance.

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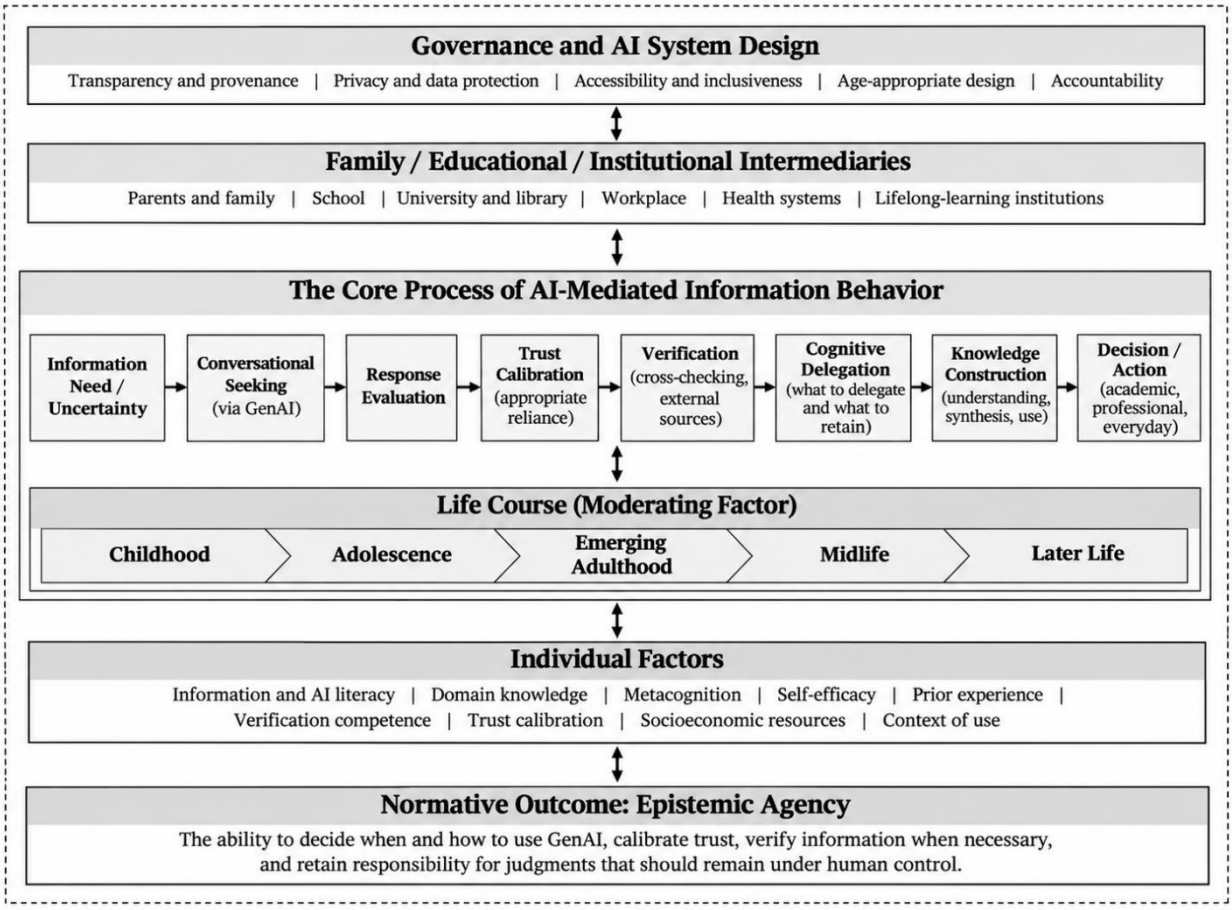



*Figure 1. A Life-Course Framework of Generative AI-Mediated Information Behavior*[2]

2 . The figure conceptualizes generative AI-mediated information behavior as a dynamic process that moves from information need or uncertainty through conversational seeking, response evaluation, trust calibration, verification, cognitive delegation, knowledge construction, and decision/action. The life course (childhood, adolescence, emerging adulthood, midlife, and later life) is treated as a moderating factor, not a direct determinant of behavior. This process is shaped by three surrounding layers: individual factors; family, educational, and institutional intermediaries; and governance and AI system design. The normative outcome of the model is epistemic agency, defined as the capacity to decide when and how to use generative AI, what to verify, and which forms of judgment should remain under human responsibility.

## 8. A Research Agenda for Knowledge-Research Studies in the Age of Generative AI

The rapid diffusion of generative AI creates a research agenda for Knowledge and Information Science that extends well beyond questions of adoption or frequency of use. The more consequential issue is how GenAI alters the processes through which information needs are articulated, sources are encountered or bypassed, credibility is assessed, trust is formed, cognitive work is delegated, and knowledge is constructed. A research agenda responsive to these changes should therefore move from technology-centered questions toward the study of AI-mediated information behavior as a sociotechnical and epistemic process.

One priority concerns the reconfiguration of information behavior itself. Future research should examine the full sequence of need recognition, conversational seeking, follow-up questioning, response evaluation, verification, and use, rather than treating AI interaction as a discrete act of tool use. Comparative studies are particularly needed to investigate when users prefer generative AI over search engines, scholarly databases, library resources, social networks, or human experts, and how movement among these sources affects information quality, confidence, and decision-making. Such research would help clarify whether GenAI is functioning primarily as a retrieval substitute, an interpretive layer, a conversational intermediary, or a cognitive collaborator in different contexts.

A second major area is epistemic trust and verification. Existing research already suggests that fluency, confidence, anthropomorphic cues, and apparent coherence can affect perceived credibility. Yet much remains unknown about how trust is formed, revised, and recalibrated over repeated interaction. Future studies should examine not only whether users trust AI, but why they trust it, under what conditions, how they respond to errors, and whether verification behavior changes over time. This is especially important in high-stakes domains such as health, finance, education, and public information.

A third, closely related is the issue of source and provenance behavior. Generative AI can weaken the visibility of conventional source boundaries by presenting synthesized responses in which the origin of individual claims is unclear. This creates a need for research on how users interpret citations, links, provenance indicators, uncertainty signals, and disclosure mechanisms embedded in AI systems. Experimental work could test whether transparent sourcing improves evaluation, whether users actually inspect cited materials, and whether provenance cues reduce overreliance or merely produce a superficial impression of credibility.

A fourth research domain concerns cognitive delegation and epistemic agency. The crucial question is not simply whether users offload cognitive work, but what kinds of work they delegate and with what consequences. Future research should distinguish between the outsourcing of routine tasks and the delegation of higher-order functions such as interpretation, argumentation, synthesis, evaluation, and judgment. Such distinctions are particularly important in educational settings, where the same AI affordance may either support learning or displace the cognitive processes through which learning occurs. Longitudinal research is needed to determine whether sustained use changes users' reasoning practices, metacognitive awareness, confidence, or independence of judgment.

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The affective dimensions of AI-mediated information behavior also warrant closer attention. Anxiety, curiosity, uncertainty, confidence, frustration, perceived competence, and self-efficacy may shape both initial adoption and the quality of subsequent interaction. The emergence of measures of AI anxiety is therefore relevant not only to technology acceptance research but also to information behavior. Future studies should examine how affective responses interact with trust, verification, avoidance, exploration, and help-seeking across different life stages.

Another underdeveloped area is intergenerational information behavior. Families and social networks increasingly function as sites in which AI-related knowledge, skills, and judgments are exchanged. Younger users may support older family members in technical interaction, while older users may contribute contextual knowledge, experience, and risk awareness. This bidirectional process suggests the value of developing the concept of intergenerational information mediation and examining how families collectively negotiate AI use, credibility, privacy, and verification. Such work would extend information behavior research beyond individual users toward shared and relational information practices.

The emerging AI divide likewise requires a broader conceptualization. Inequality should not be measured solely in terms of access to AI tools. More consequential differences may concern the capacity to formulate effective queries, evaluate responses, detect errors, verify claims, protect personal information, and convert AI access into meaningful benefit. Research should therefore examine how age, education, gender, socioeconomic position, disability, geographic location, infrastructure, language, and cultural capital interact to produce unequal forms of AI participation and unequal epistemic outcomes. This is fundamentally an issue of information justice, not merely technology diffusion.

A further priority is the study of cultural and multilingual information behavior. Much of the emerging literature on GenAI continues to be concentrated in English-speaking or technologically advanced settings. Yet trust in automated systems, attitudes toward authority, family mediation, educational norms, privacy expectations, and access to high-quality language models vary considerably across cultural contexts. Comparative research involving Persian-speaking and other non-Western populations is therefore essential, both to test the generalizability of existing findings and to identify forms of AI-mediated information behavior that remain invisible in dominant research traditions.

Methodologically, these questions cannot be addressed adequately through cross-sectional self-report surveys alone. Future studies should make greater use of longitudinal designs, controlled experiments, diary studies, prompt and interaction-log analysis, digital trace data, mixed-methods approaches, and direct observation of actual information behavior. Comparative designs across life stages and cultural contexts are particularly valuable for distinguishing developmental, contextual, and cohort-related effects. Where possible, researchers should also examine actual behavior rather than relying exclusively on users' retrospective perceptions of how they engage with AI.

Two limitations should frame this research agenda. First, the available evidence remains uneven across life stages, with midlife particularly underrepresented in direct empirical research. Second, the rapidly evolving nature of generative AI means that findings associated with particular systems, interfaces, and modes of use may have limited temporal stability. The framework proposed here should therefore be treated as an evidence-informed and theoretically grounded synthesis

that requires continued refinement as longitudinal, cross-cultural, and behaviorally grounded evidence accumulates.

Taken together, these directions point toward a broader reorientation of Knowledge and Information Science. Generative AI should not be treated merely as a new technology to be added to established models of information seeking. It introduces a new form of mediation in which the boundaries among source, interface, intermediary, and cognitive collaborator become increasingly blurred. The research challenge is therefore to explain how users preserve informed judgment, calibrated trust, and epistemic agency when the system through which they seek information also participates in constructing the answer itself.

## 9. Connecting the Argument to the Articles in This Issue

The themes developed in this editorial are closely connected to several contributions published in the present issue of the *Journal of Knowledge-Research Studies*. Taken together, these articles demonstrate that artificial intelligence is entering Knowledge and Information Science not through a single conceptual or methodological pathway, but simultaneously as an object of study, an information-processing technology, a source of affective response, an ethical and cultural challenge, and an increasingly consequential intermediary in the production, organization, and use of knowledge.

The article on the knowledge characteristics and information literacy of digital natives, particularly Generation Z and Generation Alpha, addresses a population that occupies a central position in current debates about AI-mediated information behavior. Its focus on the informational and knowledge-related characteristics of younger cohorts is especially relevant to the life-course argument advanced in this editorial. At the same time, the present analysis suggests that such generational categories should be interpreted cautiously. Labels such as Generation Z and Generation Alpha can provide useful historical and descriptive reference points, but the informational capacities of younger users should not be inferred from generational membership alone. Their interaction with AI is shaped by information literacy, educational experience, social and economic resources, family and institutional mediation, and the particular contexts in which information is sought and used. This distinction becomes increasingly important as generative AI is incorporated into the everyday information environments of children, adolescents, and university students.

A second contribution, examining the psychometric properties of an artificial intelligence anxiety questionnaire among university students, brings the affective dimension of AI use into sharper focus. Much of the early discourse on generative AI has concentrated on adoption, acceptance, usefulness, and technical competence. Yet information behavior has long been understood as involving affective as well as cognitive and behavioral dimensions. Anxiety, uncertainty, confidence, perceived competence, and self-efficacy may influence whether users engage with AI, avoid it, depend excessively upon it, or approach its outputs critically. AI anxiety should therefore not be regarded merely as a peripheral psychological variable. It may have direct implications for information seeking, trust formation, verification practices, and users' willingness to retain responsibility for their own judgments.

The contribution on the cultural requirements for the ethical implementation of artificial intelligence in Iran extends the discussion from individual competence to the wider social and normative environment in which AI systems are embedded.

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Responsible information behavior cannot be secured solely by asking users to become more literate or cautious. Cultural expectations, institutional norms, privacy practices, conceptions of authority and responsibility, language, and regulatory arrangements all influence how AI is adopted and trusted. This is particularly important in non-Western contexts, where assumptions derived from predominantly Anglophone research environments may not transfer directly. The article therefore reinforces the argument that AI-mediated information behavior must be studied as a sociotechnical phenomenon situated within specific cultural and institutional contexts.

The study on AI-based subject classification of books through abstract-text analysis and supervised learning represents another dimension of the transformation. Here, artificial intelligence is not primarily examined as a user-facing conversational system, but as a technology for knowledge organization and information processing. Its inclusion in the same issue is conceptually significant. AI is increasingly present both behind information systems, where it classifies, organizes, predicts, and structures information, and at the interface with users, where generative systems explain, synthesize, recommend, and respond conversationally. These developments suggest that the traditional distinction between the organization of information and the behavior of information users is becoming increasingly porous. The ways in which information is computationally organized may shape what users encounter, while users' interactions with AI may in turn influence how knowledge is represented, interpreted, and reused.

Viewed together, these contributions reveal a broader transition in the field. Artificial intelligence can no longer be treated as a narrowly technical topic confined to automation or information retrieval. It has become simultaneously a subject of inquiry, a cognitive and informational tool, an information intermediary, and an infrastructural force that reorganizes knowledge processes. Its effects extend across cognitive, affective, ethical, cultural, organizational, and technological dimensions.

For *Knowledge-Research Studies*, this convergence suggests a coherent and potentially productive research agenda. Future scholarship should examine not only how AI systems perform, but how people understand them, trust them, question them, depend on them, resist them, and incorporate them into individual and collective practices of knowing. It should also investigate the institutional and cultural conditions under which such interactions occur. The central scholarly challenge is therefore broader than studying artificial intelligence as a new technology. It is to understand how the relationships among people, information, knowledge, and intelligent systems are being reconfigured, and what this transformation means for information behavior, knowledge organization, information literacy, research, education, and the responsible governance of knowledge.

## 10. Conclusion: From AI Literacy to Epistemic Agency

The central question raised by generative AI is not which generation uses it more frequently, more confidently, or more effectively. A more analytically useful question is: who, at what stage of life, for what kind of information need, with what level of knowledge and literacy, in what context, and on what basis, delegates informational and cognitive judgment to generative AI? This formulation shifts attention away from generational stereotypes and toward the

interaction among life stage, informational competence, context, trust, verification, and the distribution of epistemic responsibility.

Across the life course, the challenges and opportunities associated with generative AI are configured differently. In childhood, the central issues concern source recognition, anthropomorphism, privacy, and parental mediation. In adolescence, the critical questions involve provenance awareness, credibility assessment, ethical use, and the difference between digital fluency and epistemic maturity. In emerging adulthood and university contexts, attention shifts toward cognitive offloading, academic integrity, and the preservation of independent evaluation within increasingly AI-mediated learning environments. In midlife, the available evidence points to the importance of efficiency, professional and domain-specific knowledge, and context-sensitive trust, while also revealing a notable gap in direct empirical research. In later life, the central concerns include access, self-efficacy, lifelong learning, human support networks, and the development of calibrated forms of trust, including both practice-based and delegated trust.

These differences, however, should not be interpreted as fixed characteristics of age groups. Life stage interacts with information literacy, AI literacy, domain knowledge, prior experience, socioeconomic resources, cultural context, and the quality of institutional and technological support. The same affordance may therefore be enabling in one context and risky in another. Conversational accessibility may reduce barriers to information for some users while simultaneously increasing the risk of source invisibility or misplaced trust. Cognitive offloading may reduce unnecessary effort in one task while undermining learning or judgment in another. The normative issue is not whether cognitive offloading or delegation occurs, but whether it is appropriate, proportionate, transparent, and reversible.

For this reason, the educational and policy objective should extend beyond AI literacy in its narrow operational sense. Responsible engagement with generative AI requires the combination of AI literacy, calibrated trust, verification competence, and retained epistemic agency. Users should be able to recognize what the system can and cannot reliably do, distinguish linguistic fluency from evidential credibility, verify claims when the stakes require it, and retain responsibility for judgments that should not be surrendered to an automated intermediary.

Responsibility for achieving this outcome is distributed. Individuals cannot be expected to carry the full burden of detecting hallucinations, identifying synthetic content, protecting personal data, or resisting persuasive design. Families, schools, universities, libraries, workplaces, health systems, designers, platforms, and regulatory institutions all shape the conditions under which AI-mediated information behavior develops. Responsible use therefore depends not only on more capable users, but also on more transparent systems, stronger institutional mediation, and governance arrangements that protect vulnerable users while preserving meaningful access and participation.

Generative AI marks a transition from an information environment in which systems primarily find and retrieve information to one in which they increasingly speak, synthesize, personalize, recommend, and mediate. In such an environment, the human capacity to ask good questions, doubt plausible answers, inspect sources, verify claims, compare alternatives, and make independent judgments becomes more important rather than less important. The future of responsible information behavior should therefore not be understood as a trajectory toward

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ever greater cognitive delegation. It should be understood as the development of increasingly conscious boundaries around what can be delegated, what must be verified, and what should remain fundamentally under human judgment.

From this perspective, the decisive issue for Knowledge and Information Science is not whether generative AI will become embedded in information practices; that process is already underway. The more consequential question is whether users, institutions, and systems can develop forms of mediation that enhance access and cognition without eroding the human capacity for informed judgment. The transition from AI literacy to epistemic agency offers a more demanding, but also more adequate, framework for addressing that challenge.

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