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Help me, Doctor AI? A cross-national experiment on the effects of disease threat and stigma on AI health information-seeking intentions

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ABSTRACT

Generative AI chatbots are emerging as novel sources for health information. Adopting a cross-national perspective, this study examines how disease-related factors—namely, disease threat and stigma—influence both individuals' intentions to seek health information via generative AI and their preferences for AI compared to traditional interpersonal sources like doctors and peers. In a preregistered 2x2 online experiment, participants from Austria, Denmark, France, and Serbia ($N_{total} = 1951$) encountered written scenarios about their health that manipulated disease threat (low vs. high) and stigma (low vs. high). The sample was stratified to ensure representativeness for age, gender, and educational level across the countries studied. Results showed no main effect of disease threat on AI information-seeking intentions, but stigma significantly influenced preferences, particularly in mild health conditions. Participants were more likely to consult AI over peers for stigmatized conditions, highlighting the role of AI's anonymous interface in reducing social judgment. Country differences further revealed that national contexts also shape AI adoption: while participants in Denmark and France showed a stronger preference for AI over peers, those in Serbia and Austria preferred peers over AI. Additionally, AI trust and literacy emerged as the strongest predictors of both AI usage intentions and preferences. These findings indicate that gen AI tools can play a complementary role in the health information ecosystem, particularly for stigmatized conditions and in contexts where traditional sources are perceived as less accessible or judgment-free.

1. Introduction

The advent of modern generative artificial intelligence (Gen AI) chatbots, exemplified by models like ChatGPT, has ushered in a new era of online communication (Sundar & Liao, 2023). In healthcare, Gen AI is increasingly viewed as a potential complement or substitute for traditional interpersonal communication sources, such as medical professionals or peers (Santandreu-Calonge et al., 2023). And while adoption for health-related purposes is still uneven (E. Link & Beckmann, 2024), most observers agree: the transformative potential of Gen AI in health contexts is only beginning to unfold (Sallam, 2023).

AI-mediated communication, defined by Hancock et al. (2020) as "interpersonal communication in which an intelligent agent operates on behalf of a communicator by modifying, augmenting, or generating messages to accomplish communication goals" (p. 89), blurs the line between communication channel and communicator (Guzman & Lewis, 2020; Liao et al., 2024). By providing human-like responses to health-related queries, conversational AI systems serve as "quasi-human partners" (Chen & Wen, 2021, p. 116), which allows them to potentially occupy a distinctive position among traditional interpersonal health information sources.

Despite this potential, the circumstances under which individuals

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turn to Gen AI for health information remain poorly understood. Existing research has primarily focused on individual-level predictors. For example, Liao et al. (2024) explored how factors like perceived information insufficiency and informational subjective norms influence intentions to consult AI agents, albeit outside health contexts. In healthcare, E. Link and Beckmann (2024) tested predictors of AI health information-seeking behavior using the Planned Risk Information Seeking model (PRISM; Kahlor, 2010), incorporating attitudes, AI risk perceptions, and trust in AI.

Despite these important contributions, little attention has been paid to disease-related factors, which are well-documented drivers of health information-seeking behavior as well (Gao et al., 2006; Ou & Ho, 2022; Wang et al., 2021). This study focuses on two key factors: disease threat and perceived disease stigma. On one hand, while meta-analytical evidence demonstrates that higher perceived disease threat tends to increase online information-seeking intentions (Ou & Ho, 2022), recent research suggests that users may prefer Gen AI as a health information source particularly for less personally significant matters (Al Shboul et al., 2023). Thus, higher disease threat might mitigate AI intentions. On the other hand, stigma often leads individuals to avoid discussing certain conditions openly, thereby presenting a great barrier to health information-seeking. However, Gen AI offers a personalized and anonymous platform that may lower these barriers to seeking information about stigmatized health conditions (Amram et al., 2023; Blease & Torous, 2023).

Against this backdrop, our study investigates two primary questions: First, how do disease threat and perceived stigma influence intentions to seek health information using Gen AI? Second, given the positioning of AI as a quasi-interpersonal communication source, how do these factors affect preferences for consulting Gen AI over traditional sources such as doctors or peers? The conceptual framework of this paper is primarily informed by the Comprehensive Model of Information Seeking (CMIS; Johnson & Meischke, 1993), the Planned Risk Information Seeking Model (PRISM; Kahlor, 2010), and the Situational Theory of Problem Solving (STOPS; Kim & Grunig, 2011). Our cross-national, preregistered experimental approach includes data from Austria, Denmark, France, and Serbia. By examining diverse national contexts, this study aims to determine whether the effects of disease threat and stigma on AI information-seeking behavior are consistent across Europe or if they interact uniquely with national factors. In the following, we first review the role of disease threat in health information-seeking, followed by the influence of perceived stigma. We then address potential country-specific differences and discuss how these factors shape preferences for consulting Gen AI over traditional interpersonal sources.

2. Disease threat and intentions to use gen AI for health information-seeking

Perceived threat or risk of a disease is a major driver of health information-seeking intentions (Ou & Ho, 2022; Wang et al., 2021). Perceived health risk can be conceptualized as a combination of disease severity and the probability of contracting the disease (susceptibility; El-Toukhy, 2015). The role of perceived threat is emphasized in various health information-seeking models. For example, in the CMIS (Johnson & Meischke, 1993), the salience of a disease—meaning the perceived significance or threat to oneself—acts as an underlying factor in driving information-seeking behavior. Here, it is expected that greater salience of a disease increases information-seeking intentions. Similarly, in the PRISM (Kahlor, 2010), risk perceptions play a critical but more complex role. Specifically, risk perceptions are expected to influence affective risk responses, which then increase information-seeking intentions.

Empirical evidence supports theoretical models linking perceived disease threat to health information-seeking behavior. Different meta-analytical studies (Ou & Ho, 2022; Wang et al., 2021) found a moderate effect of risk perceptions, demonstrating that individuals are more likely to seek health information online when they perceive the topic as riskier for themselves. However, while these studies provide valuable insights into traditional online health information-seeking, they predate the emergence of tools like ChatGPT and therefore may not fully capture the distinctive characteristics and perceived risks associated with AI-mediated health information sources.

Recent research suggests that individuals may hesitate to rely on AI-generated content when facing serious health risks. A qualitative study by Al Shboul et al. (2023) revealed that while users appreciated the convenience of ChatGPT for health information-seeking, they expressed concerns about its reliability for addressing complex or severe medical conditions. Thus, in cases of high-risk diseases, individuals may feel less inclined to rely on Gen AI to fulfill their health information needs. Accordingly, we hypothesize:

H1. The intention to use Gen AI for health information-seeking is higher for benign health conditions compared to more threatening ones.

3. Disease stigma and intentions to use gen AI for health information-seeking

Another crucial aspect influencing if—and how—people seek health information is the stigma associated with a disease. Health stigma refers to the social judgment attached to a specific health-related condition, often tied to social taboos (Smith, 2011; Weiss et al., 2006). Stigma occurs when four components coexist in an asymmetrical power situation, including (1) labelling, (2) stereotyping, (3) separation, and (4) discrimination and status loss (B. G. Link & Phelan, 2001). A wide range of conditions may carry stigma, including mental health disorders (Thornicroft et al., 2022), sexually transmitted infections (Dada et al., 2024), and chronic conditions such as endometriosis (Reinhardt & Eitze, 2025). Stigma functions as a social control mechanism, enforcing norms that determine what is socially accepted; those who deviate from these social norms by having—or talking about—a stigmatized condition, may face social exclusion (Goffman, 1963).

While health stigma is not explicitly addressed in traditional models of health information-seeking, it is indirectly embedded within them. For example, Kim & Grunig's (2011) STOPS framework acknowledges constraint recognition, which refers to perceived barriers—both internal and external—that hinder an individual's ability to act on a problem. We argue that stigma can be considered such a barrier, as it may deter individuals from seeking help due to fear of judgment or embarrassment.

Research on the interplay between health-related stigma and information-seeking behavior underscores these theoretical insights. Individuals with stigmatized conditions often delay seeking medical advice or discussing their health with family or friends due to fears of social exclusion (e.g., for the context of endometriosis stigma: Gao et al., 2006; Nnoaham et al., 2011). This fear may explain why the Internet has become a key resource for those facing stigmatized diseases: The anonymity of online spaces lowers barriers to seeking information, providing a non-intimidating environment where people can access resources without revealing their condition to others (Berger et al., 2005). For instance, 24 % of individuals with a prevalence for mental health issues cited the Internet as one of their primary sources for seeking information about mental health problems (Powell & Clarke, 2018).

While there is a small body of research on stigma and online health information-seeking, no studies have yet examined the relationship between health-related stigma and the use of Gen AI for this purpose. However, it seems reasonable to assume that Gen AI might be particularly appealing for individuals with stigmatized conditions. First, it provides an anonymous platform where users can disclose sensitive health concerns without fear of judgment. Second, Gen AI offers a human-like communication style that personalizes content not just in tone and complexity but also in emotional nuance. This allows it to convey empathy alongside information, which may further reduce the intimidation factor for users dealing with stigmatized conditions (Blease & Torous, 2023). Therefore, we hypothesize:

H2. The intention to use Gen AI for health information-seeking is higher for stigmatized health conditions compared to less stigmatized ones.

Notably, disease stigma does not operate in isolation but often intersects with disease threat. While some conditions, like hair loss, may be stigmatized yet largely benign, others such as mental health disorders or HIV carry both a strong stigma and significant health risks. Despite this, to our knowledge, no study has yet explored how disease stigma and threat combine to influence online health information-seeking intentions—neither in general contexts nor in relation to Gen AI specifically. Given the distinct features of Gen AI described above, it remains unclear how these factors might intersect to affect users' intentions. For example, are users more inclined to turn to Gen AI when facing stigmatized yet less severe conditions, while concerns over trust and accuracy prevent them from doing so in cases of stigmatized but severe conditions? To investigate this, we ask:

> **RQ1:** Is there an interaction effect of disease threat and disease stigma on individuals' health information-seeking intentions using Gen AI?

4. Country-specific differences in gen AI health information-seeking intentions

Recognizing that health information-seeking is not only shaped by individual-level factors such as disease threat and stigma but also by broader systemic and cultural influences, we included data from Austria, Denmark, France, and Serbia to explore potential country-specific differences in the intention to use Gen AI for health information-seeking.

Although all four nations provide universal health coverage and rely heavily on public funding for healthcare (Bachner et al., 2022; Bjegovic-Mikanovic et al., 2019; Okkels Birk et al., 2024; Or et al., 2023), they differ significantly in their levels of digitalization and related AI adoption. Key factors such as AI literacy, AI trust, and AI attitudes vary substantially across these countries. Denmark, one of Europe's most digitalized nations, demonstrates an advanced online health information seeking behavior (EUROSTAT, 2024) and generally positive attitudes toward AI. However, trust in AI remains still limited (Scantamburlo et al., 2023). In contrast, Eastern European countries like Serbia, while less engaged in online health information-seeking overall (EUROSTAT, 2024), show greater public approval of AI and trust in its output (Scantamburlo et al., 2023). Austria and France, as representatives of Central Europe, present a different picture. Both countries report lower levels of public trust in AI compared to Denmark and Serbia (Scantamburlo et al., 2023). These contextual differences underline the need to examine how national factors shape health information-seeking behavior and the integration of Gen AI into healthcare ecosystems. Yet, previous research has often treated online health information-seeking as a largely universal behavior, with limited attention to how sociocultural and technological contexts might moderate the adoption of novel AI-based health information sources.

To address these potential variations, we propose the following research questions:

> **RQ2:** What are the differences in the intention to use Gen AI for health information-seeking between the observed countries (Austria, Denmark, France, Serbia)?
> **RQ3:** What are the differences in the effects of (a) disease threat, (b) disease stigma, and (c) their interaction across the observed countries?

5. Preferences for gen AI over interpersonal health information sources

Health information channels differ in their characteristics and utility, influencing how individuals evaluate and use the information they receive (Ruppel & Rains, 2012). Gen AI, as a novel and quasi-interpersonal health information source, competes with more established channels such as doctors and friends. These traditional interpersonal sources typically enjoy higher levels of trust in provided health information (Baumann et al., 2019), prompting important questions about how the factors under observation shape preferences for Gen AI compared to these alternatives.

For disease threat, prior research suggests that individuals often avoid using Gen AI for health information in cases of severe or personally significant conditions (Al Shboul et al., 2023). In contrast, doctors and peers are typically viewed as the most trustworthy sources of health information (Baumann et al., 2019). This implies that when disease threat is high, individuals may prefer consulting doctors or peers over Gen AI, despite the latter's convenience and accessibility.

For stigmatized conditions, individuals tend to delay or entirely avoid seeking information from close friends or even doctors due to fears of judgment or embarrassment (Eitze & Reinhardt, 2025). In such contexts, the anonymity and perceived lack of judgment provided by Gen AI could make it a more appealing option (Blease & Torous, 2023). This dynamic highlights the potential of Gen AI to fill an unmet need for individuals seeking private and stigma-free health information.

Building on these considerations, we propose the following research question:

> **RQ4:** What are the effects of disease threat and stigma on participants' preferences for using (a) Gen AI over doctors and (b) Gen AI over friends to gain health information?

6. Methods

6.1. Sampling procedures

Prior to data collection, the study was preregistered (https://doi.org/10.17605/OSF.IO/S59Y6) and approved by the Institutional Review Board of the Department of Communication at the University of Vienna (ID 1205). Participants were recruited in September and October 2024 through the online panel provider *Bilendi*, an international platform that sources participants via social media, telephone surveys, and advertisements. Data collection took place in Austria, France, Denmark, and Serbia. In each country, participants were randomly selected, with sampling designed to ensure representativeness in terms of age, gender, and educational level (low vs. medium/high; in Serbia, however, the educational quota was adjusted to low/medium vs. high due to sampling constraints). Two eligibility criteria were applied: (1) participants had to be between 16 and 74 years old, and (2) speeders—those completing the survey in less than one-third of the median completion time—were excluded. All participants received compensation from the panel provider.

6.2. Sample

We aimed for a sample size of 500 participants per country (for power analysis: see preregistration on OSF). In total, we collected data from $N = 1951$ participants. By country, this included $N = 494$ participants from Austria, $N = 497$ from Denmark, $N = 486$ from France, and $N = 474$ from Serbia. The overall mean age of participants was 45.2 years ($SD = 15.7$), with 49.9 % identifying as female ($n = 974$). Regarding education, 82.2 % of participants ($n = 1603$) had achieved a medium/higher educational level (Secondary Level II or higher). In the overall sample, 40.2 % ($n = 776$) indicated that they have at least once tried Gen AI in the context of health information-seeking. A more detailed breakdown of the sample characteristics is presented in Table 1.

Table 1
Sample Characteristics

	Overall	Austria	Denmark	France	Serbia
	n (%)	n (%)	n (%)	n (%)	n (%)
Education					
≤ Secondary I	348 (18.24)	92 (18.62)	132 (26.56)	107 (22.02)	17 (3.59)
Secondary II	1,057 (55.36)	298 (60.32)	174 (35.01)	219 (45.06)	366 (77.21)
Tertiary	546 (28.39)	104 (21.05)	191 (38.43)	160 (32.92)	91 (19.20)
Gender					
Female	974 (49.92)	245 (49.56)	248 (49.90)	248 (51.02)	233 (49.16)
Male	977 (50.08)	249 (50.44)	249 (50.10)	238 (49.98)	241 (51.84)
Prior Experience					
Yes	1175 (59.80)	310 (62.76)	321 (64.59)	315 (64.82)	229 (49.32)
No	776 (40.20)	184 (37.24)	176 (35.41)	171 (35.18)	245 (51.68)
	M (SD)	**M (SD)**	**M (SD)**	**M (SD)**	**M (SD)**
Age	45.2 (15.7)	45.3 (15.1)	45.1 (16.5)	46.0 (16.1)	44.3 (15.1)

Note. Educational levels were classified as low (Secondary Level I or lower) versus medium/high (Secondary Level II or higher). An exception was made for Serbia, where, due to sampling constraints, we ensured representativeness based on low/medium (Secondary Level II or lower) versus high (Tertiary education). Prior experience: no = "I have never used Gen AI for health information seeking," yes = "I have used Gen AI for health information seeking at least rarely".

6.3. *Experimental design*

To test our hypotheses, we conducted an online experiment with a 2 × 2 factorial design, manipulating two factors: disease threat (low vs. high) and disease stigma (low vs. high). Each participant was presented with a text-based health-related scenario. To reduce potential biases from prior knowledge or personal experience, we did not specify a particular disease; rather, we conveyed its characteristics through descriptions of its health threat and stigma levels. Table 2 provides the exact wording used in each scenario. The scenarios, ranging from 61 to 69 words, were carefully translated into each language using a back-translation process to ensure accuracy and consistency across countries.

6.4. *Procedure*

After providing informed consent, participants first completed a survey part focusing on predictors of Gen AI adoption (including AI literacy and AI trust; the results of the survey will be reported in a separate paper, as preregistered). Following the survey, participants were randomly assigned to one of the four experimental conditions. In all conditions, participants were informed that they would be presented with a scenario related to their health and asked to imagine themselves in the described situation. They were instructed to read the scenario carefully and then respond to the subsequent questions. Afterwards, participants completed a manipulation check, followed by the assessment of the dependent measures. Once these were completed, the study was concluded.

6.5. *Measures*

The full operationalization of all measures can be found in Supplement S1 on OSF (https://osf.io/yaghf/). The original questionnaire versions in German, Danish, French, and Serbian are also available on OSF.

Health information-seeking intentions. Participants were asked to imagine they wanted to gather more information about their described health condition. To assess their intentions, we used two items (adapted from Eastin et al., 2015, 7-point Likert scale): "I would use Gen AI to gain information about my disease," "I would consult Gen AI for information and recommendations related to my health issue." In the same way, we also measured participants intention to consult a doctor and their intention to talk to friends. Reliability for each scale was as follows: Gen AI (Spearman-Brown $\rho = 0.94$, $M = 3.5$, $SD = 1.9$), doctor (Spearman-Brown $\rho = 0.92$, $M = 5.7$, $SD = 1.5$), and friends (Spearman-Brown $\rho = 0.88$, $M = 3.5$, $SD = 1.7$).

AI literacy. As a control variable, we measured participants' AI literacy using an adapted version of the SMIL scale by Heiss et al. (2023). Participants were asked to rate how easy or difficult they found a list of 12 AI-related tasks on a 7-point Likert scale, covering three dimensions: navigation (e.g., "Asking the right questions to Gen AI to help me find new information quickly"), appraisal (e.g., "Critically reviewing the content of Gen AI for accuracy"), and comprehension (e.g., "Understanding how Gen AI produces content"). These 12 items were combined into a mean index ($\alpha = .95$, $M = 3.6$, $SD = 1.4$).

AI trust. Trust in Gen AI was modified from Lai et al. (2024), including three items measured on a 7-point Likert scale (e.g., "I can rely on generative AI when it comes to health-related issues."). The items were combined into a mean index ($\alpha = .95$, $M = 3.4$, $SD = 1.7$)

*Sociodemographic factors***.** In addition to AI literacy, we controlled for participants' educational level, gender, and age.

Table 2
Stimulus description.

Manipulation		Threat	
		low	high
Stigma	low	Imagine you've been diagnosed **with a mild health condition** that only causes temporary inconvenience. It's something that **will pass on its own with minimal treatment**, and it doesn't lead to any long-term health complications. People around you are likely to be **understanding and supportive**. You **don't feel embarrassed or judged by others** because it is perceived as a routine health matter.	Imagine you've been diagnosed with a **serious health condition** that significantly impacts your well-being and requires ongoing treatment. It's a condition that may lead to **long-term health complications** and demands regular medical attention to manage. People around you are likely to be **understanding and supportive**. You **don't feel embarrassed or judged by others** because it is perceived as an unfortunate health matter that can happen to anyone.
	high	Imagine you've been diagnosed **with a mild health condition** that only causes temporary inconvenience. It's something that **will pass on its own with minimal treatment**, and it doesn't lead to any long-term health complications. However, people around you are likely to **have misconceptions about this condition and might view it negatively**. You **feel embarrassed or judged by others** because it is perceived as an undesirable, shameful health matter.	Imagine you've been diagnosed with a **serious health condition** that significantly impacts your well-being and requires ongoing treatment. It's a condition that may lead to **long-term health complications** and demands regular medical attention to manage. However, people around you are likely to **have misconceptions about this condition and might view it negatively**. You **feel embarrassed or judged by others** because it is perceived as an undesirable, shameful health matter.

6.6. Analytical approach

Data were analyzed using R (version 2024.09.0 Build 375). All R scripts and datasets are openly accessible on OSF (https://osf.io/yaghf/). To examine the effects of disease threat, stigma, and country—as well as their interactions—on participants' intention to use Gen AI for health information (H1–H2, RQ1–RQ3), we conducted ANCOVA using the *car* package with a Type III sum of squares approach. In line with our preregistration, the analysis controlled for age, gender, educational level, AI trust, and AI literacy.

Furthermore, to explore whether the effects of the investigated factors differ when comparing Gen AI with alternative health information sources (doctors and friends; RQ4), we computed difference scores for participants' intentions. Specifically, preference for AI over doctors was calculated as the difference between intention to use AI and intention to consult a doctor, while preference for AI over peers was computed as intention to use AI minus intention to consult peers. These difference scores were then analyzed using ANCOVA, applying the same independent and control variables as in the primary analysis.

7. Results

7.1. Manipulation check

To assess the effectiveness of the threat manipulation, participants were asked to rate the perceived threat of the described health condition on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) with the item: "The described health condition is a severe health threat." A *t*-test revealed a significant difference between the two conditions: Participants in the high-threat condition perceived the condition as more severe ($M = 5.29$, $SD = 1.57$) than those in the benign condition ($M = 2.75$, $SD = 1.74$), $t(1926.1) = 33.77$, $p < .001$.

Similarly, to assess the stigma manipulation, participants rated the extent to which the health condition was associated with a sense of shame, again using a 7-point Likert scale. The *t*-test showed a significant difference between the two conditions, with the high-stigma condition being perceived as more shameful ($M = 3.61$, $SD = 2.02$) compared to the low-stigma condition ($M = 2.70$, $SD = 1.78$), $t(1901.1) = 10.55$, $p < .001$. These results confirm that both manipulations were effective.

7.2. Effects on generative AI intention (H1-H2, RQ1-RQ3)

A summary of the findings is provided in Table 3, with detailed results described below.

7.2.1. Threat hypothesis (H1)

We hypothesized that the intention to use Gen AI for health information-seeking would be higher for benign health conditions compared to more threatening ones. However, the ANCOVA did not support this hypothesis, $F(1, 1929) = 0.37$, $p = .544$, and thus, H1 is rejected.

Table 3
Effects of disease threat, disease stigma, and country on health information-seeking intentions using gen AI (ANCOVA).

	Sum Square	df	F	p
Threat	0.6	1	0.369	0.543
Stigma	1.7	1	1.074	0.300
Country	19.5	3	4.113	**.006**
Threat x Stigma	3.4	1	2.174	0.140
Threat x Country	1.3	3	0.278	0.841
Stigma x Country	11.7	3	2.456	0.061
Threat x Stigma x Country	0.6	3	0.50	0.679
Age	41.3	1	26.127	**<.001**
Gender	4.2	1	2.661	0.103
Education	2.2	1	1.368	0.242
AI Literacy	176.1	1	111.323	**<.001**
AI Trust	1308.5	1	827.073	**<.001**

Note. $N = 1951$; threat: 0 = low, 1 = high; stigma: 0 = low, 1 = high; country: 1 = Austria, 2 = Denmark, 3 = France, 4 = Serbia; gender: 1 = male, 2 = female; education: 1 = low, 2 = high; AI literacy: 1 = very low, 7 = very high.

7.2.2. Stigma hypothesis (H2)

We also hypothesized that the intention to use Gen AI for health information-seeking would be higher for stigmatized health conditions compared to less stigmatized ones. The ANCOVA revealed no such direct effect of stigma, $F(1, 1929) = 1.07$, $p = .300$. Therefore, H2 is rejected.

7.2.3. Interaction of disease threat and stigma (RQ1)

We further explored whether there was an interaction between disease threat and stigma on individuals' intentions to seek health information using Gen AI. The ANCOVA showed no significant interaction effect, $F(1, 1929) = 2.17$, $p = .140$.

7.2.4. Direct effects of country (RQ2)

In RQ2, we investigated cross-national differences in the intention to use Gen AI for health information-seeking. The analysis revealed significant differences across the four countries, $F(3, 1929) = 4.11$, $p = .006$. Specifically, the mean intention scores were highest in Serbia ($M = 3.68$, $SE = 0.06$, 95 % CI [3.56, 3.80]), followed by Austria ($M = 3.58$, $SE = 0.06$, 95 % CI [3.46, 3.70]), France ($M = 3.36$, $SE = 0.06$, 95 % CI [3.24, 3.48]), and Denmark ($M = 3.28$, $SE = 0.06$, 95 % CI [3.17, 3.40]). Post hoc comparisons revealed significant differences between Serbia and Denmark, Austria and Denmark, as well as Serbia and France.

7.2.5. Interaction effects of country (RQ3)

We examined the potential interaction effects between country, disease threat, and stigma. We found neither a significant interaction between country and disease threat ($F(3, 1929) = 0.28$, $p = .841$), nor between country and stigma ($F(3, 1929) = 2.46$, $p = .061$) or a significant three-way interaction ($F(3, 1929) = 0.13$, $p = .940$).

7.2.6. Control variables

Age had a notable impact on intention to seek information via Gen AI, with younger participants demonstrating higher intentions, as indicated by $F(1, 1929) = 26.13$, $p < .001$. Additionally, both AI-related variables significantly predicted health information-seeking intention. AI trust emerged as the strongest predictor of Gen AI intention ($F(1, 1929) = 827.07$, $p < .001$), with higher AI trust correlating with an increased intention to use the technology for health information-seeking. The same direction of effect was found for AI literacy: The higher the AI literacy, the stronger the intention ($F(1, 1929) = 111.32$, $p < .001$).

7.3. Effects on information source preferences (RQ4)

To determine whether the predictors influenced preferences for consulting Gen AI over doctors or friends, we analyzed the difference scores. A significant positive difference indicates a stronger preference for Gen AI, whereas a negative difference reflects a stronger preference for doctors or friends. The findings are summarized in Table 4.

7.3.1. Generative AI versus doctors

The results of the comparison between Gen AI and doctors showed no significant effects of disease threat ($F(1, 1929) = 2.19$, $p = .139$), stigma ($F(1, 1929) = 0.02$, $p = .875$), country ($F(3, 1929) = 1.00$, $p = .392$), or interactions between these factors (all $p > .05$).

However, individual-level factors were significant predictors. Age was a significant determinant ($F(1, 1929) = 8.95$, $p = .003$), with younger participants exhibiting a higher preference for Gen AI. Gender also played a role ($F(1, 1929) = 14.09$, $p < .001$): while both men and women generally preferred doctors over AI for health information, men demonstrated a comparatively stronger inclination toward Gen AI ($M =$

Table 4
Effects of disease threat, disease stigma, and country on the preference of using Gen AI over doctors or friends (ANCOVA).

	Difference: AI vs doc		Difference: AI vs friends	
	F	p	F	p
Threat	2.194	0.139	2.033	0.154
Stigma	0.025	0.875	1.467	0.226
Country	0.999	0.392	5.710	**<.001**
Threat x Stigma	0.042	0.838	3.906	**.048**
Threat x Country	1.221	0.301	0.468	0.704
Stigma x Country	1.333	0.335	1.263	0.285
Threat x Stigma x Country	0.446	0.721	0.098	0.961
Control variables				
Age	8.951	**.003**	51.636	**<.001**
Gender	14.086	**<.001**	0.166	0.683
Education	2.133	0.144	0.894	0.344
AI Literacy	17.819	**<.001**	19.005	**<.001**
AI Trust	440.714	**<.001**	236.091	**<.001**

Note. $N = 1951$; threat: 0 = low, 1 = high; stigma: 0 = low, 1 = high; country: 1 = Austria, 2 = Denmark, 3 = France, 4 = Serbia; gender: 1 = male, 2 = female; education: 1 = low, 2 = high; AI literacy: 1 = very low, 7 = very high.

-2.02, $SE = 0.06$) than women ($M = -2.35$, $SE = 0.06$). Additionally, AI trust ($F(1, 1922) = 440.71$, $p < .001$) and AI literacy ($F(1, 1929) = 17.82$, $p < .001$) were positively associated with a preference for Gen AI over doctors.

7.3.2. *Generative AI versus friends*

In the comparison between Gen AI and friends, no significant main effects were found for disease threat ($F(1, 1929) = 2.03$, $p = .154$) or stigma ($F(1, 1929) = 1.47$, $p = .226$). However, significant differences emerged between countries ($F(3, 1929) = 5.71$, $p < .001$): Participants from Serbia ($M = -0.33$, $SE = 0.09$) and Austria ($M = -0.28$, $SE = 0.09$) were more likely to prefer friends over Gen AI. Conversely, participants from Denmark ($M = 0.15$, $SE = 0.08$) and France ($M = 0.30$, $SE = 0.09$) showed a stronger preference for Gen AI compared to friends.

A significant interaction between stigma and threat was also observed ($F(1, 1929) = 3.91$, $p = .048$). As illustrated in Fig. 1, for severe diseases, preferences for Gen AI and friends were similar, regardless of stigma levels. Conversely, for mild but stigmatized diseases, participants were significantly more likely to consult Gen AI than to seek advice from friends.

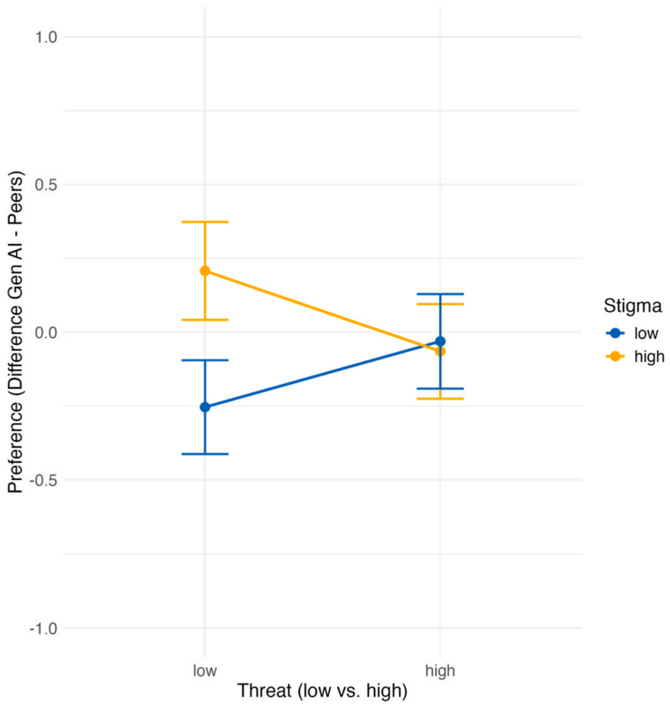

Fig. 1. Interaction of threat and stigma on the preference of AI over peers (95 % CIs).

Control variables also contributed significantly to the results. Age was a key predictor, with older participants demonstrating a higher preference for Gen AI over friends ($F(1, 1929) = 51.64$, $p < .001$). Furthermore, both AI trust ($F(1, 1929) = 263.09$, $p < .001$) and AI literacy ($F(1, 1929) = 19.00$, $p < .001$) were positively associated with the likelihood of choosing AI.

8. Discussion

This cross-national study aimed to explore the circumstances under which individuals choose Gen AI tools like ChatGPT for health information, focusing on disease-related factors (threat and stigma), national context, and AI trust and literacy. Additionally, it examined when Gen AI may rival traditional interpersonal health information sources, such as doctors or friends. The findings, while nuanced, provide valuable insights into the theoretical and practical implications of using Gen AI for health information.

8.1. *Effects of threat*

Contrary to prior meta-analytic evidence suggesting that risk perceptions increase health information-seeking behaviors (Ou & Ho, 2022; Wang et al., 2021), our study did not find a significant effect of disease threat on the intention to use Gen AI. One plausible explanation for this null effect lies in the opposing forces at play. While greater threat might motivate individuals to seek health information, it could simultaneously discourage reliance on Gen AI due to concerns about trustworthiness or perceived lack of expertise (e.g., Al Shboul et al., 2023). Over time, as AI tools become more mainstream and their accuracy improves, this dynamic may shift.

Moreover, the lack of a significant effect of disease threat on participants' preferences for consulting doctors versus Gen AI is particularly noteworthy. This finding suggests that even when a disease is perceived as risky, individuals do not necessarily rely more on doctors compared to Gen AI. This points to the possibility that Gen AI is increasingly seen as a valid and viable health information source, capable of complementing or even rivaling traditional healthcare channels in certain contexts.

8.2. *Effects of stigma*

Stigma, often linked to feelings of shame and social exclusion (Mezey et al., 2022), is a well-documented barrier to health information-seeking from traditional interpersonal sources, such as doctors or peers (Eitze & Reinhardt, 2025). In line with these findings, our results suggest that Gen AI is already becoming an attractive option for benign but stigmatized conditions, particularly when compared to peers.

This finding has significant theoretical and practical implications. Theoretically, it highlights the potential for Gen AI to serve as a "first-line" resource in the information-seeking process (Blease & Torous, 2023), especially for individuals who are hesitant to engage with personal contacts about stigmatized conditions. From a practical perspective, this suggests that AI tools could play a pivotal role in addressing health disparities by offering a nonjudgmental, easily accessible information source. However, future research should investigate whether individuals who initially consult Gen AI eventually feel empowered to seek interpersonal advice and discuss their condition within their social network.

Interestingly, stigma did not significantly influence preferences for consulting doctors versus Gen AI. This reinforces the idea that individuals generally perceive medical professionals as less likely to judge them compared to peers, even when discussing stigmatized conditions (Eitze & Reinhardt, 2025). This finding suggests that Gen AI is less likely to displace doctors for high-stigma health conditions but may supplement peer advice in contexts where social judgment is a concern.

8.3. *Cross-national effects*

Our findings reveal cross-national differences, underscoring the importance of national and cultural contexts beyond disease-related factors. First, we observed significant differences in Gen AI health information-seeking intentions across countries. Serbian participants exhibited the highest intentions, followed by Austria, France, and Denmark. One possible explanation for Serbia's high intentions may be the lower trust in the healthcare system commonly reported in the Western Balkans (Maljichi et al., 2022), which could drive individuals to rely more on alternative, easily accessible sources such as Gen AI. In contrast, Denmark, known for its robust public trust in the healthcare system (Olagnier & Mogensen, 2020), may provide individuals with fewer reasons to seek alternative health information sources like AI.

However, when we shifted our focus to preferences for Gen AI over peers, a contrasting pattern emerged. Participants from Denmark and France were more likely to prefer consulting Gen AI over peers, while those from Austria and Serbia showed the opposite tendency, favoring peers over AI. One potential explanation for these findings lies in cultural norms regarding the sharing of health information. In societies where discussing health matters is considered more private or sensitive, individuals may feel more comfortable consulting AI rather than engaging peers in conversations about personal health issues (Miladinov, 2022). Conversely, in cultures where relational networks play a central role in decision-making or where trust in close social circles is high, individuals might prioritize peers over Gen AI.

These findings suggest that relational networks and cultural norms significantly shape preferences for health information sources. Future research should explore how these factors interact with broader systemic influences, such as trust in healthcare systems and digital health literacy, to provide a more comprehensive understanding of cross-national differences in health information-seeking behaviors.

8.4. *Effects of AI trust and AI literacy*

This study underscores the central role of individual-level factors—AI trust and AI literacy—in shaping intentions to use AI for health information (E. Link & Beckmann, 2024). Across all analyses, these two variables consistently emerged as the strongest predictors. This finding suggests that the use of AI in health contexts is driven less by perceptions of the health condition itself and more by individual characteristics such as familiarity with AI tools and confidence in their reliability.

Participants with higher AI trust and literacy showed significantly greater intentions to consult Gen AI and were more likely to prefer it over traditional sources like doctors or peers. The role of trust aligns with broader theories of technology acceptance, such as UTAUT2 (Venkatesh, 2012), which emphasizes perceived usefulness as a critical factor in driving technology adoption. AI literacy, in turn, can increase the effort expectancy pronounced in UTAUT2, further reinforcing this intention by enhancing individuals' confidence in their ability to effectively use these tools. Therefore, theoretically, these findings reinforce the centrality of individual-level predictors in technology adoption models.

Looking forward, it is reasonable to predict that AI literacy—and potentially trust—will increase as Gen AI technologies become more sophisticated, widely used, and integrated into daily life. With greater exposure and familiarity, public confidence in AI tools is likely to grow, reducing skepticism and improving adoption rates. From a health perspective, this trend implies a potential rise in the use of Gen AI for health information-seeking.

8.5. *Limitations*

Several limitations of the present study should be noted. First, the education distribution in the Serbian sample (low/medium vs. high) differed from the categorization used in the other three countries (low vs. medium/high) due to sampling constraints. However, since education was controlled for in the analyses and showed no significant effect on intention, it is unlikely that this discrepancy has affected the cross-country comparability.

Second, the selection of Austria, Denmark, France, and Serbia was driven by collaboration opportunities rather than a systematic sampling of European regions. While offering valuable insights into diverse sociocultural and health infrastructure contexts, the findings may not fully capture the broader heterogeneity of health information-seeking behaviors across Europe.

Third, the health scenarios presented were hypothetical. Although they reflected varying levels of threat and stigma, real-life health conditions may evoke stronger emotional reactions, potentially influencing health information-seeking behavior differently.

Fourth, while the manipulation of stigma was successful, the mean score in the high-stigma condition was moderate. A stronger manipulation might have produced more pronounced effects on health information-seeking intentions.

Fifth, the survey design did not experimentally vary the order of components, leaving potential priming effects unexamined.

Finally, the use of an online panel may have introduced selection bias, as participants might have been more tech-savvy than the general population.

8.6. *Directions for future research*

Building on these limitations, several avenues for future research emerge. First, future studies should aim for more harmonized sampling across countries, particularly regarding education levels, to enhance comparability. Expanding the geographic scope to additional European regions or beyond would also allow for a more comprehensive understanding of cross-cultural differences.

Second, research should investigate whether stronger emotional engagement—through real or personally relevant health scenarios—amplifies the effects of disease threat and stigma on Gen AI usage intentions. Designing more robust stigma manipulations could help to further clarify the role of perceived social stigma in shaping information-seeking behavior.

Finally, using alternative sampling strategies, such as telephone or mixed-mode surveys, could help mitigate potential tech-savviness biases associated with online panels and improve the generalizability of findings.

9. Conclusion

This study provides nuanced insights into the factors shaping Gen AI adoption in health information-seeking. By examining disease-related factors, national contexts, and individual predictors like AI trust and literacy, it highlights both barriers and facilitators to integrating AI into health information behaviors.

The findings reveal no significant effect of disease threat, suggesting that the novelty of Gen AI and uncertainties about its reliability may offset its appeal. In contrast, stigma significantly influenced preferences for AI over peers, particularly in mild but stigmatized conditions, where individuals may value its anonymous yet conversational platform for seeking sensitive health information. Cross-national differences further highlight the importance of systemic and cultural contexts, such as healthcare system trust and norms surrounding the sharing of personal health information. For instance, while participants from Serbia showed high intentions to use Gen AI, likely reflecting lower trust in traditional healthcare systems, participants from Denmark exhibited lower intentions, consistent with their strong public trust in healthcare. On an individual level, AI trust and literacy emerged as the most significant predictors of Gen AI adoption, underscoring their central role in technology acceptance.

Based on our findings, we recommend that AI developers should consider tailoring chatbot communication styles to sensitive topics to better serve individuals dealing with stigmatized health conditions. Policymakers and healthcare providers could leverage Gen AI as a supplementary, low-threshold resource to improve access to information, particularly in underserved populations.

Overall, this study underscores the transformative potential of Gen AI to address health information needs, particularly in contexts where stigma creates barriers to seeking advice and support from peers. However, so far, AI chatbots remain a supplementary resource rather than a replacement for healthcare professionals.

CRediT authorship contribution statement

Anne Reinhardt: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jörg Matthes:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Ljubisa Bojic:** Writing – review & editing, Validation, Funding acquisition. **Helle T. Maindal:** Writing – review & editing, Validation, Funding acquisition. **Corina Paraschiv:** Writing – review & editing, Validation, Funding acquisition. **Knud Ryom:** Writing – review & editing, Validation.

Disclosure statement

The authors report there are no competing interests to declare.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to check grammar and spelling. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2025.108718.

Data availability

Data and R scripts are openly available on OSF (link in manuscript)

References

Al Shboul, M. K. I., Alwreikat, A., & Alotaibi, F. A. (2023). Investigating the use of ChatGpt as a novel method for seeking health information: A qualitative approach. *Science & Technology Libraries*, 1–10. https://doi.org/10.1080/0194262X.2023.2250835

Amram, B., Klempner, U., Shturman, S., & Greenbaum, D. (2023). Therapists or replicants? Ethical, legal, and social considerations for using ChatGPT in therapy. *The American Journal of Bioethics, 23*(5), 40–42. https://doi.org/10.1080/15265161.2023.2191022

Bachner, F., Bobek, J., Habimana, K., Ladurner, J., Lepuschütz, L., Ostermann, H., Rainer, L., Schmidt, A. E., Zuba, M., Quentin, W., & Winkelmann, J. (2022). *Austria health system summary 2022 (health systems in transition)*. European Observatory on Health Systems and Policies. https://iris.who.int/bitstream/handle/10665/365423/9789289059367-eng.pdf?sequence=1.

Baumann, E., Czerwinski, F., Rosset, M., & Großmann, U. (2019). *Wie informieren sich die Deutschen zu Gesundheitsthemen?* Stiftung Gesundheitswissen *[How do Germans seek health-related information?]* (No. 1) https://www.stiftung-gesundheitswissen.de/sites/default/files/pdf/trendmonitor_Ausgabe%201.pdf.

Berger, M., Wagner, T. H., & Baker, L. C. (2005). Internet use and stigmatized illness. *Social Science & Medicine, 61*(8), 1821–1827. https://doi.org/10.1016/j.socscimed.2005.03.025

Bjegovic-Mikanovic, V., Vasic, M., Vukovic, D., Jankovic, J., Jovic-Vranes, A., Santric-Milicevic, M., Terzic-Supic, Z., & Hernández-Quevedo, C. (2019). *Serbia health system review (No. 21(3); health systems in transition)*. European Observatory on Health Systems and Policies. https://iris.who.int/bitstream/handle/10665/331644/HiT-21-3-2019-eng.pdf?sequence=1.

Blease, C., & Torous, J. (2023). ChatGPT and mental healthcare: Balancing benefits with risks of harms. *BMJ Mental Health, 26*(1), Article e300884. https://doi.org/10.1136/bmjment-2023-300884

Chen, Y.-N. K., & Wen, C.-H. R. (2021). Impacts of attitudes toward government and corporations on public trust in artificial intelligence. *Communication Studies, 72*(1), 115–131. https://doi.org/10.1080/10510974.2020.1807380

Dada, D., Abu-Ba'are, G. R., Turner, D., Mashoud, I. W., Owusu-Dampare, F., Apreku, A., Ni, Z., Djiadeu, P., Aidoo-Frimpong, G., Zigah, E. Y., Nyhan, K., Nyblade, L., & Nelson, L. E. (2024). Scoping review of HIV-related intersectional stigma among sexual and gender minorities in sub-Saharan Africa. *BMJ Open, 14*(2), Article e078794. https://doi.org/10.1136/bmjopen-2023-078794

Eastin, M. S., Kahlor, L. A., Liang, M.-C., & Abi Ghannam, N. (2015). Information-seeking as a precaution behavior: Exploring the role of decision-making stages: Information-seeking as precaution behavior. *Human Communication Research, 41*(4), 603–621. https://doi.org/10.1111/hcre.12062

Eitze, S., & Reinhardt, A. (2025). Keep Period pain a secret? Expanding the theory of planned behavior with endometriosis knowledge and menstrual stigma to explain women's intentions to talk about menstrual discomfort. *Health Psychology*, 1–12. https://doi.org/10.1037/hea0001502. Online first.

El-Toukhy, S. (2015). Parsing susceptibility and severity dimensions of health risk perceptions. *Journal of Health Communication, 20*(5), 499–511. https://doi.org/10.1080/10810730.2014.989342

EUROSTAT *Individuals – internet activities*. (2024). https://doi.org/10.2908/ISOC_CI_AC_I.

Gao, X., Yeh, Y.-C., Outley, J., Simon, J., Botteman, M., & Spalding, J. (2006). Health-related quality of life burden of women with endometriosis: A literature review. *Current Medical Research and Opinion, 22*(9), 1787–1797. https://doi.org/10.1185/030079906X121084

Goffman, E. (1963). *Stigma: The management of spoiled identity*. Penguin.

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human–machine communication research agenda. *New Media & Society, 22*(1), 70–86. https://doi.org/10.1177/1461444819858691

Hancock, J. T., Naaman, M., & Levy, K. (2020). AI-mediated communication: Definition, research agenda, and ethical considerations. *Journal of Computer-Mediated Communication, 25*(1), 89–100. https://doi.org/10.1093/jcmc/zmz022

Heiss, R., Nanz, A., & Matthes, J. (2023). Social media information literacy: Conceptualization and associations with information overload, news avoidance and conspiracy mentality. *Computers in Human Behavior, 148*, Article 107908. https://doi.org/10.1016/j.chb.2023.107908

Johnson, J. D., & Meischke, H. (1993). A comprehensive model of cancer-related information seeking applied to magazines. *Human Communication Research, 19*(3), 343–367. https://doi.org/10.1111/j.1468-2958.1993.tb00305.x

Kahlor, L. (2010). Prism: A planned risk information seeking model. *Health Communication, 25*(4), 345–356. ufh.

Kim, J.-N., & Grunig, J. E. (2011). Problem solving and communicative action: A situational theory of problem solving. *Journal of Communication, 61*(1), 120–149. https://doi.org/10.1111/j.1460-2466.2010.01529.x

Lai, C. Y., Cheung, K. Y., Chan, C. S., & Law, K. K. (2024). Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. *Computers and Education: Artificial Intelligence, 6*, Article 100246. https://doi.org/10.1016/j.caeai.2024.100246

Liao, W., Weisman, W., & Thakur, A. (2024). On the motivations to seek information from artificial intelligence agents versus humans: A risk information seeking and processing perspective. *Science Communication, 46*(4), 458–486. https://doi.org/10.1177/10755470241232993

Link, E., & Beckmann, S. (2024). AI at everyone's fingertips? Identifying the predictors of health information seeking intentions using AI. *Communication Research Reports*, 1–11. https://doi.org/10.1080/08824096.2024.2427609

Link, B. G., & Phelan, J. C. (2001). Conceptualizing stigma. *Annual Review of Sociology, 27*(1), 363–385. https://doi.org/10.1146/annurev.soc.27.1.363

Maljichi, D., Limani, B., Spier, T. E., Angjelkoska, V., Stojković Zlatanović, S., Maljichi, D., Alloqi Tahirbegolli, I., Tahirbegolli, B., Kulanić, A., Agolli Nasufi, I., & Kovač-Orlandić, M. (2022). (Dis)trust in doctors and public and private healthcare institutions in the Western Balkans. *Health Expectations, 25*(4), 2015–2024. https://doi.org/10.1111/hex.13562

Mezey, G., White, S., Harrison, I., Bousfield, J., Killaspy, H., Lloyd-Evans, B., & Payne, S. (2022). Modelling social exclusion in a diagnostically-mixed sample of people with severe mental illness. *International Journal of Social Psychiatry, 68*(2), 420–428. https://doi.org/10.1177/00207640211001893

Miladinov, G. (2022). The family as a source of social capital in three Balkans countries: Key indicators. *Studies in Social Science & Humanities, 1*(3). https://doi.org/10.56397/SSSH.2022.10.02

Nnoaham, K. E., Hummelshoj, L., Webster, P., d'Hooghe, T., de Cicco Nardone, F., de Cicco Nardone, C., Jenkinson, C., Kennedy, S. H., & Zondervan, K. T. (2011). Impact of endometriosis on quality of life and work productivity: A multicenter study across ten countries. *Fertility and Sterility, 96*(2), 366–373.e8. https://doi.org/10.1016/j.fertnstert.2011.05.090

Okkels Birk, H., Vrangbæk, K., Rudkjøbing, A., Krasnik, A., Eriksen, A., Richardson, E., & Smith Jervelund, S. (2024). *Denmark health system review (No. 26(1); health systems in transition)*. European Observatory on Health Systems and Policies. https://iris.who.int/bitstream/handle/10665/376116/9789289059558-eng.pdf?sequence=1.

Olagnier, D., & Mogensen, T. H. (2020). The Covid-19 pandemic in Denmark: Big lessons from a small country. *Cytokine & Growth Factor Reviews, 53*, 10–12. https://doi.org/10.1016/j.cytogfr.2020.05.005

Or, Z., Gandré, C., Seppänen, A.-V., Hernández-Quevedo, C., Webb, E., Michel, M., & Smith Jervelund, K. (2023). *France health system review (No. 25(3); health systems in transition)*. European Observatory on Health Systems and Policies. https://iris.who.int/bitstream/handle/10665/371027/9789289059442-eng.pdf?sequence=4.

Ou, M., & Ho, S. S. (2022). A meta-analysis of factors related to health information seeking: An integration from six theoretical frameworks. *Communication Research, 49*(4), 567–593. https://doi.org/10.1177/00936502211043024

Powell, J., & Clarke, A. (2018). Internet information-seeking in mental health: Population survey. *British Journal of Psychiatry, 189*(3), 273–277. https://doi.org/10.1192/bjp.bp.105.017319

Reinhardt, A., & Eitze, S. (2025). Breaking the endometriosis silence: A social norm approach to reducing menstrual stigma and policy resistance among young adults. *Psychology and Health, 40(6), p. 881-903*. https://doi.org/10.1080/08870446.2023.2277838

Ruppel, E. K., & Rains, S. A. (2012). Information sources and the health information-seeking process: An application and extension of channel complementarity theory. *Communication Monographs, 79*(3), 385–405. https://doi.org/10.1080/03637751.2012.697627

Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare, 11*(6), 887. https://doi.org/10.3390/healthcare11060887

Santandreu-Calonge, D., Medina-Aguerrebere, P., Hultberg, P., & Shah, M.-A. (2023). Can ChatGPT improve communication in hospitals? *El Profesional de la Información.* , Article e320219. https://doi.org/10.3145/epi.2023.mar.19

Scantamburlo, T., Cortés, A., Foffano, F., Barrué, C., Distefano, V., Pham, L., & Fabris, A. (2023). *Artificial Intelligence across Europe: A Study on awareness, Attitude and trust* (version 1). *arXiv*. https://doi.org/10.48550/ARXIV.2308.09979

Smith, R. A. (2011). Stigma, communication, and health. In T. L. Thompson, R. Parrott, J. F. Nussbaum, & Hrsg (Eds.), *The routledge handbook of health communication* (pp. 455–468). Routledge.

Sundar, S. S., & Liao, M. (2023). Calling BS on ChatGPT: Reflections on AI as a communication source. *Journalism & Communication Monographs, 25*(2), 165–180. https://doi.org/10.1177/15226379231167135

Thornicroft, G., Sunkel, C., Alikhon Aliev, A., Baker, S., Brohan, E., El Chammay, R., Davies, K., Demissie, M., Duncan, J., Fekadu, W., Gronholm, P. C., Guerrero, Z., Gurung, D., Habtamu, K., Hanlon, C., Heim, E., Henderson, C., Hijazi, Z., Hoffman, C., … Winkler, P. (2022). The Lancet Commission on ending stigma and discrimination in mental health. *The Lancet, 400*(10361), 1438–1480. https://doi.org/10.1016/S0140-6736(22)01470-2

Venkatesh, T., & Xu. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157. https://doi.org/10.2307/41410412

Wang, X., Shi, J., & Kong, H. (2021). Online health information seeking: A review and meta-analysis. *Health Communication, 36*(10), 1163–1175. https://doi.org/10.1080/10410236.2020.1748829

Weiss, M. G., Ramakrishna, J., & Somma, D. (2006). Health-related stigma: Rethinking concepts and interventions 1. *Psychology Health & Medicine, 11*(3), 277–287. https://doi.org/10.1080/13548500600595053