Motivations and Barriers to Using Generative AI for Health Information Seeking: A Behavioural Reasoning Theory Approach

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Abstract

Background: As generative artificial intelligence (GenAI) tools become more widespread, their application for health information seeking has also become increasingly prevalent. Understanding motivational drivers and barriers shaping user attitudes and intentions is essential for the responsible integration of these tools into healthcare. Yet, the traditional technology acceptance models do not capture efficiently the simultaneous effect of motivations and barriers regarding the adoption decision in healthcare framework.

Objective: This study aims to investigate the factors influencing the adoption of GenAI tools for health information seeking among young adults. In doing so, it simultaneously accounts for both motivational drivers and barriers.

Method: In this cross-sectional study, data were collected from 471 participants through a questionnaire developed based on relevant literature. The proposed hypotheses, structured according to the research model, were tested using structural equation modelling (SEM).

Results: The findings show that convenience and interaction have a significant positive relationship with the attitude towards using GenAI tools for health information seeking, whereas tradition has a significant negative relationship with the attitude. Contrary to expectations, innovativeness, perceived usefulness, AI hallucination and risk do not have a significant relationship with attitude.

Discussion: The findings of the study emphasize the importance of convenience and interactivity in the design of GenAI tools, while habituation to traditional methods is a barrier to adaptation. The findings are discussed in the context of the literature related to AI in health information seeking.

Implications: Implications for developers, policy makers and health information managers on the factors affecting young adults' adaptation to GenAI tools are provided. Furthermore, interventions to empower users are suggested based on the role of health education and AI experience in this process.

Keywords: Generative Artificial Intelligence, Information Seeking Behaviour, Healthcare, Decision Making, Technology Assessment, Behavioural Reasoning Theory

1. Introduction

Development of artificial intelligence (AI) technologies is gaining momentum, and new prospects in different areas are emerging, with the health industry being one of the most promising directions to introduce radical changes. In this respect, generative AI (GenAI) models, such as ChatGPT, are becoming increasingly important in the context of their ability to process vast quantities of data and generate responses that are very sensitive to human rationality when responding to challenging questions (Brown et al., 2020). By doing so, the technology has facilitated novel ways of collecting health-related information, thus holding an extraordinary potential to drastically change the access to health data and the management of individual health (Semigran et al., 2015). GenAI medical applications span across preventive care and diagnostic help and treatment strategy development and wellness guidance to create a new healthcare system for disease prevention and management (Topol, 2019).

People now depend on healthcare experts for information about health matters because digital and interactive materials have replaced paper-based literature and healthcare expert services (Aboueid et al., 2019). People now access health information like never before through this transformation, which provides immediate and accessible and complete answers to their health questions (Bickmore et al., 2018). GenAI technology presents an enormous potential to enhance the retrieval of health-related information. The system's ability to collect data from various sources enables better evidence-based choices and simultaneously enhances user health understanding (Miner et al., 2020). Secondly, its omnipresent availability has augmented the health-related information-access practices to be interactive and conversational as it is in face-to-face dialogue (Kuroiwa et al., 2023). Besides, GenAI has demonstrated potential in medical diagnosis, transcribing accounts of patients into graphical forms, therefore simplifying differential diagnosis and improving inferential reasoning in clinical practice (Hirosawa and Manabe, 2024).

Recent research reports indicate that there is high demand among the population to use GenAI to acquire information related to health. Findings of the different studies conducted show that a significant proportion of respondents have used or are willing to use such apps as ChatGPT to pose health-related questions, which include diverse topics and ranging from simple questions to a complex symptom assessment (Shahsavar & Mozaffari, 2023). There are certain inherent factors that have led to this adoption. The GenAI is valuable, especially considering that it produces quick and thorough responses to health queries without temporal and geographical restrictions (Bickmore et al., 2018). The interactive nature of these tools enables them to answer questions and provide explanations and context-based responses, which makes them accessible to users at different health literacy levels. The conversational nature of GenAI systems enables users to interact more easily which leads to better information retention and understanding. The case study by Burns et al. (2024) demonstrates how interactive system features in GenAI applications enhance complex health understanding according to their research on reproductive health literacy.

GenAI system implementation in healthcare faces various challenges that organizations must address. The health information sector faces particular security threats because GenAI systems create vulnerabilities in data privacy (Reddy et al., 2020). AI hallucination creates a major risk for health advice and personal evaluation practices because it generates inaccurate and false data (Hirosawa and Manabe, 2024). The main concerning aspect involves how AI systems affect traditional medical treatments while simultaneously weakening doctor-patient relationships (Topol, 2019). The practice of seeking medical information through doctor consultations and official health websites and educational materials creates a major obstacle to modern healthcare practices (Aboueid et al., 2019). People tend to trust expert medical advice more than AI-generated advice because traditional healthcare methods receive priority status thus requiring careful and informed use of these technologies (Gabriel et al., 2024).

There has been a recent emphasis in research on people’s attitudes and behaviours toward AI-based health tools. Shahsavar and Mozaffari (2023) showed that the willingness of users to use ChatGPT for self-diagnosis is strongly correlated with exaggerated beliefs about its performance and positive attitudes toward risks. However, according to Baldauf et al. (2020), while a vast number of users are more likely to use AI-based tools for health purposes, they would rather use these tools to complement, not replace, traditional healthcare providers.

Even as the generative power of AI advances, its uses in health information seeking, in principle, continue to be rather incompletely understood in terms of how people perceive and use these tools when they are adopted in the medical community (Asan et al., 2020). Technology is advancing at a pace unprecedented in human history, but adoption and use of such technology in individual fields, such as medicine, in relation, might not be advancing equally. This difference has created the urgent need for in-depth studies into factors deciding the adoption or rejection of GenAI in health contexts. Within this framework, health - related technologies have extensively used traditional technology adoption models such as Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Tao et al., 2024). However, such models may not fully capture the specific intricacies involved in the adoption of GenAI in health information-seeking contexts, particularly the conflicting "reasons for" and "reasons against" that simultaneously shape user decision-making.

The current study aims to fill a noted gap within existing research by adopting the Behavioural Reasoning Theory (BRT) as its chosen theoretical framework (Westaby, 2005). BRT provides a comprehensive perspective regarding technology acceptance, including both factors promoting adoption and opposing factors preventing it, and including attitudes and values. Application of this theoretical framework has been shown previously to be valuable when applied to AI-powered diagnosis systems (Li et al., 2024) and can directly relate to an investigation into health information seeking within GenAI adoption. Within this framework, the following hypotheses were formulated:

H1: There is a positive relationship between innovativeness and attitude towards using GenAI for health-seeking behaviour.

H2: There is a positive relationship between convenience and attitude towards using GenAI for health-seeking behaviour.

H3: There is a positive relationship between interactivity and attitude towards using GenAI for health-seeking behaviour.

H4: There is a positive relationship between perceived usefulness and attitude towards using GenAI for health-seeking behaviour.

H5: There is a negative relationship between AI hallucination and attitude towards using GenAI for health-seeking behaviour.

H6: There is a negative relationship between risk and attitude towards using GenAI for health-seeking behaviour.

H7: There is a negative relationship between tradition and attitude towards using GenAI for health-seeking behaviour.

H8: There is a positive relationship between attitude and intention to using GenAI for health-seeking behaviour.

The proposed study will provide valuable data to a wide variety of stakeholders within the healthcare industry by testing the hypotheses. Understanding how users feel about and their concerns for GenAI can help AI developers create systems that bring value to users and uphold trust in health information retrieval (He et al., 2019). The healthcare professionals can obtain patient behaviour insights about health information retrieval AI systems through this research, which will help them develop effective patient introduction methods and system adaptations (Blandford et al., 2020). The research results will enable policymakers to develop policies, which maintain an appropriate equilibrium between protection of people and other considerations (Walsh et al., 2020).

Further, a detailed analysis of factors that contribute to and inhibit the recall of health information post-GenAI will occur to ensure proper and balanced incorporation of such emerging technologies in health care. The goal of this initiative is to establish AI systems that would enhance access to health-related data and maximize health outcomes given the potential risks and ethical issues posed by using AI-based health information retrieval.

The remainder of this paper is organized as follows: Section 2 describes our methodology, Section 3 presents results, Section 4 discusses findings and implications, and Section 5 concludes.

2. Method

In this part of the study, the different phases of the undertaken research methodology (Figure 1) are described.

2.1 Measurements and data collection

The data of this cross-sectional study were collected through online (Microsoft Forms) questionnaire between February and April 2025. The participants consisted of young adults with prior experience using GenAI tools. Considering the significant use of these tools by younger people (Pew Research Centre, 2024; Statista, 2025), the study focused on individuals aged 18-25. Participants are from İzmir, the third largest city in Turkey. Additionally, to assess the role of education background in attitudes towards health information seeking in GenAI tools, participants enrolled in different programs (health-focused, engineering-focused, economics-focused, and humanities and social sciences-focused) were included in the study. Purposive sampling technique was employed in the study due to criteria such as AI experience, age group and educational background.

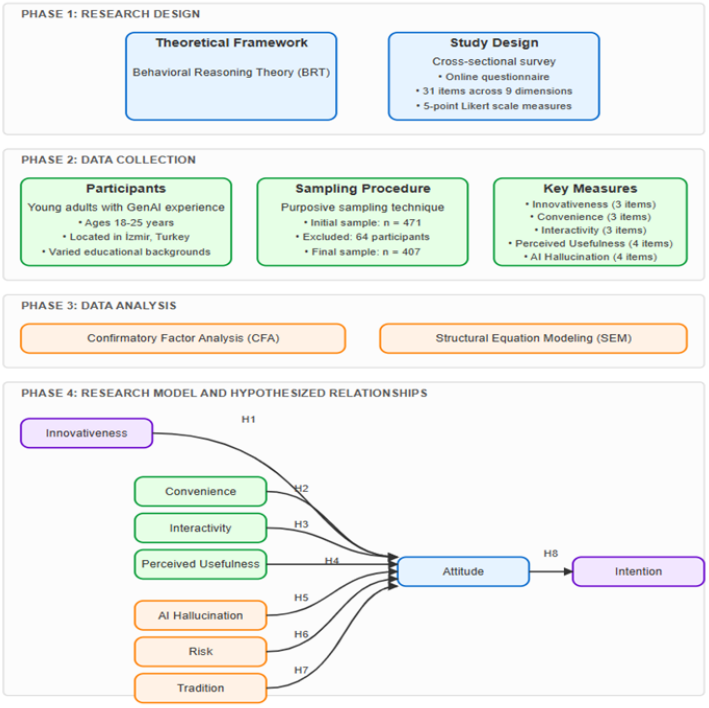

Figure 1. Research Methodology Phases (Source: Authors' own work)

To test the hypotheses developed in line with the research model, the questionnaire included 31 items representing 9 dimensions (Table 4 as appendix).

Each item was compiled from relevant studies in the literature and tailored to the context of the study. Additional items were also included to capture participants' knowledge and usage levels of AI, as well as their demographic characteristics. All responses were recorded on a five-point Likert scale (1: Strongly disagree to 5: Strongly agree).

The sample size of the current study is adequate considering the widely accepted method of determining sample size according to model complexity (Kline, 2015) or the 10 times rule for each parameter (Raykov and Marcoulides, 2000).

The questionnaire was shared with participants in classrooms and via e-mail. A total of 471 participants were included in the study. The responses of 48 individuals with no prior experience using GenAI, 1 individual who did not consent to the voluntary participation form, 15 individuals who failed the attention-check items, and 4 individuals over the age of 25 were excluded. The final sample size consisted of 403 participants. This study was approved by Izmir Bakircay University Research Ethics Committee (approval no. 1889) on December 11, 2024.

2.2 Data Analysis

SPSS 27 and AMOS 26 software programs were utilized for data analysis. Through SPSS, procedures such as data cleaning, and analyses related to reliability and validity were conducted to prepare the dataset for further statistical testing. Confirmatory factor analysis and model testing were carried out using AMOS. Tests for normality, factor analysis, descriptive statistical analyses, as well as reliability and validity assessments, were performed with the assistance of these programs.

Table 1 presents the reliability of the constructs, as measured by Cronbach's alpha, composite reliability (CR) and average variance extracted (AVE). Other than tradition, the Cronbach's alpha values are above 0.60 threshold (Hair et al., 2010). Similarly, except for the tradition, the CR and AVE values exceed the threshold levels (respectively 0.60 and 0.50) established in the literature (Fornell and Larcker, 1981). Despite the limitations in the reliability and validity values of the tradition, its inclusion in the analysis can be justified for several reasons. Hair et al. (2010) emphasize that flexibility may be exercised for constructs that are exploratory in nature, contain a limited number of items, or are newly developed or adapted to a different context for the first time. In this study, tradition was adapted from mobile banking to the context of GenAI tools and health information-seeking behaviour, and consisted of only two items. Furthermore, the confirmatory factor analysis (CFA) results indicated acceptable model fit indices, and the tradition functioned meaningfully within the conceptual model. Therefore, despite certain limitations, its inclusion was deemed appropriate.

Table 1. Reliability and Validity Indicators of the Proposed Model

Variable	Cronbach's Alpha	CR	AVE
Innovativeness	0.88	0.88	0.79
Convenience	0.85	0.85	0.66
Interactivity	0.73	0.75	0.51
Perceived Usefulness	0.77	0.77	0.62
AI Hallucination	0.85	0.86	0.61
Risk	0.88	0.88	0.79
Tradition	0.54	0.57	0.40
Attitude	0.85	0.85	0.66
Behavioural Intention	0.89	0.89	0.62

Source: Authors' own work

The dataset was evaluated for normality, multicollinearity, and common method bias. Skewness and kurtosis statistics were reviewed to determine if the data followed a normal distribution. The findings revealed that these values were within acceptable range, as outlined by Kline (2011). To assess multicollinearity, both correlation coefficients between variables and variance inflation factor (VIF) scores were examined. Since all values were within the acceptable range suggested by Hair et al. (2010), multicollinearity was not deemed an issue. Moreover, to assess potential common method bias, the Harman's single-factor test was employed (Podsakoff et al., 2003). The test showed that a single factor explained 32% of the total variance, which is below the critical cutoff. Hence, common method bias was not considered a problem in this study. Finally, according to the correlation values and AVE of each variable (Fornell and Larcker, 1981), discriminant validity was established for all constructs except for behavioural intention. The high correlation between behavioural intention and attitude can be explained by the well-established strong relationship between these two constructs in the literature.

3. Results

3.1 Descriptive Data Analysis

The participants of this study were 258 women (64%) and 139 men (34.5%). 6 participants (1.5%) stated that they did not want to specify their gender. The age of participants ranged between 18-25 years (M=20.83, SD=1.53). Table 2 presents the correlation values, means, and standard deviation scores of the variables included in the study.

Table 2. Descriptive Statistics

Variable	1	2	3	4	5	6	7	8	9
Innovativeness	-								
Convenience	0.17**	-							
Interactivity	0.18**	0.65**	-						
Per. Usefulness	0.09	0.63**	0.65**	-					
AI Hallucination	0.04	-0.32**	-0.25**	-0.29**	-				
Risk	0.01	-0.14**	-0.15**	-0.08	0.50**	-			
Tradition	0.02	-0.26**	-0.19**	-0.18**	0.16**	0.09	-		
Attitude	0.20**	0.65**	0.62**	0.54**	-0.32**	-0.18**	-0.22**	-	
Beh. Intention	0.17**	0.65**	0.62**	0.55**	-0.30**	-0.14**	-0.31**	0.82**	-
Mean	4.25	3.55	3.75	3.42	3.53	2.91	3.37	3.45	3.47
SD	0.59	0.79	0.65	0.78	0.75	0.99	0.81	0.79	0.76

*p < .05, ** p < .001; Per.: Perceived; Beh.: Behavioural

Source: Authors' own work

The most prominent finding among these statistics is that both attitude and intention to use AI tools for health information seeking are significantly related to motivations and barriers in the expected directions.

The study also examined whether education created any differences in the intention to use GenAI tools for seeking health information. A one-way ANOVA revealed that educational background had a significant effect on the intention to use GenAI tools for health information purposes, $F(3, 387) = 9.13$, $p < .001$. According to the Games-Howell post hoc test, participants enrolled in health-focused programs ($M = 3.73$, $SD = 0.61$) differed significantly from those in economics-focused ($M = 3.33$, $SD = 0.73$) and humanities and social sciences-focused programs ($M = 3.20$, $SD = 0.86$). However, no significant difference was observed between individuals in health-focused and engineering-focused programs, nor between those in economics-focused and humanities and social sciences-focused programs.

3.2 Structural Equation Modelling

The measurement model was tested with confirmatory factor analysis (CFA). Based on the results of the CFA, several items were eliminated to improve model fit, following a review of the modification indices and internal consistency measures. Results indicate that the model satisfied generally accepted fit criteria ($\chi2$ / df = 1.811; GFI= 0.918; CFI= 0.964; TLI= 0.955; RMSEA= 0.045). The factor loadings of the items are above 0.50. Additionally, the factor loadings and standardized estimate values for items were significant ($p < .001$). All the other details related to variables and measurement items are displayed in Table 3 as appendix.

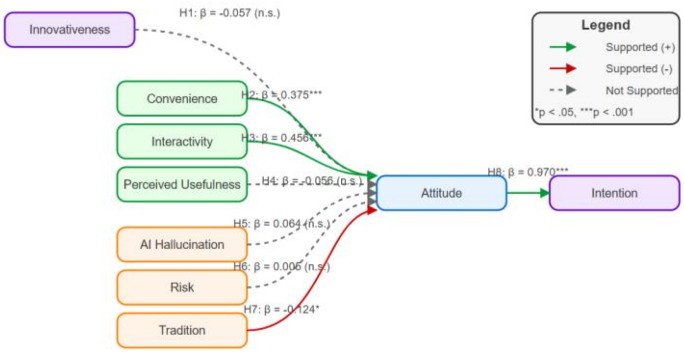

Figure 2. Structural Model (Source: Authors' own work)

Finally, the structural model was tested (Figure 2). According to the results the structural model showed a good fit ($\chi2$ / df = 1.771; GFI= 0.918; CFI= 0.965; TLI= 0.958; RMSEA= 0 .044). The results of the hypotheses are presented in Table 3.

Table 3. Summary of the findings

Hypotheses	Findings	Path Coefficient	SE
H_1: There is a positive relationship between innovativeness and attitude towards using GenAI for health-seeking behaviour.	Not supported	0.047	0.055
H_2: There is a positive relationship between convenience and attitude towards using GenAI for health-seeking behaviour.	Supported	0.367	0.091
H_3: There is a positive relationship between	Supported	0.463	0.169

interactivity and attitude towards using GenAI for health-seeking behaviour.			
H_4: There is a positive relationship between perceived usefulness and attitude towards using GenAI for health-seeking behaviour.	Not supported	-0.056	0.141
H_5: There is a negative relationship between AI hallucination and attitude towards using GenAI for health-seeking behaviour.	Not supported	-0.072	0.080
H_6: There is a negative relationship between risk and attitude towards using GenAI for health-seeking behaviour.	Not supported	0.002	0.043
H_7: There is a negative relationship between tradition and attitude towards using GenAI for health-seeking behaviour.	Supported	-0.128	0.068
H_8: There is a positive relationship between attitude and intention to using GenAI for health-seeking behaviour.	Supported	0.971	0.052

Source: Authors' own work

Within the context of using GenAI tools for seeking health information, the results indicate that among the motivational factors, convenience ($\beta = 0.367$, $p < 0.001$) and interactivity ($\beta = 0.463$, $p < 0.001$) have a significantly positive effect on attitudes toward using these tools. Regarding barriers to usage, only tradition ($\beta = -0.128$, $p < 0.05$) was found to have a significantly negative impact on attitudes toward the use of GenAI tools for health information purposes. Finally, attitudes toward using these tools for seeking health information were also found to have a significantly positive effect on behavioural intention ($\beta = 0.971$, $p < 0.001$). Therefore, hypotheses H2, H3, H7, and H8 are supported. On the other hand, innovativeness, perceived usefulness, risk and AI hallucination, were not found to have a significant effect on attitudes toward using GenAI tools for health information seeking. Based on these findings, H1, H4, H5, and H6 are not supported.

4. Discussion

Our structural equation modelling results reveal that convenience and interactivity serve as significant positive motivators for using GenAI in health information seeking, while tradition acts as a barrier. As opposed to our hypotheses, innovativeness, perceived usefulness, AI hallucination concerns, and perceived risk did not significantly affect the attitude toward using GenAI to seek health information.

Interactivity and convenience were the primary and secondary predictors, respectively, of positive attitudes towards GenAI use in health-related searching. These results support available literature that emphasizes conversationality as one of the major characteristics of GenAI compared to traditional non-dynamic sources of health information (Kuroiwa et al., 2023; Chervonski et al., 2024). The capacity to facilitate two-way question-answer communication appears to overcome a significant drawback as compared to health-related related websites and web-based search (search engines). This aspect allows users to request clarifications on the doubts they have, ask for explanations to suit their individual levels of knowledge, and receive results suitable to their individual needs (Lent et al., 2023; Toiv et al., 2024).

The convenience appeal emphasizes the constant presence of GenAI products, which does not impose any limitations to access (such as mandatory appointments, location, and time) (Bilal et al., 2024). The same argument is observed in Bickmore et al. (2018), where the authors reported accessibility as one of the determining factors regarding the usage of health-informing resources. This factor is particularly relevant to the population under study, the young adults, as the necessity to have instant access to information and to technology on their own terms has been observed by the Pew Research Centre (2024).

The close relationship between attitude and behavioural intention is the reason why BRT and technology adoption models (Westaby, 2005) have postulated foundation principles on the importance of positive attitudes as the best predictor of intention to use technology. Such a finding implies that attitude change initiatives might represent a potential key element that can support the adequate use of GenAI within the framework of searching information on health issues.

Conversely, the negative inverse correlation, which was determined between attitude and tradition, implies that loyalty to the existing sources of health information is a barrier to accepting GenAI. This finding validates the argument stated by Aboueid et al. (2019) that the element of trust in expert health opinion serves as a barrier to the use of new health information technology. Moreover, it supports the findings of Gabriel et al. (2024) who found that patients tend to choose the existing healthcare practice and regard the opinion of experts as better than the suggestions of AI.

The adoption of GenAI technology showed substantial educational variations between different academic fields. The results showed that health students demonstrated stronger intentions to adopt GenAI than economics and humanities students, but health students performed equally to engineering students. The results indicate that domain-specific knowledge affects how people accept new technologies. Health students demonstrate superior understanding of AI healthcare applications and show better comfort with medical terminology and professional value (Han et al., 2025; Tao et al., 2024; Fawaz et al., 2025). The research indicates that healthcare education should include AI literacy training which should emphasize both critical evaluation methods and ethical aspects (Cervantes et al., 2024; Simms, 2024). The development of specialized training programs will enable future professionals to teach patients about correct GenAI utilization (Lindbäck et al., 2025).

Outcomes that seem counterintuitive to expectations are also worthy of investigation. First, the absence of a strong relationship between attitudes and innovativeness is contradictory to our initial hypothesis, as well as the prevalent assumptions of technological adoption, which posit a central place for innovativeness (Sivanthanu, 2018). It is reasonable to assume the transition from the early adopter to the mainstream usage of GenAI tools by young adults is a reflection of a weaker effect of personal innovativeness. Furthermore, an open disposition to new experiences does not automatically imply the acceptance of AI tools for health-related uses, possibly because of increased stakes and perceived danger associated with the accuracy of health information (Bragazzi et al., 2025; Yau et al., 2024). Young adults would be cautious towards the application of health-focused AI versus other types of technological innovations regardless of their general innovativeness.

Notably surprising is the insignificant impact of perceived usefulness, especially given its central importance in accepted TAMs. The finding constitutes a possible challenge to much-held assumptions related to the TAM and raises the prospect that a number of plausible explanations are worthy of further inquiry. First, when dealing with the health information domain, factors of a more experiential type like interactivity and convenience can supersede utility considerations for young adults. Second, it is possible that the participants have not had a long-enough period to form robust perceptions of usefulness because of their limited past experiences with health-related applications.

Third, contrary to prominent concerns expressed in the literature (Hirosawa and Manabe, 2024), neither AI hallucination incidence nor the resultant risk concerns had a significant impact on attitudes. This unexpected result could reflect limited awareness of AI limitations among young adults or mean that the motivators (convenience and interactivity) outweigh the concerns in this group. This finding is contrary to an extensive body of literature recognizing these concerns as significant barriers to AI uptake in healthcare (May et al., 2024; Christensen et al., 2024). Several explanations are possible, starting with the limited awareness factor. Young adults lack complete understanding of AI hallucination risks in healthcare situations, which results in their failure to recognize potential dangers (Chervonski et al., 2024; Toiv et al., 2024). The phenomenon occurs because people tend to hold optimistic views about their abilities. Young adults demonstrate excessive confidence in their digital skills to detect false information and their ability to handle risks (Siu et al., 2024; Lent et al., 2023). The risk perception of participants varies based on context because they view AI health information retrieval as safer than using AI for medical diagnosis or treatment choices (Gezer & Armangil, 2025; Burns et al., 2024).

Health information managers need to bridge this knowledge gap through educational initiatives and system design improvements because users and experts have different risk perceptions about AI systems.

4.1 Implications for Health Information Management

Our research results generate important consequences for health information management practice.

Health information systems that implement GenAI need to focus on user-centred design principles, fast response times, and interactive features for follow-up questions because these elements matter more than technical accuracy and practicality for user acceptance.

The negative effects of traditional practices demonstrate the requirement to understand and solve cultural obstacles that prevent people from adopting new technologies. GenAI should function as an additional resource, which supports traditional healthcare sources instead of replacing them because it needs implementation methods that enhance their value as supplementary resources for professional medical consultation.

The educational differences between users indicate that specific approaches exist which match their needs require. Health information managers can create interfaces and educational materials that match the health literacy level and academic background of their users. The strong interest of health students toward these tools demonstrates their potential use in educational settings of health institutions.

Users lack complete understanding of how AI hallucinations can produce wrong health information because their attitudes do not show a statistical connection to these concerns. System designers together with health information managers must establish strong protection systems and warning messages and educational content because users will not request them directly.

4.2 Limitations

Several limitations should be considered when interpreting our findings. First, our sample consisted exclusively of young adults (18-25 years) with prior experience using GenAI tools from a single geographic region (İzmir, Turkey). This limits generalizability to broader populations, particularly older adults who may have different attitudes toward technology and healthcare, and to other cultural contexts where attitudes toward healthcare and technology may differ substantially. Future research should explicitly examine cross-generational and cross-cultural differences in GenAI adoption for health information seeking.

Second, the cross-sectional design prevents examination of how attitudes and adoption intentions might evolve over time, particularly as GenAI technologies rapidly advance. Longitudinal studies would provide greater insight into the stability of the identified relationships and how user perceptions shift as these technologies become more sophisticated and widely used.

Third, self-reported measures may introduce social desirability bias, particularly regarding health information seeking practices. Additionally, while our model explained a significant portion of variance in attitudes and intentions, other unmeasured factors likely influence GenAI adoption for health purposes.

Finally, the rapid evolution of GenAI capabilities means that user perceptions are likely shifting as these technologies improve. Our findings represent a snapshot of attitudes during the early mainstream adoption phase (early 2025) and may not reflect future perceptions as these technologies become more sophisticated and widely used.

4.3 Future Research Directions

Our research results suggest multiple promising directions for upcoming investigations. The research needs to study how GenAI adoption for health information retrieval affects different population groups who have different levels of technology experience and health understanding abilities.

Research on user preferences regarding health information types from GenAI systems versus traditional sources would generate detailed knowledge about user behaviour patterns. The research design should include qualitative methods to study how users decide between AI-based health information and human health information sources. The evaluation of GenAI health information accuracy together with user accuracy perceptions will help researchers identify discrepancies between system performance perception and actual system performance.

Research should analyse how social influences and normative elements impact GenAI adoption for health information retrieval to improve the BRT model used in this study. The study of peer recommendations and healthcare provider attitudes and media coverage effects on adoption intentions will help develop better health information management strategies.

The increasing use of GenAI in health information systems requires ongoing research to understand how these tools affect population-based health information retrieval and medical choice-making processes.

5. Conclusion

The research used BRT to identify which elements affect young adults to use GenAI tools for seeking health information. Our research examined both the driving factors and obstacles that influence young adults to seek health information through GenAI tools, which revealed the intricate process of their decision-making behaviour. The research findings show multiple complex relationships which support and contradict current theories about healthcare technology adoption.

The research results have significant effects on various groups who interact with this technology. Technology developers should focus on creating systems, which offer users easy access and interactive features because these elements proved to be the most influential factors for positive user perceptions. Healthcare organizations need to create strategies that demonstrate how GenAI functions as an addition to conventional medical services to reduce opposition from practitioners who follow established healthcare protocols. The development of new policies by regulators requires them to create systems, which reveal AI boundaries to users while funding programs that teach people about AI usage. Educational institutions should teach AI literacy through practical training that helps students develop their ability to evaluate AI systems effectively because students from different academic fields show different levels of interest in adopting AI technology.

This research provides evidence-based guidance for responsible GenAI integration, establishing a foundation for future research in this rapidly evolving field.

Acknowledgments section

n/a

Authors Contributions

Both authors equally worked throughout the sections of this study.

Ethical approval and informed consent statements

This study was approved by Izmir Bakircay University Research Ethics Committee (approval no. 1889) on December 11, 2024.

Declaration of conflicting interest

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Data availability

The data of this study is available upon request.

REFERENCES

1. Aboueid, S., Liu, R. H., Desta, B. N., Chaurasia, A., and Ebrahim, S. (2019). The use of artificially intelligent self-diagnosing digital platforms by the general public: Scoping review. JMIR Medical Informatics, 7(2):e13445.
2. Anayat, A., Hasan, K., and Bhutta, M. H. (2023). Behavioural intention to use ai-enabled content generators: Role of personality traits, performance, and process satisfaction. Technology in Society, 74:102241.
3. Asan, O., Bayrak, A. E., and Choudhury, A. (2020). Artificial intelligence and human trust in healthcare: Focus on clinicians. Journal of Medical Internet Research, 22(6):e15154.
4. Bagozzi, R. P. and Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. Journal of the Academy of Marketing Science, 40(1):8–34.
5. Baldauf, M., Fröhlich, P., and Przybylski, M. (2020). Trust me, I'm a doctor user perceptions of ai-driven apps for mobile health diagnosis. In Proceedings of the 19th International Conference on Mobile and Ubiquitous Multimedia, pages 167–178.
6. Bickmore, T. W., Trinh, H., Olafsson, S., O'Leary, T. K., Asadi, R., Rickles, N. M., and Cruz, R. (2018). Patient and consumer safety risks when using conversational assistants for medical information: An observational study of Siri, Alexa, and google assistant. Journal of Medical Internet Research, 20(9):e11510.
7. Bilal, M., Jamil, Y., Rana, D., and Shah, H. H. (2024). Enhancing awareness and self-diagnosis of obstructive sleep apnoea using ai-powered chatbots: The role of ChatGPT in revolutionizing healthcare. Annals of Biomedical Engineering, 52:901–907.
8. Blandford, A., Wesson, J., Amalberti, R., AlHazme, R., and Allwihan, R. (2020). Opportunities and challenges for telehealth within, and beyond, a pandemic. The Lancet Global Health, 8(11):e1364–e1365.
9. Bragazzi, N. and Garbarino, S. (2024). Assessing the accuracy of generative conversational artificial intelligence in debunking sleep health myths: mixed methods comparative study with expert analysis. Jmir Formative Research, 8, e55762. https://doi.org/10.2196/55762
10. Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. (2020). Language models are few-shot learners. arXiv preprint arXiv:2005.14165.
11. Burns, C., Bakaj, A., Bakaj, A., Hristidis, V., Deak, P., & Equils, O. (2024). Use of GenAI for improving health literacy in reproductive health: case study. Jmir Formative Research, 8, e59434. https://doi.org/10.2196/59434
12. Cervantes, J., Smith, B., Ramadoss, T., D'Amario, V., Shoja, M., & Rajput, V. (2024). Decoding medical educators' perceptions on generative artificial intelligence in medical education. Journal of Investigative Medicine, 72(7), 633-639. https://doi.org/10.1177/10815589241257215
13. Chervonski, E., Harish, K., Rockman, C., Sadek, M., Teter, K., Jacobowitz, G., … & Maldonado, T. (2024). Generative artificial intelligence chatbots may provide appropriate informational responses to common vascular surgery questions by patients. Vascular, 33(1), 229-237. https://doi.org/10.1177/17085381241240550
14. Choudhury, A. and Shamszare, H. (2023). Investigating the impact of user trust on the adoption and use of ChatGPT: survey analysis. Journal of Medical Internet Research, 25, e47184. https://doi.org/10.2196/47184
15. Christensen, J., Hansen, J. M., and Wilson, P. (2024). Understanding the role and impact of Generative Artificial Intelligence (AI) hallucination within consumers' tourism decision-making processes. Current Issues in Tourism, pages 1–16.
16. Fawaz, M., Malti, W., Alreshidi, S., & Kavuran, E. (2025). Exploring health sciences students' perspectives on using generative artificial

intelligence in higher education: a qualitative study. Nursing and Health Sciences, 27(1). https://doi.org/10.1111/nhs.70030

17. Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of marketing research, 18(1), 39-50.
18. Gabriel, R., Litake, O., Simpson, S., Burton, B., Waterman, R., & Macias, A. (2024). On the development and validation of large language model-based classifiers for identifying social determinants of health. Proceedings of the National Academy of Sciences, 121(39). https://doi.org/10.1073/pnas.2320716121
19. Gupta, A. and Arora, N. (2017). Understanding determinants and barriers of mobile shopping adoption using behavioral reasoning theory. Journal of Retailing and Consumer Services, 36:1–7.
20. Han, S., Kang, H., Gimber, P., & Lim, S. (2025). Nursing students' perceptions and use of generative artificial intelligence in nursing education. Nursing Reports, 15(2), 68. https://doi.org/10.3390/nursrep15020068
21. Hair, J.F., Black, J.W., Babin, B.J. and Anderson, E.R. (2010), Multivariate Data Analysis, (7th Edition), Pearson Education, New York.
22. He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., and Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. Nature Medicine, 25(1):30–36.
23. Hirosawa, T. and Manabe, T. (2024). The potential, limitations, and future of diagnostics enhanced by generative artificial intelligence. Diagnosis, 11(1):145–148.
24. Kline, R. B. (2011). Principles and practice of structural equation modelling. Third Edition, Guilford Publications.
25. Kuroiwa, T., Sarcon, A., Ibara, T., Yamada, E., Yamamoto, A., Tsukamoto, K., and Fujita, K. (2023). The potential of ChatGPT as a self-diagnostic tool in common orthopaedic diseases: Exploratory study. JMIR Medical Education, 9(1):e48962.
26. Lent, H., Ortner, V., Karmisholt, K., Wiegell, S., Nissen, C., Omland, S., … & Hædersdal, M. (2023). A chat about actinic keratosis: examining capabilities and user experience of ChatGPT as a digital health technology in dermato-oncology. Jeadv Clinical Practice, 3(1), 258-265. https://doi.org/10.1002/jvc2.263
27. Li, W., Wang, X., and Zhang, J. (2024). Determinants of artificial intelligence-assisted diagnostic system adoption intention: A behavioural reasoning theory perspective. Technology in Society, 76:102415.
28. Lindbäck, Y., Schröder, K., Engström, T., Valeskog, K., & Sonesson, S. (2025). Generative artificial intelligence in physiotherapy education: great potential amidst challenges- a qualitative interview study. BMC Medical Education, 25(1). https://doi.org/10.1186/s12909-025-07106-w
29. May, R., Krüger, J., and Leich, T. (2024). Sok: How artificial-intelligence incidents can jeopardize safety and security. In ACM International Conference Proceeding Series, pages 198– 212.
30. Miner, A. S., Laranjo, L., and Kocaballi, A. B. (2020). Chatbots in the fight against the covid-19 pandemic. NPJ Digital Medicine, 3(1):1–4.
31. Pew Research Centre (2024), https://www.pewresearch.org/short-reads/2024/03/26/americans-use-of-chatgpt-is-ticking-up-but-few-trust-its-election-information/
32. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research: a critical review of the literature and recommended remedies. Journal of applied psychology, 88(5), 879.
33. Raykov, T., & Marcoulides, G. A. (2012). A First Course in Structural Equation Modelling. First Edition, Routledge.
34. Reddy, S., Allan, S., Coghlan, S., and Cooper, P. (2020). A governance model for the application of ai in health care. Journal of the American Medical Informatics Association, 27(3):491–497.
35. Semigran, H. L., Linder, J. A., Gidengil, C., and Mehrotra, A. (2015). Evaluation of symptom checkers for self diagnosis and triage: audit study. BMJ, 351:h3480.
36. Shahsavar, Y. and Mozaffari, A. (2023). User intentions to use ChatGPT for self-diagnosis and health-related purposes: Cross-sectional survey study. JMIR Human Factors, 10:e48317.
37. Simms, R. (2024). Work with ChatGPT, not against. Nurse Educator, 49(3), 158-161. https://doi.org/10.1097/nne.0000000000001634
38. Sivanthanu, B. (2018). Adoption of internet of things (IoTs) based wearables for healthcare of older adults – a behavioural reasoning theory (BRT) approach. Journal of Enabling Technologies, 12(4):169–185.
39. Statista (2025), https://www.statista.com/statistics/1609022/france-ai-usage-among-age-groups-by-type/
40. Tao, W., Yang, J., & Qu, X. (2024). Utilization of, perceptions on, and intention to use ai chatbots among medical students in China: national cross-sectional study. Jmir Medical Education, 10, e57132-e57132. https://doi.org/10.2196/57132
41. Toiv, A., Saleh, Z., Ishak, A., Alsheik, E., Venkat, D., Nandi, N., … & Zuchelli, T. (2024). Digesting digital health: a study of appropriateness and

readability of ChatGPT-generated gastroenterological information. Clinical and Translational Gastroenterology, 15(11), e00765. https://doi.org/10.14309/ctg.0000000000000765

42. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine, 25(1):44–56.
43. Walsh, C. G., Chaudhry, B., Dua, T., Goodman, K. W., Kaplan, B., Kavuluru, R., Saria, S., and Zeng-Treitler, Q. (2020). Stigma, biomarkers, and algorithmic bias: recommendations for precision behavioural health with artificial intelligence. JAMIA Open, 3(1):9–15.
44. Westaby, J. D. (2005). Behavioural reasoning theory: Identifying new linkages underlying intentions and behaviour. Organizational Behaviour and Human Decision Processes, 98(2):97–120.
45. Yau, J., Saadat, S., Hsu, E., Murphy, L., Roh, J., Suchard, J., … & Langdorf, M. (2024). Accuracy of prospective assessments of 4 large language model chatbot responses to patient questions about emergency care: experimental comparative study. Journal of Medical Internet Research, 26, e60291. https://doi.org/10.2196/60291
46. Yim, D., Khuntia, J., Parameswaran, V., & Meyers, A. (2024). Preliminary evidence of the use of GenAI in health care clinical services: systematic narrative review. Jmir Medical Informatics, 12, e52073. https://doi.org/10.2196/52073

Appendix

Table 4. Variables, items, source, factor loadings

	Source	Factor Loadings
Values (Innovativeness)		
1. I like to experience new things.	Sivanthanu, 2018; Anayat et al., 2023	0.836
2. I am open to new experiences.		0.938
Convenience		
1. Using ChatGPT for health issues is convenient way of solving my problems.	Gupta and Arora, 2017	0.860
2. Using ChatGPT for health issues saves time and effort.		0.796
3. Using ChatGPT for health issues is easy way of managing them.		0.778
Interactivity		
1. ChatGPT allows easy conversations about health issues.	Anayat et al., 2023	0.790
2. ChatGPT is understanding and responsive about health issues.		0.725
3. It will be good to get vivid responses from ChatGPT about health issues.		0.610
Perceived Usefulness		
1. ChatGPT provides me with a comprehensive and wide range of information about my health issues.	Christensen et al., 2024	0.811
2. ChatGPT helps me to find the best recommendations on my health issues.		0.765
AI Hallucination		
1. ChatGPT can generate false information and present it as factual, leading to incorrect decisions or actions about health issues.	Christensen et al., 2024	0.847
2. ChatGPT can make up and create imaginary scenarios that have no basis in reality, leading to confusion and misinterpretation of data related to health issues.		0.836
3. ChatGPT can make erroneous predictions based on flawed or incomplete data, leading to incorrect assumptions and misguided health related decisions		0.808
4. ChatGPT can be vulnerable to hacking or manipulation, leading to the dissemination of false or misleading information about health issues.		0.609
Risk		
1. I fear that while using ChatGPT for health issues, my information will be misused.	Gupta and Arora, 2017; Anayat et al., 2023	0.884
2. I fear that while using ChatGPT for health issues, my personal information will be shared with other entities without my authorization.		0.896
Tradition		
1. Only doctors and health workers can offer personalized services to the customers.	Gupta and Arora, 2017	0.507
2. I feel satisfied visiting doctor for health issues as compared to newer ways.		0.742

Attitude		
1. Using ChatGPT to learn about health issues is a good idea.		0.705
2. I am interested in using ChatGPT to learn about health issues.	Christensen et al., 2024	0.853
3. I like using ChatGPT to learn about health issues.		0.878
Behavioural Intention		
1. I intend to use ChatGPT to learn about health issues.		0.878
2. I predict I will use ChatGPT for health issues in the future.		0.714
3. I plan to use ChatGPT to learn more about health issues.	Christensen et al., 2024	0.840
4. The use of ChatGPT could increase my likelihood of diagnosing health related problems.		0.730
5. It is very likely that I will recommend using ChatGPT to my friends and family for learning about health issues		0.755

Source: Authors' own work