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Empowering individuals to adopt artificial intelligence for health information seeking: A latent profile analysis among users in Hong Kong☆

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ABSTRACT

Rationales: Using AI for health information seeking is a novel behavior, and as such, developing effective communication strategies to optimize AI adoption in this area presents challenges. To lay the groundwork, research is needed to map out users' behavioral underpinnings regarding AI use, as understanding users' needs, concerns and perspectives could inform the design of targeted and effective communication strategies in this context.
Objective: Guided by the planned risk information seeking model and the comprehensive model of information seeking, our study examines how socio-psychological factors (i.e., attitudes, perceived descriptive and injunctive norms, self-efficacy, technological anxiety) and factors related to information carriers (i.e., trust in and perceived accuracy of AI), shape users' latent profiles. In addition, we explore how individual differences in demographic attributes and anthropocentrism predict membership in these user profiles.
Methods: We conducted a quota-sampled survey with 1051 AI-experienced users in Hong Kong. Latent profile analysis was used to examine users' profile patterns. The hierarchical multiple logistic regression was employed to examine how individual differences predict membership in these user profiles.
Results: The latent profile analysis revealed five heterogeneous profiles, which we labeled "Discreet Approachers," "Casual Investigators," "Apprehensive Moderates," "Apathetic Bystanders," and "Anxious Explorers." Each profile was associated with specific predictors related to individual differences in demographic attributes and/or aspects of anthropocentrism.
Conclusion: The findings advance theoretical understandings of using AI for health information seeking, provide theory-driven strategies to empower users to make well-informed decisions, and offer insights to optimize the adoption of AI technology.

Artificial intelligence (AI) enables computers and other machines to simulate a wide range of human capabilities—learning, comprehension, decision-making, and even autonomy (Stryker and Kavlakoglu, 2024). Especially since OpenAI's ChatGPT was released to the public, AI tools based on large language models trained to understand and generate human language at nearly human-like levels have attracted significant attention (Wu et al., 2023). Those capabilities also enable AI technology to serve as an alternative source and tool for people seeking health information and thereby have the potential to promote positive health outcomes, such as improving the ability to make informed healthcare choices and facilitating healthcare outcomes (Al Shboul et al., 2024; Clusmann et al., 2023). For example, AI-powered information search tools offer conversational search capabilities that enable more personalized search results, satisfy individual needs through user-adapted explanations, and provide tailored medical and other health-related recommendations (Clusmann et al., 2023). However, when it comes to providing health information, AI technology has also raised concerns, including about the spread of misinformation and risky content (J. Park et al., 2023) and the invasion of users' privacy (Y. J. Park, 2021). Users who overly rely on AI-generated health recommendations without

☆ Although this study and the other paper (https://doi.org/10.1080/08838151.2024.2377244) use data from the same large-scale survey on AI conducted in Hong Kong, the datasets used are entirely separate with no overlap. The variables analyzed in this study have not been used in the other paper.

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carefully evaluating them risk severe consequences for such advice can sometimes be detrimental to their psychological and/or physical well-being (Clusmann et al., 2023; J. Park et al., 2023).

Using AI technology to seek out health information—that is, for *health information seeking*—is a novel behavior. As such, developing effective communication strategies to optimize AI adoption presents challenges due to the scarcity of research in this area. To lay the groundwork, research is needed to understand why users adopt AI technology for health information seeking. For this reason, before developing communication strategies, it is essential to map out the behavioral underpinnings, including users' needs, concerns and perspectives, regarding the use of AI in that context. Such a foundation matters in efforts to create straightforward, unambiguous models that elucidate users' patterns of motivation (Joyal-Desmarais et al., 2022; Slater, 1996).

In our study, drawing on the planned risk information seeking model (PRISM; Kahlor, 2010) and the comprehensive model of information seeking (CMIS; Johnson and Meischke, 1993), we conducted a latent profile analysis to categorize users into heterogeneous groups, each with specific needs, concerns and perspectives based on factors derived from the perspectives of both users and information carriers (Slater, 1996; Wang et al., 2021). In turn, given established individual-level differences associated with health practices (e.g., Agyemang-Duah et al., 2020; Johnson and Meischke, 1993) and the adoption of technology (e.g., Lombard and Xu, 2021; Venkatesh and Davis, 2000), we examined how individuals' demographic attributes and levels of anthropocentrism predict their profiles as users of AI technology.

The findings are expected to expand current theoretical understandings of health information seeking by incorporating sociopsychological factors and factors related to information carriers related to AI technology. Understanding different user profiles can enable communication professionals to better allocate resources and develop communication strategies for each user segment and thereby assist users in making empowered, well-informed decisions when seeking health information using AI.

1. Antecedents derived from user-focused perspective

According to the PRISM, actions in health information seeking can be driven by individuals' global perceptions and evaluations of such actions in light of the specific information carrier (Ajzen, 1985; Kahlor, 2010). Given that assumption, individuals' actions in health information seeking can be further conceptualized as functions of attitudes toward the behavior, normative perceptions, and self-efficacy (Kahlor, 2010).

To begin, *attitudes* refer to beliefs that a particular behavior will have certain outcomes and that those outcomes will be either positive or negative (Yzer, 2011). Individuals who believe that seeking health information via AI will lead to positive outcomes are more likely to proactively engage in the behavior, whereas ones with negative evaluations of the behavior may avoid it, resist it, and/or engage with it cautiously (Kahlor, 2010).

Meanwhile, *normative perceptions* refer to estimations of a behavior's prevalence (i.e., perceived descriptive norms) and expectations of approval from the social environment for engaging in the behavior (i.e., perceived injunctive norms; Rimal and Lapinski, 2015). According to the PRISM framework, normative perceptions related to information seeking exert social pressure that influences individuals' information behavior (Kahlor, 2010). Individuals may especially rely on normative perceptions during the early diffusion of new technology, for the absence of direct experience such perceptions often serve as shortcuts in decision-making about adopting AI technology for health information seeking. Thus, the motivation for using AI technology for health information seeking may differ depending on individual perceptions of social norms (Alshurafat et al., 2021; Venkatesh and Davis, 2000). In the context of our study, individuals who perceive that using AI for health information seeking is prevalent or approved by important others are more likely to be motivated to adopt the behavior.

Last, *self-efficacy* refers to an individual's belief in their ability to perform a given behavior (Yzer, 2011). In the PRISM framework, self-efficacy in information seeking is shaped by past experiences and influences subsequent behavioral intentions to engage in information seeking (Kahlor, 2010). Building on that foundation, individuals who believe they are capable of seeking health information using AI technology are more likely to proactively engage in the behavior than ones who lack confidence.

2. Antecedents derived from information-carrier-focused perspective

Added to the sociopsychological factors derived from the perspective of users, instrumental evaluations could also drive health information seeking (Wang et al., 2021). In particular, content-related attributes and the utility of the information carrier, which could manifest as relevant beliefs about the information carrier, could influence health information seeking (Griffin et al., 1999; Wang et al., 2021).

According to the CMIS, because AI technology can be regarded as an information carrier, individuals' beliefs about its trustworthiness and their assessments of the quality of information provided, including its accuracy, relevance, comprehensiveness, and currency, influence their level of trust in that information (Lee et al., 2002). Furthermore, the perceived accuracy of the information provided by AI technology (Shin and Park, 2019) may generally consist of a salient estimation of utility—that is, the estimated extent to which it satisfies users' preferences and needs. For example, individuals who trust and believe that AI operates with high accuracy are more likely to adopt it (Choung et al., 2023; Glikson and Woolley, 2020; Shin and Park, 2019). Therefore, regarding antecedents from the perspective of information carriers, we focused on users' trust and perceived accuracy of AI when it serves as an information carrier.

Because AI technology is a new and emerging tool, individuals may experience negative feelings (e.g., apprehension) when using it (Compeau et al., 1999), which can affect their willingness to use AI technology in seeking out health information. Such emotional responses are captured by the concept of *technology anxiety*, which refers to negative emotions that lead to avoiding information and communication technology altogether (Wilson et al., 2023). Depending on their level of technology anxiety, individuals may engage either proactively or cautiously in health information seeking using AI technology.

By integrating those factors that drive actions in health information seeking, we formulated our first research question (RQ), which addresses the underlying pattern of motivations for using AI technology in health information seeking.

RQ1. What user profiles can be identified based on the factors of attitude, perceived descriptive norms, perceived injunctive norms, self-efficacy, trust in AI, AI's perceived accuracy, and technological anxiety?

3. Depicting user profiles based on individual differences

3.1. Demographic attributes

The CMIS postulates that an individual's perceptions and beliefs regarding a specific health issue, as well as their demographic characteristics, act as antecedents of health information seeking behaviors (Johnson and Meischke, 1993). For example, in terms of diseases-related factors, individuals' salience of the disease—that is, its perceived threat—and beliefs in their efficacy in preventing and/or treating the disease are theorized to shape their health information seeking behaviors. However, because our study focused on general health information seeking behavior, which is not specific to any disease, we aimed to examine how individuals' demographic attributes affect their use of AI for health information seeking—specifically, how such demographic factors are associated with individuals' predicted profiles as users of AI technology.

As for demographic antecedents of health information seeking using AI technology, factors such as level of education, age, gender, and income may affect both the motivation to seek health information and the choice of channels utilized. For instance, level of education provides the foundation for determining what health information is needed, which channels are appropriate for seeking it, and how to assess the quality of the information obtained (Johnson and Meischke, 1993). Likewise, age, gender, and income can also influence the types of health information that individuals seek, their frequency of doing so, and their preferences for channels and sources of information (Agyemang-Duah et al., 2020; Fareed et al., 2021; Zimmerman, 2018).

Such demographic factors are also associated with individuals' use of AI technology. Recent research has suggested that level of education equips individuals with the foundational and advanced technological skills required for adopting the use of AI (Biswas and Murray, 2024). Age, gender, and income could also influence individuals' preferences, frequency of use, and the specific purposes for which they engage with AI technology (Kreacic and Stone, 2024; Zhang and Dafoe, 2019).

3.2. Individual differences in anthropocentrism

Along with demographic attributes, other individual differences, especially in perceptions of AI, may also shape individuals' health information seeking behavior using AI technology. A major individual difference in the perception of AI is *anthropocentrism*, meaning the extent to which individuals adopt a human-centered perspective in perceiving objects (Nass et al., 1995). Applying that concept to understanding individuals' attitudes toward technology, Nass et al. identified three dimensions underlying anthropocentrism: physical anthropomorphism, psychological anthropomorphism, and acceptance of technology in human roles.

To begin, *physical anthropomorphism* refers to individuals' belief that technology can possess the physical capabilities of humans, including watching, listening, and speaking. By contrast, *psychological anthropomorphism* refers to individuals' belief that technology possesses human psychological capabilities, including the ability to feel annoyed or sympathetic. Last, the *acceptance of technology in human roles* refers to the extent to which individuals believe that technology can take on roles traditionally performed by humans. This dimension can be split into three subsets (Nass et al., 1995): acceptance of technology in routinized roles (e.g., bank tellers), interpretive roles (e.g., editorial writers), and personal roles (e.g., babysitters). When testing individuals' acceptance of computers in human roles in the 1990s, Nass et al. found that participants were more comfortable with computers in routinized roles but less comfortable with them in interpretive and personal roles. Moreover, although participants' past experience with computers did not affect their acceptance of computers' taking human roles, their genders did have an impact, such that women were less likely than men to accept computers in such roles.

We examined anthropocentrism in our study for two reasons. First. Nass et al.'s (1995) findings about anthropocentrism were published about three decades ago. The evolution of technology, including AI-based technology (e.g., smartphones, chatbots, large language models, and recommendation systems), may have greatly changed users' attitudes and responses to technology since then (Gambino et al., 2020). In turn, users' physical anthropomorphism, psychological anthropomorphism, and acceptance of AI in various social roles may have undergone major reconfigurations as well. Therefore, it is worthwhile to revisit how those different dimensions underlying anthropocentrism motivate different user groups to adopt AI technology today. Second, a recent framework that has extended the computers are social actors (CASA) paradigm to the media are social actors (MASA) paradigm (Lombard and Xu, 2021) lists anthropocentrism as a factor that informs individual differences in social responses to AI technology. Accordingly, a person high in anthropocentrism (i.e., who perceives the world from a more human-centered perspective) would be less likely to believe that AI can and should take on physical or psychological attributes of human beings. Conversely, ones with low anthropocentrism might be more likely to accept AI technology's taking human roles. Thus, drawing on the MASA paradigm, we sought to clarify how each subdimension of anthropocentrism predicts different user groups' adoption of AI. We therefore proposed a second RQ.

RQ2. How are individuals' differences in demographic attributes and anthropocentrism associated with their predicted profiles as users of AI technology?

4. Method

4.1. Participants and procedure

In May 2023, we recruited 1360 permanent residents of Hong Kong via Qualtrics, with survey quotas set that referred to census data about Hong Kong's adult population considering gender and age. After those residents reviewed the written informed consent statement and provided their consent to participate, we provided them with a definition of *AI* (Zhang and Dafoe, 2019) and several examples of AI applications to aid their comprehension and thereby ensure a consistent understanding of AI. Respondents subsequently answered questions addressing the study's variables and reported their demographic information.

Among the participants, 30 of them reported no experience with AI technologies, and 279 of them provided incomplete responses across all study variables, resulting in missing values in those cases. After eliminating those responses, a total of 1051 participants remained in the final sample for further analysis. The excluded cases and the final sample did not significantly differ in their demographic composition, χ^2_{Gender} (1) = 0.06, $p = .81$; $\chi^2_{Education}$ (3) = 3.02, $p = .39$; t_{Age} (1358) = −0.03, $p = .98$; t_{Income} (1358) = 1.54, $p = .12$.

In the final sample, participants (49.95 % women, $n = 525$) were 48.96 years old ($SD = 15.66$) on average and had a median monthly household income ranging from HK $50,001 to HK $60,000 (approx. US $6410–$7692). The Institutional Review Board of the first author's university approved the questionnaire and procedure.

4.2. Measures

4.2.1. Intention to seek health information using AI technology

On a scale from 1 (*extremely unlikely*) to 7 (*extremely likely*), participants rated how likely they were to use AI technology to seek health information in the coming month ($M = 4.85$, $SD = 1.36$).

4.2.2. Attitudes toward seeking health information using AI technology

Participants rated their attitudes toward health information seeking using AI technology on four 7-point semantic differential items: (a) "foolish" to "wise," (b) "unhelpful" to "helpful," (c) "worthless" to "valuable," and (d) "harmful" to "beneficial" (Fishbein and Ajzen, 2010). We averaged responses to those four items to create the attitude scale, on which higher values indicated a more favorable attitude ($M = 5.42$, $SD = 0.99$, $\alpha = .86$).

4.2.3. Perceived descriptive norms

Perceived descriptive norms toward using AI for health information seeking were measured with three items on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*: (a) "People close to me use AI technology to seek health information," (b) "People I know are willing to use AI technology to seek health information," and (c) "People important to me use AI technology to seek health information" (Fishbein and Ajzen, 2010). We averaged responses to those three items to create a scale for perceived descriptive norms ($M = 4.62$, $SD = 1.29$, $\alpha = .91$).

4.2.4. Perceived injunctive norms

Participants rated the extent to which (a) people close to them, (b) people they know, and (c) people important to them approve their use of AI for seeking health information (Fishbein and Ajzen, 2010). on a 7-point scale ranging from 1 (*strongly disapprove*) to 7 (*strongly approve*). We averaged the scores of the three items to create a scale for perceived injunctive norms ($M = 4.95$, $SD = 1.07$, α = .89).

4.2.5. Self-efficacy

Because individuals' past experience is a critical source of their self-efficacy (Bandura, 1994), we used participants' past health information seeking behavior using AI technology as a proxy measure for their self-efficacy in performing the behavior. On a 7-point scale ranging from 1 (*never*) to 7 (*always*), participants reported the frequency with which they had used AI technology to seek health information in the past month ($M = 4.25$, $SD = 1.58$).

4.2.6. Trust in AI

Using the items adapted from Shin et al. (2020), participants indicated the extent to which they agreed with three statements: "I trust the recommendations by AI," "Content recommended by AI is trustworthy," and "I believe that AI's recommendations are reliable" on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). We averaged the scores of those three items to create a scale of trust in AI ($M = 4.66$, $SD = 1.09$, α = .87).

4.2.7. Perceived accuracy of AI

The perceived accuracy of AI technology was assessed with three items (Shin et al., 2020) on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*): (a) "I think the content produced by AI is accurate," (b) "Content recommended by AI are in general accurate," and (c) "AI's recommendations are exact and correct." We averaged responses to those three items to create a scale for perceived accuracy ($M = 4.67$, $SD = 1.09$, α = .87).

4.2.8. Technological anxiety

Using items adapted from Wilson et al. (2023), we assessed technological anxiety with 11 items on a 7-point scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Items included "I am not a technology person," "I feel uneasy using technology," and "Using technology makes me nervous." Responses to those 11 items were averaged to create a technological anxiety scale ($M = 3.23$, $SD = 1.14$, α = .94).

4.2.9. Anthropocentrism

Using items adapted from Nass et al. (1995), we assessed five aspects of anthropocentrism: (1) physical anthropomorphism, (2) psychological anthropomorphism, (3) acceptance of AI in routinized roles, (4) acceptance of AI in interpretive roles, and (5) acceptance of AI in personal roles.

For physical anthropomorphism, participants rated the extent to which they believe that current AI technology can hear, see, and understand spoken Chinese and understand written Chinese on a 5-point scale ranging from 1 (*definitely cannot*) to 5 (*definitely can*), $M = 3.79$, $SD = 0.63$, α = .76.

For psychological anthropomorphism, participants rated the extent to which they believe that current AI technology can express anger, annoyance, shame, embarrassment, forgiveness, frustration, impatience, jealousy, loneliness, nervousness, sympathy, and worry on a 5-point scale ranging from 1 (*definitely cannot*) to 5 (*definitely can*), $M = 2.80$, $SD = 0.83$, α = .95.

Last, participants rated their acceptance of AI in three types of human roles on a 5-point scale ranging from 1 (*completely unacceptable*) to 5 (*completely acceptable*): (1) routinized roles, including accountants, auto mechanics, bank tellers, and telephone operators ($M = 3.49$, $SD = 0.78$, α = .77); (2) interpretive roles, including editorial writers, news reporters, and novelists ($M = 3.00$, $SD = 0.89$, α = .77); and (3) personal roles, including babysitters, bosses, judges, and psychiatrists ($M = 2.74$, $SD = 0.89$, α = .81).

The correlations between the study's variables appear in Table S1 in the Supplementary Materials.

4.3. Data analysis

To answer RQ1, we employed latent profile analysis (LPA) using the *tidyLPA* package (Rosenberg et al., 2019; version 1.1.0) in RStudio (version 4.4.1). First, we selected attitudes, perceived descriptive and injunctive norms, trust and perceived accuracy, self-efficacy, and technological anxiety as indicators to identify latent profiles. In the model's specification, we used a class-invariant unrestricted parameterization with the potential to capture more information when creating profiles, because it allows estimating covariance while maintaining parsimony by restricting variance to be equal across profiles (Rosenberg, 2021). Next, we specified a two-profile model and proceeded to increase the number of profiles incrementally until the additional improvement in model fit no longer justified the decrease in parsimony resulting from specifying another latent profile (Nylund et al., 2007). To evaluate the model fit for each model, we assessed five model fit statistics: the Akaike information criterion (AIC), the Bayesian information criterion (BIC), sample-size-adjusted BIC (SABIC), the bootstrapped likelihood ratio test (BLRT), and entropy. Based on recommendations from previous studies involving LPA, lower AIC, BIC, and SABIC values indicate a better model fit, whereas significant p-values ($p < .05$) for BLRT suggest the improved fit of a k-class model over a (k – 1)-class model. Entropy values greater than 0.80 indicate less uncertainty, and the profiles are distinct within which model (Campion and Csillag, 2022; Chawla et al., 2020). We also followed the recommendation of past studies using LPA by constructing an elbow plot for consistent AIC (CAIC) and BIC values to gauge where the values began to flatten and to determine the profile solution (e.g., Campion and Csillag, 2022; Chawla et al., 2020).

To answer RQ2, we built upon the results obtained from RQ1 regarding the latent profiles and conducted hierarchical multiple logistic regression for each profile. For each model, the dependent variable was whether an individual was categorized into a particular profile (1 = *Yes*, 0 = *No*). The independent variables—demographic attributes and aspects of anthropocentrism—were entered into the model in a hierarchical structure.

5. Results

5.1. Latent profiles

The model fit indices for the six estimated LPA models appear in Table 1. The fit statistic's elbow was observed for the five-profile solution (see Fig. S1in the Supplementary Materials), which suggested that the five-profile solution was the best possible solution. Moreover, an entropy value (0.812) greater than 0.80 was observed for the five-profile model, whereas the p-value for BLRT for the six-profile model was not significant, thereby indicating no improvement in model fit by adding a

Table 1
Comparative model fit indices of LPA models (2- to 6- profile models) (N = 1051).

No. of Profiles	AIC	BIC	SABIC	BLRT p	Entropy
2	18797.31	19010.48	18873.90	0.010	0.904
3	18823.53	19076.36	18914.38	0.267	0.765
4	18593.80	18886.30	18698.90	0.010	0.793
5	**18522.20**	**18854.35**	**18641.55**	**0.010**	**0.812**
6	18530.52	18902.33	18664.12	0.366	0.761

Note. AIC = Akaike information criterion, BIC = Bayesian information criterion, SABIC = sample-size-adjusted Bayesian information criterion, BLRT = bootstrapped likelihood ratio test. The 5-profile model (in bold) was selected as the best solution.

sixth profile. Considering the fit statistics, parsimony, and interpretability, we selected the five-profile model as the best-fitting model.

Profile 1 ($n = 107$), labeled "Discreet Approachers" and comprising 10.18 % of participants, represented participants with the lowest levels of perceived descriptive norms ($M = 2.57$, $SE = 0.13$) and self-efficacy ($M = 2.32$, $SE = 0.22$) about using AI for health information seeking among the five profiles. However, their perceived injunctive norms ($M = 4.74$, $SE = 0.12$) and attitudes ($M = 5.46$, $SE = 0.10$) toward health information seeking using AI technology were much higher or more positive than in other groups. Moreover, compared with the other four groups, "Discreet Approachers" exhibited medium levels of trust in AI ($M = 3.89$, $SE = 0.12$), AI's perceived accuracy ($M = 3.96$, $SE = 0.11$), and technological anxiety ($M = 3.02$, $SE = 0.14$).

Profile 2 ($n = 388$), labeled "Casual Investigators" and comprising 36.92 % of participants, had the second-highest number of participants. They exhibited the most favorable attitudes toward seeking health information using AI technology ($M = 6.01$, $SE = 0.04$) and the highest levels of perceived descriptive norms ($M = 5.52$, $SE = 0.07$) and perceived injunctive norms ($M = 5.64$, $SE = 0.06$). At the same time, they exhibited the least technological anxiety ($M = 2.28$, $SE = 0.04$). They also reported moderately high levels of self-efficacy ($M = 5.20$, $SE = 0.08$), trust in AI ($M = 5.25$, $SE = 0.06$), and AI's perceived accuracy ($M = 5.26$, $SE = 0.07$).

Profile 3 ($n = 455$), labeled "Apprehensive Moderates," was the profile with the most participants (43.29 %). Of all five profiles, they exhibited the least favorable attitudes ($M = 4.81$, $SE = 0.06$) and moderately high levels of perceived descriptive norms ($M = 4.30$, $SE = 0.06$), perceived injunctive norms ($M = 4.38$, $SE = 0.06$), and medium level of self-efficacy ($M = 3.66$, $SE = 0.09$). For the channel-related indicators regarding health information seeking, they reported medium levels of trust in AI ($M = 4.18$, $SE = 0.06$), AI's perceived accuracy ($M = 4.22$, $SE = 0.05$), and technological anxiety ($M = 3.79$, $SE = 0.06$).

Profile 4 ($n = 26$), labeled "Apathetic Bystanders," was the profile with the fewest participants (2.47 %), who reported the lowest level of perceived injunctive norms ($M = 3.44$, $SE = 0.61$), along with low levels of perceived descriptive norms ($M = 2.96$, $SE = 0.41$) and technological anxiety ($M = 2.31$, $SE = 0.38$). By contrast, they exhibited favorable attitudes ($M = 5.93$, $SE = 0.32$) and moderate levels of self-efficacy ($M = 4.40$, $SE = 0.55$), trust in AI ($M = 4.53$, $SE = 0.54$), and AI's perceived accuracy ($M = 4.46$, $SE = 0.47$).

Last, Profile 5 ($n = 75$), labeled "Anxious Explorers" and comprising 7.14 % of participants, reported favorable attitudes ($M = 5.82$, $SE = 0.11$), perceived descriptive norms ($M = 5.48$, $SE = 0.13$), and perceived injunctive norms ($M = 5.59$, $SE = 0.13$). They also exhibited the highest levels of self-efficacy ($M = 5.54$, $SE = 0.19$), trust in AI ($M = 5.53$, $SE = 0.17$), AI's perceived accuracy ($M = 5.44$, $SE = 0.20$), and technological anxiety ($M = 5.24$, $SE = 0.16$).

Table S2 in the Supplementary Materials shows the estimated mean of the indicators and mean of intention for each profile. Fig. 1 and Fig. S2 in the Supplementary Materials visualize the differences regarding those sociopsychological factors among the five profiles.

5.2. Predictors of user profile

The results of hierarchical multiple logistic regressions for predicting user profiles appear in Table 2.

5.2.1. Profile 1: Discreet Approachers

Regarding demographic characteristics, individuals who were men ($B = -0.64$, odds ratio [OR] = 0.53, $p = .004$), were older ($B = 0.02$, $OR = 1.02$, $p = .03$), and had lower income levels ($B = -0.15$, $OR = 0.86$, $p < .001$) were more likely to be categorized as "Discreet Approachers."

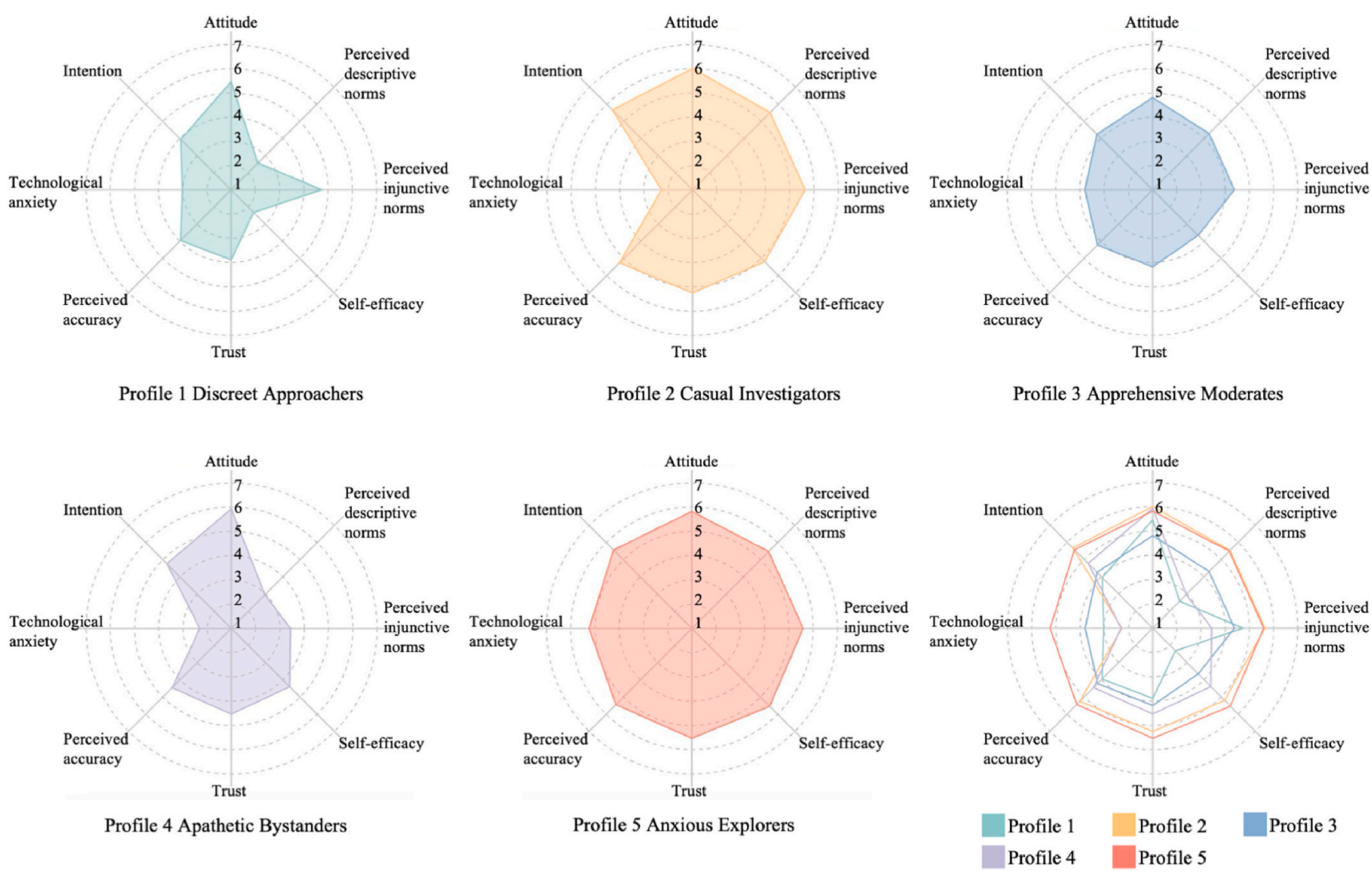

Fig. 1. Radar Plots for Profiles
Note. The dynamic plots could be retrieved from our OSF webpage: https://osf.io/cd93e/?view_only=908897a1f5644b3f8ab7f0dfa884095d

Table 2
Hierarchical multiple logistic regressions predicting profile membership (N = 1051).

Independent variables	Profile 1 Discreet Approachers (n = 107)		Profile 2 Casual Investigators (n = 388)		Profile 3 Apprehensive Moderates (n = 455)		Profile 4 Apathetic Bystanders (n = 26)		Profile 5 Anxious Explorers (n = 75)	
	B	*OR*	*B*	*OR*	*B*	*OR*	*B*	*OR*	*B*	*OR*
Block 1: Demographics										
Gender (men = 0)	−0.64[b]	0.53	−0.13	0.88	0.32[c]	1.38	−0.44	0.64	0.46	1.59
Age	0.02[c]	1.02	−0.01[b]	0.99	−0.01	0.99	−0.00	1.00	0.04[a]	1.04
Education	0.25	1.28	−0.06	0.94	−0.12	0.89	0.24	1.27	0.15	1.16
Income	−0.15[a]	0.86	0.08[b]	1.08	−0.02	0.98	−0.05	0.95	0.12[c]	1.13
Nagelkerke R^2		0.045		0.037		0.033		0.014		0.073
Block 2: Anthropocentrism										
Physical anthropomorphism	0.45[c]	1.57	0.63[a]	1.87	−1.00[a]	0.37	0.33	1.39	0.26	1.29
Psychological anthropomorphism	−0.20	0.82	−0.06	0.95	0.01	1.01	−0.70[b]	0.50	0.94[a]	2.55
Acceptance of routinized roles	0.28	1.32	0.48[a]	1.61	−0.41[a]	0.66	−0.29	0.75	−0.87[b]	0.42
Acceptance of interpretive roles	−0.20	0.82	0.26[b]	1.29	−0.13	0.88	−0.23	0.80	−0.25	0.78
Acceptance of personal roles	−0.26	0.78	−0.09	0.92	−0.30[b]	0.74	0.53	1.70	1.88[a]	6.56
Nagelkerke R^2		0.080		0.156		0.241		0.060		0.366

Note. For each regression model, the dependent variable is membership in the column profile versus membership in all other profiles (i.e., membership in column profile = 1, non-membership in column profile = 0). OR is odds ratio.
[a] $p < .001$.
[b] $p \leq .01$.
[c] $p \leq .05$.

However, level of education (B = 0.25, OR = 1.28, p = .09) did not significantly influence the likelihood of being associated with the profile. In terms of aspects of anthropocentrism, individuals with greater physical anthropomorphism (B = 0.45, OR = 1.57, p = .02) were more likely to be associated with the profile. However, psychological anthropomorphism (B = −0.20, OR = 0.82, p = .14) and the acceptance of routinized (B = 0.28, OR = 1.32, p = .10), interpretive (B = −0.20, OR = 0.82, p = .19), and personal roles (B = −0.26, OR = 0.78, p = .13) did not significantly influence the likelihood of being associated with the profile.

5.2.2. *Profile 2: Casual Investigators*

Concerning demographic characteristics, individuals who were younger (B = −0.01, OR = 0.99, p = .002) and had higher income levels (B = 0.08, OR = 1.08, p = .01) were more likely to be categorized as "Casual Investigators." Gender (B = −0.13, OR = 0.88, p = .35) and level of education (B = −0.06, OR = 0.94, p = .53) did not significantly influence the likelihood of being in the profile. In terms of anthropocentrism, individuals with greater perceptions of physical anthropomorphism (B = 0.63, OR = 1.87, $p < .001$) and a higher acceptance of AI in routinized (B = 0.48, OR = 1.61, $p < .001$) and interpretive roles (B = 0.26, OR = 1.29, p = .01) were more likely to be in the profile. Neither the perception of psychological anthropomorphism (B = −0.06, OR = 0.95, p = .53) nor the acceptance of personal roles (B = −0.09, OR = 0.92, p = .44) significantly influenced the likelihood of being in the profile.

5.2.3. *Profile 3: Apprehensive Moderates*

In terms of demographic characteristics, individuals who were women (B = 0.32, OR = 1.38, p = .02) were more likely to be categorized as "Apprehensive Moderates." Age (B = −0.01, OR = 0.99, p = .24), level of education (B = −0.12, OR = 0.89, p = .21), and income (B = −0.02, OR = 0.98, p = .50) did not significantly influence the likelihood of being associated with the profile. Regarding aspects of anthropocentrism, individuals with lower perceptions of physical anthropomorphism (B = −1.00, OR = 0.37, $p < .001$) and a lower acceptance of AI in routinized (B = −0.41, OR = 0.66, $p < .001$) and personal roles (B = −0.30, OR = 0.74, p = .01) were more likely to be categorized in the profile. Neither psychological anthropomorphism (B = 0.01, OR = 1.01, p = .91) nor acceptance of interpretive roles (B = −0.13, OR = 0.88, p = .23) significantly influenced the likelihood of being associated with the profile.

5.2.4. *Profile 4: Apathetic Bystanders*

Regarding demographic characteristics, neither gender (B = −0.44, OR = 0.64, p = .30), age (B = −0.00, OR = 1.00, p = .76), level of education (B = 0.24, OR = 1.27, p = .41), nor income (B = −0.05, OR = 0.95, p = .51) significantly influenced the likelihood of being in the "Apathetic Bystanders" profile. In terms of anthropocentrism, individuals with lower perceptions of psychological anthropomorphism (B = −0.70, OR = 0.50, p = .01) were more likely to be categorized in the profile. However, none of the other aspects of anthropocentrism—physical anthropomorphism (B = 0.33, OR = 1.39, p = .34), acceptance of routinized roles (B = −0.29, OR = 0.75, p = .37), interpretive roles (B = −0.23, OR = 0.80, p = .42), or personal roles (B = 0.53, OR = 1.70, p = .13)—significantly influenced the likelihood of being in the profile.

5.2.5. *Profile 5: Anxious Explorers*

Last, in terms of demographic characteristics, individuals who were older (B = 0.04, OR = 1.04, $p < .001$) and had a higher level of income (B = 0.12, OR = 1.13, p = .05) were more likely to be categorized in the profile labeled "Anxious Explorers." Gender (B = 0.46, OR = 1.59, p = .11) and level of education (B = 0.15, OR = 1.16, p = .44) did not significantly influence the likelihood of being in the profile. Regarding aspects of anthropocentrism, individuals with higher perceptions of psychological anthropomorphism (B = 0.94, OR = 2.55, $p < .001$), a lower level of acceptance of routinized roles (B = −0.87, OR = 0.42, p = .01), and a greater level of acceptance of personal roles (B = 1.88, OR = 6.56, $p < .001$) were more likely to be categorized in the profile. However, physical anthropomorphism (B = 0.26, OR = 1.29, p = .35) and acceptance of interpretive roles (B = −0.25, OR = 0.78, p = .33) did not significantly influence the likelihood of being associated with the profile.

6. Discussion

Although research on AI in communications has burgeoned in recent years, it remains unclear how sociopsychological factors and factors related to information carriers contribute to the underlying patterns of motivation that drive health information seeking using AI technology. In our study, guided by the PRISM and CMIS, we found that both sociopsychological antecedents of information seeking and factors related to information carriers are pivotal in constructing patterns of motivation that drive health information seeking behavior. This provides a foundational framework for group segmentation in this context, addressing a gap that remains unaddressed in previous research. Furthermore, our study demonstrates the advantages of LPA technique, which enables a systematic examination of how these socio-psychological and information carrier-related factors shape the patterns of motivation in health information seeking. The results of LPA segmented users into five distinct profiles, which we labeled “Discreet Approachers,” “Casual Investigators,” “Apprehensive Moderates,” “Apathetic Bystanders,” and “Anxious Explorers.” Each profile was associated with predictors regarding individual differences in demographic attributes and anthropocentrism. Those findings on group segmentation offer insights into designing communication strategies to assist individuals in adopting AI technology for health information seeking and to help individuals stay well-informed about the potential perils of using the technology. For instance, based on this groundwork, the findings can further inform strategies to optimize AI adoption in support of the United Nations’ Sustainable Development Goal of promoting good health and well-being (United Nations, 2024). The findings are also expected to inform the designing of AI-powered products for information seeking to suit users’ profiles and, in turn, meet their needs.

6.1. *Apprehensive Moderates*

Of the five profiles that emerged from the data, the largest was the “Apprehensive Moderates,” which was distinguished by medium levels of all sociopsychological antecedents of information seeking as well as factors related to information carriers. Those characteristics indicate that participants associated with the profile were motivated to seek health information using AI technology when necessary but did not fully trust AI’s recommendations. It is possible that such individuals may be more cautious about the information provided by AI and alert to the potential misinformation fabricated by it. Using logistic regression, we found that women were more likely than men to be “Apprehensive Moderates,” which is consistent with past findings showing that women held less favorable attitudes toward AI than men did (e.g., Grassini and Ree, 2023). Several aspects of anthropocentrism also indicated membership in the profile. In particular, participants who did not believe that AI should take on physical attributes of humans or did not accept them in routinized human roles (e.g., as accountants and bank tellers) were more likely to be “Apprehensive Moderates.”

In sum, the profile indicates that its users generally tend to deny AI’s human characteristics, view AI as a tool, and remain cautious about AI as well as its recommendations. Thus, the group may need little intervention in adopting AI for information seeking or staying alert to potential risks posed by such behavior. Regarding their preferences, the group may prefer AI products with clear instrumental value—for example, indications of its reliable, accurate working mechanisms (e.g., data sources and algorithms)— compared with AI products emphasizing human-AI interaction.

6.2. *Casual Investigators*

The second-largest profile was “Casual Investigators,” whose members were highly motivated to seek health information from AI, had high levels of trust in AI technology and its recommendations, and were comfortable as well as confident in engaging with the technology. As such, they seem ready to adopt AI for health information seeking, as indicated by their high value of intention (i.e., 5.67 out of 7.00). Nevertheless, they may also be easily subject to certain risks of such information seeking—for instance, compromising their privacy and being misled by misinformation—due to their high or even excessive trust in AI. Therefore, although the group may not need further encouragement to adopt AI technology, communication efforts could focus on enhancing their awareness of data privacy. Specifically, personal health data is a unique asset that could be susceptible to misuse, highlighting the need to raise awareness of privacy risks, such as data security breaches, when using AI for health information seeking (Y. J. Park, 2021; Y. J. Park and Jones-Jang, 2023). Among other results, participants who were younger and had higher level of income were more likely to be in the “Causal Investigators” profile, as were individuals who tended to attribute physical characteristics of humans to AI technology and accept AI technology in routinized and interpretive roles.

Those findings indicate that “Casual Investigators” prefer AI products designed with physical traits, including speaking, moving, and interacting with people, as well as with abilities to complete routinized, repetitive, and interpretive work. Such AI products can fulfill their needs and facilitate their health information seeking behavior.

6.3. *Discreet Approachers*

The profile of “Discreet Approachers” was unique due to its low levels of perceived descriptive norms and self-efficacy in seeking health information from AI despite being favorable to the behavior, perceiving approval from significant others, and feeling moderately comfortable using AI. Such participants also had medium levels of trust in AI and its perceived accuracy. Thus, communication efforts need to offer efficacy-related information to promote the adoption of AI in health information seeking, including how to effectively craft prompts for generative AI tools and distinguish the advantages of different AI tools in health information seeking. Although individuals’ self-efficacy in a given behavior largely depends on their past experience (Bandura, 1994) and is difficult to improve through messaging alone, such instructional messages specifically designed to improve self-efficacy could provide operational guidance for individuals to seek health information using AI technology.

The low level of perceived descriptive norms that we found for “Discreet Approachers” is also understandable, for individuals in the group are likely to interact with similar others who also resist seeking health information from AI. One approach to shaping their perceived descriptive norms may be to alter their reference group, including by shifting them from their close significant others to a broader group in their community or society at large, for such groups may adopt AI at far higher rates than their proximate social groups. However, communication efforts also need to improve the perceived relevance and importance of such broader reference groups to them in their decision-making. Those ends can be achieved, for example, by emphasizing their group identification with broader reference groups or increasing their involvement with them.

6.4. *Anxious Explorers*

Among the five profiles of users, “Anxious Explorers” were distinguished by their substantially higher level of technological anxiety as the only group with a value higher than 5 on a 7-point scale. However, such high anxiety did not impede their information seeking behavior, for they also reported a high level of behavioral intention (i.e., 5.57 out of 7); such a high level of intention could be explained by their high scores for all sociopsychological antecedents of information seeking as well as their high level of trust in AI. Our findings also indicated that participants who tended to attribute psychological human characteristics to AI were more likely to be labeled “Anxious Explorers.” Meanwhile, participants who were inclined to accept AI in personal roles but not in routinized ones were also more likely to be associated with the profile. In fact, psychological anthropomorphism and the acceptance of personal roles served as significant, positive predictors of membership in “Anxious Explorers” but not for any other profile.

Similar to “Causal Investigators,” “Anxious Explorers” do not require further encouragement to adopt AI for health information seeking. Instead, communication-oriented efforts should focus on informing them about potential risks associated with such behavior due to their high trust in AI. Moreover, messages need to convey knowledge about emerging technology and information on problem-solving skills (Clusmann et al., 2023), which may help to reduce their anxiety with technology. In terms of product design, emphasizing affective interactions between users and AI to align with the group's perceptions of AI may be beneficial. Added to that, designing an intuitive interface for AI products may help to reduce their anxiety when seeking health information from AI.

6.5. Apathetic Bystanders

The profile with the fewest participants was the "Apathetic Bystanders," who were least motivated to seek health information from AI. Although the group had favorable attitudes toward health information seeking using AI technology, they showed low levels of normative perceptions and technological anxiety but neutral evaluations of self-efficacy and factors related to information carriers regarding information seeking. Furthermore, participants who did not believe that AI technology has psychological attributes were more likely to be associated with the profile. Therefore, the group has significant room for improvement in terms of information seeking from AI. To address the sociopsychological antecedents and communicate the benefits of using AI technology for health information seeking, communication-oriented efforts need to shift their perceptions regarding the low social norms associated with the behavior and enhance their self-efficacy by offering clear, instrumental guidance. To accurately target their behavioral barriers—for example, specific behavioral beliefs impeding their information seeking behavior—further formative research is warranted.

Communication strategies need to cultivate a moderate level of trust in AI among members of the 'Apathetic Bystanders' profile. In addition, policies can regulate and enhance algorithmic transparency within AI systems, promoting the establishment of trustworthy AI and its sustainability (Y. J. Park, 2021; Y. J. Park and Jones-Jang, 2023). By addressing both sociopsychological and AI-related factors, as well as promoting tech-policy development, these efforts may improve individuals' motivation to adopt AI in their health information seeking. Moreover, though the profile had fewer users than the other four profiles, it could represent a large number of people if we generalize our findings to all 7.5 million citizens of Hong Kong. Promoting AI's adoption for health information seeking for this least-motivated group is expected to yield significant social benefits and impacts.

6.6. Limitations

Our findings have several limitations, largely due to stemming from one of the first studies conducted to map profiles of users of AI in health information seeking. First, to ensure consistency in understanding among participants, we provided a definition of *AI* and investigated their health information seeking using AI. While we aimed to maintain consistency by providing participants with a definition of AI before examining their health information-seeking behavior, discrepancies in their interpretations may still exist. Our study did not address the role of those differences in AI-based applications and tools. Building on our findings, future research should conduct more nuanced examinations of individuals' health information seeking behavior based on different AI products and models.

Second, future studies could explore other individual differences beyond demographic attributes and anthropocentrism in shaping the intention to use AI for information seeking. In fact, the features and capacities of technology serve as fundamental enablers and constraints in the communication process (Banks and de Graaf, 2020). That dynamic suggests that future research could investigate how a specific AI model's or application's inherent features, including its interface and (users' perceptions of) its algorithm, might shape users' health information-seeking behavior.

Third, Hong Kong's government currently seeks to develop the city as a high-tech hub, which will need a supportive environment for its citizens to adopt AI technology (Cremer, 2023). In that light, our findings may have limited generalizability to other social contexts where emerging technology is underdeveloped or less accepted by society in general. Therefore, future research could focus on replicating these findings in different social contexts with varying levels of acceptance of AI technology, to provide broader understandings.

7. Conclusion

In our study, we consulted the PRISM and CMIS frameworks to investigate the underlying patterns of motivation for engaging in health information seeking using AI technology. We segmented users into five heterogeneous groups based on their sociopsychological factors and factors related to the information carrier that consisted of the underlying patterns of motivation. Furthermore, we identified individual differences in demographic attributes and anthropocentrism as the predictors associated with the profile memberships. The findings advance the theoretical understanding of AI in health information seeking, offer theory-driven strategies to empower users to make informed decisions, and provide insights to optimize AI adoption. Furthermore, building on this foundation, the findings are expected to inform the development of tech-policy principles, ultimately promoting sustainable development in this domain.

CRediT authorship contribution statement

Jingyuan Shi: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaoyu Xia:** Writing – original draft, Visualization, Formal analysis, Conceptualization, Methodology. **Huijun Zhuang:** Writing – original draft, Formal analysis, Conceptualization, Methodology, Visualization. **Zixi Li:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Kun Xu:** Writing – review & editing, Data curation, Conceptualization.

Statement of ethical approval

The Research Ethics Committee of Hong Kong Baptist University (hkbu_rec@hkbu.edu.hk) has granted approval for the questionnaire and procedures associated with this study.

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Appendix A. Supplementary data

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Data availability

Data will be made available on request.

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