



The case for friction in AI-mediated information seeking and learning

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Abstract

Introduction. This paper challenges the assumption that frictionless AI-mediated information seeking represents progress. We argue that AI systems eliminating productive friction, such as uncertainty, exploration, and reflective processes, undermine intellectual virtues essential for critical thinking in an AI-saturated information environment.

Method. This conceptual article employs a theory synthesis approach, drawing on library information science (LIS) theories of information behaviour, experience, and literacy, virtue epistemology, and human-computer interaction (HCI) friction design literature.

Analysis. We map intellectual virtues such as curiosity, thoroughness, and intellectual humility onto the Association of College and Research Libraries (ACRL) Framework for Information Literacy for Higher Education, building on and extending previous analyses. We connect dimensions of virtuous search to AI system design principles and align friction types with specific intellectual virtues.

Results. We propose three design principles for human-centred AI systems (representation, affordance, and facilitation) and develop a typology that maps friction interventions to intellectual virtues, providing concrete examples for each.

Conclusion. Productive friction should be understood as a feature supporting intellectual development, not a barrier to efficiency. The design choices made today will determine whether AI serves as intellectual scaffolding or cognitive crutch.

Introduction: The frictionless myth

Many of us now spend hours in dialogue with systems that respond fluently and generously. These conversations feel warm and productive. They move quickly. They give us the sense that we are understanding more and expressing ourselves with greater ease. The danger lies in the fact that this confidence can form within a closed loop. It is possible to build meaning that feels complete while drifting further away from the grounded knowledge that comes from friction and experience. (Boymal, 2025)

The above passage, taken from a LinkedIn post by Jonathan Boymal, encapsulates the issues associated with the frictionless promise. This phenomenon has become increasingly normalised with the advent of generative artificial intelligence (GenAI). The promise of artificial intelligence in information seeking has been largely framed around the elimination of friction, the removal of barriers, delays, and uncertainties that impede rapid access to answers. Corporate AI philosophies often celebrate seamless, instant responses that bypass the complex cognitive and affective processes traditionally associated with learning and discovery. Yet this frictionless ideal represents a fundamental misunderstanding of how meaningful knowledge construction occurs, and it threatens to undermine the intellectual capacities essential for navigating today's complex information environments (Allison & DeRewal, 2024).

Library and information science has a robust body of literature examining human information behaviour, particularly information seeking in various contexts (Eisenberg et al., 2016; Ellis, 1989; Kuhlthau, 2004; Marchionini, 1997). However, the increasing use of AI tools as sources of information challenges long-standing assumptions within this body of work, especially those related to the information-seeking process. Sundin (2025) notes that traditional library information science perspectives focus on how systems provide sources of information to users, while AI systems tend to offer answers or content, rather than the sources themselves. As Lo (2026) opines, 'inquiry is now often answer first rather than search first' (p.1). This shift carries significant implications for how users evaluate information and perceive authority. Sundin (2025) warns that such changes could lead to the deskilling of core information literacy practices, particularly those tied to search and evaluation, and result in the transfer of 'some of the previously required analytical skills from the user to the system' (p. 298). He further observes that 'changes in the information infrastructure make it increasingly difficult for people to recognise sources' (p. 292).

Loru et al. (2025) demonstrate this empirically: even when large language model outputs matched human evaluations, the underlying judgment formation differed significantly, relying on 'lexical associations and statistical priors rather than contextual reasoning or normative criteria' (p. 1). The authors termed this divergence 'epistemia: the illusion of knowledge emerging when surface plausibility replaces verification' (p.1). Perc (2025), in a commentary on the Loru et al. (2025) study, argues that 'recognizing and addressing this divergence is essential if automated systems are to enhance—rather than erode—the integrity of human knowledge and deliberation' (p. 2). This is especially important considering that large language models are now used across domains for evaluation purposes.

Current AI developments mark a new phase in the evolution of the information ecosystem and challenge us with questions about the very nature of judgment itself. As Perc (2025) argues, the architecture of collective knowledge is susceptible to distortion. This comes not just from the presence of misinformation, but from the 'epistemic procedures used to assess it' (p. 2). Drosos et al. (2025) raise related concerns, highlighting the tendency toward mechanised convergence: the homogenisation of output when knowledge workers become over reliant on GenAI tools. Doshi and Hauser (2024) provide empirical support for this effect, finding that while GenAI tools increased individual creativity in creative writing tasks, participants produced more similar

content overall, with gains in individual output coming at the expense of collective novelty. The underlying pattern is an offloading of effortful cognitive tasks to AI tools, where people are unwilling to devote the time and mental resources required for deliberate thinking.

Drawing on the literature above, we theorise that the AI-infused information infrastructure can result in the erosion of information literacy skills that play a role in critical thinking. As such, there is a growing need to critically examine the nature of friction in information seeking and learning. Rather than viewing it solely as an obstacle, we propose reframing certain types of friction as productive. For this purpose, we define productive friction as encompassing both the cognitive and affective processes inherent to learning and information seeking, such as inquiry and uncertainty. These processes are essential to the development of the intellectual virtues necessary for responsible and reflective information use, and the deliberate system design features that counter the frictionless paradigm by prompting critical thinking. To develop this argument, we employ a conceptual approach (Jaakkola, 2020), drawing on library information science theories of behaviour and experience (Association of College & Research Libraries [ACRL], 2016; Belkin, 1980; Gorichanaz, 2024; Kuhlthau, 2004), virtue epistemology (Baehr, 2015; Heersmink, 2018), and human-computer interaction friction design literature (Chalmers & Galani, 2004; Cox et al., 2016; Sung, 2021). The framework presented here can inform future empirical research on productive friction and intellectual virtues in AI-mediated information seeking and guide the design of systems that foster intellectual virtue development through deliberate friction features.

Methodology

This paper is a conceptual article that combines elements of theory synthesis and theory adaptation (Jaakkola, 2020). Jaakkola (2020) defines a theory synthesis paper as seeking to ‘achieve conceptual integration across multiple theories or literature streams’ (p. 21), offering an enhanced or new view of a concept by connecting previously unlinked literature in a novel way. Theory adaptation papers seek to amend an existing theory by introducing alternative frames of reference that reveal dimensions the original theory does not adequately address. Our approach combines both: we synthesise literature across information behaviour, virtue epistemology, and friction design that has not previously been connected in this configuration, and we do so to adapt current understandings of information literacy for an AI-mediated context by introducing lenses that reveal dimensions the existing literature does not adequately address. Figure 1 presents the overall research design. The three literature streams shown represent broad traditions rather than exhaustive citation lists; within each stream, additional sources contribute to the analysis as detailed in subsequent sections.

Information behaviour & information literacy	Virtue epistemology	Friction design
ACRL Framework; Belkin; Kuhlthau; Sundin	Baehr; Heersmink	Chalmers & Galani; Cox et al.; Tomalin
Establishes what is at stake in information seeking	Articulates which capacities are at risk	Distinguishes which types of friction are productive
Cross-framework synthesis 1. Map intellectual virtues onto ACRL Framework 2. Connect Gorichanaz's dimensions of virtuous search to design principles 3. Align Tomalin's friction types with specific intellectual virtues		

Figure 1. Conceptual research design (following Jaakkola, 2020)

Three literature streams inform the synthesis, each selected because it addresses a distinct dimension of the problem. Literature on information behaviour and information literacy from the library and information science field establishes what is at stake in information seeking and learning, including the cognitive, affective, and exploratory processes that current AI systems risk bypassing. Virtue epistemology articulates which human capacities are at risk when these processes are eliminated, providing a language for the character-level dispositions that effortful information seeking cultivates. Human-computer interaction friction design literature distinguishes which types of friction are productive, offering design-level categories that enable systematic analysis of how AI systems might preserve or introduce friction that supports intellectual development.

The synthesis proceeds through four guiding questions:

- (1) How has friction been understood and approached in library information services?
- (2) What are the characteristics of friction as seen in information seeking and learning-related literature?
- (3) How can productive friction help with intellectual development in the AI age?
- (4) How is friction understood and defined in human-computer interaction literature?

The analytical process involves three interrelated cross-framework mapping exercises. First, we examine the ACRL Framework for Information Literacy for Higher Education's (2016) disposition statements (the attitudes and values the Framework associates with area of information) against Baehr's (2015) intellectual virtues, identifying both explicit references and latent alignments across the frames (the six interconnected frames that anchor the Framework), building on and extending McMenemy and Buchanan's (2019) earlier analysis. Second, we connect Gorichanaz's (2024) four dimensions of virtuous search (motivation, affect, competence, and judgment) to three design principles (representation, affordance, and facilitation) drawing on Smith and Matteson's (2018) concept of machines that teach. Third, we align Tomalin's (2023) friction categories with specific intellectual virtues, producing the typology presented in Table 2. At each stage, theories are selected and mapped based on their complementary fit and their ability to address a dimension of the problem that other components of the framework could not.

Scope and limitations

As a conceptual article, this paper does not aim to empirically test the proposed relationships. Rather, it produces a framework comprising design principles and a friction-virtue typology

intended to guide future empirical investigation and inform the design of human-centred AI systems. The causal chain we propose, from frictionless AI leading to cognitive offloading leading to diminished intellectual virtue development, is presented as a theoretically grounded proposition supported by a growing body of empirical evidence (Fan et al., 2025; Georgiou, 2025; Gerlich, 2025a; Hong et al., 2025; Hsiao & Chiu, 2025; Ji et al., 2025; Ju, 2023; Kosmyrna et al., 2025; Singh et al., 2025a; Tang & Zhang, 2025) rather than as an established causal claim. The cross-framework mappings presented are interpretive. Key questions requiring empirical validation include how friction tolerance varies across novice and expert users, how virtue development can be measured over time in AI-mediated contexts, and whether the design interventions proposed here produce the intended effects in practice.

The learning value of friction

In the Information Search Process (ISP) model, Kuhlthau (2001, 2004) highlights the presence of uncertainty, confusion, and anxiety as a natural part of the search process. This raises an important question in today's AI context: When sources are bypassed in favour of direct answers, do such feelings still have a role, or might they manifest differently during the search process?

Belkin's (1980) model of an anomalous state of knowledge (ASK) aligns closely with Kuhlthau's framework, positioning uncertainty as the basic motivator for information seeking. Similarly, in Dervin's (1998) work, information seeking or search is initiated by a need to make sense, and people are seen as engaged in a search for meaning. As Case and Given (2016) note in describing Dervin's work, emotions are 'at least as important as cognitions in "gappy" situations: searchers may be intent upon reducing their anxiety as much as their uncertainty' (p. 87).

In all three models, friction, whether cognitive or affective, can motivate continuation of the search process or its discontinuation.

Recent scholarship has begun applying these foundational theories to AI contexts. Ravuri and Mardis (2025) highlight Kuhlthau's work as 'useful for understanding and improving users' interactions with AI-driven chatbots' (p. 267). Similarly, Charette and Ghosh (2025) use Belkin's work as a framework to study human-AI interactions, noting its utility 'for understanding human-GenAI interaction as a process of communication that imparts information and impacts users on both cognitive and emotional level' (p. 114).

These cognitive and affective dimensions of information seeking find a parallel in educational theory. In learning, liminality refers to an in-between state, when one finds oneself between confusion and understanding. Experiencing liminality is a crucial aspect of developing an understanding of a threshold concept. The learning that happens in liminal spaces is non-linear; there is 'an ebb and flow of understanding, oscillation in terms of the ontological dimension of variation, and "stuck places"' (Baillie et al., 2013, p. 240). Savin-Baden (2019), drawing on Trafford (2008), views conceptual *lostness* as a form of liminality, noting that students value doubt as a way of traversing liminal space. The *lostness* is seen to be valued as a 'central principle of learning' (Savin-Baden, 2019, p. 48). One could draw parallels between this idea of liminality and the feeling of confusion, uncertainty, and anxiety that is part of the information search process as enumerated by Kuhlthau (1993), who views uncertainty as arising from a 'lack of understanding, a gap in meaning, or a limited construct' (p. 347). Similarly, Hur, Twidale and Bosch (2025), examining student use of metaphors to describe confusion during learning, note that confusion is 'complex as it can either deepen understanding or hinder progress, depending on its resolution' (p. 2973).

As with Kuhlthau's and Belkin's models, friction in the form of uncertainty or confusion can act as a motivator for continuation or discontinuation of the search process. Willson (2019) acknowledges Kuhlthau's work on uncertainty as pivotal in the recognition of the experience of

uncertainty as encompassing cognition, affect, and behaviour, thereby providing a ‘more holistic picture of the information-seeking process’ (p. 844).

Considering the role that information seeking plays in learning and knowledge creation, liminality offers a useful lens to describe the productive friction associated with it. It needs to be noted that the ACRL Framework for Information Literacy for Higher Education (2016) uses the idea of threshold concepts and draws on work on threshold concepts in information literacy by Townsend et al. (2016). Further, in a related study, Tucker (2016) studies threshold concepts in the development of search expertise; a mapping of these concept is presented in Table 1.

Dimension	Information seeking	Learning (liminality)	Role of friction
Affective	Anxiety, uncertainty	Doubt, frustration	As a motivator to continue with the search or adopting new strategy
Cognitive	Confusion, inconsistency	Stuck places, conceptual lostness	Shifts in thinking, reevaluating existing mental models
Behavioural	Seeking, querying, browsing	Ebb and flow marked by trial and error	Enables action to bridge the gap, or resolve the anomalous state of mind, or end the search process

Table 1. Mapping concepts from information seeking and learning to their role as friction

When a search process begins due to an anomalous state of knowledge, or a sense of a gap or uncertainty, a liminal state is entered marked by friction in the form of anxiety, confusion, or uncertainty. Allison and DeRewal (2024) define friction as ‘any process that results in the deliberate slowing of information or user action’ (p. 3). They go on to note that unlike AI companies that view friction as a problem to eliminate, ‘information science values a degree of friction in search; feelings of frustration and doubt, slow processes, and experiences of indeterminacy are important in knowledge production’ (p. 3).

Originating in organisation science, the concept of productive friction is defined as ‘the process of overcoming obstacles in a productive way that, in turn, leads to individual learning and collaborative knowledge construction’ (Holtz et al., 2018, p. 440). The concept of designed friction, however, has roots in human-computer interaction, where Cox et al. (2016) proposed ‘microboundaries’ as small obstacles that shift users from automatic to deliberate processing. As employed in user experience in game design, productive friction refers to the idea of the intentional introduction of friction in games, which can lead to productive outcomes and which again draws on various frameworks such as productive failure and slow design, apart from microboundaries. Sung (2021) further defines productive friction for games as that which engenders productive outcomes through shifts in thinking and learning outcomes.

It is important to distinguish productive friction from what Tomalin (2023) calls ‘any unnecessary retardation of a process or activity (e.g. a financial transaction, the uploading of a picture, or an

unsolicited pop-up window)' (p. 2). Combined with the convenience-focused design of online search, such unproductive friction can result in satisficing or making do during information seeking.

Pickens (2021) argues that friction is essential for users to develop meaningful control over their information systems, a point echoed by Shah and Bender (2022), who note the 'tremendous value in information seekers exploring, stumbling, and learning through the process of querying and discovery' (p. 230). Singh et al. (2025b) point out that this aligns with Dewey's theory of reflective thinking, which requires enduring a 'state of perplexity, confusion, or doubt' as a prerequisite for genuine inquiry (p. 3), corresponding to the liminal space between confusion and understanding. This is precisely the state that polished, synthesised AI outputs may prematurely resolve. Nasr et al. (2025) provide empirical support for this dynamic, identifying a 'resolution gap' in students' AI-mediated inquiry: passive, AI-directed use supports early phases of cognitive engagement, triggering questions, exploring information, and beginning to integrate ideas but fails to support the final synthesis and resolution stage. Students progress to the liminal space but never traverse the threshold, leaving critical synthesis underdeveloped. Similarly, Drosos et al. (2025) find that when AI-assisted tasks included friction interventions, users sometimes experience what the authors call 'productive confusion', which leaves them with more questions than answers (p. 21). Rather than a failure, participants found this valuable because it pushed them to reconsider assumptions and articulate their reasoning.

What these studies reveal is that productive friction preserves decision points, moments in which users, whether professionals or students, must pause, weigh alternatives, and practice discernment. Each time a student decides which source to trust, which search strategy to pursue, or how to reconcile conflicting evidence, they rehearse the judgment which constitutes intellectual virtue. AI systems optimised for efficiency remove these decision points entirely. The student receives an answer without navigating the territory that produced it. Over time, this atrophies the capacity for discernment itself, not because students lack information, but because they have had too few opportunities to practice evaluating it.

In Kuhlthau's (2001, 2004) work, the end stages of the information search process are marked by reflection and relief, where the searcher feels they have gained knowledge which can be taken to their next search. Viewed this way, we see alignment with the ACRL Framework for Information Literacy for Higher Education (2016), especially the frame Searching as Strategic Exploration, where search is defined as 'encompassing inquiry, discovery, and serendipity' (p. 9). A disposition associated with this frame is to 'recognize the value of browsing and other serendipitous methods of information gathering' (p. 9). Liu and Almeda (2025) contrast hypertextual systems with algorithmic ones. In the former, each link followed is a deliberate choice that constructs the learner's path through knowledge; in the latter, the path is predetermined, removing navigation as a site of judgment.

This exploratory understanding of search aligns with deeper epistemological frameworks about how knowledge is constructed through dialogue rather than delivery. AI systems eliminate the friction of encountering diverse perspectives, navigating scholarly disagreements, or sitting with uncertainty. These are precisely the conditions under which intellectual virtues develop. As we will argue, the ACRL Framework explicitly names intellectual virtues such as curiosity, open-mindedness, and intellectual humility as core dispositions, a connection to virtue epistemology that current AI design threatens to bypass. The question arises: Do AI tools support these liminal, productive experiences, or do they bypass them entirely?

Allison and DeRewal (2024) cite a study from the Pew Research Center (Sidoti & Gottfried, 2023) to show that students clearly believe AI tools like ChatGPT have the potential to remove non-elective friction by offering them the information they seek in an instant. As Tomalin (2023)

argues, 'a frictionless future may appear ideal and desirable from certain ideological perspectives, yet it is clearly hugely problematical when viewed from other vantage points' (p. 12). Haider and Sundin (2019) document this dynamic with search engines and find that as interfaces become simpler, their technical workings grow increasingly opaque, leaving users with fewer opportunities for critical reflection. They call this the 'mundane-ification' of search (p. vii).

AI systems intensify this pattern. Where search engines at least return links requiring users to evaluate sources, generative AI synthesises and delivers answers directly, removing even that residual friction. Empirical evidence confirms this: Chapekis and Lieb (2025) find that 'Google users who encounter an AI summary are less likely to click on links to other websites than users who do not see one' (para 4). Shibani et al. (2024) also find that over ninety per cent of students demonstrate shallow, transactional interactions with ChatGPT, 'treating it like a search engine by entering key terms' (p. 5) rather than engaging in critical dialogue. This reveals a growing disconnect between the ways users engage with these tools and how academia conceptualises their use. A thorough understanding of how people use these tools across various contexts and the information practices associated with them is urgently needed.

Intellectual virtues as an antidote

According to Baehr (2016), 'intellectual virtues have their basis in something like a love of learning and can be understood as the deep personal qualities or character traits required for lifelong learning and critical thinking' (p. 4). In proposing a framework for virtuous search, Gorichanaz (2024) defines it as 'online search that cultivates the intellectual virtues' (p. 538), arguing that intellectual virtues are relevant to information science, given their relationship to information and learning. Along similar lines, Bivens-Tatum (2021) puts forward the concept of virtue information literacy (VIL), described as an 'ethical, character based approach analysing information literacy through intellectual virtues and vices' (p. 1).

Gorichanaz (2024) draws on the work of Heersmink (2018), who states that 'unreflexively using Internet-based sources poses epistemic risks for information-seeking and knowledge acquisition' (p. 1), a stance echoed by Sundin (2025). As examples, Heersmink (2018) notes the prioritisation of false or misleading information by search engines, filter bubbles that engender confirmation bias, and even autocomplete suggestions that can mislead one to take the wrong path in an inquiry. These risks have only been exacerbated by AI-generated content. Drawing on Baehr (2015), Heersmink (2018) presents nine intellectual virtues: curiosity, intellectual autonomy, intellectual humility, attentiveness, intellectual carefulness, intellectual thoroughness, open-mindedness, intellectual courage, and intellectual tenacity. Gorichanaz (2024) argues that sociotechnical systems should support their cultivation, a need made more urgent by AI as an 'arrival technology' that reshapes society 'regardless of individual choice or adoption' (Hanegan & Rosser, 2025, p. ix). Highlighting the importance of work relating to information literacy, he states that viewing information literacy through the lens of intellectual virtues can provide additional theoretical grounding and guide instructional activities.

The ACRL Framework and intellectual virtues

The Framework for Information Literacy for Higher Education (ACRL, 2016), with its frames, knowledge practices, and dispositions, is grounded in intellectual virtues more explicitly than previous analyses have recognised. McMenemy and Buchanan (2019) apply Baehr's nine intellectual virtues to the Framework and identify a latent presence in four of the six frames. However, the Framework's disposition lists name three of Baehr's virtues: curiosity, open-mindedness, and intellectual humility, the last being the only virtue explicitly defined in the Framework. McMenemy and Buchanan (2019) also note that the Framework's use of the term 'dispositions' is itself 'a potential indication that the approach taken in the development of the Framework is cognisant of character issues' (p. 78).

Building on McMenemy and Buchanan's (2019) analysis, and drawing on Bivens-Tatum's (2021) pedagogical applications, Baehr's (2024) mappings of intellectual virtues and information literacy, and our own instructional mapping, Table 3 presents a more comprehensive alignment of intellectual virtues across all six ACRL frames, including representative framework language and examples of how each virtue manifests in AI-mediated information seeking.

ACRL frame	Virtues identified	Representative framework language	AI context example
Authority is Constructed and Contextual	Autonomy, carefulness, courage, curiosity, humility, open-mindedness	'an attitude of informed skepticism and an openness to new perspectives, additional voices, and changes in schools of thought' (p. 4)	Evaluating whether an AI response reflects diverse or mainstream-only perspectives; questioning the authority behind AI-curated sources
Information Creation as a Process	Carefulness, curiosity, thoroughness	'are inclined to seek out characteristics of information products that indicate the underlying creation process' (p. 5)	Recognising that an AI summary collapses the production process behind its sources
Information Has Value	Autonomy, humility, open-mindedness	'see themselves as contributors to the information marketplace rather than only consumers of it'; 'respect the original ideas of others' (p. 6)	Questioning whether sharing unverified AI output is responsible
Research as Inquiry	Attentiveness, curiosity (explicit), humility (explicit), open-mindedness (explicit), tenacity, thoroughness	'value intellectual curiosity'; 'demonstrate intellectual humility'; 'maintain an open mind and a critical stance'; 'value persistence', 'follow ethical guidelines'(p. 7)	Persisting with keyword refinement after initial AI responses prove insufficient; acknowledging what one does not yet know
Scholarship as	Carefulness, humility, open-	'a discursive	Seeking

ACRL frame	Virtues identified	Representative framework language	AI context example
Conversation	mindedness, thoroughness	practice in which ideas are formulated, debated, and weighed against one another' (p. 8)	perspectives beyond what the AI surfaces; entering scholarly dialogue rather than accepting a synthesised answer
Searching as Strategic Exploration	Humility, open-mindedness, tenacity	'mental flexibility to pursue alternate avenues as new understanding develops'; 'persist in the face of search challenges' (p. 9)	Trying alternative search strategies rather than accepting a single AI response; recognising that first attempts may not produce adequate results

Table 2. Mapping ACRL Framework language to intellectual virtues in AI-mediated contexts. Builds on McMenemy and Buchanan (2019), Bivens-Tatum (2021), Baehr (2024), and the authors' instructional mapping. All Framework language is quoted from ACRL (2016).

Notably, intellectual courage and tenacity, the virtues most connected to managing fear and embracing struggle, are never explicitly named in the Framework despite being implicitly required by many dispositions. If AI tools reduce the friction that would otherwise cultivate these virtues, students may never develop the persistence and risk-taking essential to genuine inquiry. Bivens-Tatum (2021) makes this pedagogical implication concrete through the Scholarship as Conversation frame, describing an intellectual vice common in students he terms 'ignarrogance': epistemic arrogance combined with ignorance (p. 14). The frame, he argues, teaches that scholarly conversation requires open-mindedness and humility to be transformed through engagement with other perspectives. These are dispositions that frictionless AI interactions do not demand.

To illustrate how this alignment extends to AI-mediated contexts, the Research as Inquiry frame, contains the most explicit virtue language. In instructional work translating this frame into practice, specific information literacy activities map directly to corresponding intellectual virtues. Background research requires humility (acknowledging what one does not yet know) and curiosity (generating questions from that uncertainty). Keyword selection requires tenacity (trying multiple approaches when initial searches fail) and the humility to recognise when one's framing is too narrow.

The contemporary information environment intensifies the demand for these virtues as algorithmic filtering creates echo chambers requiring open-mindedness to resist, while the attention economy rewards surface engagement, requiring attentiveness and thoroughness to pursue verification across sources. When students turn to ChatGPT out of frustration after unsuccessful searches, the virtues most conspicuously absent are tenacity, humility, and curiosity, precisely the dispositions the Framework asks learners to cultivate. Archambault (2023; Archambault et al., 2024) and Ali and Wilson (2025) further demonstrate how the ACRL

Framework lends itself to AI literacy, mapping its dispositions to ethical principles and the intellectual virtues essential for critically engaging with algorithmic systems.

Connecting virtuous design to search

Smith and Matteson (2018) argue that information literacy models tend to collapse the complexity of the search process, including understanding the task, synthesis, reflection, and communication, 'into the internal state of the user prior to access' (p. 75). We argue that this collapsed space represents the liminal space where friction exists and, importantly, is not wholly system engendered.

Gorichanaz (2024) situates virtuous search within four dimensions. The first dimension, motivation, concerns the drive behind search; convenience and least effort often dominate, especially with AI tools that sound authoritative. As Gorichanaz warns, 'when people settle (even unknowingly) for incomplete or inaccurate information out of convenience, truth may be obstructed' (p. 543). Bivens-Tatum (2021) argues that making do shows a 'lack of intellectual thoroughness as well as open-mindedness and intellectual humility' (p. 26). The second dimension, affect, 'refers to the positive feelings experienced when a person exercises virtue. In the case of intellectual virtues, a virtuous searcher finds joy and meaning in exercising for their own sake the virtues such as curiosity, thoroughness, and tenacity' (Gorichanaz, 2024, p. 543). According to McKay et al. (2025), browsing exemplifies this, as 'not all who wander are lost' (p. 525). This aligns with the ACRL frame Searching as Strategic Exploration (ACRL, 2016).

The third dimension, competence, is the ability to exercise virtues in practice, for example asking questions and adopting new perspectives, which connects to the Authority is Constructed and Contextual frame's emphasis on informed scepticism and openness (Gorichanaz, 2024). The fourth dimension, judgment, involves applying virtues flexibly across situations, aligning with Searching as Strategic Exploration's emphasis on non-linear, iterative search and the mental flexibility to pursue alternate avenues. This also calls for intellectual humility, accepting that 'our beliefs — indeed our entire conception of ourselves — are never final' (Bivens-Tatum, 2019, p. 27).

The ACRL Framework draws on Mackey and Jacobson's (2014) metaliteracy, which expands traditional information skills to include collaborative production and sharing of information in participatory digital environments. This expanded conception is applicable to today's AI-saturated information environment, where related literacies include AI literacy. However, Fulkerson, et al. (2017) observe that the Framework downplays metaliteracy and metacognition in its final version, leading to unintended consequences for its usefulness as a teaching tool. This may partly explain why the connection between the Framework and virtue epistemology appears latent rather than explicit. Metacognition, which Fulkerson et al. call the 'linchpin' connecting the affective, behavioural, and cognitive domains of metaliteracy, ties directly to the importance of intellectual virtues. While there have been calls for the expansion of the Framework (Archambault, 2023; Ndungu, 2024), it can serve as a useful foundation for AI literacy when the connection between metaliteracy, metacognition, and intellectual virtues is made more explicit.

From theory to practice: Designing virtue-based AI systems

A growing body of empirical evidence supports the causal chain from frictionless AI use to cognitive offloading and diminished critical engagement. Gerlich (2025a) finds that increased reliance on AI tools is associated with reduced critical thinking, with cognitive offloading identified as a mediating factor. Georgiou (2025) documents a self-perceived decline in cognitive engagement during ChatGPT-assisted academic writing, while Kosmyna et al. (2025) corroborate this pattern at the neurological level, using EEG to show reduced neural engagement during AI-assisted writing. Ju (2023) demonstrates that full reliance on generative AI for writing reduced comprehension accuracy by approximately twenty-five per cent, suggesting that AI

summarisation improves output quality while short-circuiting the internal processes on which learning depends.

Hsiao and Chiu (2025) extend this temporally, showing that although ChatGPT use enhances short-term learning outcomes, students with weaker background knowledge who rely heavily on AI show signs of declining independent thinking and problem-solving ability over time. Ji et al. (2025) also find a revealing pattern in a study involving a STEM course and ChatGPT-assisted groups. Those assisted by ChatGPT show improved learning performance and reduced cognitive load but score lower on critical thinking than the non-AI group, suggesting that reduced cognitive demand leads to more passive engagement rather than deeper analytical reasoning. Fan et al. (2024) describe this dynamic as 'metacognitive laziness': in a randomised comparison of ChatGPT, human expert, analytics tools, and no-tool conditions, the AI group shows altered self-regulated learning processes despite similar final performance, indicating that surface-level outcomes can mask underlying erosion of metacognitive engagement.

Critically, the evidence also suggests that this pattern is not inevitable. Gerlich (2025b) finds that structured prompting reduces cognitive offloading and significantly improves critical reasoning compared to unguided AI use. Similarly, Hong (2025) demonstrates through the interactive cognitive offload (ICO) framework that strategically delegating mechanical writing tasks to generative AI reduces extraneous cognitive load while increasing germane cognitive load, thereby enhancing critical thinking skills such as argument depth and evidence synthesis. In addition, Singh et al. (2025b) provide direct evidence for the value of metacognitive friction in GenAI search: students who receive metacognitive prompts during perplexity-based searches explore significantly more topics, demonstrate greater persistent inquiry, and engage more deeply with sources. Without such prompts, six of twenty participants end their search within ten minutes after a single query, overestimating the sufficiency of the initial AI response, a pattern consistent with the cognitive offloading and satisficing behaviours documented across the studies above.

Hong et al. (2025), however, provide the strongest longitudinal evidence for this pattern. In a twelve-week quasi-experiment, students whose instruction deliberately delegated lower-order writing tasks to generative AI while requiring them to perform analysis, evaluation, and reflection demonstrate significantly greater critical thinking gains than a control group. Mediation analysis confirms that cognitive offloading behaviour partially explains the relationship between AI use and critical thinking improvements. This suggests that the issue is not offloading per se, but what learners are required to do with the freed cognitive resources, a finding that directly supports the case for designing productive friction into AI systems.

Tang and Zhang (2025) find that students themselves articulate these concerns: they worry about becoming 'too dependent on AI and too lazy to think' (p. 1102), question whether outputs represented their own achievement or the AI's and acknowledge that convenience comes at the cost of learning. These concerns map directly onto intellectual virtues, including carefulness in verifying outputs, courage to struggle with problems independently, and the sense of ownership that motivates thoroughness. This suggests that the convenience-focused design of current AI systems actively impedes the intellectual development that friction-based learning supports.

To resolve this, we propose adapting Gorichanaz's (2024) four dimensions of virtuous search, motivation, affect, competence, and judgment as actionable design principles. Drawing on Smith and Matteson's (2018) concept of machines that teach, we envisage AI systems structured around three core principles that preserve productive friction while leveraging AI capabilities. These comprise representation, affordance, and facilitation.

These three principles address different questions about how AI systems interact with users. Representation addresses what the system shows, how it presents where information comes

from, how reliable it is, and what the broader landscape of sources and perspectives looks like. Affordance addresses what the system lets users do, namely the features that enable exploration, comparison, and evaluation. Facilitation addresses how the system guides users, for example through prompts, questions, and scaffolding that shape the user's thinking process during the interaction. While these inevitably overlap, distinguishing them helps clarify what kind of design choice each principle involves.

Representation should support both motivation and competence. AI systems should present context information using human-understandable knowledge structures, helping users grasp the broader informational landscape and the big picture of where information comes from. This directly addresses Sundin's (2025) concern that seamless answers obscure source context, making evaluation difficult for novices. Similarly, Shah and Bender (2022) argue that 'just knowing a range of viewpoints exists, without any contextualization of how widely supported each is or what kinds of source documents support each, does not position users to build on their information literacy' (p. 228). For example, systems might display how a source was prioritised by relevance, search history, or citation count, making the basis for selection visible rather than hidden.

Affordance should foster positive affect and develop judgment: interfaces should enable easy navigation of context, encouraging exploration and critical evaluation. These affordances support affect by fostering curiosity, engagement, and a sense of discovery during the search process. They also cultivate judgment by prompting users to weigh diverse perspectives, recognise ambiguity, and make informed decisions based on context. Features such as toggles to view how results are ranked, options to adjust personalisation settings, expandable panels showing alternative perspectives, or tools to compare sources side by side give users control over their information environment without directing their thinking.

Facilitation integrates all the dimensions by helping people learn from using the system, not merely use it efficiently. Rather than emphasising efficiency alone, systems should scaffold the information-seeking process. This includes scaffolding how users formulate queries, prompting them to refine vague questions rather than simply generating answers from poorly formed inputs. This supports the intellectual virtue of carefulness or learning to ask questions with precision. Ravuri and Mardis (2025) argue that librarian-patron reference interviews offer a model in which chatbots, like librarians, can use clarifying questions to enhance engagement and understanding. They emphasise that while AI can integrate web search, databases, and generative responses, key tasks, such as defining topics and assessing sources, should remain human-led. Danry et al. (2023) provide empirical support for this approach, showing that AI systems that ask users questions significantly outperform systems that provide explanations when participants evaluate flawed reasoning. Notably, participants who receive direct explanations are more satisfied with the information given and thus less likely to seek verification, exposing them to 'risks of their erroneous prior beliefs or their lack of critical thinking without double-checking extra sources' (p. 11).

Facilitative AI systems create conditions for developing intellectual virtues. By prompting reflection, encouraging clarification, and guiding users through ambiguity, such systems nurture intellectual humility, curiosity, thoroughness, and courage. Facilitation thus becomes pedagogical, helping users learn how to seek well, not just quickly. Drosos et al. (2025) offer empirical support for this approach, introducing 'provocations', or short text prompts designed to induce critical thinking in AI-assisted tasks by 'highlighting risks, biases, limitations, and alternatives of GenAI suggestions' (p. 2).

Emerging approaches to AI-powered learning tools show how facilitation principles can be implemented in practice. Systems designed around Socratic questioning guide users through

structured observation, evidence-based interpretation, and open-ended inquiry rather than providing direct answers. These systems demonstrate how AI can scaffold virtue development rather than bypass it, which progressively shifts cognitive responsibility to the learner.

Design principles for virtue-based friction

While the machines that teach framework (Smith & Matteson, 2018) provides foundational design principles, Tomalin's (2023) typology offers a more precise approach to implementing specific types of productive friction in AI systems. As Tomalin argues, 'not all (e)friction is inherently undesirable' (p. 3). The key lies in distinguishing between friction that serves learning versus friction that merely impedes. This perspective is echoed by practitioners navigating AI integration. Aal et al. (2025) argue that AI systems optimised for speed and probability 'risk amplifying our cognitive shortcuts and limiting exposure to diversity' (p. 12). They propose designing productive friction into AI interfaces to highlight contrasting viewpoints, flag simplified answers, and require clarifying questions that 'encourage more thought, rather than passive acceptance' (p. 12). Such design choices create conditions for intellectual humility, open-mindedness, and thoroughness to develop.

To be clear, the argument here is not that more friction is always better. Virtue epistemology, following Aristotle, adopts the doctrine of the mean, in which each virtue is a mean between deficiency and excess (Baehr, 2021). Tenacity, for instance, sits between giving up at the first obstacle (deficiency) and refusing to pivot when the evidence warrants (excess). A student who abandons a research question because AI cannot immediately answer it displays deficient tenacity. But so too does the student who stubbornly clings to an original thesis despite encountering disconfirming evidence. The goal is not to maximise struggle but to calibrate challenge, thereby preserving enough friction that students develop judgment, while removing friction that serves no pedagogical purpose.

This framework is intended as a guide rather than a specification. The question of what counts as productive friction in a given context cannot be answered purely at the theoretical level and requires testing with real users.

The goal is not to maximise friction across all dimensions simultaneously but to calibrate it, preserving enough friction that users develop judgment and removing friction that serves no learning purpose. Not every interaction requires all three principles at full intensity. Source information (representation) should be available but need not always be prominent. Exploration features (affordance) should invite, but not require, engagement, while scaffolding prompts (facilitation) should guide thinking without doing the thinking for users. The right balance will vary by context, task, and user expertise. Lee and Nguyen (2025) show that novice users prefer simple friction interventions, while experienced users are more receptive to cognitively demanding ones. Singh et al. (2025a) similarly find that the effectiveness of metacognitive prompts during GenAI search varies with students' metacognitive flexibility. Together, these findings suggest that friction must be calibrated to the learner's readiness and existing metacognitive capacities.

Tomalin's (2023) framework distinguishes friction across several key dimensions. Elective friction is knowingly chosen by users, while non-elective friction is imposed without their explicit awareness. Elective friction can be impeding, preventing or slowing the main activity, or distracting, providing additional information without stopping the task. Both types can serve protective functions, safeguarding against harm, or informative purposes, offering contextual knowledge. Friction may also be reflexive, with users applying it to themselves, or transitive, imposed for the benefit of others, such as the broader community.

Rieger et al. (2024) offer evidence for this distinction. Testing interventions to mitigate confirmation bias during web search, they find that reflective friction, such as warning labels prompting users to consider their choices, successfully encourages engagement with diverse viewpoints, while automatic friction, or obfuscations that hide content by default, merely reduces engagement with whatever it is applied to, regardless of appropriateness. Users, it turns out, have greater capacity for active choice than designers often assume. The implication for virtue-based design is clear: friction should prompt reflection, not bypass it. In related work, Rieger et al. (2023) describe this as the difference between 'boosting' and 'nudging', the former developing metacognitive capacity, including intellectual humility, while the latter merely redirects behaviour without learning.

We can map intellectual virtues to specific friction types that support the representational, affordance, and facilitation goals outlined above (see Table 3).

Friction Type	Example	Virtue Cultivated	Function
Elective, impeding, protective	'Enable fact-checking mode' requiring cross-referencing before bookmarking/copying	Attentiveness, carefulness	Virtue cultivation
Elective, distracting, informative	Expandable panels: confidence notes, historical context, methodology notes	Autonomy, intellectual curiosity, open-mindedness, thoroughness	Virtue cultivation
Transitive	Pre-sharing prompts: not all researchers agree on this topic. Would you like to see dissenting views before continuing?	Carefulness, courage, intellectual humility, open-mindedness	Structured practice
Non-elective, protective	Mandatory disclosures: this response was personalised based on your search history and location data	Autonomy, carefulness	Awareness-building

Table 3. Mapping friction types to design examples and intellectual virtues

Elective, Impeding, Protective Friction. Users can voluntarily activate enhanced verification modes that slow their research but provide additional protection. For instance, users might choose 'Enable fact-checking mode', which then requires them to cross-reference claims with verification databases before bookmarking, copying or pasting information. This optional setting supports carefulness by encouraging users to verify information quality but engages only when users deliberately choose this protective measure.

Elective, Distracting, Informative Friction. Users can voluntarily activate contextual information that appears alongside AI responses, which they can choose to view or ignore. For example, expandable panels might offer 'Confidence note: this response draws from fifteen high-quality sources', 'Historical context: view how this topic has evolved since 2010', or 'Methodology note: this answer combines peer-reviewed studies with news reports'. These voluntary information layers encourage intellectual curiosity by providing deeper context, open-mindedness by highlighting alternative perspectives, and thoroughness by revealing methodological details without interrupting the main interaction or requiring user action.

Transitive Friction. AI systems can impose scaffolding for the broader research community by prompting users, for example, 'Before sharing this response, consider: not all researchers agree

on this topic. Would you like to see dissenting views before continuing?' This approach aligns with the reference librarian model (Ravuri & Mardis, 2025), in which Socratic questioning supports both individual learning and collective knowledge-building by encouraging responsible information sharing and careful verification of claims.

Non-Selective, Protective Friction. Mandatory system-generated disclosures that appear automatically regardless of user preference, such as 'This response was personalised based on your search history and location data' or 'Information current only to [training cutoff date]'. Virtue epistemology holds that intellectual virtues are cultivated through willing practice rather than imposed compliance (Baehr, 2015, 2021). A mandatory warning does not, in itself, cultivate autonomy or carefulness. However, it can build the awareness of AI limitations and bias, and a consciousness that outputs require critical evaluation, which is a precondition for these virtues. For that awareness to mature into genuine virtue, learners must eventually recognise the need and choose to practise it independently. Non-selective friction thus occupies a legitimate but limited place in the framework, as a starting point, not an end state.

Different friction types serve different developmental functions. Non-selective friction builds awareness, transitive friction scaffolds structured practice, and selective friction supports genuine virtue cultivation. The design trajectory should move towards greater user agency over time, developing from mandatory awareness through scaffolded practice to internalised virtue. This aligns with Chalmers and Galani's (2004) concept of seamful design, in which system boundaries are deliberately revealed so that users develop the kind of conscious attention to their tools that virtue epistemology requires.

For AI literacy, this suggests designing systems where friction acts as metacognitive scaffolding, helping users recognise when to slow down, verify information, or consider alternative perspectives, while preserving the curiosity and agency essential to productive learning. Recent work viewing AI as provocateur (Sarkar, 2024) or antagonist (Cai et al., 2024) points to the value of such designed friction in both learning and information seeking.

Conclusion: Friction as feature, not bug

In responding to the call for human-centred AI, it is important to remember that truly centring human needs means supporting the development of human intellectual capabilities rather than replacing them. The most helpful AI systems maintain space for human uncertainty, curiosity, and growth, even when this means accepting productive friction in the service of learning. The design choices made today will determine whether AI serves as intellectual scaffolding or as a cognitive crutch.

Future research should empirically evaluate how different friction interventions affect the development of specific intellectual virtues, including how tolerance for friction varies between novice and expert users, and whether reframing AI's role from answer provider to inquiry partner might normalise productive friction. One promising direction is the development of instruments to assess virtue development in AI-mediated contexts, pairing self-assessment tools adapted from virtue epistemology alongside behavioural measures such as voluntary verification of AI outputs, breadth of source consultation, and resistance to algorithmic confirmation bias.

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