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Exploring Trust and Literacy in Engagement With Generative AI and Science Information Behavior

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Abstract

As generative AI (GenAI) becomes increasingly embedded in everyday information environments, understanding how citizens engage with this technology is critical for science communication. This study examines public engagement with GenAI in Denmark, focusing on trust, AI literacy, experience with GenAI tools, and exposure to science-related information. Denmark provides a relevant case due to its high levels of institutional and scientific trust. Using data from a nationally representative survey conducted in 2024 (n = 514) as part of the cross-national ScI-AI project, we analyze how respondents encounter GenAI, assess its trustworthiness, understand its technical and epistemic features, and engage with science-related information across platforms. Descriptive results show moderate trust in GenAI, uneven AI and GenAI literacy, and concentrated experience centered primarily on ChatGPT, alongside pronounced concerns about misinformation and societal risks. To examine how these dimensions relate, we apply a probabilistic graphical model to 29 variables spanning trust, literacy, experience, science-related information exposure, and demographics. The analysis reveals that trust occupies a central position, mediating between technical understanding of GenAI's functioning and epistemic beliefs about the reliability and truthfulness of its outputs. Science-related information exposure is largely disconnected from trust and GenAI literacy and links to general AI literacy primarily through gender. Overall, the findings highlight the importance of treating trust and literacy as multidimensional and context-sensitive constructs for understanding how GenAI reshapes science-related information encounters.

Keywords
AI literacy; engagement with AI; generative AI; information behavior; trust in AI

1. Introduction

1.1. The Promise and Perils of Generative AI in Science Communication

The rapid spread of generative AI (GenAI) technologies has sparked both enthusiasm and concern among science communication scholars and practitioners. Tools like ChatGPT promise to democratize science communication by enabling scientists and communicators to generate accessible explanations, summarize research findings, and engage audiences in new, interactive ways (Alvarez et al., 2024). These capabilities are particularly promising in contexts that demand scalable and responsive communication, such as education, health, and climate change. However, the very strengths of GenAI—its fluency, speed, and scalability—also present serious risks. Studies warn that these tools may produce misleading or inaccurate content, amplify existing biases, and obscure errors behind well-written prose (Schäfer, 2023).

Furthermore, concerns have been raised about the loss of diversity in communicative voices and the erosion of trust in science if public institutions begin to rely too heavily on algorithmically generated outputs (Alvarez et al., 2024; Kaufenberg-Lashua et al., 2024). In this emerging landscape, it becomes essential to empirically investigate public engagement with GenAI tools, including people's trust, literacy, experience, and perceptions of risks and benefits, as these factors are paramount for understanding the changes that these tools bring to the contexts in which people consume scientific content. In this emerging landscape, it is essential to empirically investigate how aspects such as people's trust, experience, AI literacy, and demographic variables create contexts for engagement with scientific content.

1.2. The ScI-AI Project: A Cross-National Survey on GenAI and Science-Related Information

This article is based on our contribution to the project Science Information Search with AI Technologies (ScI-AI), a multi-country survey designed to explore how citizens across seven technologically advanced countries engage with GenAI for science-related information search (Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Middleton, et al., 2025; Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Nielsen, et al., 2025). Conducted in 2023 and 2024, the survey collected data from over 4,000 participants in Australia, Denmark, Germany, Israel, South Korea, Taiwan, and the United States. The project investigates how widely tools like ChatGPT are used to retrieve scientific information, how they compare to traditional intermediaries like search engines, and what role trust and literacy play in this evolving media environment.

The project frames GenAI as both an information intermediary and an active communicator, emphasizing its capacity to shape—not just transmit—science-related content. Empirical findings from earlier project publications indicate that users who turn to GenAI for science searches tend to express greater trust in the tools, have higher literacy regarding AI, and show stronger awareness of its limitations (Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Nielsen, et al., 2025). Against this background, the present article focuses specifically on the Danish sub-sample to explore how these general patterns manifest in a high-trust national context (Svendsen & Svendsen, 2016).

1.3. Science-Related Information Behavior and GenAI as an Epistemic Technology

Science-related information behavior may be defined as the range of practices through which people encounter, access, and engage with scientific information—across different media platforms and social contexts (Agarwal, 2023; Case & Given, 2016), including coming across science-related content in news outlets, on social media, or through digital tools such as search engines and GenAI systems. Significantly, the practices of science-related information behavior span both active engagement—information searching and information seeking (Bates, 2017) where information is interpreted, evaluated, and re-communicated in personal, professional, or public settings—and passive exposure where information is simply encountered (Wilson, 1999). In this study, the survey items primarily capture the passive dimension of science-related information behavior—that is, how often individuals are exposed to science-related content across different platforms.

Research on information behavior increasingly identifies trust as a core condition shaping how people engage with information in complex, digitally mediated environments (Huvila & Gorichanaz, 2025). In contexts characterized by information abundance and algorithmic mediation, trust influences what individuals attend to, accept, or disregard when encountering information. Trust is not merely a property of sources but a relational and situational judgment that emerges through interactions with technologies, institutions, and social expectations (Blanco, 2025). In AI-mediated settings, this judgment becomes especially salient, as users must evaluate systems that both retrieve and generate content while remaining partly opaque in their operation. As Pawlick-Potts (2022) suggests, trust in AI is negotiated through experience and perceived agency rather than accuracy alone, shaping how AI-generated information is interpreted and integrated into everyday knowledge practices.

These practices unfold within a broader communication environment shaped by technological, institutional, and social conditions that determine how information circulates, gains visibility, and becomes meaningful (Klein-Avraham et al., 2024; Scheufele et al., 2017; Taddicken & Krämer, 2021). As GenAI tools evolve and become increasingly embedded in this environment, their role extends beyond transmitting scientific information. They also operate as epistemic technologies that generate epistemic claims, influencing how knowledge is produced, trusted, and disseminated in society (Alvarado, 2023). Viewing GenAI in this way highlights both its promise and its risks for science communication and underscores the crucial roles of trust and literacy in shaping how people interpret and integrate GenAI outputs into their information practices.

1.4. AI Literacy and Trust in AI

Science-related information behavior is conditioned by people's capacities and dispositions for navigating increasingly complex digital environments. Among these, AI literacy and trust in AI play pivotal roles.

Recent work defines AI literacy as a multidimensional set of competencies enabling individuals to understand, evaluate, and interact responsibly with AI systems (Lintner, 2024; Long & Magerko, 2020; D. T. K. Ng et al., 2021). This literacy extends beyond technical knowledge to include ethical awareness, critical judgment, and the ability to contextualize AI's operations and outputs within broader social and epistemic settings. As digital technologies such as GenAI become embedded in everyday information behaviors, AI literacy emerges as an increasingly consequential—yet still underexplored—determinant of how people recognize, interpret, and evaluate AI-generated information. Existing research shows that while AI literacy can enhance appropriate reliance and trust in AI systems, evidence of its broader cognitive and behavioral effects remains limited and mixed (Pinski & Benlian, 2024, p. 14).

Complementing literacy, trust in AI represents the relational and normative dimension of how people engage with GenAI for science-related information. Trust involves both cognitive judgments about system reliability and social evaluations shaped by fairness, accountability, and institutional credibility (Afroogh et al., 2024; S. W. T. Ng & Zhang, 2025). Although early approaches emphasized transparency and explainability as the technical foundations of "trustworthy AI" (Thiebes et al., 2021), recent research in psychology underscores that trust cannot simply be engineered—it arises through users' contextual experiences and perceptions of legitimacy (Dang & Liu, 2025; Lalot & Bertram, 2025).

In this sense, AI literacy, trust, and experiences are deeply intertwined. Understanding how AI works informs when and why people choose to trust it, while trust itself feeds back into how users engage with GenAI—whether they approach its outputs with critical scrutiny, cautious reliance, or confident acceptance. This reciprocal dynamic suggests that literacy, trust, and engagement co-evolve over time (Möllering, 2006): Each interaction with GenAI can reinforce, recalibrate, or erode users' understanding and confidence in the technology, thereby shaping their broader science-related information behavior.

1.5. Research Questions

Building on research on science-related information behavior, AI literacy, and trust in AI, this study examines how Danish citizens engage with GenAI in contexts where they encounter science-related information. Prior work has shown that trust and literacy are central to how people evaluate scientific information mediated by digital technologies (Fage-Butler et al., 2025), and that GenAI, understood as an epistemic technology (Alvarado, 2023), introduces new challenges by actively generating epistemic claims rather than merely transmitting information (Hendriks et al., 2025; Klein-Avraham et al., 2024). Existing findings from the SciI-AI project further indicate that trust in GenAI, knowledge about AI, and experience with specific tools are closely related, but also that these relationships vary across national contexts and remain insufficiently understood at a more fine-grained, structural level (Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Nielsen, et al., 2025).

The present study focuses on the Danish case using data from the 2024 wave of the SciI-AI survey. Denmark provides a particularly relevant context due to its high levels of institutional trust and digitalization, which may shape how GenAI is integrated into everyday science-related information behavior. Our aim is to provide a detailed snapshot of how trust, literacy, and experience are configured at this specific moment, and how these factors jointly condition people's encounters with science-related information.

To this end, we combine descriptive analyses with a probabilistic graphical model approach that allows us to examine how different dimensions of trust, AI literacy, and GenAI experience are interrelated, without imposing strong a priori assumptions about their structure. This approach complements earlier SciI-AI analyses by moving beyond usage patterns and mean differences to explore the conditional dependencies that underpin public engagement with GenAI.

Accordingly, we address the following research questions:

- RQ1 (descriptive): What characterizes Danish citizens' trust in, literacy about, and experience with GenAI tools in 2024 in the context of science-related information encounters?
- RQ2 (relational): How are key dimensions of trust, AI literacy, and experience with GenAI tools conditionally interrelated with each other and with demographic characteristics and exposure to science-related information across different platforms?

2. Methods and Materials

2.1. Survey Design and Data Collection

Data for this study were collected through an online panel survey administered in two waves: June–July 2023 and August–September 2024. These two surveys represent independent cross-sectional samples, not repeated measurements of the same respondents. Both surveys were conducted as part of the international SciI-AI project (Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Nielsen, et al., 2025), which investigates how citizens in technologically advanced countries engage with GenAI for science-related information behavior. In Denmark, data collection and panel recruitment were carried out by Analyse Danmark using the Norstat online panel.

Respondents were recruited from Norstat's pool of Danish citizens, who receive compensation for participation. Quotas were established to ensure samples broadly representative of the Danish adult population in terms of gender, age, education, and regional distribution. The cleaned datasets included 505 respondents in 2023 and 514 in 2024. The 2024 questionnaire closely resembled the 2023 version but included several modifications, especially in items related to literacy, trust, experience, and use of GenAI tools. Because of these changes, the present study focuses exclusively on the 2024 data.

Both questionnaires were translated into Danish and back-translated into English to ensure linguistic and conceptual equivalence. The full Danish and English versions of the 2024 survey, together with a detailed description of all constructs and their operationalization, are available in Table S1 (Supplementary Material). A concise overview of the constructs and variables is provided in Table 1.

Table 1. Constructs, variables, and their abbreviations.

Construct	Variables	Abbreviation	Description
Trust	TRUST_overall, TRUST_DIAL_responsive, TRUST_BEN_help, TRUST_BEN_prioritize, TRUST_COMP_competent, TRUST_DIAL_welcome, TRUST_TRANS_comprehensible, TRUST_COMP_reliable	TrustOverall, TrustResp, TrustHelp, TrustPrior, TrustComp, TrustWelc, TrustCompr, TrustRel	Respondents' perceptions of GenAI's reliability, responsiveness, and benevolence.
AI Literacy	LIT_AI1–5	LitAI1–5	Knowledge about AI's functioning, learning mechanisms, and output accuracy.
GenAI Literacy	LIT_GenAI1–4	LitGen1–4	Knowledge about how GenAI generates outputs, incorporates conversational context, and the accuracy and sources of its responses.
Experience	EXP_chatgpt, EXP_bard, EXP_bing, EXP_perplex	ExpChat, ExpBard, ExpBing, ExpPerpl	Self-reported familiarity and use of GenAI tools.
Science-Related Information Exposure	SCIENCENEWS1–3	SciNews1–3	Frequency of encountering science-related content across different media platforms.
Demographics	AGE, GENDER, EDUCATION, REGION, LIVING	Age, Gender, Educ, Region, Living	Background variables used to contextualize differences in trust and literacy.

Note: Full operationalizations, scales, and item wordings are provided in Table S1 (Supplementary Material).

2.2. Data Analysis and Modeling

Although existing research indicates that trust, literacy, and experience are central to public engagement with GenAI, the literature offers limited guidance on how their multiple dimensions are structurally interrelated when examined simultaneously. Given this complexity, and the novelty of GenAI as an epistemic technology, we employ a probabilistic graphical model to examine conditional dependencies among these variables within a multivariate inferential framework grounded in graphical model theory.

Descriptive analysis was used to summarize the distribution of key variables related to trust, AI literacy, GenAI literacy, experience with GenAI tools, science-related information exposure, and background characteristics. Given the ordinal and categorical nature of most variables, these summaries are reported as response distributions rather than means and standard deviations. A concise overview of all measures is provided in Table S2 (Supplementary Material).

Beyond descriptive patterns, the analysis sought to examine how variables relate to one another when considered jointly. Preliminary inspection indicated substantial interdependencies among variables, suggesting that simple pairwise associations or correlation matrices would be insufficient and potentially misleading due to indirect or spurious relationships. To address this, we applied a probabilistic graphical model, an established inferential approach designed to identify conditional dependence structures by estimating which associations remain when all other variables are considered. In this context, "graphical" refers to the mathematical representation of dependencies as a graph rather than to visualization (Lauritzen, 1996).

The model included 29 variables spanning trust, AI literacy, GenAI literacy, experience with GenAI tools, science-related information exposure, and demographic characteristics. Although the survey included a broader set of trust-related items, the graphical model analysis focuses on eight trust indicators capturing interactional, competence, and reliability dimensions; see Table 1.

Interpretation of the resulting graph relies on the separation principle of graphical model theory: If a set of variables S separates two other variables A and B, then A and B are conditionally independent given S (Lauritzen, 1996). Accordingly, the absence of an edge between two variables indicates that they are not directly associated. If variables are connected only through intermediary nodes, any observed association can be explained by conditioning on those separating variables; if no connecting path exists, the variables are conditionally independent given all others in the model. The graphical model was inferred by selecting the structure with the minimal Bayesian Information Criterion (BIC) using the R package gRapHD (Abreu et al., 2010).

While the graphical model identifies conditional dependencies net of all other variables, contingency tables are used in a complementary manner to illustrate the marginal distributions and bivariate associations that provide descriptive context for the modeled relationships.

2.3. Ethical Considerations

In accordance with the General Data Protection Regulation (GDPR) of the EU, participants were informed about the purpose of the study prior to participation, and their consent was obtained via their agreement to the Norstat panel's terms and conditions. Participation was fully anonymous, and no data collected can be traced back to individual respondents.

3. Results

3.1. Descriptive Statistics for Key Variables

We begin by presenting descriptive statistics for variables central to our research questions. These analyses outline key features of public engagement with GenAI in Denmark in 2024, focusing on trust in GenAI, AI and GenAI literacy, experience with GenAI tools, and exposure to science-related information across different platforms. Together, these results establish the empirical context for the subsequent graphical model analysis of interdependencies among variables.

3.1.1. Public Trust in GenAI

Public trust in GenAI technologies was moderate and internally differentiated. Overall, 18% of respondents agreed or strongly agreed that they could trust GenAI technologies, while 36% disagreed or strongly disagreed and 39% selected the midpoint of the scale. A further 7% responded "don't know," indicating residual uncertainty (Table S2).

Across specific trust dimensions, respondents expressed comparatively higher agreement with statements describing GenAI as welcoming and comprehensible than with those emphasizing reliability or benevolence. For example, 43% agreed that GenAI technologies welcome user engagement, and 41% agreed that they deliver comprehensible information. By contrast, only 14% agreed that GenAI technologies are reliable, and 9% agreed that they prioritize users' well-being. Substantial proportions of "don't know" responses across trust items (16–27%) suggest that evaluations of GenAI remain provisional rather than firmly established.

3.1.2. AI Literacy Levels

Levels of AI literacy were uneven and characterized by pronounced uncertainty. For general AI knowledge items, between 69% and 81% of respondents correctly identified that some AI systems learn from user interactions, recognize patterns in training data, and are shaped by training examples. In contrast, understanding of more critical or definitional aspects was considerably lower. Only 27% correctly rejected the claim that all algorithms are a form of AI, and 42% correctly rejected the claim that AI-based decisions are always free of bias. These items elicited high proportions of "don't know" responses (35% and 47%, respectively), pointing to uncertainty rather than consistent misperceptions (Table S2).

A similar pattern was observed for GenAI-specific literacy. While 76% correctly rejected the claim that GenAI outputs are always true, only 40% correctly identified that GenAI systems generate text by probabilistically predicting the next word. Across GenAI literacy items, "don't know" responses ranged from 20% to 46%, indicating limited confidence in understanding the epistemic mechanisms underlying GenAI.

3.1.3. Experience and Use of GenAI Tools

Experience with GenAI tools was highly concentrated around a single platform. Nearly half of respondents (48%) reported having used ChatGPT at least once, while an additional 40% had heard of it but never used it. In contrast, familiarity and use of other tools were markedly lower. Only 19% reported any use of Microsoft Copilot (formerly Bing), 6% reported use of Google Gemini (formerly Bard), and 2% reported use of Perplexity AI. For these tools, most respondents indicated that they were hearing about them for the first time (Table S2).

These patterns suggest that public experience with GenAI in Denmark in 2024 was driven primarily by exposure to ChatGPT, rather than by engagement with a broader ecosystem of GenAI systems.

3.1.4. Science-Related Information Exposure

Respondents reported regular exposure to science-related information, though frequency varied by content type. Science and technology news were encountered most frequently, with 39% of respondents reporting weekly or daily exposure and only 5% reporting no exposure. Professionally produced science content was encountered less often, with 19% reporting weekly or daily exposure and 15% reporting none. User-generated science content on social media platforms was encountered least frequently: 22% reported never encountering such content, while 22% encountered it weekly or daily (Table S2).

Overall, science-related information appears to be a routine component of respondents' media environments, but it is more commonly encountered through traditional news outlets than through professional or user-generated online sources.

While these descriptive results outline key patterns in trust, literacy, experience, and exposure, they do not capture how these dimensions relate to one another. In the next section, we therefore use a probabilistic graphical model to examine the conditional dependencies among these variables and to identify the structures that organize science-related information exposure with GenAI in Denmark.

3.2. Dependence Structure Among Key Variables

To move beyond descriptive patterns and examine how trust, literacy, experience, and science-related information exposure are interrelated, we estimated a probabilistic graphical model using the 2024 data. The resulting dependence graph is shown in Figure 1. The graph visualizes conditional dependencies among the 29 selected variables: Nodes represent variables, and edges indicate associations that cannot be explained by the remaining variables in the model. Conversely, the absence of an edge implies conditional independence given the rest of the variables.

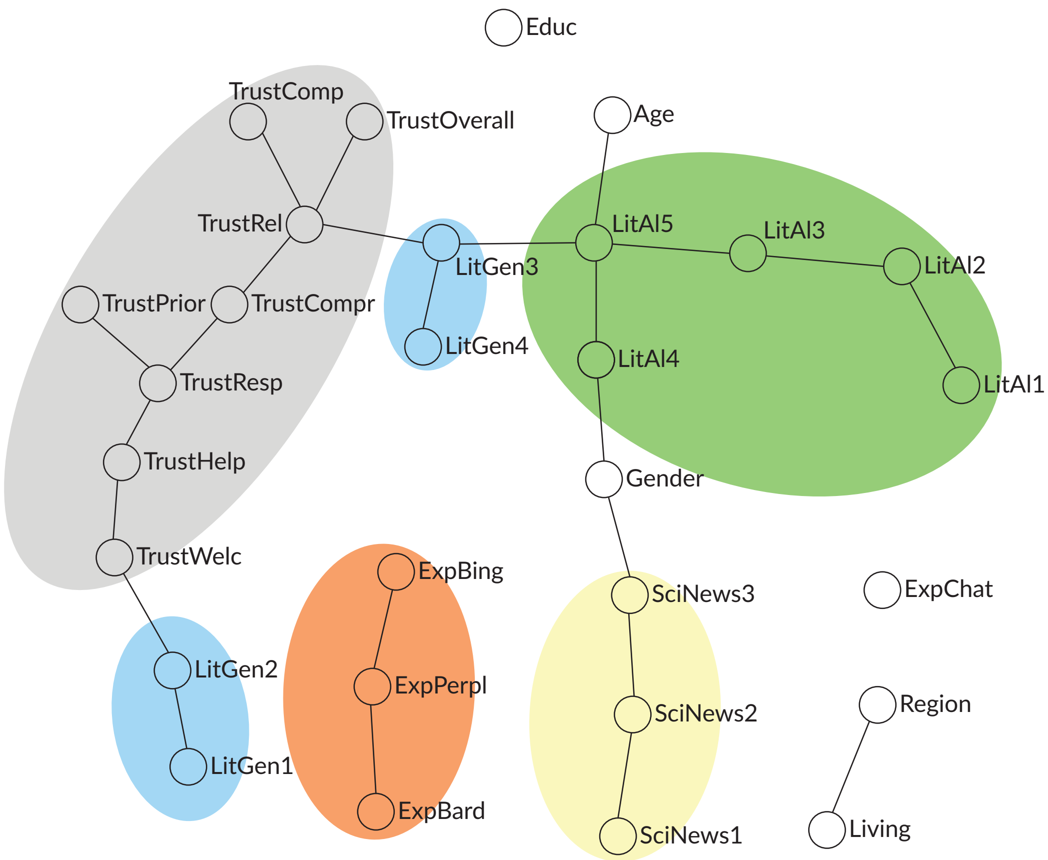

Figure 1. Graphical representation of the conditional dependence structure among 29 selected variables in the 2024 dataset. Each variable is depicted as a node (vertex), and edges between nodes indicate conditional dependence—meaning the variables share information that cannot be explained by the remaining variables in the model. The absence of an edge implies conditional independence: Once the other variables are accounted for, the two unconnected variables do not provide additional information about each other.

Overall, the graph reveals a highly structured pattern in which trust variables form a dense and central cluster, literacy variables occupy bridging positions between trust and science-related information exposure, and experience with GenAI tools appears largely disconnected from the rest of the model. Below, we describe the most salient structures in detail, drawing on the contingency tables reported in Tables S3–S7 (Supplementary Material) to substantiate key associations.

3.2.1. Trust in GenAI and AI Literacy

A prominent feature of the dependence graph is a tightly connected cluster of trust-related variables. Within this cluster, trust in GenAI's reliability (TrustRel) plays a particularly important structural role. TrustRel acts as a separator between respondents' beliefs about the epistemic quality of GenAI outputs and sources and other trust dimensions.

Specifically, TrustRel separates the GenAI literacy items LitGen3 (belief that GenAI relies only on trustworthy sources) and LitGen4 (belief that GenAI outputs are always true) from the remaining trust variables. This indicates that perceived reliability mediates how respondents connect trust in GenAI to beliefs about the correctness and sourcing of its outputs. Once trust in reliability is accounted for, beliefs about source trustworthiness and output truthfulness are conditionally independent of other trust dimensions and of respondents' technical understanding of how GenAI works.

The substantive nature of this mediation is illustrated in Table S3, which shows a strong association between TrustRel and LitGen3. Respondents who expressed high trust in GenAI's reliability were substantially more likely to endorse the incorrect belief that GenAI systems rely only on trustworthy and knowledgeable sources. Conversely, respondents expressing low trust in reliability were more likely to reject this claim or to select "don't know." This pattern suggests that confidence in GenAI's reliability may foster epistemic overgeneralization rather than critical evaluation of underlying data sources.

A parallel but distinct structure emerges around trust in GenAI as welcoming user engagement (TrustWelc). This variable separates two GenAI literacy items, LitGen1 (understanding that GenAI generates text by probabilistically predicting the next word) and LitGen2 (understanding that GenAI considers conversational context), from the rest of the trust cluster. In this configuration, the perception that GenAI technologies welcome user interaction functions as a mediating trust mechanism linking respondents' technical understanding of how GenAI generates outputs to broader trust orientations toward the technology.

As shown in Table S4, higher agreement with TrustWelc is positively associated with correct understanding that GenAI takes conversational history into account when generating responses. Respondents who perceived GenAI as welcoming and interactive were more likely to demonstrate accurate technical knowledge about contextual processing, whereas those expressing low trust or uncertainty along this dimension were more likely to respond incorrectly or select "don't know." Together, these two patterns indicate that different trust dimensions mediate different aspects of GenAI literacy rather than operating uniformly across knowledge domains.

3.2.2. AI Literacy, Science-Related Information Exposure, and Gender

Beyond the trust–GenAI literacy nexus, the dependence graph reveals two additional clusters: one related to science-related information exposure (SciNews1–3) and another comprising general AI literacy items (LitAI1–5). These clusters are not directly connected but are linked through specific literacy variables that function as conceptual bridges.

One such bridge is LitAI5, which captures understanding that AI-based decision-making is not free of bias. LitAI5 connects the general AI literacy cluster to GenAI literacy and, indirectly, to trust-related variables. This position suggests that awareness of bias in AI systems plays a key role in linking technical and epistemic knowledge about AI to broader evaluative orientations toward GenAI.

Gender also appears as a separator between the science-related information exposure cluster and parts of the AI literacy cluster. However, closer inspection of the contingency tables indicates that this association should be interpreted cautiously. Table S5 (Supplementary Material) shows that while men were slightly more likely than women to provide the correct answer to LitAI4 (rejecting the claim that all algorithms are a form of AI), the most pronounced gender difference occurred in the "don't know" category. Women were substantially more likely to select "don't know," suggesting higher expressed uncertainty rather than a systematically higher rate of incorrect beliefs.

A similar pattern appears in Table S6, which examines the association between gender and exposure to user-generated science content on social media (SciNews3). Although men reported encountering such content more frequently, women were again more likely to select "don't know," complicating straightforward interpretations of gender differences in exposure. Taken together, these findings suggest that gendered patterns in the graph are driven at least in part by differential willingness to express uncertainty rather than by clear differences in knowledge or engagement.

Age shows a more straightforward association with AI literacy. As detailed in Table S7, younger respondents were substantially more likely to correctly reject the claim that AI-based decisions are always unbiased (LitAI5), whereas older respondents were more likely either to endorse the incorrect statement or to select "don't know." This age gradient positions bias awareness as an important generational fault line in AI literacy and helps explain why LitAI5 occupies a structurally salient position in the dependence graph.

3.2.3. Insulated Variables

Finally, we note that some of the demographic variables—education, region, and living (urban or rural)—as well as the four experience variables, were not connected to any of the trust, literacy, or science news variables in the graph. Additionally, ExpChat was disconnected from the other three experience variables, indicating that respondents' experience with ChatGPT is not explained by their experience with Gemini, Copilot, or Perplexity AI, and vice versa. More notably, the absence of connections between any of the experience variables and the rest of the graph suggests that, given the information from the other variables, respondents' experience with common GenAI tools appears to be independent of their trust in GenAI, AI and GenAI literacy, science news exposure, and demography.

4. Discussion

4.1. Summary of Main Findings

This study examined how Danish citizens engage with GenAI in the context of science-related information encounters, focusing on the roles of trust, literacy, and experience. Addressing RQ1, which concerned public perceptions, adoption, and understanding of GenAI in 2024, the findings show a pattern of moderate trust, uneven literacy, and asymmetric experience concentrated around a small number of widely visible tools, most notably ChatGPT. Respondents expressed ambivalence: Optimism about potential benefits—particularly in education and health—coexisted with pronounced concerns about misinformation and societal risks. Knowledge about how GenAI works varied substantially, with many respondents holding incomplete or inaccurate beliefs while nonetheless expressing confidence in GenAI's reliability.

With respect to the broader context of science-related information encounters, respondents reported being most regularly exposed to science-related content through news media, followed by professional and user-generated sources. Across these three forms of exposure, no systematic associations with sociodemographic variables were observed, except for gender. This gender-related pattern is explored further below. Overall, these findings suggest that variations in trust, literacy, and experience with GenAI emerge within a relatively shared landscape of science information exposure rather than being strongly structured by demographic differences.

A more systematic consideration of sociodemographic differences further contextualizes these findings. Across the sample, education level, region of residence, and living area (urban vs. rural) showed no consistent associations with the main constructs examined here, including trust in GenAI, AI and GenAI literacy, and science-related information exposure. Gender emerged as a relevant structuring variable, particularly in relation to the association between science-related information exposure and general AI literacy. In addition, age was specifically associated with one aspect of AI literacy: awareness of the potential bias of AI-based decision-making, with younger respondents more likely to recognize such bias. Overall, these results suggest that sociodemographic differences play a limited but selective role in shaping public engagement with GenAI.

Addressing RQ2, the analysis shows that trust, literacy, and experience are conditionally interrelated rather than independent predictors of engagement. Trust variables occupy a central mediating position, linking two distinct clusters of GenAI literacy. One cluster—LitGen1 and LitGen2—captures understanding of GenAI as an interactive system that generates text probabilistically and considers conversational context, and connects to trust through perceptions of GenAI as welcoming user engagement. The other cluster—LitGen3 and LitGen4—reflects beliefs about the trustworthiness and truthfulness of GenAI outputs and connects to trust via perceived reliability. Notably, LitGen3 bridges the trust cluster with broader AI literacy, which is linked to science-related information exposure through gender. Overall, trust mediates between epistemic framings of GenAI as interactive system versus authoritative source, shaping how literacy relates to science-related information encounters.

Taken together, these findings suggest that public engagement with GenAI in Denmark is shaped less by linear effects of "more literacy → more trust" than by contextual combinations of beliefs, experiences, and trust orientations that structure how GenAI is interpreted and used in science-related information contexts. Patterns of science-related information exposure form part of the broader context in which engagement with AI is situated, not as a direct driver of trust or literacy, but as a background condition that may be weakly patterned across groups. In our data, this is visible only indirectly and should be interpreted cautiously, as the observed association with general AI literacy operates through gender and appears to be driven primarily by differences in response uncertainty rather than substantive differences in knowledge.

4.2. GenAI as an Epistemic Technology in Science Communication Contexts

These findings resonate with, but also refine, earlier insights from the ScI-AI project that situated the Danish case within a broader comparative context. Cross-national analyses have shown that individuals who use GenAI for science-related information retrieval tend to display higher trust in these technologies and a more developed understanding of their functioning and limitations (Greussing, Guenther, Baram-Tsabari, Dabran-Zivan, Jonas, Klein-Avraham, Taddicken, Agergaard, Beets, Brossard, Chakraborty, Fage-Butler, Huang, Kankaria, Lo, Nielsen, et al., 2025). Rather than reproducing these patterns descriptively, our analysis adds conceptual depth by examining how trust, literacy, and experience are structurally related within a high-trust national context. The graphical model reveals that these dimensions are not simply correlated but organized through specific dependency structures, highlighting the mediating role of trust beliefs in shaping how epistemic understandings of GenAI translate into science-related information practices.

The graphical model analysis shows that trust mediates between respondents' technical understanding of how GenAI generates content and their epistemic beliefs about the reliability and credibility of its outputs. This pattern does not merely reflect differences in familiarity or attitudes toward technology; rather, it indicates that users engage with GenAI as a system that produces knowledge claims requiring evaluation. While this pattern does not constitute a direct empirical test of Alvarado's (2023) theoretical framework, it is interpretatively relevant to it, as it shows that users do not treat GenAI merely as a neutral channel for information. As a technology that shapes information behavior, GenAI's primary social function lies not only in the transmission of information but in the generation of claims that invite judgment, acceptance, or rejection. Within science communication, this reconfigures established roles, as GenAI simultaneously operates as intermediary, content producer, and conversational interface, thereby blurring traditional boundaries between sources, mediators, and audiences.

Importantly, respondents' evaluations of GenAI varied with how they implicitly framed the technology in use. Trust in GenAI's reliability was lower among respondents who recognized limitations in training data or output accuracy, whereas perceptions of GenAI as engaging and responsive were associated with knowledge of probabilistic text generation and conversational context. This pattern reflects what can be described as ontological flexibility: GenAI is alternately framed as an information source, a functional tool, or a conversational partner, with each framing foregrounding different trust criteria. Importantly, because these framings are not fixed but may shift from one encounter to the next—depending, for example, on the task at hand (Yang & Ma, 2025)—trust in GenAI should be regarded as dynamic and contextual rather than monolithic.

4.3. Trust, Literacy, and Their Interrelations

This study offers several conceptual contributions to research on science communication and public engagement with AI.

First, the graphical model underscores the centrality of trust in shaping how people relate to GenAI. The trust cluster functioned as a hub, linking otherwise separate domains of literacy and information practices. This suggests that, in the context of science-related information behavior, GenAI cannot be fully understood only as a matter of technical proficiency or epistemic reasoning because the willingness to place trust—or withhold it—shapes how citizens approach, interpret, and use GenAI in these interactions.

Second, our findings show that trust and literacy cannot be treated as independent constructs. The graphical model revealed that the two dimensions interact in complex and structured ways, with literacy often acting as a bridge between trust variables and patterns of science-related information exposure. This interdependence highlights the need for research and practice in science communication to avoid treating literacy initiatives as detached from questions of trust, and vice versa.

Third, the results demonstrate that trust in GenAI is multidimensional rather than monolithic. Within our analysis, two dimensions were particularly important mediators: trust in GenAI's reliability, which mediated associations with the belief that GenAI uses only trustworthy sources; and trust that GenAI welcomes user engagement, which mediated associations with understanding that GenAI considers conversational context. These mediating roles reveal that some trust dimensions carry more structural weight than others in organizing how literacy and science-related information behavior relate to GenAI.

Fourth, the study contributes to understanding AI literacy as a multidimensional construct, which is well-established in the literature on media literacy, algorithm literacy, and AI literacy (e.g., Dogruel et al., 2022; Gagrčin et al., 2024; Long & Magerko, 2020). Our contribution lies in empirically demonstrating how distinct components of literacy relate differently to specific trust dimensions within a concrete science-related information environment, moving beyond abstract typologies toward relational insight.

4.4. Sociodemographic Differences and Framing Effects

Sociodemographic variables played a contextual rather than uniform role in our findings. Gender appeared as a separator in the graphical model linking literacy and science-related information exposure. However, contingency analyses indicate that these patterns are driven less by substantive knowledge gaps than by differential use of "don't know" responses, suggesting varying thresholds for expressing certainty rather than differences in understanding per se (Cai et al., 2017).

This finding cautions against stereotypical interpretations (e.g., framing AI as primarily of interest to men). Instead, it suggests that technical framings of AI may generate uncertainty among some groups, which should not be conflated with ignorance. From a science communication perspective, this suggests the importance of framing GenAI not only as a technical system but also as a social, epistemic, and ethical phenomenon.

4.5. Practical and Policy Implications

Our findings underline that both trust and literacy should be understood as dynamic and context-dependent rather than stable attributes. They take on different meanings depending on how people frame GenAI in each situation. For scholars and practitioners aiming to support critical and informed use of GenAI, this implies that it is insufficient to promote generic notions of "appropriate trust" or "more literacy." Instead, interventions should attend to the epistemic assumptions users bring to specific contexts of use and to how these assumptions shape when, why, and how GenAI is relied upon in science-related information encounters.

More broadly, the results suggest that public engagement with GenAI should not be approached solely through technical or techno-scientific framings. Narrowly technical discussions risk alienating individuals who express uncertainty rather than lack of interest or capability. Emphasizing the epistemic, social, and ethical dimensions of GenAI—such as how claims are generated, evaluated, and situated within broader knowledge practices—may foster more inclusive forms of engagement. Continued efforts to support AI literacy are therefore needed, particularly forms of literacy that enable users to critically assess the trustworthiness and limitations of AI-generated content in science-related contexts.

4.6. Limitations

Several limitations of this study should be acknowledged.

First, a few key variables, most notably experience with GenAI tools and exposure to science-related information, were measured using single-item indicators. While such measures are common in large-scale surveys and suitable for capturing broad patterns of engagement, they limit the depth of construct coverage and preclude assessments of internal reliability. As a result, these measures should be interpreted as indicative rather than exhaustive representations of the underlying phenomena.

Second, AI literacy and GenAI literacy were operationalized through factual knowledge questions assessing respondents' understanding of selected technical and epistemic aspects of AI systems. This approach captures important elements of literacy but does not encompass the full range of competencies emphasized in contemporary AI literacy frameworks, such as critical evaluation, contextual judgment, or ethical reflection (Cox, 2024). Moreover, the relatively small number of literacy items and the inclusion of "don't know" response options complicate the use of conventional reliability metrics. Rather than treating such responses as mere missing data, they can be understood as expressing uncertainty or ambivalence, which may itself be a meaningful feature of public engagement with emerging technologies.

Third, the study relies on self-reported survey data, which may be affected by recall bias or limited awareness of GenAI functionalities embedded in digital platforms. Respondents may therefore underestimate their actual exposure to or use of AI-based systems. In addition, although the Danish sample is broadly representative of the adult population, the sample size constrains more fine-grained subgroup analyses, particularly when examining sociodemographic differences.

Finally, the cross-sectional design limits the ability to assess how trust, literacy, and experience evolve over time. Given the rapid development and normalization of GenAI technologies, longitudinal approaches will be necessary to capture how public understanding and engagement change as these systems become more deeply integrated into everyday information environments.

4.7. Future Research Directions

Future research should examine whether the dependency patterns observed in Denmark replicate in other national contexts, particularly in lower-trust societies. Longitudinal studies are needed to track how trust and literacy evolve as GenAI becomes more deeply embedded in everyday information practices. Qualitative approaches could add interpretive depth by examining how users frame GenAI ontologically—as a tool, agent, or authority—and how these framings shape epistemic trust. Given that many respondents in our study identified the risk of false or misleading content as a key concern, further research should also explore trust in AI in relation to perceived epistemic risks (Jacobson et al., 2022). In addition, domain-specific studies in areas such as health, climate, or education could clarify how GenAI's epistemic role interacts with established infrastructures of science communication.

Beyond empirical extensions, our findings highlight the need for further conceptual development. Trust and literacy should be theorized not as static, simple constructs but as dynamic, multidimensional, and context-dependent (Fage-Butler et al., 2022; Ledderer et al., 2026). Future work should refine these concepts by examining how specific trust dimensions and forms of literacy interact to shape engagement with GenAI. Equally important is a broader understanding of the communication environment of science-related information behavior, encompassing not only GenAI but also traditional media, social media, interpersonal networks, and institutional communicators. Situating GenAI within this wider media ecology will be crucial for understanding how publics navigate, evaluate, and act on scientific information in a rapidly changing information landscape.

5. Conclusion

This article examined how Danish citizens engage with GenAI in the context of science-related information encounters, focusing on the roles of trust, literacy, and experience. Addressing RQ1, the study shows that public engagement with GenAI in 2024 is characterized by moderate levels of trust, uneven and domain-specific forms of literacy, and highly asymmetric experience concentrated around a small number of prominent tools, most notably ChatGPT. Respondents expressed ambivalent evaluations, combining optimism about potential benefits—particularly in education and health—with pronounced concerns about misinformation and broader societal risks.

Addressing RQ2, the analysis demonstrates that trust, literacy, and experience are not independent dimensions but are conditionally interrelated in systematic ways. Specific trust orientations—especially trust in GenAI's reliability and perceptions of GenAI as welcoming user engagement—play a mediating role between different forms of technical and epistemic understanding. These patterns suggest that how people engage with GenAI in science-related information contexts depends less on isolated levels of "trust" or "literacy" than on how these orientations are configured and activated in specific situations.

Taken together, the findings highlight the importance of conceptualizing trust and literacy as multidimensional and context-sensitive features of science-related information behavior. Rather than treating trust as a simple outcome of increased knowledge, the study shows that trust operates as a key interpretive lens through which GenAI-generated claims are evaluated and acted upon. For science communication research and practice, this underscores the need to attend not only to what people know about GenAI, but also to how they frame its epistemic role within an increasingly hybrid human–machine communication environment.

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Conflict of Interests

The authors declare no conflict of interests.

Data Availability

The dataset analyzed in this study is publicly available on Zenodo at: https://doi.org/10.5281/zenodo.18268918

LLMs Disclosure

The authors used ChatGPT 5.2 (OpenAI) as a language model-based writing assistant during manuscript revision, including for improving clarity, structure, and phrasing of the text and responses to reviewers. The tool was not used for data analysis, interpretation of results, or generation of empirical content. All substantive decisions and interpretations remain the responsibility of the authors.

Supplementary Material

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

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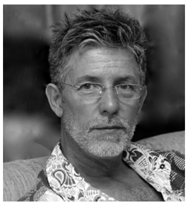

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