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AI at everyone's fingertips? Identifying the predictors of health information seeking intentions using AI

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ABSTRACT

The advent of AI tools has the potential to transform how health information is sought, which increases the need for insights into why individuals turn to AI. The study, guided by channel-specific predictors covered by the Planned Risk Information Seeking Model, additionally considers trust and risk perceptions toward AI, and examines the predictors of one's AI-seeking intention. The results of an online survey ($N = 1,121$) indicated that attitudes toward seeking, seeking-related norms, and perceived seeking control were significant predictors of individuals' intention to seek health information from AI. In contrast, trust and risk perceptions were of minor relevance.

KEYWORDS

Health information seeking; norms; perceived seeking control; attitudes toward seeking; artificial intelligence

Introduction

Health inequalities represent a significant challenge in global public health. Given that health information mediates the relationship between social status and health inequalities, the evolving digital health information landscape has the potential to reduce inequalities (Jacobs et al., 2017; Morita et al., 2024). In particular, the advent of new AI tools is transforming how information is sought. Conversational AI, such as chatbots, serves as a "quasi-human partner" (Chen & Wen, 2021, p. 116) that provides responses that are personalized (Carmona et al., 2022; Choudhury & Shamszare, 2023). This approach is assumed to circumvent the complexity of health information, promote a deeper understanding of information, and reduce the effects of information overload and misinformation (Morita et al., 2024; Xiao et al., 2023). Given these potentials of health information-seeking behaviors (HISB) using AI, we aim to enrich the understanding of its drivers (Liao et al., 2024) as the goal-directed selection of channels such as AI is understood as one of the basic decisions individuals can make regarding information seeking (Johnson & Case, 2012). Therefore, this study aims to explore individual-level predictors of AI-HISB.

As a starting point, we refer to the Planned Risk Information Seeking Model (PRISM) (Kahlor, 2010), which represents one of the most

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comprehensive models summarizing individual-level factors proposed in prior models that impact HISB. The PRISM conceptualizes HISB as "the effort expended to locate information" (Kahlor, 2010, p. 346), defining it as a deliberate, planned behavior to acquire information. It was designed to elucidate HISB in diverse health and risk contexts and is valid across channels including online sources (see Link et al., 2021; Wang et al., 2021). Against this backdrop, we aim to test the applicability of predictors focusing particularly on individuals' perceptions of specific channel characteristics of AI such as attitudes, norms and perceived seeking control influencing the intention to turn to it. This seems crucial as the first extant research assumes that AI blurs the distinction between communication channels and communicators, which could be a boundary condition of HISB models (Liao et al., 2024). Furthermore, we extend this set of predictors by including trust in and risk perceptions toward AI, which are often discussed as crucial factors determining the adaptation of AI (e.g., Liao et al., 2024; Morita et al., 2024). In conclusion, the current study offers preliminary insights into the predictors of AI-HISB, contributing to the theoretical understanding of this phenomenon and identifying potential facilitators or barriers to its implementation.

Predictors of AI health information seeking behaviors

As a robust foundation for advancing our understanding of AI-HISB, we refer to the PRISM (Kahlor, 2010), which identified the general individual-level sociopsychological factors that motivate HISB. The PRISM describes that attitudes toward seeking, seeking-related subjective norms, perceived seeking control, risk perceptions, affective risk responses, and knowledge insufficiency contribute to individuals' seeking intent (for a comprehensive overview of the PRISM, see Kahlor, 2010). Aiming for a comprehensive understanding of the channel-specific processes of HISB, we consider AI-specific attitudes, perceived seeking control, and norms as access points for further theory development (Basnyat et al., 2018; Link et al., 2021) instead of examining the entire PRISM in this initial inquiry.

Adapting the predictors proposed by Kahlor (2010) to AI, attitudes toward seeking focus on the relative benefits and usefulness of AI-HISB. While perceived seeking control considers individuals' beliefs to possess the capacity to use AI, understood as a self-perception of agency (Liao et al., 2024), subjective norms recognize whether AI is a socially accepted channel to acquire health information and whether individuals perceive social pressure toward information seeking or that their social surrounding already relies on AI-provided information for health-related purposes. In line with the assumptions of the PRISM and extant research on AI (Liao et al., 2024), we postulate that all three predictors are positively related to a higher seeking intent using AI (Hypothesis 1–3; see Table 2).

As a result of our focus on AI, we supplement the introduced predictors in two respects. First, we add trust in AI as extant research stresses that trust is critical for users' adoption of AI (Carmona et al., 2022; Choudhury & Shamszare, 2023; Morita et al., 2024). Particularly when individuals lack the knowledge to understand AI, trust serves as a heuristic to provide vast and effective attitude formation and decision-making (Cummings, 2014). Trust describes a certain attitude toward AI referring to the willingness to accept vulnerability and take chances based on the recommendations made by AI (Choudhury & Shamszare, 2023). Trust manifests in relying on AI to execute a particular task based on positive expectations and evaluations of AI's performance, process, and purpose (Siau & Wang, 2018). Thus, we propose that trust in AI will be positively related to intentions to seek health information via AI (H4).

The extant literature on the integration of (mis-)trust into the PRISM indicates that a higher willingness to rely on a source is associated with a higher value placed on the information provided, which is reflected in more positive attitudes toward HISB (Link et al., 2024a, 2024b; Wang et al., 2021). Consequently, we put forth the proposition that a higher willingness to rely on AI is related to more positive attitudes toward AI HISB (see H6). Further, trust in AI is proposed to be related to more pronounced subjective AI-related seeking norms (see H8) as individuals' need for consistency in beliefs suggests that individuals overestimate the level to which others share their beliefs, attitudes, and behaviors (Link et al., 2024b; see also Festinger, 1957). Regarding perceived seeking control, it can be posited that trust in AI determines the perceived effort and challenges associated with using AI. Therefore, we propose that higher trust is positively related to the perceived seeking control (H10).

Second, the implementation of AI also depends on individuals' risk perceptions (Chen & Wen, 2021; Neyazi et al., 2023). Risk perception is a cognitive and affective response to a threat that can be associated with technology (Neyazi et al., 2023; So, 2013). It is the result of subjective judgment of whether using a technology is potentially harmful and evaluating the seriousness, likelihood, and acceptability of the respective technology (Renn & Benighaus, 2013), which might be related to feeling anxious or uncertain. Using AI to acquire health information might be related to risks of false, biased, or inappropriate answers relying on uncurated information. Against this understanding, we propose that both cognitive and affective risk responses are negatively related to one's intention to seek health information via AI (H5a/b).

In line with the rationale for the role of trust outlined above, it can be suggested that cognitive and affective risk responses will also negatively relate to more negative attitudes toward AI-seeking (H7a/b), less pronounced subjective AI-seeking-related norms (H9a/b) and perceiving one's seeking control as lower as the task is perceived to require more effort to use (H11a/b).

Materials and methods

Participants and procedure

To test our hypotheses, we conducted an online survey ($N = 1,121$) of a sample of members of a German online survey panel (SoSci-Panel; Leiner, 2016). The respondents were between the ages of 18 and 94 ($M = 52.4$; $SD = 16.0$), with 60.8% identifying as female. The sample was comprised of individuals with a high level of education, with educational backgrounds ranging from a secondary school certificate (18.4%) to a high school diploma (23.3%) to a BA degree and higher (58.2%). For this type of data collection, according to German standards it was considered exempt from needed ethical approval. All participants were asked for their informed consent and were advised of their right to withdraw from participation at any time.

Measures

All measurements were adapted from earlier literature. Examples of the item wording, the type of scale used, and the fit of the measurement models can be found in Table 1. Unless otherwise stated, all items were measured on a 5-point Likert-type scale ranging from 1 "does not apply at all" to 5 "does apply fully."

For AI-specific health information-seeking intention, attitudes toward AI-seeking, subjective AI-seeking related norms, perceived seeking control, and risk perceptions related to AI, items adapted from Kahlor (2010) and Kahlor et al. (2020) were used. The four-item measure of seeking intent indicated whether respondents intend to use AI for health-related purposes in the near future ($M = 2.38$, $SD = 1.13$). The measure of attitudes consists of seven 5-point differential pairs describing how the respondents evaluate information seeking via AI ($M = 3.16$, $SD = .78$). Subjective norms were measured by five items covering how common and approved AI-HISB is among an individual's peers ($M = 1.63$, $SD = .79$). AI-related perceived seeking control was measured with four items asking whether the respondents know how to use AI for health information acquisition ($M = 2.50$, $SD = 1.09$). Trust in AI was assessed by a single item asking individuals' degree of trust in AI ($M = 2.35$, $SD = .93$). In line with former research often relying on single items and indicating its reliability (e.g., Castro et al., 2023), we opted for a global assessment approach,

Table 1. Overview of the measures.

Construct	Examples of item wording	Response scale	Descriptive	Model fit to the data	Source
AI seeking intent	Are you planning to seek for health information via AI chatbots such as ChatGPT in the future? IS1: I plan to seek health information via AI in the near future. IS2: I will try to seek health information via AI in the near future.	five-point Likert-type scale from 1 "does not apply at all" to 5 "does apply fully"	$M = 2.38$, $SD = 1.13$	α = .94 [.93; .95]; χ^2 (1) = 2.17, $p = .141$; CFI = .999; RMSEA = .032, 90%CI [.000; .088], SRMR = .015	Kahlor (2010)
Attitudes toward AI information seeking	Seeking information using AI such as chatbots is AT1 - . . . bad or good. AT2 - . . . harmful or beneficial. AT3 - . . . unhelpful or helpful.	five-point semantic differential scale	$M = 3.16$, $SD = .78$	α = .93 [.92; .94], χ^2 (14) = 95.28, $p \leq .001$, CFI = .976, RMSEA = .072 90%CI [.062; .083], SRMR = .025	Kahlor (2010)
AI-related subjective seeking-related norms	SN1: Most people who are important to me think that I should seek for health information via AI. SN2: People from my social environment whose opinion I value inform themselves about health issues via AI.	five-point Likert-type scale from 1 "does not apply at all" to 5 "does apply fully"	$M = 1.63$, $SD = .79$	α = .90 [.89; .91], χ^2 (5) = 31.15, $p \leq .001$; CFI = .977, RMSEA = .069, 90 CI [.055; .083], SRMR = .029	Kahlor (2010)
AI-related perceived seeking control (PSC)	PSC1: When it comes to finding information about my health via AI, I know where to go. PSC2: When it comes to health information from AI, I know how to separate fact from fiction.	five-point Likert-type scale from 1 "does not apply at all" to 5 "does apply fully"	$M = 2.50$, $SD = 1.09$	α = .91 [.90; .92], χ^2 (5) = 15.79, $p = .007$; CFI = .995; RMSEA = .044, 90%CI [.024; .065], SRMR = .013	Kahlor (2010)
Trust in AI	To what extent do you trust the following institutions or technologies? AI	five-point Likert-type scale from 1 "not at all" to 5 "completely"	$M = 2.35$, $SD = .93$		Self-developed
Cognitive dimension of AI-related risk perception	RP1: Please rate the overall level of risk posed by using AI to acquire health information. RP2: How serious are the risks posed by using AI to acquire health information?	five-point Likert-type scale from 1 "not at all high/serious" to 5 "extremely high/serious"	$M = 3.55$, $SD = .82$	Spearman-Brown-Coefficient = .82	Kahlor et al. (2020)
Affective dimension of AI-related risk perception	When you think about the use of AI to acquire health information how do you feel: How . . . AFF1 - . . . worried do you feel? AFF2 - . . . scared do you feel? AFF3 - . . . uncertain do you feel?	five-point Likert-type scale from 1 "not at all" to 5 "extremely"	$M = 2.99$, $SD = .91$	α = .87 [.85; .88], χ^2 (1) = 1.74, $p = .187$; CFI = .999; RMSEA = .026, 90%CI [.000; .086], SRMR = .013	Kahlor et al. (2020)

as our primary focus was not on the impact of individual dimensions of trust. Regarding risk perception toward AI, we captured the cognitive risk perception with two items that describe the components of overall risks posed to the individual and the severity of these risks (Kahlor et al., 2020) ($M = 3.55$, $SD = .82$). To capture the affective components of risk perceptions, participants were asked to indicate their negative affective risk responses to a three-item measure on a 5-point semantic differential scale ($M = 2.99$, $SD = .91$).

Data analysis

A latent variable structural equation model was conducted in R using the package Lavaan. We used two-step modeling to verify all measurement models before testing the structural model. For all models, indicators of model fit were χ^2, comparative fit index (*CFI*; values close to or greater than .95), root mean square error approximation (*RMSEA*; values lower than .08), and standardized root mean residual (*SRMR*; values lower than .08; Hu & Bentler, 1999).

Results

The model for individuals' intention to use AI showed a satisfactory fit (χ^2 (279) = 665.78, $p \leq .001$, CFI = .979, RMSEA = .036 [.032, .039], SRMR = .038). The model accounted for 54.9% of the variance in individuals' AI-related health information-seeking intention. Overall, 12 of the 15 hypothesized relationships held up for the individuals' intention to use AI for health-related

Table 2. Hypotheses testing results.

	Path	standard. β-Coefficients	p-values	Supported
H1	Attitudes toward AI seeking → AI seeking intent	.416	≤.001	Supported
H2	AI subjective seeking-related norms → AI seeking intent	.160	≤.001	Supported
H3	AI-related perceived seeking control → AI seeking intent	.208	≤.001	Supported
H4	Trust in AI → AI seeking intent	.065	.021	Supported
H5a	Cognitive dimension of AI-related risk perceptions → AI seeking intent	.000	.995	Not supported
H5b	Affective dimension of AI-related risk perception → AI seeking intent	−.159	≤.001	Supported
H6	Trust in AI → attitudes toward AI seeking	.262	≤.001	Supported
H7a	Cognitive dimension of AI-related risk perceptions → attitudes toward AI seeking	−.243	≤.001	Supported
H7b	Affective dimension of AI-related risk perception → attitudes toward AI seeking	−.300	≤.001	Not supported
H8	Trust in AI → AI subjective seeking-related norms	.113	≤.001	Supported
H9a	Cognitive dimension of AI-related risk perceptions → AI subjective seeking-related norms	−.117	≤.001	Supported
H9b	Affective dimension of AI-related risk perception toward AI → AI subjective seeking-related norms	−.013	.815	Not supported
H10	Trust in AI → AI-related perceived seeking control	.173	≤.001	Supported
H11a	Cognitive dimension of AI-related risk perceptions → AI-related perceived seeking control	.062	.292	Not supported
H11b	Affective dimension of AI-risk perception → AI-related perceived seeking control	−.334	≤.001	Supported

purposes (see Table 2). In line with hypotheses 1 to 4, the findings revealed that attitudes toward AI seeking (H1; $\beta = .416$; $p \leq .001$), AI seeking-related norms (H2; $\beta = .160$; $p \leq .001$), AI-related perceived seeking control (H3; $\beta = .208$; $p \leq .001$), and trust in AI (H4; $\beta = .065$; $p = .021$) were positively related to one's higher AI seeking intentions. Whereas the association between attitudes and intentions was very strong, the relationship between trust and one's intention was revealed to be rather weak. The affective risk responses to AI were negatively associated with AI-seeking intentions ($\beta = -.159$; $p \leq .001$), which supports hypothesis 5b. In contrast, the relationship between cognitive risk perceptions toward AI and seeking intent was not significant. Thus, H5a was not supported ($\beta = .000$; $p = .995$).

Focusing on the role of trust in AI, the findings supported that higher trust in AI was significantly linked to more positive attitudes (H6; $\beta = .262$; $p \leq .001$), more pronounced AI subjective seeking-related norms (H8; $\beta = .131$; $p \leq .001$), and AI-related perceived seeking control (H10; $\beta = .173$; $p \leq .001$).

For the cognitive risk perceptions toward AI, we confirmed its negative relationship to one's attitudes toward AI seeking (H7a; $\beta = -.243$; $p \leq .001$) and AI subjective seeking-related norms (H9a; $\beta = -.117$; $p \leq .001$), while the assumed association between cognitive risk perceptions and AI-related perceived seeking control could not be supported (H11a; $\beta = .062$; $p = .292$).

Affective risk responses were confirmed to be negatively related to attitudes toward AI seeking (H7b; $\beta = -.300$; $p \leq .001$) and AI-related perceived seeking control (H11b; $\beta = -.334$; $p \leq .001$) but the link to subjective seeking-related norms was not significant (H9b; $\beta = -.013$; $p = .815$). Therefore, H9b could not be supported.

Discussion

As highly relevant benefits for health information acquisition are assigned to AI tools such as chatbots, we provide a theoretically sound analysis of predictors of AI-HISB. Despite research questioning the boundaries of extant models of HISB for explaining AI-HISB, our results reveal the selected predictors of the PRISM to be an effective framework for predicting one's intention to turn to AI. In line with findings on online HISB (Link et al., 2021), attitudes toward seeking health information via AI provide the most crucial predictor followed by perceived seeking control related to AI and subjective AI-related norms. The particularly strong association between attitudes and intentions should be interpreted against the background of a heterogeneous and insufficient state of research (Liao et al., 2024; Wang et al., 2021) demanding more research addressing the role of attitudes and under which conditions they are influential for individuals' HISB. Considering trust and risk perception provides relevant insights to clarify the role of attitudes. The findings showed in line with our postulates that attitudes were strongly positively related to trust and negatively related to both dimensions of risk perceptions (Link et al., 2024a; Wang et al., 2021).

The relatively strong relationship between one's perceived seeking control and one's intentions to turn to AI for health-related purposes is consistent with the findings of Liao et al. (2024). This finding might be attributed to individuals' awareness of challenges associated with the low transparency of AI, the risks of unreliable information, and the necessity for new skills to effectively use prompts or critically evaluate the information (e.g., Carmona et al., 2022). Support for this interpretation is provided by the impact of trust and affective risk responses associated with one's AI-related perceived seeking control. Whereas trust was associated with higher perceived seeking control, individuals feeling more concerned, worried, and anxious reported being less in control and capable of using AI for health-related purposes.

Regarding the relatively weak association between subjective norms and AI-HISB intention, the findings suggest in line with research on online HISB (Link et al., 2021) that channel-specific norms are less relevant to individuals' behavioral intentions. In addition, the descriptive data indicate that AI-related seeking norms are not well internalized so far. This might be related to the early phase of AI implementation in the public's everyday life and explains a comparatively weaker association compared to other studies. The internalization was found to be promoted by trust in AI, whereas one's cognitive risk perception serves as a barrier to more pronounced internalization.

While the predictors derived from the PRISM (Kahlor, 2010) were identified as most essential for AI-HISB, the often-discussed predictors of trust in AI and risk perceptions toward AI were found to be of secondary relevance (e.g., Carmona et al., 2022; Choudhury & Shamszare, 2023; Liao et al., 2024; Morita et al., 2024). They were rather weakly associated with individuals' intentions to use AI for health-related purposes. Instead, trust and risk perceptions were revealed to be crucial for predicting one's attitudes, norms, and perceived seeking control, which is also a crucial addition to the state of research and contributes to a better understanding of HISB and its predictors in general.

The study involves several limitations and provides starting points for further research. First, the study was based on cross-sectional data. The associations were theoretically derived and focused on intentions to rule out reverse causality, but the study is not able to examine causal claims per se (Rohrer et al., 2022). Second, the global assessment of trust using a single item neglects its multidimensionality and might only provide an incomplete understanding of the role of trust. Third, it should be noted that the survey relied on a highly educated sample resulting in an educational bias. As education is suggested to impact a more positive assessment and make the use of AI more likely (e.g., Kreps et al., 2023), the data might have limited between-person variance. Future research should particularly focus on more vulnerable groups (e.g., individuals with low socio-economic status, and low health literacy) to assess whether AI is used to acquire health information. Fourth, we considered only individuals' intentions to use AI instead of actual HISB, which is crucial to determine its potential to reduce health inequalities. Fifth, as an initial inquiry, we focus on channel-specific predictors neglecting to consider individuals' information insufficiency, their health-related risk perceptions, and affective risk perceptions more comprehensively. Future research could test whether the entire PRISM provides further insights to explain AI-HISB. Further constructs that might be relevant in the AI context are AI-specific literacies or one's technological knowledge. Sixth, the study is conducted in the German context, where ChatGPT received rather high levels of awareness and acceptance (Kero et al., 2023).

To conclude, the study is one of the first to examine one's intention to use AI to acquire health information. The findings suggest that extant theoretical models such as the PRISM are still valid in the rapidly changing media landscapes providing us with robust explanations and sufficient understanding of information behaviors. Particularly, the high cross-channel utility of attitudes, norms, and perceived seeking control revealed by the analysis suggests that they are key predictors of information behaviors in general. For theory specification, this common ground can be supplemented by channel-specific predictors. Further, the data provide suggestions on how to encourage AI-HISB. Besides the need to develop training to improve one's capabilities to use and assess AI, the data indicate strategically utilizing attitudes and social norms. In this vein, AI should be framed in a way that ensures clarity on AI capabilities and addresses whether AI provides reliable information (Liao et al., 2024). This is of particular importance in the context of health to prevent the emergence of new obstacles to the dissemination of health information and new causes of inequality, as well as to capitalize on opportunities such as navigating the complexity of health information, fostering a more nuanced understanding, and mitigating the risks associated with information overload and misinformation (Morita et al., 2024; Xiao et al., 2023).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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