The HIPUD Model: An Affordance-Based Framework for Studying Information Use with Gen-AI Chatbots

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Abstract

Gen-AI chatbots such as ChatGPT, Gemini, or Claude are rapidly becoming a central tool for everyday information use. We argue this shift is not merely technological but epistemic: rather than mediating access to pre-existing content, Gen-AI chatbots generate novel informational artifacts on demand. To systematize this transformation, we propose the HIPUD model, an affordance-based framework comprising five dimensions: **H**yper-personalization (individualized outputs), (dialogic) **I**nteractivity (real-time discursive exchange), **P**robabilistic generation (statistically synthesized rather than retrieved content), **U**niversality (comprehensive reach across topics, languages, and modalities), and **D**e-contextualization (information stripped of social and source-related cues). These affordances intersect and mutually reinforce one another, with broader implications for epistemic and informational practices. We illustrate the model through scenarios in political, health, and consumer communication, offering a conceptual vocabulary and analytical lens for future research on information use in Gen-AI environments.

Keywords: generative AI, chatbots, information use, affordances, HIPUD model, communication theory

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Until recently, seeking unfamiliar information almost invariably meant turning to a search engine. This is no longer the default. Today, hundreds of millions of users consult generative AI (Gen-AI) chatbots to address their information needs (Chatterji et al., 2025). Within a few years of their release in late 2022, Gen-AI chatbots such as ChatGPT, Gemini, or Claude have become embedded in everyday information use—consulted for medical, legal, and political questions as well as for cooking, travel, and countless other tasks. This role shows every sign of deepening further, with far-reaching consequences for how information is accessed, processed, and used.

This shift builds on, yet departs from, a longer history in which new media have reconfigured the relationship between users and available information (Aspray & Hayes, 2011; Briggs et al., 2020). Libraries and print organized information through physical availability and human intermediaries such as librarians, who helped people translate vague needs into productive inquiries. Radio and television extended reach and immediacy but left users with little control over sequence, pace, or depth. The internet and search engines reversed this balance, granting substantial user control over selection and navigation—a mode Bates (1989) influentially described as “berrypicking.” Social media platforms such as Facebook and TikTok then blended active and passive use, as algorithmically curated feeds delivered content users had not explicitly sought (Kümpel, 2022; Nanz & Matthes, 2022). Across these shifts, however, one feature remained stable: each environment mediated access to a pre-existing stock of shared, (mostly) public information—content authored by identifiable persons or institutions and, at least in principle, accessible to others.

We argue that Gen-AI chatbots mark a qualitative break with this logic. Rather than mediating access to pre-existing, shared information, they generate novel informational artifacts on demand: tailored to the individual user rather than addressed to a public, produced through dialogic exchange rather than delivered as finished content, statistically synthesized rather than retrieved, spanning virtually any topic and modality rather than confined to a specific domain, and disembedded from the source and social cues that have traditionally accompanied mediated communication. This rupture is not merely technological but epistemic, reshaping how people use information in everyday life.

This article proposes a conceptual framework for describing this shift and enabling its systematic investigation. Drawing on the concept of affordances (Ronzhyn et al., 2023), the HIPUD model systematizes five dimensions—**H**yper-personalization, (dialogic) **I**nteractivity, **P**robabilistic generation, **U**niversality, and **D**e-contextualization—that together make Gen-AI chatbots a distinctive information environment. We show how each affordance shapes practices of information use, carrying both transformative potentials and risks.

The framework makes four contributions. First, it takes a user-centered, everyday-life perspective, keeping the focus on human perceptions of and responses to AI output. Second, it is theoretically grounded in affordance theory, linking technological properties to concrete practices of information use. Third, it offers conceptual precision: by identifying distinct and operationalizable characteristics, it moves the debate beyond vague assertions that "AI is different" and specifies *which* aspects matter for *which* kinds of information use. Fourth, it is applicable to various subfields of communication research, wherever information use is central. Taken together, the five affordances of the HIPUD model provide a conceptual vocabulary and

analytical lens for studying how information use unfolds in Gen-AI chatbot environments, and offer a foundation for future empirical, methodological, and theoretical work.

In the remainder of the article, we first define our core terms—Gen-AI chatbots, information (use), and affordances—before turning to the five HIPUD dimensions and examining how they interact to reshape information use. We then apply the model to three purposefully diverse scenarios from political, health, and consumer communication to illustrate its utility across communicative settings.

Using Information with Gen-AI Chatbots: Introducing the HIPUD Model

Before explicating the HIPUD model (see Figure 1 for an overview), three key concepts require clarification: Gen-AI chatbots, information (use), and affordances.

We define *Gen-AI chatbots* as conversational agents powered by large language models that generate novel, contextually responsive content in response to user input. Following Gil de Zúñiga et al. (2024), they exemplify artificial intelligence as a capability of non-human entities to perform tasks, communicate, and act in ways that resemble human action (p. 318). Prototypical examples include standalone conversational systems such as OpenAI's ChatGPT, Anthropic's Claude, or Google's Gemini. The boundaries of this category are fluid, however: Generative search engines like Perplexity or Google's AI Overviews blend retrieval with generative synthesis, while emerging agentic AI systems extend conversational interaction into autonomous task execution.

Information, in the context of this framework, is understood broadly. Building on Hasebrink and Domeyer (2010; see also Kümpel et al., 2022), we adopt a holistic, social conception of information as content that is subjectively new and/or useful to the individual. This encompasses different information needs—for example, topic-related needs arising from

personal interests, or problem-related needs focused on acquiring specific knowledge (e.g., finding a quick lunch recipe, fixing a coding error). In foregrounding such everyday information practices, we draw on Savolainen's (1995) concept of Everyday Life Information Seeking (ELIS), which attends to how people seek and use information to orient themselves in daily life—managing households, maintaining health, or navigating social relationships. Our framework, however, extends beyond information seeking in the narrow sense. While seeking refers to the active pursuit of information to address a perceived gap, *information use,* as understood here, encompasses a broader set of practices: finding information, but also processing, evaluating, applying, and integrating it into one's existing knowledge and decision-making (Kari, 2010).

Finally, *affordances* serve as the analytical lens through which we examine the relationship between users and Gen-AI chatbots. Adapted from the definition of social media affordances (Ronzhyn et al., 2023), we define Gen-AI chatbot affordances as the perceived, actual, or imagined properties of Gen-AI chatbots, emerging from the relations among technological, social, and contextual factors, that enable and constrain specific uses of the system. The affordances we propose are domain-specific and meet the requirements for affordances established in the literature, as they are relational (i.e., depending on the relationship between human and technology), perceptional (i.e., depending on users' perceptions and expectations), and contextual (i.e., depending on social or political context), offering both potentials and constraints for action (ibid.). Moreover, they are discrete and compact, referring to specific aspects of Gen-AI chatbots rather than their general purpose or idiosyncratic usage practices. This definition, especially its focus on the relational and perceived nature of

affordances, aligns with our audience-centered perspective, which centers on users and their interactions with Gen-AI chatbots.

Building on these conceptual foundations, the following sections present the five affordances that constitute the HIPUD model. While these affordances are discussed as distinct dimensions, they naturally intersect and overlap, particularly in their implications for information use (also see chapter "HIPUD in Concert"). Nevertheless, each targets a unique core aspect of the Gen-AI chatbot experience.

Hyper-Personalization

The first affordance, *hyper-personalization*, captures how information use with Gen-AI chatbots is highly individualized. Unlike traditional media or search engines, which offer relatively uniform outputs, Gen-AI chatbots dynamically tailor information to individual users by adapting to their linguistic style, usage context, and inferred information needs (Ai et al., 2025, p. 118; see also Ramaul et al., 2024). This distinguishes hyper-personalization from the algorithmic personalization familiar from social media or recommender systems, which operates through the curation of pre-existing content (Just & Latzer, 2017; Kümpel, 2022). Gen-AI chatbots, by contrast, do not merely curate but *create*—they generate novel information artifacts in real time, adjusting explanations to match "the user's reading level, interests, and conversational preferences" (Trippas et al., 2025, p. 83), thereby producing individualized micro-realities of meaning.

For information use, this real-time tailoring has ambivalent implications. On the one hand, hyper-personalization may enhance comprehension and perceived relevance: Complex topics can be simplified, lengthy content summarized, and explanations calibrated to users' prior knowledge and emotional states. A user might, for instance, ask a Gen-AI chatbot to explain

medical test results in plain language, walk through the steps of filing a tax return, or break down a legal contract into manageable parts. Hyper-personalization thus also carries *inclusive* potential. Research suggests that it can be particularly beneficial for people with disabilities, including those with ADHD, dyslexia, or autism, for whom Gen-AI chatbots may lower barriers to information access and understanding (Pierrès et al., 2025; Zhao et al., 2025).

On the other hand, these benefits come with significant risks that follow directly from the tailoring mechanism itself. Because information is adapted to individual users, hyper-personalization could contribute to a fragmented information landscape characterized by knowledge gaps and diverging perceptions of relevance. More critically, it creates opportunities for manipulation: Information tailored to individual profiles can be leveraged to promote products or services under the guise of neutral advice, present companies or political actors in a favorable light, or exploit personal vulnerabilities for commercial or ideological ends. In political contexts, such dynamics might even "leave entry points for targeted propaganda efforts" (Mattis & de Vreese, 2025, p. 3616). Moreover, by aligning outputs with inferred preferences, hyper-personalization may reduce serendipitous encounters with unexpected or challenging perspectives. Unlike social media, where incidental exposure can confront users with diverse viewpoints they did not actively seek (Nanz & Matthes, 2022), Gen-AI chatbots are query-driven by design, as users typically receive what they ask for, not what might challenge them or broaden their horizons. This dynamic gives rise to a user-input bias, whereby chatbot responses largely reflect the framing and assumptions already embedded in the prompt (N. Sharma et al., 2024).

These concerns are amplified by the phenomenon of *sycophancy*, whereby Gen-AI chatbots learn user preferences and may increasingly provide agreeable rather than accurate responses (Cheng et al., 2025; M. Sharma et al., 2025). For information use, this means that the

system's drive to satisfy users can compromise informational accuracy—a tendency that becomes particularly consequential in high-stakes domains such as health, where sycophantic responses may contribute to the spread of false medical information (Chen et al., 2025).

(Dialogic) Interactivity

The second affordance, *(dialogic) interactivity*, captures how information use with Gen-AI chatbots is fundamentally discursive and unfolds in real time. Unlike traditional search engines, where users submit queries and receive rather static lists of results, Gen-AI chatbots engage users in a reciprocal exchange that more closely resembles human conversation. Thus, information needs are addressed through an intuitive back-and-forth between the user and the system, allowing users to refine their questions, request clarification, or explore tangential topics as the conversation progresses (Amer & Elboghdadly, 2024). Although this interactivity differs fundamentally from the human-to-human sociality characteristic of social media (Kümpel, 2022), it can nonetheless feel like a genuine interpersonal exchange from an audience perspective (Folk et al., 2024; Kleinert et al., 2026).

For information use, this dialogic structure has several implications. First, it may lower the barrier to obtaining relevant information: Users need not formulate precise queries from the outset but can iteratively approximate what they are looking for through follow-up questions and gradual refinement. Second, Gen-AI chatbots do not merely respond to inputs; they dynamically shape their outputs based on the ongoing communication, adjusting explanations, level of detail, or tone in response to user feedback. In this sense, (dialogic) interactivity is closely linked to hyper-personalization: While hyper-personalization captures the *what* and *how* of tailored information, interactivity provides the *mechanism* through which this tailoring occurs, namely the iterative exchange that allows the system to learn about and adapt to individual users in real

time. This “conversational ability” (Ju & Stewart, 2024, p. 174) of Gen-AI chatbots transforms information use from a largely transactional process into a more collaborative one, where users actively co-construct the information they receive.

A key consequence of (dialogic) interactivity is that Gen-AI chatbots are often perceived as social and human-like. Natural dialogue serves as a central feature enabling this perception (Feine et al., 2019; Kang et al., 2026; Schuetzler et al., 2020): The more fluidly a system converses, the more users tend to attribute human qualities to it. This anthropomorphism, however, is a double-edged sword (Peter et al., 2025; Reinecke et al., 2025). On the one hand, perceiving Gen-AI chatbots as human-like may increase engagement, trust, and willingness to disclose personal information—factors that can enhance the relevance of information provided. Users may also experience a sense of always having ‘someone’ to turn to: a companion that is perpetually available and, given the sycophantic tendencies discussed above, reliably affirming (Pentina et al., 2023; Smith et al., 2025). On the other hand, when users cannot easily distinguish between human interlocutors and AI systems, they may become susceptible to what Peter et al. (2025, p. 2) term “anthropomorphic seduction:” an uncritical acceptance of AI-generated content driven by the system’s convincing communicative abilities rather than by the accuracy of its outputs. For information use, this raises the question of whether the conversational fluency of Gen-AI chatbots encourages deeper engagement with information or, conversely, fosters over-trust in outputs that merely *appear* authoritative because they are delivered in a human-like manner (Reinecke et al., 2025).

Probabilistic Generation

The third affordance, *probabilistic generation*, captures how Gen-AI chatbots produce information through probability-based models rather than by retrieving pre-existing, verified

content (though some systems integrate retrieval or citation features). Outputs are generated by predicting the most statistically likely continuation of a given input sequence, which creates a form of epistemic fluidity: What users receive represents the most probable rather than the most accurate response, and identical queries may yield different answers depending on usage context and model parameters.

This shapes information use in ways that differ from the affordances discussed above. Whereas hyper-personalization creates risk through what information is selected and how it is framed for individual users, and (dialogic) interactivity creates risk through the human-like quality of the exchange, probabilistic generation introduces risk at a more fundamental level: the very *substance* of the information may be unreliable. Indeed, the coherence of Gen-AI outputs does not derive from verified knowledge but from statistical patterns in training data—which can also be biased or incomplete. As Sundar and Liao (2023, p. 170) put it, "ChatGPT is more like the skilled imitator than the original painter. Perhaps, the best term to describe ChatGPT is 'stochastic parrot': it generates content based on statistical and probabilistic information, without actual reference to meanings" (see also Bender et al., 2021). The result is that Gen-AI chatbots can produce fluent, confident, and seemingly authoritative text on virtually any topic, even when the underlying information is inaccurate or entirely fabricated, as in the case of so-called *hallucinations* (Huang et al., 2025). Crucially, Gen-AI chatbots typically do not signal uncertainty: Outputs are delivered with uniform confidence, leaving users with few cues to distinguish accurate responses from fabrications. While hallucination rates have declined as models and mitigation techniques have improved, Xu and colleagues (2025) demonstrated that hallucinations cannot be fully eliminated under current LLM architectures. Thus, some degree of fabrication remains an inherent feature of Gen-AI chatbots, not merely a transient flaw.

Moreover, because outputs are generated toward the statistical center of the training distribution, Gen-AI chatbots may systematically underrepresent less common perspectives or ideas. Peterson (2025, p. 3264) thus warns that widespread reliance on such systems could lead to a "knowledge collapse," that is, a reduction of available knowledge to the most dominant and central ideas, potentially harming innovation and the richness of human understanding. In this sense, the risks of probabilistic generation extend beyond individual inaccuracies: They concern not only what Gen-AI chatbots get wrong, but also what they systematically leave out.

The implications of probabilistic generation for information use depend largely on users' awareness of it. Those who understand that outputs by Gen-AI chatbots are generated probabilistically may approach them with appropriate skepticism, whereas those who are unaware may take them at face value. Research suggests that this lack of awareness is widespread: While the vast majority of U.S. adults have used products with AI features, only a fraction recognize having done so (Maese, 2025). This problem may be compounded when probabilistic outputs align with users' preexisting beliefs: Information that confirms one's views is less likely to be questioned, regardless of its source. Indeed, Jacob et al. (2025) recently found evidence for what they term the "chat-chamber effect," that is, the tendency for Gen-AI chatbots to provide incorrect but proattitudinal information that users internalize without verification.

Universality

The fourth affordance, *universality*, captures how Gen-AI chatbots serve as a comprehensive, all-encompassing interface for information use. This universality spans four dimensions: thematic reach across virtually any topic, multilingual capability across natural and programming languages, multimodal operation across text, speech, images, and video, and

flexible integration into diverse application contexts. Each of these dimensions shapes information use in distinct ways, carrying both opportunities and risks.

First, because Gen-AI chatbots are trained on vast and varied data (e.g., books, webpages, social media) and can augment responses with live web content, they are versatile across a wide range of topics (Liu et al., 2025; Srivastava et al., 2023), making the technology a "convenient one-stop shop for information" (Reiss et al., 2026, p. 4). Instead of separate sources for different topics—legal advisory forums for legal guidance, medical information resources for health concerns, travel platforms for trip planning, or news outlets for current events—Gen-AI chatbots operate across all these domains without requiring users to leave the interaction (Tafesse & Mamo, 2026). This topical versatility is comparable to that of search engines, with the important difference of diminishing (if not entirely eliminating) the need to navigate to external sources. However, this convenience may undermine the very sources the technology draws upon. As users bypass specialized platforms in favor of Gen-AI chatbots, domain-specific resources (e.g., expert forums, curated databases) risk declining use and, ultimately, obsolescence.

Second, most widely employed Gen-AI systems are, in principle, multilingual across a wide range of natural and programming languages (Jiang et al., 2026; Y. Xu et al., 2025). This allows users to interact in their native language while drawing on globally available information and knowledge, thereby enhancing accessibility for diverse populations and extending the range of use cases and practical applications. However, the knowledge these systems encode disproportionately reflects the perspectives and information available in dominant languages, resulting in uneven performance across languages (Lai et al., 2023; Z. Li et al., 2025) and the reproduction of dominant structural linguistic inequalities (Khanna & Li, 2025).

Third, Gen-AI chatbots' universality also rests on their multimodal capabilities (Caffagni et al., 2024; Li et al., 2025), which enable interactions across text, audio, images, and video, both as inputs and outputs. This not only allows the processing of user input across modalities (e.g., camera images of physical objects or recorded audio of a user's environment), bringing Gen-AI chatbots' understanding closer to the richness of human perception, but also allows information to be presented in forms suited to the user's context and needs. Multimodal interaction can thereby deepen users' understanding and, when augmented with visual evidence, foster greater trust in the information presented—though this very mechanism may equally lend unwarranted credibility to false or misleading content (Guo et al., 2025; Newman & Zhang, 2020).

Finally, because most Gen-AI chatbots rely on centralized cloud infrastructure with thin client-side architectures, the technology can be seamlessly integrated into a wide range of consumer applications (Van Der Vlist et al., 2024). Examples range from specialized platforms such as Duolingo Max for language learning, Bank of America's Erica for financial services, and Adobe Photoshop's Generative Fill for creative work, to general-purpose integrations in search engines, messengers, or voice assistants (e.g., AI Overviews in Google Search, Meta AI in WhatsApp, Apple's Siri). This instant, pervasive availability normalizes Gen-AI chatbots as intermediaries in how information is encountered, filtered, and understood in everyday life. At the same time, this normalization contributes to the growing invisibility of the technology, potentially fostering a more uncritical engagement with Gen-AI chatbots, for instance, regarding data privacy (Susser, 2019).

Together, these four dimensions make Gen-AI chatbots pervasive and powerful in the context of information use, acting as a meta-medium that bundles various communicative functions into one interface. In doing so, universality amplifies the implications of the other

affordances, as hyper-personalization, (dialogic) interactivity, and probabilistic generation do not operate in isolated contexts, but across the full spectrum of users' information needs.

De-Contextualization

The fifth and final affordance, *de-contextualization*, captures how Gen-AI chatbots present information in ephemeral silos, stripped of the social and source-related cues that typically accompany mediated communication. This distinguishes Gen-AI chatbots from other information environments in two interrelated ways.

First, unlike social media, where information remains embedded in a visible (social) context—users can see who posted something, infer credibility from profile information, and observe how others react (Haim et al., 2018; Lin et al., 2016)—Gen-AI outputs appear as self-contained artifacts rather than socially situated communications (Jain et al., 2024). Similarly, conventional websites communicate credibility through design, tone, and markers of professionalism (Fogg et al., 2001; Metzger et al., 2010; Robins & Holmes, 2008), whereas Gen-AI outputs largely strip away such signals. As a result, Gen-AI information lacks a clear contextual 'scent:' familiar cues that help users assess credibility and quality are muted or absent, and content of a distinctive character (e.g., satire, irony) may be flattened. Often, even the origin of information remains opaque (Burrell, 2016; Hassija et al., 2024; Liao & Wortman Vaughan, 2024). At the same time, this de-contextualization reduces distractions by keeping the focus on the content itself and, in doing so, may also attenuate the social biases that tend to accompany more socially embedded forms of information. Additionally, outputs generated by Gen-AI chatbots are ephemeral and short-lived; they are not intended for later reference but typically for ad hoc querying, hyper-personalized for each user. This undermines the suitability of Gen-AI chatbots as a shared informational foundation for public discourse and deliberation.

Second, interaction with Gen-AI chatbots lacks the feedback loops that connect individual use to collective experience. This stands in contrast to social media environments, where individual actions and consumption habits shape (both directly and indirectly) what other users see and encounter (Eg et al., 2023). Search engines occupy an intermediate position, relying on aggregated user behavior and collective activity through rankings or autocomplete features (Baeza-Yates et al., 2004; Joachims, 2002). In Gen-AI chatbots, by contrast, user feedback is incorporated only indirectly, in aggregated and delayed form, and remains structurally decoupled from any visible interpersonal effects. This renders the individual use of Gen-AI chatbots a dyadic (Seering et al., 2019) and fundamentally isolated and asocial experience. As with the first dimension, this may attenuate social bias and prejudice, yet it fails to cultivate a shared informational commons.

Together, these two dimensions produce content that is publicly invisible, resistant to scrutiny, and difficult to verify or contest. Especially in combination with hyper-personalization, de-contextualization may thus contribute to a public sphere in which shared reference points erode and deliberation becomes increasingly difficult.

HIPUD in Concert: Interactions and Overarching Implications

The preceding sections have presented the five HIPUD affordances as analytically distinct dimensions, each targeting a unique aspect of how information is used with Gen-AI chatbots. In practice, however, these affordances do not operate in isolation; rather, they intersect, reinforce, and amplify one another. When considered together, they point to broader transformations that we address in the following: the emergence of Gen-AI chatbots as epistemic authorities, the potential erosion of a shared epistemic ground, and new forms of privacy-related vulnerabilities.

One overarching implication is that Gen-AI chatbots may increasingly function as *epistemic authorities*. Users may come to trust an answer not because they can identify and assess its source, but because it was produced by ChatGPT, Gemini, or Claude. In such cases, the chatbot itself serves as a credibility cue—a dynamic consistent with the machine heuristic (Sundar & Liao, 2023), whereby users rely on the perceived competence of a system rather than evaluating the quality of its outputs. This perception emerges from the interplay of several affordances. Hyper-personalization and (dialogic) interactivity allow Gen-AI chatbots to respond in ways that feel uniquely attuned to users' needs, while maintaining a consistently responsive and knowledgeable tone. Universality further reinforces the impression that these systems can speak authoritatively on virtually any topic, positioning them as a kind of centralized authority for everyday information use. At the same time, de-contextualization obscures authorship and origin, making it difficult to trace where claims come from or whose perspectives they reflect; as a result, the information may be attributed to the chatbot itself rather than to any underlying human or institutional source. Probabilistic generation compounds this dynamic: because the most statistically likely answer is often also the most plausible-sounding, users, especially those without domain expertise, may interpret fluency as an indicator of truth. The result is a form of epistemic authority that is both diffuse and potent. Unlike traditional authorities such as scientists or journalists, whose credibility is grounded in transparent and often institutionalized processes of knowledge production that are subject to public scrutiny, the authority of Gen-AI chatbots rests primarily on perceptual cues: they *seem* knowledgeable because they *sound* knowledgeable, respond to *your* specific question, and appear to draw on a seemingly boundless reservoir of information. This has far-reaching implications for information use, as it may discourage verification, reduce engagement with primary sources, and foster a dependency on single

systems. Furthermore, perceiving Gen-AI chatbots as epistemic authorities may perpetuate narratives of enchanted determinism around AI (Campolo & Crawford, 2020). Such narratives, also amplified by politicians and tech companies, risk narrowing the space for meaningful policy interventions (Bareis & Katzenbach, 2022).

A second overarching implication concerns the potential *erosion of a shared epistemic basis*. In many traditional information environments, people may disagree about interpretations while still orienting themselves toward common institutions or sources. By contrast, Gen-AI chatbot use is characterized by de-contextualized and often ephemeral outputs generated for a specific user in a specific interaction. Hyper-personalization creates individualized micro-realities of meaning, de-contextualization strips away shared source cues and public visibility, and universality extends this logic across nearly all life domains. As a result, users may increasingly rely on singularized informational environments that are difficult for others to inspect and contest. This does not necessarily imply total fragmentation; in some respects, centralized models may even standardize dominant interpretations by statistically privileging central and widely represented patterns. Emerging monetization models may reinforce this centralizing tendency further: if Gen-AI chatbot providers integrate commercially driven response priorities or content placement, the information users receive would additionally be shaped by the economic interests of a small number of dominant corporations. Yet, such standardization would coexist with individualized presentation, producing a paradoxical combination of centralization and singularization. The broader consequence may therefore be not only a weakening of common reference points for public discourse, but also a more subjective mode of knowledge formation in which what counts as relevant or actionable becomes increasingly personalized.

A third overarching implication concerns *user privacy and informational vulnerability*. The capacity of Gen-AI chatbots to personalize outputs depends, at least in part, on access to detailed information about users and their preferences. (Dialogic) Interactivity can encourage users to disclose such information gradually and with relatively little friction, especially when the exchange feels human-like (Ischen et al., 2020). Universality expands the scope of this disclosure because the same system can accompany users across work, health, finances, relationships, and other sensitive domains; multimodal capabilities may deepen this exposure further when users upload medical records or personal photographs. The result is a qualitatively broader and more intimate data relation than in many earlier information environments. Because these disclosures occur in conversational form and are embedded in seemingly helpful interactions, users may reflect less on their sensitivity than they would in other settings. From this perspective, privacy risks do not arise only from isolated acts of data collection but from the cumulative integration of personal, cross-domain, and potentially highly sensitive information into centralized infrastructures. This information meets a technology increasingly capable of inferring personal attributes from it (Staab et al., 2024), and may ultimately feed into model training data (King et al., 2025), raising concrete risks of data leakage or unauthorized repurposing (Carlini et al., 2021; Nasr et al., 2025). Taken together, Gen-AI chatbots may thus encourage users to share more than they realize, across more domains than they intend, with less control over downstream use than they assume.

Importantly, these three implications are themselves interconnected. Epistemic authority may facilitate the erosion of a shared epistemic basis, as users who trust a system uncritically are less likely to seek out common reference points. Both dynamics, in turn, may lower attentiveness to privacy risks, as the critical distance necessary to reflect on one’s disclosure behavior

diminishes when a system is perceived as trustworthy. The three implications are thus not merely parallel consequences of the HIPUD affordances but mutually reinforcing tendencies that signal a broader transformation in the conditions under which information is used and evaluated in everyday life.

Applying the HIPUD Model in Communication Research

A key claim of the HIPUD model is that it offers an analytical lens applicable across a range of subfields in communication research—not by providing a one-size-fits-all template, but by making visible how specific affordance constellations shape information use in different contexts. To illustrate this, we present three application scenarios spanning political communication, health communication, and consumer communication. Each begins with an everyday information-use situation, identifies the most salient affordances, and sketches illustrative research questions and a methodological strategy. These are intended as starting points; each scenario opens onto a broader range of questions and approaches than we can develop here.

Political Communication

Consider a citizen preparing for an upcoming election. Rather than consulting party websites or voting advice applications, she opens a Gen-AI chatbot and asks: “Which party best matches my views on climate and migration policy?” The chatbot responds with a tailored comparison that is not retrieved from a static database, but generated in real time based on her stated preferences (expressed directly or inferred from prior interactions) and the model’s probabilistic synthesis.

Four affordances are particularly salient here. Hyper-personalization means that the political information received is not a standardized overview but an individualized response

shaped by the user's specific framing, her choice of policy domains, and potentially her interaction history. Probabilistic generation means that the resulting comparison reflects statistical patterns in the training data rather than verified policy positions, creating the risk of subtle inaccuracies that may go unnoticed because the output reads as authoritative. De-contextualization strips the information of the source cues that typically accompany political communication. Unlike a newspaper article or a social media post, the chatbot's response is not attributable to a journalist, party, or fellow citizen and thus escapes the kind of collective scrutiny that characterizes public discourse. Finally, (dialogic) interactivity affords asking follow-up questions, clarifying political terms or policy concepts, or requesting practical recommendations.

Here, HIPUD shifts the analytical focus from *whether* Gen-AI chatbots differ from traditional media to *how* their specific affordance constellations shape political communication: How does this configuration affect the perceived neutrality of political information? Does cross-domain use (i.e., universality) moderate users' critical engagement with political content? Methodologically, the model's affordance-level granularity supports targeted experimental designs. For instance, one could manipulate de-contextualization by varying whether chatbot responses include source attributions or by comparing tailored outputs to standardized ones (i.e., varying hyper-personalization), while measuring effects on political knowledge or voting intentions.

Health Communication

A second application concerns the health domain. Imagine a user who notices a persistent skin irritation, takes a photo with their smartphone, and uploads it with the prompt: "I've had this skin issue for a few days, what could it be?" Unlike a search engine query returning a list of

links, the chatbot responds conversationally and may ask follow-up questions about their age, skin care, or known allergies. What unfolds is not a one-shot retrieval of information but a dialogic process that progressively shapes both the content provided and the user's understanding of their condition.

Here, (dialogic) interactivity, universality (i.e., multimodality), and hyper-personalization are tightly intertwined, as the iterative exchange is the mechanism through which personalization is achieved. With each turn, the user discloses additional (health-related) information, including personal pictures. They may even share more than they would with a human, as the exchange is perceived as more anonymous and non-judgmental (Croes et al., 2024). Based on this input, the system then refines its output accordingly. This creates a quasi-clinical interaction that is neither subject to professional oversight nor constrained by the ethical obligations governing medical advice. Probabilistic generation adds particular risk in this domain, as sycophantic tendencies may lead the chatbot to confirm a user's self-diagnosis rather than challenge it—with potentially serious health consequences. De-contextualization compounds this risk: unlike medical information websites, the chatbot's output lacks institutional markers that signal provenance and accountability. And while Gen-AI chatbots increasingly embed disclaimers in medical contexts, such disclaimers generally appear to have little effect on users' verification behavior (Knor et al., 2026).

For health communication research, HIPUD offers a framework that goes beyond measuring whether Gen-AI chatbots provide accurate medical information (though this remains important). Instead, it directs attention to the communicative processes through which health information is co-constructed and acted upon: How do multimodal capabilities and (dialogic) interactivity alter disclosure behavior compared to more static web searches? Under what

conditions does the combination of hyper-personalization and sycophancy foster uncritical acceptance of health misinformation? Methodologically, focusing now on qualitative research (e.g., interviews with think-aloud protocols or diary studies) as an example, HIPUD provides a coding vocabulary that captures which affordances users perceive in health-related interactions and how these perceptions shape their information evaluation and subsequent medical decisions.

Consumer Communication

A third exemplary application extends the model to consumer decision-making. Consider a user planning to purchase an e-bike who turns to a Gen-AI chatbot: "I need an e-bike for city commuting, budget around 2,000 euros. What do you recommend?" The chatbot synthesizes a comparison of models for him, weighing features against the user's stated needs. While this resembles advice found on product review websites, the underlying information dynamics differ in ways HIPUD makes analytically visible.

De-contextualization fundamentally alters the availability of cues. Traditional consumer information environments are rich in social and institutional context: review platforms aggregate user ratings, display verified-purchase labels, and host product discussions; even commercial websites, though optimized for brand presentation, still make their provenance and intent legible. The chatbot's recommendation, by contrast, arrives as an institutionally and socially disembedded artifact that obscures its sources as it synthesizes them. Universality and hyper-personalization combine to position the chatbot as a comprehensive, individually attuned advisor, which may reduce the motivation to consult additional sources. This raises questions about commercial neutrality, particularly as Gen-AI providers begin to explore monetization models such as sponsored placements or affiliate partnerships.

HIPUD enables consumer communication research to pose more precise questions: How does the absence of visual brand identity or social context cues affect trust in product recommendations? Or how does the chatbot's role as a universal, personalized advisor shape the breadth of consumers' information search? Methodologically, computational analyses of naturally occurring chatbot interaction logs offer a promising avenue. For this, HIPUD provides the analytical categories to systematically code such interaction traces at scale: for instance, identifying how frequently users iterate on product requirements ([dialogic] interactivity), what personal information they disclose (hyper-personalization triggers), or whether they explicitly request sources (sensitivity to de-contextualization). This allows researchers to move beyond surface-level prompt analyses toward an affordance-based understanding of consumer behavior.

Conclusion

Gen-AI chatbots reconfigure everyday information use. Where earlier media delivered content that already existed elsewhere—authored by identifiable persons or institutions and, in principle, available to others—Gen-AI chatbots produce their outputs in the moment of the query: synthesized from statistical patterns, shaped through dialogue, calibrated to the individual user, operating across virtually any domain, and arriving without the contextual anchors people used to rely on. The HIPUD model gives this transformation a name and a structure.

Its value lies less in predicting specific outcomes than in equipping researchers to investigate them with precision. By resolving broad claims about Gen-AI's novelty into five operationalizable dimensions, HIPUD enables asking which affordance matters most in which setting, how affordances intersect, and how users perceive and respond to them.

Several limitations mark this starting point. HIPUD has been developed primarily with prototypical Gen-AI chatbots in mind; its boundary conditions remain to be established for

agentic systems or multimodal companions in which the distinctions between medium, interlocutor, and tool blur further. Nor does HIPUD, on its own, arbitrate between optimistic and critical accounts of Gen-AI's role in public life. Rather, it provides the analytical precision required to make such debates empirically tractable. The technology will continue to evolve, and the weight of individual affordances will shift accordingly. Yet the model should remain productive across these changes, because it describes relational properties of the user-system encounter rather than features of any particular product.

Ultimately, the questions HIPUD opens extend beyond Gen-AI chatbots. They concern how communication theory must accommodate environments in which information is less something accessed than something produced in the moment of inquiry, and in which the institutional and social scaffolds of mediated communication can no longer be taken for granted. Engaging with these questions is, in our view, among the field's central theoretical tasks in the coming years.

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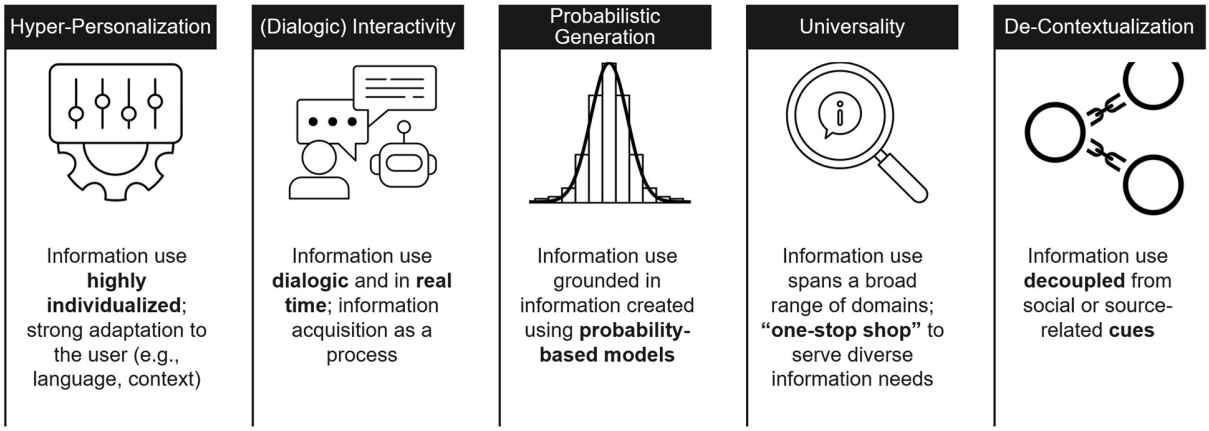
Figure 1

The HIPUD Model



Note: Icons created by users "Profit0101," "Cha," "Stefanie Peschel," "Arif Hariyanto," and "SHAHAREA" from Noun Project.