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Information Foraging With Generative AI: Usage Patterns in Germany and Israel

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Abstract

Generative artificial intelligence (GenAI) alters how people seek information, regardless of its susceptibility to epistemic limitations such as producing inaccurate or biased information. Studies of individuals' usage patterns of GenAI for accessing information remain scarce. Here, we examined how individuals perceive and use GenAI for various information purposes and at different complexity levels across cultures. Based on online surveys of representative samples from Germany ($N = 562$) and Israel ($N = 500$), the findings showed that Germans rated GenAI higher in providing comprehensive information, whereas Israelis perceived GenAI as more responsive to users' information needs. Latent class analysis (LCA) of regular GenAI users (Germany: $n = 159$; Israel: $n = 254$) identified culturally distinct user profiles: three in Israel (e.g., Favoring Pragmatists, Reserved Experts, and Skeptical Minimalists) and four in Germany (e.g., Naïve Enthusiasts, GenAI-Savvy Abstainers, Cautious Skeptics, and Passive Optimists). Harnessing the information foraging theory, we focused on the diverging balance between the currencies (perceived benefits, i.e., responsiveness of GenAI and comprehensibility of its content), costs (epistemic AI knowledge, i.e., awareness of GenAI's limitations), and "forager attributes" (previous experience with GenAI and knowledge of its workings). The information foraging theory prism highlighted two cross-cultural similarities: the avoidance pattern of users reporting low perceived benefits, and the inclination to utilize GenAI for more complex and risk-involving science-related information, characterizing users who demonstrated high perceived benefits and low epistemic knowledge.

Keywords
artificial intelligence; cross-cultural comparison; epistemic knowledge; generative AI; science communication

1. Introduction

Tales abound of people using generative artificial intelligence (GenAI) to access complex information and being misled or dramatically affected. For instance, Allan Brooks, who had over 300 hours of conversations with ChatGPT, ended up being misled to believe that he had discovered a groundbreaking new mathematical principle (Hill & Freedman, 2025). More stories like these are expected to emerge with the increasing usage of GenAI to access information (Greussing et al., 2025; Liu & Wang, 2024). In today's post-truth era, when the consequences of inaccurate or misleading information are far-reaching, a better grasp of how people use GenAI tools for information purposes is crucial.

GenAI not only functions as a channel but also as a fairly autonomous communicator (Greussing et al., 2025). This makes GenAI a unique information environment in terms of the contexts, spaces, and systems in which individuals seek, evaluate, and use information (Ragavan & Alipour, 2024; Sandstrom, 1994). GenAI is a type of AI that generates new content in response to human-provided prompts based on training data (Chen & Feng, 2024). Here, we use the term primarily to refer to chatbots based on large language models, such as ChatGPT and Gemini.

Recent studies suggest that GenAI transforms information-seeking behaviors by providing contextualized, personalized responses to natural-language prompts, making it easier for users to access complex information (Chan & Zhou, 2023; Zhou & Li, 2026). However, GenAI suffers from epistemic limitations, including susceptibility to generating fabricated compelling information, "AI Sycophancy" that produces misinformation to satisfy user prompts, and biases inherited from training data (Kidd & Birhane, 2023; Sharma et al., 2025; Spitale et al., 2023). Thus, although GenAI can potentially bridge knowledge disparities by providing comprehensible information, it simultaneously risks disseminating misinformation at scale (Karell et al., 2024; Kidd & Birhane, 2023).

The broadening role of GenAI in information-seeking behavior underscores the need to understand how individuals perceive these technologies and what characterizes their usage patterns when seeking information. Studies that focus on usage patterns, either in information retrieval or GenAI use, often employ segmentation analysis to compare how different groups of people engage with the technology (e.g., Chang et al., 2025; Lin et al., 2026). For instance, Chang et al. (2025) found that positive attitudes and perceived control positively influenced ChatGPT's acceptance among college students with both weak and strong AI digital abilities. Lin et al. (2026), as another example, classified GenAI users as a function of their trust in the technology. They showed that users who employed GenAI for artistic creation and conversation were more likely to trust GenAI across all trust aspects, while users who employed it for information retrieval were less likely to demonstrate distrust. Although the literature has identified GenAI usage patterns, it tends to zoom in on particular aspects or populations. Much less is known about what characterizes the use of GenAI for information purposes in the general public, particularly for complex information.

Complex information requires greater processing, burdens comprehension, and can impede the acquisition of objective knowledge (Schmitt et al., 2019). Because complex information not only diffuses rapidly but also changes over time, misunderstandings or distortions in its content can trigger social panic or unrest (Y. Wang et al., 2025). In this sense, complex information epitomizes GenAI's tension as an information source: It can simplify and ease comprehension, but its epistemic limitations can distort perceptions at scale. Studies often assess information complexity in terms of readability, i.e., the length and familiarity of words and the length or syntactic structure of sentences (Schmitt et al., 2019). Given that GenAI excels in generating text that supports simple delivery, an analysis of text readability is ill-suited to this study's aims. Instead, we draw on definitions of knowledge complexity (Duan et al., 2023), defining complex information as involving an abundant and diverse body of knowledge whose interrelated elements require combining and integrating; complex information is associated with ambiguity and is difficult to comprehend.

The study, therefore, aims to examine how people perceive GenAI tools as a source of information and what characterizes regular users of the technology for different information purposes and at different levels of information complexity. To do so, we analyzed data collected for the Science Information Search With AI Technologies (SciI-AI) project. This survey explored how people perceive and use GenAI for science-related information in seven countries: Australia, Denmark, Germany, Israel, South Korea, Taiwan, and the United States (e.g., Greussing et al., 2025). Specifically, we drew on our 2024 contribution to SciI-AI, comparing the reported use of GenAI for information purposes between representative samples from Germany and Israel. These populations reflect technologically advanced cultures but with differences in GenAI adoption and trust in the technology. To investigate information-seeking behaviors, we used the principles of information foraging theory (IFT) which characterizes the trade-offs between the perceived benefits and costs of information sources as keys to their usage.

2. Theoretical Background

People use GenAI tools for various information purposes at varying degrees of complexity. For example, people employ GenAI to obtain quick factual knowledge and definitions. GenAI is used to generate drafts, outlines, or full-length texts, or to edit and revise texts users write themselves (Moulaei et al., 2024; Schuetzler et al., 2024). GenAI tools are also used for inspiration, e.g., for cooking recipes or travel recommendations (Huang et al., 2025; Lin et al., 2025). In terms of information complexity, writing and editing, or seeking inspiration involve lower information complexity than factual knowledge, as factual knowledge demands understanding and often involves integrating diverse, interrelated elements into a coherent narrative or explanation (see Duan et al., 2023). By contrast, users wanting writing assistance or inspiration can tap GenAI for information without personally integrating or grasping the underlying knowledge domains.

GenAI is also used to access science-related information, presenting an interesting information purpose: while it involves high stakes in terms of decision-making and has notorious consequences for misinformation consumption (Kidd & Birhane, 2023; Swire-Thompson & Lazer, 2020), accessing science-related information is booming (Greussing et al., 2025). Science-related information refers to knowledge produced through scientific methods and according to scientific standards, describing phenomena, processes, or relationships in the natural or social world (see OECD, 2023). Science-related information encompasses the accurate and natural sciences, health and environmental issues, and others. Accessing science-related information is essential at both the individual and societal levels because it supports informed decision-making on critical issues and enables individuals to participate in socio-scientific debates (e.g., climate crisis; Hendriks et al., 2020).

Science-related information constitutes a complex form of information, which GenAI excels at simplifying (Biyela et al., 2024). Its complexity stems from its ambiguous nature (McMahan & Evans, 2018) and the background knowledge required for comprehension, which encompasses not only domain-specific topics and related fields but also scientific methods, epistemology, and culture (Hendriks et al., 2020; OECD, 2023). Therefore, here we viewed science-related information as more complex than general factual knowledge. Although GenAI excels at providing simplified and dialogic science communication (Biyela et al., 2024), to the best of our knowledge, the link between these advantages of GenAI and users' perceptions of GenAI as an information source remains understudied.

2.1. Using GenAI for Information Purposes in a Cultural Context

The performance and outputs of GenAI tools, as information sources, are subject to cultural context, as they incorporate cultural values and function differently in low-resource languages (e.g., Trinn et al., 2025; D. Wang, 2025). Cultural context also shapes how people envision an ideal human–AI interaction. For example, Americans prefer the AI's subordination and minimal emotionality, whereas the Chinese value connection with the AI, and treat it as a relational partner (Ge et al., 2024). Nevertheless, cross-cultural research remains scarce, even though such comparisons are essential for a macro-level understanding of media and technology use (Boomgaarden & Song, 2019), based on the generalizability of cultural similarities and the specification of cultural differences.

Here, we compared the German European context and the Israeli Middle Eastern one. Although both nations are technologically advanced and exhibit high internet penetration and engagement with digital tools (World Intellectual Property Organization, 2024), they have different social and political cultures that shape their approach and use of technology. For instance, during the Covid-19 pandemic, Israel prioritized life-saving surveillance over privacy by using GPS tracking, whereas Germany emphasized privacy protection through a voluntary Bluetooth-based monitoring app (Sommerlad & David, 2022). More generally, Germans express higher acceptance of the idea that power is unequally distributed (higher power distance) and lower loyalty and obligation toward one's own group (in-group collectivism) than Israelis (Yeshua-Katz & Efrat-Treister, 2021). These cultural tendencies among Germans are associated with more negative attitudes toward AI (S. Wang, 2025). Both Germans and Israelis tend to access science information through multiple channels, primarily digital media and news. However, Germans tend to rely more on institutionalized science journalism within a strong public-service media system, whereas Israelis mostly access science information through social media and interpersonal channels, reflecting differences in media systems and communication cultures (Mede et al., 2025).

Both nations cultivate advancement in the AI field through national strategies. Germany, as is the case elsewhere in Europe, provides financial support for scientific progress in AI with an ethical focus (Kieslich et al., 2024). Israel's as a "start-up nation," represents a dynamic high-tech economy driven by national efforts to advance technological and scientific development of AI (Vasiliu & Yavetz, 2024). In 2024, Germany and Israel were closely ranked in 7th and 9th place, respectively, in *The Global AI Index* (Tortoise Media, n.d.). Trust in AI is similar in both nations (34–35%); however, more Israelis (53%) than Germans (42%) consider that the benefits of AI outweigh its risks (Gillespie et al., 2023).

Comparing the two nations' adoption and use of GenAI is challenging due to the limited information available about the Israeli context. In the German population, younger, highly educated, and male segments have higher adoption rates (Renn & Schäfer, 2025). Half of all German GenAI users utilize it for writing or correcting texts, 48% for seeking information of all kinds, and 36% for creative tasks such as seeking inspiration (TÜV Verband, 2025). Although the corresponding Israeli data are unavailable, among businesses, Israel lags behind Germany in the adoption rate of AI. Specifically, 41% of all German firms reported using AI in 2025, compared to 28% in Israel (Be'eri, 2025). By contrast, Israel has higher rates of ChatGPT adoption among individuals, with 30.4% of Israelis reporting regular use compared to 11.4% for Germans. In 2024, far fewer Israelis (11.4%) than Germans (17.1%) reported discovering ChatGPT for the first time, suggesting greater familiarity among Israelis (Greussing et al., 2025). The scant cross-cultural comparative research, especially in the Israeli context, further underscores the knowledge gap regarding GenAI usage patterns for information purposes.

2.2. Users of GenAI as Information Foragers

IFT "is an approach to the analysis of human activities involving information access technologies" (Pirolli & Card, 1995, p. 51) that focuses on "understanding how strategies and technologies for information seeking, gathering, and consumption are adapted to the flux of information in the environment" (Pirolli & Card, 1999, p. 643). Originating in ethological studies of animal searching behavior, IFT posits that individuals adapt their information-seeking strategies to maximize the value of the information obtained while minimizing the costs involved in accessing and acquiring it. In other words, IFT considers the trade-off between the gains and costs involved in accessing different information sources to obtain different types of information (Quinn & Gutt, 2025; Sandstrom, 1994). Online information exhibits a *patchy* structure where similarly relevant web pages are (hyper)linked to form patches of web pages, which eases the navigation between them. By contrast, moving from one patch to another may require more effort (Pirolli, 2005). Hence, foragers must decide whether to allocate their efforts between patches or within patches (Pirolli & Card, 1999). Their decision often relies on cues of *information scent*, i.e., brief textual or graphical signals (e.g., a URL, an identification of the information source) that hint at the expected information value of following a certain hyperlink (Pirolli, 2005; Ragavan & Alipour, 2024).

From an IFT perspective, GenAI provides a novel and interesting information environment (Flores et al., 2024), inter alia, due to its conversational interaction, its contextual memory of ongoing and previous conversations, and its capability to generate new content in response to idiosyncratic prompts (Kim et al., 2025; Ragavan & Alipour, 2024). Ragavan and Alipour (2024) considered GenAI to be a single patch, or rather a non-patchy environment that evolves with each interaction between the user and the GenAI. Foraging information in a GenAI environment could thus blind users to other, more profitable sources, because the potential benefits of alternative sources are unknowingly forfeited (Ragavan & Alipour, 2024). GenAI epitomizes the tension between ease of access to complex information and its liability of generating biased and inaccurate content (Yen et al., 2025); similarly, traditional scent cues are not necessarily accurate (e.g., fabricated sources) or available.

While IFT suggests a methodology that focuses on foragers' actual behaviors and decision-making (see Pirolli & Card, 1999), it is applicable to small sample sizes. Aiming for a cross-cultural comparison and relying on previously collected data, we used IFT as a conceptual architecture rather than a specific methodological approach, drawing on Sandstrom's (1994) early, original interpretation of the framework (Pirolli & Card, 1999).

In this context, IFT focuses our investigation on two complementary concepts. “Dietary breadth” refers to the relative width or narrowness of the range of information sources, or for GenAI, information types. “Prey choice” refers to the decision to take or reject information sources once they are encountered, based on whether their handling would yield a valuable return (Sandstrom, 1994). In the context of GenAI, we refer to prey choice as users’ decisions to harness the technology for different information purposes, based on the complexity of the information.

To analyze the dietary breadth and prey choice of information foragers, key factors need to be defined (Sandstrom, 1994): “Currency” refers to the benefits or gained value that an information forager seeks to maximize through its foraging behavior; “costs” refers to the downside and sacrifices involved in information foraging, for example obtaining misleading information, time and mental effort, etc.; and “forager attributes” refer to the foragers’ characteristics that can explain the searching and information acquisition behavior (see also Quinn & Gutt, 2025; Yen et al., 2025). The following identifies these factors as they are manifested in the GenAI information environment (see summary Table in Supplementary Material 1).

In regard to currency, two benefits of GenAI are closely related to communicating science-related information. First, GenAI provides comprehensible information by translating professional jargon into accessible language, summarizing knowledge simply and concisely, and incorporating visual or audiovisual explanations (Biyela et al., 2024; Zhou & Li, 2026). Second, GenAI is responsive to users’ information needs by affording dialogical communication through immediate, personalized answers adapted to users’ prompts and understanding (Biyela et al., 2024; Zhou & Li, 2026). The interactive discussion supports informal learning and engagement with scientific content (Dubovi & Tabak, 2021; Tsovaltzi et al., 2017). However, it remains unclear whether perceived comprehensiveness and responsiveness are what distinguish GenAI users who utilize the technology to access science-related information from those who do not.

The costs of using GenAI for information access center on the technology’s epistemic limitations, whereas traditional costs (i.e., time and effort) constitute GenAI’s relative strengths compared to search engines (Schuetzler et al., 2024; Zhou & Li, 2026). Because epistemic limitations are inherent to GenAI, we can evaluate individuals’ actual knowledge of it. The optimal foraging approach, which focuses on animals and from which IFT draws inspiration, assumes “that foragers behave as if they have complete knowledge of relevant variables” (Sandstrom, 1994, p. 417), which IFT cannot test directly. By measuring epistemic AI knowledge, we assessed foragers’ actual knowledge of the information environment, thus overcoming one of the framework’s limitations. Klein-Avraham et al. (2026) reported negative associations between trust in GenAI and epistemic knowledge about it: In other words, knowing more about the epistemic limitations of GenAI was associated with trusting it less.

As for forager attributes, individuals’ intrinsic limitations and characteristics shape their information behavior and decision-making. IFT considers foragers’ skill to be a key attribute (Sandstrom, 1994). Skills encompass abilities developed to search for and handle information efficiently. Because we could not measure skills directly, we measured individuals’ previous experience with GenAI tools—i.e., frequency of GenAI use and number of tools regularly used—and their knowledge of what AI is and how GenAI works as proxies. In a GenAI environment, skills, along with tool familiarity, positively influence the effectiveness of prompts in generating the desired response (Schuetzler et al., 2024). This positive effect of prior experience extends to users’ capability to obtain and report more accurate science-related information (Lai, 2025). Knowledge about GenAI and its workings, i.e., content and procedural AI knowledge, contributes to more efficient and critical use (Klein-Avraham et al., 2026; Long & Magerko, 2020). Studies have found a positive association between AI knowledge and the use of GenAI tools (Chan & Zhou, 2023; Liu & Wang, 2024).

Harnessing IFT, therefore, to investigate cross-cultural differences in the perceptions of GenAI as a source of information and usage patterns for information purposes, we examined three research questions:

> RQ1: How do Germans and Israelis, in general and regular users in particular, perceive GenAI in terms of providing comprehensive content and being responsive to users' information needs?
>
> RQ2: How diversified and complex are the information purposes for which regular users utilize GenAI?
>
> RQ3: What characterizes German and Israeli regular users of GenAI for information purposes?

3. Method

The analyses drew on pre-existing data collected via online surveys conducted in Germany (n = 562) and Israel (n = 500) in August–September 2024. Participants were recruited through online access panels administered by survey companies in each country. Quota sampling was applied to approximate the adult online populations with respect to age, gender, and education. In Germany, the mean age of the participants was 44.9 (SD = 14.6); 51.2% were female, and 37% reported having a higher education (e.g., a university degree). In Israel, the mean age of the participants was 44.1 (SD = 17.3); 52.1% were female, and 54.2% had a higher education (Supplementary Material 2). The survey was designed in English (Supplementary Material 5) and translated into the respective national languages. Not all the original questionnaire variables were used in this study; see Supplementary Material 1 for the included variables.

3.1. Measurements

The measurements used to collect the data were developed, validated, and published by Greussing et al. (2025).

Benefits (i.e., currency) were measured using two variables, each assessed with a single author-developed item. Perceived Comprehensibility of AI-Generated Information was measured with the statement "generative AI technologies deliver comprehensible information" (M = 3.56, SD = 0.98). Responsiveness of GenAI to Users' Information Needs was measured with "generative AI technologies are responsive to users' information needs" (M = 3.63, SD = .99). Respondents rated each item on a 5-point scale (1 = *strongly disagree*, 5 = *strongly agree*), or "I don't know." Although single-item constructs may "facilitate more accurate interpretations of predictor-outcome relations," and "allow researchers to test more holistic or thorough models of relations among constructs" (Fisher et al., 2016, p. 5), they lack the psychometric robustness of multi-item constructs. Nevertheless, given the novelty of the technology and the constraints of the previously collected data, we used these self-developed, previously validated single items, which were originally inspired by Reif et al. (2025; see also Greussing et al., 2025).

Costs were measured through epistemic knowledge of AI. This assessment included three true/false/I don't know items (Supplementary Material 1) developed in consultation with AI experts and informed by previous research (Greussing et al., 2025). Correct responses were summed to yield a knowledge score ranging from 1 = *none of the answers is correct* to 4 = *all three answers are correct* (M = 2.69, SD = 1.11).

Skills included three variables: Frequency of AI use, number of GenAI tools regularly used, and content and procedural knowledge about GenAI. For the first two, we followed Fletcher and Nielsen (2024), asking respondents to rate their prior experience with four GenAI tools: ChatGPT, Copilot, Perplexity AI, and Gemini. Participants indicated whether they were hearing about the tool for the first time, had heard the name but never used it, had used it once or twice, used it several times a month, used it several times a week, or used it daily. Based on these responses, we derived two variables:

- Frequency of GenAI Use captured the highest reported level of use across the four applications. Values ranged from 1 = *I'm hearing about it for the first time* to 6 = *I use it daily* (M = 3.22, SD = 1.43). This variable was subsequently used to identify regular users. The subsample of regular users covered participants who reported using at least one GenAI tool several times a month (n_{total} = 413; n_{Germany} = 159; n_{Israel} = 254).
- Number of GenAI Tools Regularly Used represents the sum of GenAI tools participants reported using at least several times a month (i.e., regularly). Values for regular users ranged from 1 = *using one GenAI regularly* (56.4%) to 4 = *using all four GenAI included in the questionnaire regularly* (6.5%).

Skills also include "content & procedural knowledge of AI," which was measured using six true/false/I don't know items (Supplementary Material 1). Correct answers were summed, with scores ranging from 1 = *none of the answers were correct* to 7 = *all six answers were correct* (M = 4.65, SD = 1.67).

To measure information purposes, we presented regular users with a multiple-choice item capturing their purposes for using GenAI (see Fletcher & Nielsen, 2024), including facts and knowledge, writing assistance, and inspiration, among others (Supplementary Material 1). The question addressed GenAI broadly (e.g., ChatGPT, Gemini). Participants were also shown the list of GenAI applications they reported using regularly and were asked whether they used each of them for accessing science-related information. Based on these responses, we derived two variables:

- "Dietary breadth": the number of reported purposes for which GenAI tools were used. Values ranged from 0 = *reporting not to use GenAI for information purposes* to 4 = *reporting to use the technology for all four information purposes included in the questionnaire* (M = 2.41, SD = 1.11).
- "Prey choice": the highest complexity level for which participants reported using GenAI, ranging from 1 = *for writing assistance or seeking inspiration* (8.5%), 2 = *for facts and knowledge* (16.5%), and 3 = *for science-related information* (68.8%). Note that using GenAI for writing or seeking inspiration could involve more complex information. To minimize potential misunderstanding, the statements in the questionnaire framed these information purposes as more simplistic: "Assistance with language or writing (e.g., translating text, spell-checking, drafting content)" and "seeking inspiration (e.g., generating ideas for cooking or travel)."

3.2. Data Analysis and Use of GenAI Tools

Independent-sample t-tests were run on IBM SPSSv29 to compare perceived comprehensibility and responsiveness between the two cultures. To identify usage patterns among GenAI regular users, we employed the poLCA package (Linzer & Lewis, 2011, 2022) in *R*, conducting LCA separately for each country, including the perceived currencies, costs, and forager attributes. This person-centered procedure supports the analysis of mixed data (i.e., ordinal and continuous variables) and the detection of latent subgroups based on participants' responses (Weller et al., 2020). We then calculated ANOVAs with Scheffé post-hoc tests as well as Kruskal-Wallis H tests to compare the identified groups.

4. Results

Germans and Israelis had similar ratings of GenAI as a source of information (RQ1) in terms of perceived comprehensibility ($t_{(968.56)} = -1.59$, $p = 0.113$), although the Germans' perceptions were slightly less positive ($M = 3.51$, $SD = 1.05$) than the Israelis' ($M = 3.61$, $SD = 0.90$). Significant cultural differences emerged for perceived responsiveness ($t_{(900.94)} = -11.03$, $p < 0.001$), where the Israeli perceptions were more positive ($M = 3.98$, $SD = 0.77$) than the Germans' ($M = 3.32$, $SD = 1.06$). Focusing solely on GenAI regular users, in line with IFT, elucidates the cultural differences further: While perceived comprehensibility among Germans ($M = 3.92$, $SD = 0.911$) was significantly higher than Israelis' ($M = 3.65$, $SD = 0.913$; $t_{(397)} = 2.87$, $p = 0.004$), perceived responsiveness among Israelis ($M = 4.02$, $SD = 0.786$) was significantly higher than Germans' ($M = 3.68$, $SD = 0.922$; $t_{(286.512)} = -3.781$, $p < .001$).

The analyses of the diversity and complexity of information purposes among regular GenAI users in both countries (RQ2; Supplementary Material 3) indicated that regular users tended to utilize GenAI for diverse information purposes, including for more complex information. For dietary breadth, the mean number of information purposes per user was 2.41 ($SD = 1.11$). Most users (83.3%) reported employing GenAI for multiple information purposes, with the largest proportion (34.6%, $n = 143$) using it for three purposes. Notably, 6.3% ($n = 26$) did not use GenAI for any information purposes. For "prey choice," most respondents (68.8%, $n = 284$) reported employing GenAI for accessing science-related information, which represented the most complex information in this study.

To characterize the regular users who employed GenAI for different information complexities and purposes (RQ3), we conducted an LCA separately for each cultural context to support cultural comparison. Following the IFT framework, the LCA included the perceived currencies, costs, and forager attributes. Specifically, for currencies, we included perceived comprehensibility and responsiveness; for costs, we included epistemic AI knowledge; and for foragers' attributes, we included content and procedural AI knowledge, reported number of GenAI tools regularly used, and frequency of using GenAI tools in the LCA.

Starting with the Israeli regular GenAI users ($n = 254$), the model selection procedure suggested that a three-class solution provided the most appropriate balance between statistical fit and substantive interpretability (Table 1). The three-class solution revealed distinct user profiles with varying levels of perceived benefits, knowledge about AI and GenAI, and reported experience with GenAI tools (see Figure 1; a detailed account is available in Supplementary Material 4). Class 1, the Skeptical Minimalists ($n = 66$, 26%), demonstrated the lowest perceived comprehensibility ($M = 2.74$, $SD = 0.60$) and responsiveness ($M = 3.47$, $SD = 0.62$), as well as the lowest scores in AI knowledge (content & procedural: $M = 4.86$, $SD = 1.35$;

epistemic: $M = 2.77$, $SD = 1.13$) and the least experience with GenAI tools ($M = 1.24$, $SD = 0.66$; 80.3% reported using GenAI several times a month). Class 2, the Reserved Experts ($n = 56$, 22%), exhibited the highest levels of content and procedural knowledge ($M = 5.57$, $SD = 1.16$) and epistemic knowledge ($M = 3.27$, $SD = 0.98$), and reported regularly using multiple GenAI tools ($M = 2.39$, $SD = 0.73$); half reported using GenAI daily. However, their perceived comprehensibility ($M = 3.49$, $SD = 0.81$) and responsiveness ($M = 3.75$, $SD = 0.95$) were moderate. Class 3, the Favoring Pragmatists ($n = 132$, 52%), was the largest group. This class exhibited the highest perceived comprehensibility ($M = 4.16$, $SD = 0.69$) and responsiveness ($M = 4.39$, $SD = 0.55$), but moderate content and procedural knowledge ($M = 5.48$, $SD = 1.20$), epistemic knowledge ($M = 2.7$, $SD = 1.00$), and experience, with a small number of GenAI tools used regularly ($M = 1.44$, $SD = 0.7$), mostly up to several times a week.

To compare the dietary breadth and prey choices between the three classes, we analyzed the number of information purposes and the highest level of information complexity for which GenAI was used. Of the three classes, the Reserved Experts (Class 2) and the Favoring Pragmatists (Class 3) reported similar trends, whereas the Skeptical Minimalists (Class 1) reported lower engagement, consistent with their characterizing values. Specifically, dietary breadth differed significantly between classes ($F_{(2,251)} = 5.168$, $p = 0.006$), with Skeptical Minimalists reporting fewer information purposes ($M = 2.17$, $SD = 1.18$) compared to both Reserved Experts ($M = 2.75$, $SD = 1.05$, $p = 0.016$) and Favoring Pragmatists ($M = 2.63$, $SD = 1.09$, $p = 0.023$). The differences between Classes 2 and 3 were not significant. For prey choice, although the Kruskal-Wallis test approached significance ($H = 4.26$, $p = 0.119$), the overall pattern indicated that Skeptical Minimalists were more likely to engage in moderate-complexity tasks (21.2% for knowledge and facts) than the other groups. All three classes reported high rates of accessing complex science-related information (Reserved Experts: 73.2%; Favoring Pragmatists: 75.8%; Skeptical Minimalists: 62.1%), with Favoring Pragmatists reporting the highest rate.

In German regular GenAI users ($n = 159$), the model selection indicated that the four-class solution provided the optimal balance between model fit, parsimony, and substantive interpretability (Table 2). The LCA revealed user profiles specific to the German sample (Figure 2 and Supplementary 4). Class 1, the GenAI-Savvy Abstainers ($n = 94$, 59%), reported relatively high perceived comprehensibility ($M = 4.10$, $SD = 0.68$) and responsiveness ($M = 3.83$, $SD = 0.77$), and exhibited the highest levels of AI knowledge (content and procedural: $M = 5.54$, $SD = 0.99$; epistemic: $M = 3.32$, $SD = 0.78$). This group reported infrequent use of GenAI tools ($M = 1.53$, $SD = 0.81$), with most (55.3%) using GenAI only several times a month. Class 2, the Naïve Enthusiasts ($n = 24$, 15%), reported the highest perceived comprehensibility ($M = 4.42$, $SD = 0.65$) and responsiveness ($M = 4.46$, $SD = 0.51$), and were the most engaged with GenAI (number of tools used: $M = 3.38$, $SD = 0.88$; 70.8% reported using GenAI daily). Although understanding the workings of GenAI tools (content and procedural AI knowledge: $M = 4.67$, $SD = 1.9$), these users exhibited the lowest epistemic knowledge ($M = 1.33$, $SD = 0.76$). Class 3 and Class 4 had only slight differences. Class 3, the Cautious Skeptics ($n = 21$, 13%), reported the lowest perceived comprehensibility ($M = 2.72$, $SD = 0.58$) and responsiveness ($M = 2.78$, $SD = 0.43$), along with relatively low AI knowledge (content and procedural: $M = 3.67$, $SD = 2.03$; epistemic: $M = 2$, $SD = 1.10$) and minimal tool use (number of tools used regularly: $M = 1.29$, $SD = 0.46$; 71.4% up to several times a week). Class 4, the Passive Optimists ($n = 20$, 13%), expressed slightly higher perceived comprehensibility ($M = 3.58$, $SD = 1.35$) and responsiveness ($M = 2.84$, $SD = 1.12$), with slightly lower AI knowledge (content and procedural: $M = 3.05$, $SD = 1.64$; epistemic: $M = 2.25$, $SD = 0.97$) compared to Class 3. Their reported experience with GenAI was similarly restricted (number of tools used regularly: $M = 1.45$, $SD = 0.51$; 55% reported use several times a week, and 45% reported use several times a month).

Table 1. Model fit indices for the LCA of Israeli regular users (n = 254), indicating that the three-class solution provided the best fit.

Number of classes	Log-likelihood	Residual *df*	BIC	ABIC	AIC	CAIC	Likelihood-ratio	Min n%	Max n%	Entropy
2	−1,801.646	209	3,852.471	3,709.812	3,693.291	3,897.471	940.403	24.30	75.70	0.667
3	−1,766.463	186	3,909.465	3,693.89	3,668.926	3,977.465	869.263	23.80	52.23	0.733
4	−1,741.057	163	3,986.011	3,697.522	3,664.114	4,077.011	819.657	18.78	32.68	0.771
5	−1,721.718	140	4,074.692	3,713.288	3,671.436	4,188.692	784.571	13.34	29.03	0.853
6	−1,710.864	117	4,180.344	3,746.025	3,695.729	4,317.344	764.8	11	19.43	0.805

Notes: BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; AIC = Akaike Information Criterion; CAIC = Consistent AIC; lower BIC/ABIC values indicate better model fit; entropy values closer to 1 indicate better classification accuracy.

Table 2. Model fit indices for the LCA of German regular users (n = 159) indicating that the four-class solution provided the best fit.

Number of classes	Log-likelihood	Residual *df*	BIC	ABIC	AIC	CAIC	Likelihood-ratio	Min n%	Max n%	Entropy
2	−1,195.332	114	2,618.765	2,476.316	2,480.665	2,663.765	836.207	22.17%	77.83%	0.804
3	−1,157.688	91	2,660.062	2,444.804	2,451.376	2,728.062	761.516	15.62%	56.71%	0.842
4	−1,131.876	68	2,725.022	2,436.956	2,445.751	2,816.022	715.424	13.09%	58.05%	0.889
5	−1,118.753	45	2,815.362	2,454.488	2,465.507	2,929.362	687.432	8.95%	27.99%	0.798
6	−1,098.724	22	2,891.888	2,458.207	2,471.448	3,028.888	646.496	7.55%	30.82%	0.871

Notes: BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; AIC = Akaike Information Criterion; CAIC = Consistent AIC; lower BIC/ABIC values indicate better model fit; entropy values closer to 1 indicate better classification accuracy.

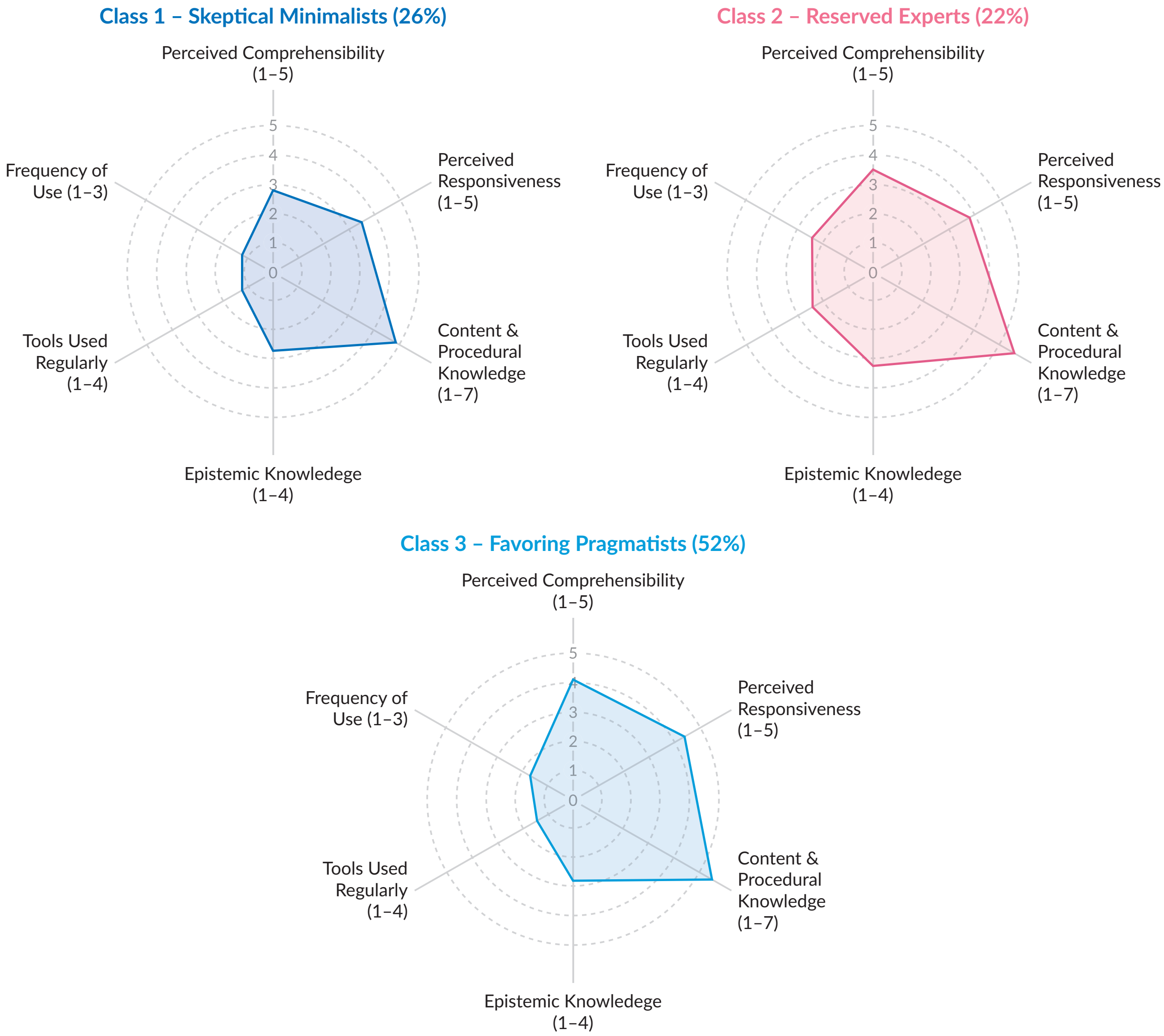

Figure 1. Item-response probability of the three Israeli classes.

Figure 2. Item-response probabilities for the four German classes.

The four classes differed in both dietary breadth and prey-choice patterns. The number of information purposes for which GenAI was used (dietary breadth) differed significantly ($F_{(3,155)} = 6.589$, $p < 0.001$) between the smaller number of information purposes of the Cautious Skeptics (Class 3, $M = 1.43$, $SD = 0.93$) and the higher number reported by the GenAI-Savvy Abstainers (Class 1, $M = 2.40$, $SD = 1.01$, $p = .002$) and Naïve Enthusiasts (Class 2, $M = 2.46$, $SD = 0.72$, $p = .011$). Other pairwise comparisons were not significant, with Passive Optimists (Class 4, $M = 1.85$, $SD = 1.39$) falling between the extremes. A Kruskal-Wallis test revealed significant differences ($H = 42.854$, $p < 0.001$) in the highest complexity level of information accessed using GenAI (prey choice) across classes. Naïve Enthusiasts differed significantly from all other classes (all $p \leq .004$), with consistent engagement with science-related information (100%). By contrast, GenAI-Savvy Abstainers demonstrated a more balanced pattern, with 62.8% using GenAI for complex information, whereas Cautious Skeptics (52.4%) and Passive Optimists (40%) showed lower rates of complex information seeking. The Passive Optimists were more likely to use GenAI for non-information-related purposes (25%) than the other classes. No significant differences were found between Classes 1, 3, and 4 in their complexity patterns.

A cross-cultural comparison of information foraging behaviors revealed largely incongruent patterns between the Israeli and German GenAI users. In both contexts, the classes characterized by skepticism and limited engagement—the Israeli Skeptical Minimalists and the German Cautious Skeptics—reported using GenAI for fewer information purposes (narrower dietary breadth) than the other classes. These two classes, however, differed from each other: The German Cautious Skeptics exhibited the most restrictive breadth (M = 1.43) compared to Israeli Skeptical Minimalists (M = 2.17), indicating potentially stronger skepticism in the German context. Regarding prey choice, i.e., the level of information complexity, the Israeli users showed relatively homogeneous complexity preferences across classes (62.1–75.8% engaging with science-related information), whereas the German classes exhibited significant differences. The German Naïve Enthusiasts were uniformly inclined to use GenAI to access science-related information (100%), thus differentiating themselves from the other German classes (40–62.8%). This suggests that among more technology-savvy GenAI users, less epistemic AI knowledge could lead to less critical use of the technology. A more IFT-centered comparison is discussed in Section 5.

5. Discussion

This study examined how people perceive GenAI as an information source and characterized regular users who utilize these technologies for various information purposes, with a particular focus on cross-cultural comparisons. Based on online surveys of representative samples in Germany and Israel, the findings indicated that among regular users of GenAI, the perceived comprehensibility of GenAI-provided content was higher in Germany than in Israel, whereas the perceived responsiveness of GenAI was higher in Israel. These divergent trends likely stem from cultural differences that shape people's interactions with GenAI. Trinn et al. (2025) showed that German users found ChatGPT's interface easy to navigate and the text size and font satisfactory; however, they were less satisfied with the technology's features and functionalities. These patterns are consistent with the higher comprehensibility and lower responsiveness found here. By contrast, the coexistence of higher perceived responsiveness and lower perceived comprehensibility among Israelis may be due to linguistic performance, given GenAI's lesser output quality in low-resource languages such as Hebrew (see D. Wang, 2025).

Drawing on IFT, we investigated GenAI users' information dietary choices across both nations. Most participants used GenAI for multiple purposes, including accessing science information which is the most complex. LCAs revealed largely incongruent patterns between countries. Among Israelis, three classes emerged: Skeptical Minimalists (26%), Reserved Experts (22%), and Favoring Pragmatists (52%). Among Germans, four classes emerged: GenAI-Savvy Abstainers (59%), Naïve Enthusiasts (15%), Cautious Skeptics (13%), and Passive Optimists (13%). These divergent classification patterns may reflect cultural orientations toward AI and risk perception. Whereas Germany's user landscape was dominated by knowledgeable yet restrained users (GenAI-Savvy Abstainers), Israel's usage patterns were dominated by Favoring Pragmatists who combined high perceived benefits with moderate knowledge. These differences may be attributed to Germany's relatively higher power distance and lower in-group collectivism, which are associated with more negative attitudes toward AI (S. Wang, 2025; Yeshua-Katz & Efrat-Treister, 2021). These differences can also be attributed to Israelis' more optimistic view of AI, given that they were found to perceive AI's benefits as outweighing its risks (Gillespie et al., 2023).

Observing the LCA results of the two populations through the IFT prism highlights two underlying similarities which suggest their relevance across cultures. First, focusing on regular users with both high perceived benefits of GenAI as an information source and limited awareness of GenAI's epistemic limitations (high currencies, low costs). This pattern characterized the German Naïve Enthusiasts and Israeli Favoring Pragmatists who reported the highest rates of accessing science-related information through GenAI (100% among Naïve Enthusiasts). Given that science-related information is more complex and involves high-risk decision-making, these patterns indicate that users with the lowest epistemic knowledge engaged the most with such information. These findings reaffirm the importance of educating the general public about the epistemic limitations of GenAI to support a more critical use of AI-generated information (C. Wang et al., 2024). These patterns, of linking favorable GenAI perceptions with its use for multiple and more complex information purposes, also add to the literature that generally links high trust and positive attitudes with the acceptance and use of GenAI (e.g., Chan & Zhou, 2023; Chang et al., 2025).

The second cross-cultural similarity concerns regular users with less favorable perceptions of GenAI as a source of information (low currencies). The German Cautious Skeptics, Passive Optimists, and the Israeli Skeptical Minimalists demonstrated patterns of avoidance. These users tended not only to report less experience with GenAI tools, but also to minimize the number of information purposes and the level of information complexity for which they use the technology. These avoidance patterns might contribute to or exacerbate the AI divide, i.e., AI-related access, capability, or outcome disparities among users, consequently perpetuating social or structural inequalities (C. Wang et al., 2024).

Finally, the results also provide empirical evidence for a theorized association in the science communication literature. Whereas scholars often highlight GenAI's potential benefits for accessing science-related information (e.g., Biyela et al., 2024), the current findings demonstrate that the perceived benefits of GenAI also contribute to its use for this purpose.

While this study provides valuable insights into cross-cultural GenAI usage patterns, it has four major limitations, primarily due to its reliance on previously collected data for the ScI-AI project (Greussing et al., 2025), which led us to use IFT as a conceptual architecture rather than a specific methodological approach. First, the operationalization of currency and costs focused on perceptions of GenAI and epistemic knowledge about it rather than capturing specific information-seeking episodes or behavioral efforts during interactions with GenAI. These adaptations weaken the construct validity of these measurements. Second, key constructs, such as perceived comprehensibility and responsiveness, were measured using single-item constructs which can undermine psychometric robustness. Third, the frequency and purposes of GenAI use were measured via self-reports, which may be subject to bias. These limitations weaken the reliability and depth of these assessments; however, these methodological choices allowed for greater survey efficiency and enabled testing a more comprehensive model incorporating multiple constructs without overburdening the participants. Fourth, although the LCA successfully identified meaningful user typologies, it provides a descriptive statistical approach and specific class solutions may vary with different indicators or larger, more diverse samples. Future studies could focus on actual behaviors while incorporating more robust constructs. Studies could also explore how individuals perceive and use GenAI for other information purposes and at different complexity levels in more countries, thus extending our understanding of cultural specifications of GenAI use.

This study offers three main contributions. First, by harnessing IFT, the study portrays how users navigate the trade-offs between GenAI's benefits as an information source and its epistemic limitations across cultures. Thus, the study enriches our understanding of culturally dependent and independent aspects of GenAI adoption. Second, the study suggests that the IFT framework can be useful for analyzing large-sample surveys, thus extending the type and scope of insights IFT can yield. Third, the study identifies worrisome patterns where users who had high perceived benefits and low epistemic knowledge tended to engage with more complex, high-stakes science-related information through GenAI across cultures. These insights underscore the need to cultivate GenAI epistemic and general knowledge to ensure GenAI's democratization potential while maintaining a critical use of AI-generated information.

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Conflict of Interests

In this article, editorial decisions were undertaken by Shakked Dabran-Zivan (Technion—Israel Institute of Technology).

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ChatGPT and Claude were used for grammar and style improvement, Undermind and Consensus were employed for specific literature searches, and NotebookLM was used for inspiration for the literature review. After using these tools, the authors reviewed and edited the text as needed and take full responsibility for the content of the published article.

Supplementary Material

Supplementary material for this article is available online in the format provided by the author (unedited).

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