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Development and psychometric validation of the artificial intelligence-assisted health- seeking behavior scale (AI-HSBS): A cross-sectional study

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Abstract

Background

While AI-driven tools are rapidly transforming how individuals seek medical advice, there is a lack of specialized instruments to measure this specific behavioral shift. This study addresses the gap in digital health literature by developing a multidimensional scale to evaluate AI-supported health-seeking patterns and their impact on modern patient dynamics.

Purpose

As health behaviors rapidly digitize, a gap remains in tools measuring actual behavioral patterns regarding artificial intelligence. To address this, the “Artificial Intelligence Health-Seeking Behavior Scale (AI-HSBS)” was developed as the first instrument in digital health literature to directly evaluate such behavior. This research aims to develop a measurement tool capable of evaluating the AI-supported health-seeking behaviors of individuals in Istanbul, Türkiye.

Methods

This cross-sectional study involved an online survey with individuals residing in Istanbul (N = 388). Structural validity was evaluated through EFA and CFA. Internal consistency and reliability were assessed using Cronbach’s Alpha coefficients. The scale exhibits a structure comprising 15 items and four dimensions: Perceived Benefit, Perceived Risk, Health Information Verification Behavior, and Usage Inclination.

Results

Significant positive correlations were identified between Perceived Benefit and all other dimensions. Furthermore, a significant positive correlation was observed between Health Information Verification Behavior and Usage Inclination. This study provides empirical evidence that individuals in Turkish society have developed a balanced, cautious, and adaptive behavioral profile.

Conclusions

While participants perceive AI-based applications as beneficial, they remain acutely aware of associated risks. Health managers must recognize potential shifts in the healthcare system and patient-physician relationships as AI usage grows. The results are essential for healthcare administrators to navigate the shifting dynamics of the patient-physician relationship and facilitate safe technological integration. This

scale empowers health institutions to align with the expectations of digitally engaged patients while enhancing their strategic health frameworks.

Introduction

The post-2010 era of rapid digitalization has fundamentally transformed information technologies, with the internet driving significant advancements in Artificial Intelligence (AI) [1, 2]. AI involves computational systems that emulate human cognitive functions, such as deep learning, reasoning, and sensory understanding [3]. Beyond its integration into defense and finance, AI is increasingly utilized in healthcare to enhance clinical efficiency and reduce operational costs [4]. According to the Technology Acceptance Model (TAM), individual adoption of these technologies is primarily driven by perceived usefulness and ease of use [5].

Research indicates that AI improves clinical processes, reduces care costs, and overcomes social barriers to healthcare access, particularly in developing nations [6, 7]. By bridging urban-rural disparities and contributing to social welfare, AI has reshaped how individuals manage their health [8, 9]. Consequently, health-seeking behavior—the actions taken to identify treatment pathways—has undergone a digital revolution [10, 11, 12]. Health-seeking behavior can sometimes arise from an active health crisis or out of curiosity [13]. This shift marks a transition from traditional sources, such as physicians and scientific literature, toward AI-supported digital environments [11, 14, 15].

Global trends highlight this transformation: in 2021, online health-seeking reached 80% in Finland and 77% in the Netherlands, while the 2023 EU average stood at 56% [16, 17]. Furthermore, nearly one in six adults worldwide now exhibits AI-based health-seeking behavior [18]. In Türkiye, the Ministry of Health's "Neyim Var" application (2021) exemplifies this trend, utilizing AI to direct patients to correct medical specialties and enhance system efficiency [19].

AI-driven health-seeking empowers individuals to become proactive participants in their care, offering a comfortable platform for discussing sensitive topics and managing chronic conditions or lifestyle changes [7, 18, 20, 21]. However, risks persist; AI may provide misleading information or fail to account for complex personal medical histories [7]. Such limitations can lead to risky behavioral patterns, including the decision to bypass professional medical consultation.

While existing literature focuses on the link between health literacy and general health-seeking behavior [15, 22, 23, 24], AI-driven health-seeking remains a nascent phenomenon. Despite emerging research into motivational patterns, a validated scale specifically designed to measure AI-assisted health searches is lacking [21]. This study addresses this gap by developing and validating a comprehensive scale to measure AI-supported health-seeking behaviors among individuals aged 18 and over in Türkiye. By establishing a theoretical foundation and assessing construct validity, this research provides a cornerstone for future models in this evolving field.

Methodology

Objective of the Research

The primary objective of this study is to develop a scale for "Artificial Intelligence Health-Seeking Behavior" and to establish its validity and reliability. The research is particularly significant as current literature lacks a multidimensional instrument that evaluates perceived benefits, risks, verification behaviors, and usage tendencies within a single integrated framework. By addressing this gap, the study aims to provide a robust methodology for future research in the field of healthcare within an increasingly digitalized world.

The English version of the developed scale is provided as a supplementary file (Supplementary File 1).

Population and Research Sample

The population of this study consists of individuals aged 18 and over living in Istanbul. According to TÜİK (2024) [25] data, the population of Istanbul is 15,701,602 as of 2025. In this study, which utilized a convenience sampling method, a sample size of 384 individuals was determined to be sufficient to represent this population within a 95% confidence interval and a 5% margin of error [26]. Regarding the required sample size for scale development, various perspectives exist within the literature. One prevailing view suggests that the sample size should be at least five to ten times the number of items in the scale [27]. Similarly, Bryman and Cramer [28] state that a participant count exceeding ten times the number of questions used in a scale development study is adequate. In this research, the scale consists of 18 items. Since 18x10 = 180, a minimum of 180 participants was required for the scope of this study. A total of 388 usable survey forms were obtained. Based on these scholarly benchmarks, it was concluded that the reached sample size is representative of the population and is statistically sufficient.

Statistical Methods Used in the Research

IBM SPSS Statistics 26.0 software was utilized for the data analysis. To determine the suitability of the data for normal distribution, skewness and kurtosis tests were performed. According to George and Mallery [29], values falling between + 2.0 and − 2.0 indicate that the data are normally distributed. Since the data used in this study met these criteria, the analysis incorporated descriptive statistical methods, correlation analysis, exploratory and confirmatory factor analysis, and independent samples t-tests. All data were analyzed at a 95% confidence level ($p < 0.05$).

Scale Development Process

The scale development process was guided by the framework proposed by DeVellis [30]. According to this model, the development stages are structured as follows:

- Clearly determining the construct to be measured,
- Generating an item pool,
- Determining the format of measurement,
- Reviewing the initial item pool based on expert opinions,
- Ensuring the inclusion of valid items,
- Administering the items to the designated sample,
- Evaluating the items (through various coefficients and analyses),
- Optimizing the scale length (finalizing the instrument).

Identification of the Measurement Construct

The dimensions were conceptualized based on similar studies in the existing literature. While the initial literature review [22, 15, 23, 24, 21] initially suggested a three-factor structure, this study adopted a four-dimensional approach to capture a more holistic and homogeneous representation of the construct. The dimensions are defined as follows:

Perceived Benefit Dimension

This factor aims to identify individuals' perceptions of the advantages associated with AI-driven health-seeking behavior. Higher scores indicate a higher level of perceived benefit.

Perceived Risk Dimension

This factor measures the perceived risks individuals associate with using AI tools for health searches. Higher scores reflect a higher level of perceived risk.

Health Information Verification Behavior Dimension

This factor assesses the extent to which individuals verify AI-generated health information through traditional sources (such as physicians or scientific literature). Higher scores indicate a stronger tendency toward verification.

Usage Inclination Dimension

This factor aims to determine individuals' tendencies and intentions to utilize AI tools for health-seeking purposes. Higher scores represent a higher inclination to use these technologies. A 5-point Likert-type scale was employed as the data collection instrument, with items scored from "1 = Strongly Disagree" to "5 = Strongly Agree" [31].

Item Pool

In this study, items related to AI-driven health-seeking behavior were identified by drawing upon national and international literature [22, 15, 23, 24, 21]. Due to the limited theoretical framework currently available in the literature, an inductive approach was preferred for generating the item pool [26]. Accordingly, an initial pool of 30 items was designed. These items were evaluated independently, and those expressing equivalent judgments or redundant meanings were removed. As a result, a draft scale consisting of 21 items was established.

Content Validity of the Scale

Content validity assesses whether an instrument's items adequately represent the targeted phenomenon [32]. While a group of five experts is often considered ideal, a Content Validity Index (CVI) of at least 0.75 is required when consulting eight or more reviewers [29]. For this study, the draft scale was evaluated by 12 experts (7 academics, 5 professionals) using the Davis technique. Experts rated items based on representativeness and necessity for revision. Following the evaluation, three items with CVI values below 0.80 were excluded. In the final 18-item version, CVI values ranged between 0.82 and 1.00, confirming robust content validity.

Pilot Study

Pilot Study
One of the most critical aspects of this stage is ensuring that the sample accurately represents the target population. It is asserted that a pilot study sample comprising 10% of the projected population size is generally sufficient [32]. Accordingly, the pilot study was conducted with 50 participants. During this process, Cronbach’s alpha coefficients were calculated for internal consistency, and preliminary exploratory factor analysis was performed.

Within the scope of the reliability analysis, item-total correlations were evaluated. Following this examination, items with a correlation coefficient below 0.40 were excluded from the scale. These excluded items are as follows:

- "When I have a health-related problem, one of the primary sources I consult is AI-supported applications."
- "AI-supported applications make it easier for me to make health-related decisions."
- "I believe that AI-supported applications can present health information in a selective and suggestive manner."

In the subsequent stage, exploratory factor analysis was carried out to assess the structural suitability of the scale. Finally, Cronbach's alpha coefficients were recalculated. As a result of the pilot application, a 15-item scale was established, consisting of the dimensions: "Perceived Benefit" (4 items), "Perceived

Risk" (3 items), "Health Information Verification Behavior" (3 items), and "Usage Inclination" (5 items) (Table 1).

Data Collection and Analysis

Data were collected via an online survey method between December 6 and December 25, 2025. Analysis and testing were conducted based on a total of 388 valid survey responses. The kurtosis value was found to be 0.873, and the skewness value was − 0.160. These results indicate that the data follow a normal distribution, as they fall within the recommended range of -2.0 to + 2.0 [27]. In the subsequent stage, validity and reliability analyses of the scale were performed, with all statistical evaluations based on a 95% confidence level.

Validity and Reliability Analyses

Factor analysis was employed to test the construct validity of the scale. Factor analysis is typically conducted in two distinct forms: exploratory and confirmatory [32]. The structural properties and item distributions of the Artificial Intelligence Health-Seeking Behavior Scale (AI-HSBS) are presented in Table 1.

Table 1
Artificial intelligence health-seeking behavior scale

Scale: 1. Strongly Disagree, 2. Disagree, 3. Neutral, 4. Agree, 5. Strongly Agree	**1**	**2**	**3**	**4**	**5**
Perceived Benefit					
1. Searching for health information through AI-supported applications is faster compared to traditional methods.					
2. It is easy for me to conduct health-related searches using AI-supported applications.					
3. I believe that I have the technical competence to use AI-supported applications.					
4. I have easy access to AI-supported applications.					
Perceived Risk					
6. I believe that AI-supported applications might make mistakes when I try to obtain health-related information.					
7. I am concerned about privacy and personal data security when conducting health searches through AI-supported applications.					
8. I have doubts regarding the up-to-dateness of the health information I obtain from AI-supported applications.					
Health Information Verification Behavior					
9. I cross-reference the health advice obtained from AI-supported applications with physician opinions and scientific sources.					
10. After searching for health information via AI-supported applications, I still consult my physician regarding this information.					
11.I scrutinize the recommendations provided by AI-supported applications through a critical lens.					
Usage Inclination					
5. I consider the health information from AI-supported applications to be sufficiently accurate and dependable.					
12. The information I obtain from AI-supported applications exerts an influence on my behaviors.					
13. I follow the advice provided by AI-supported applications regarding medication use.					
14. I engage with AI-supported health applications on a regular basis.					
15. I would recommend AI-supported health applications to those close to me.					

Results

The socio-demographic characteristics of the participants were examined using frequency analysis (%) as presented in Table 2.

Table 2
Socio-demographic characteristics of participants (n = 388)

Variables	Frequency (n)	Percentage (%)	Variables	Frequency (n)	Percentage (%)
Gender			**Marial Status**		
Female					
Male					
Chronic Disease Status			**Generation**		
Yes	64	16.5	Generation X	71	18.3
No	324	83.5	Generation Y	167	43.0
			Generation Z	150	38.7
Income Level (TRY)			**Educational Level**		
22,000–32,000	172	44.3	Primary School	6	1.5
32,001–42,000	33	8.5	High School	61	15.7
42,001–52,000	27	7.0	Associate Degree	90	23.2
52,001–62,000	33	8.5	Bachelor's Degree	169	43.6
62,001 and above	123	31.7	Postgraduate	62	16.0

Of the individuals participating in the study, 254 (65.5%) were female and 234 (60.3%) were single. In terms of generational distribution, 167 (43%) belonged to "Generation Y." Regarding educational background and economic status, 169 (43.6%) held a bachelor's degree, and 172 (44.3%) reported an income level between 22,000 and 32,000 TRY. Additionally, the vast majority of the participants, 324 (83.5%), did not have any chronic diseases.

Exploratory Factor Analysis

In this section, the findings of the validity and reliability analysis for the "Artificial Intelligence Health-Seeking Behavior Scale" are presented. Exploratory factor analysis (EFA) was performed to evaluate the construct validity of the scale. As a result of the analyses, the 15-item scale was structured under four dimensions (Table 3). As shown in Table 3, the minimum factor loading was determined to be 0.50. The Kaiser-Meyer-Olkin (KMO) value was found to be 0.836, and the Bartlett’s Test of Sphericity was

statistically significant ($p < 0.001$). The final version of the "Artificial Intelligence Health-Seeking Behavior Scale" consists of 15 items across four dimensions: perceived benefit, perceived risk, health information verification behavior, and usage inclination. The total variance explained by this structure is 65.446%.

Table 3
Results of the validity and reliability analysis of the scale

Factors / Items	Factor Loading	Variance Explained (%)	Cronbach's Alpha
Perceived Benefit		**1.443**	**0.844**
Item 1	0.680		
Item 2	0.786		
Item 3	0.780		
Item 4	0.816		
Perceived Risk			
Item 6	0.687	2.359	0.714
Item 7	0.822		
Item 8	0.845		
Health Information Verification Behavior			
Item 9	0.724	1.143	0.706
Item 10	0.905		
Item 11	0.507		
Usage Inclination			
Item 5	0.642	4.872	0.827
Item 12	0.654		
Item 13	0.867		
Item 14	0.751		
Item 15	0.697		
Note: **Model Fit Indices**			

KMO Measure of Sampling Adequacy 0.836 Total Variance Explained 65.446%

Bartlett’s Test of Sphericity (X^2) 2274 Total Cronbach’s Alpha 0.839

Degrees of Freedom (df) 105 Significance (p) $p < 0.001$

Confirmatory Factor Analysis

Confirmatory Factor Analysis was performed to validate the structure identified in the EFA. All standardized factor loadings exceeded the threshold value of 0.40. As shown in Table 3, the scale demonstrated high internal consistency, with Cronbach’s alpha (α) coefficients of 0.844 for "Perceived Benefit," 0.714 for "Perceived Risk," 0.706 for "Health Information Verification Behavior," and 0.827 for "Usage Inclination." The overall scale reliability was 0.839, indicating that the instrument and its sub-dimensions are highly reliable for assessing AI-driven health-seeking behaviors.

In this stage, CFA was applied, and the results are presented in Fig. 1. The ranges of fit indices and the obtained findings to determine the suitability of the CFA model are shared in Table 4.

Note

F1: Perceived Benefit; **F2**: Perceived Risk; **F3**: Health Information Verification Behavior; **F4**: Usage Inclination. **s1-s15**: Observed scale items; **e1-e15**: Measurement error terms. All path coefficients are statistically significant at the $p < .001$ level.

Table 4
Model fit indices of the research

Fit Indices	Acceptable Fit Criteria	Good/Perfect Fit Criteria	Obtained Indices	Result
X^2 /df	≤ 5	≤ 3	3.387	Acceptable
GFI	0.85 ≤ GFI < 0.90	0.90 ≤ GFI ≤ 1	0.915	Good Fit
AGFI	0.85 ≤ AGFI < 0.90	0.90 ≤ GFI ≤ 1	0.876	Acceptable
NFI	0.90 ≤ NFI < 0.95	0.95 ≤ NFI	0.903	Acceptable
IFI	0.90 ≤ IFI < 0.95	0.95 ≤ IFI	0.916	Acceptable
NNFI (TLI)	0.90 ≤ NNFI < 0.95	0.95 ≤ NNFI	0.902	Acceptable
CFI	0.90 ≤ CFI < 0.95	0.95 ≤ CFI	0.911	Acceptable
RMSEA	0.05 < RMSEA < 0.08	0.05 ≥ RMSEA	0.069	Acceptable
SRMR	0.05 ≤ SRMR ≤ 0.08	SRMR < 0.05	0.041	Good Fit
RMR	0.05 ≤ RMR ≤ 0.08	0.05 < RMR	0.065	Acceptable

As a result of the confirmatory factor analysis (CFA) conducted for the 15-item and four-dimensional Artificial Intelligence Health-Seeking Behavior Scale, it was determined that the factor loadings of all items exceeded the 0.40 threshold. The model fit indices were found to demonstrate a good fit (Table 4). The specific CFA results for the scale are summarized as follows (Table 5). The standardized factor loadings of all items in the scale are at an acceptable level. The standardized loading values for all items are sufficient. Covariance paths were established between the error terms e3–e4 and e12–e13 within the model to improve fit. With an SRMR value of 0.041, the error level is within acceptable and favorable limits. No low factor loadings (< 0.40) necessitating item elimination were observed. The detailed CFA results identified within the scope of the research are presented in Table 5.

Table 5
CFA results for the AI health-seeking behavior scale

Factors	Items	(β)	Unstandardized Estimates (B)	S.E.	t-value (C.R.)	P	AVE	CR
Perceived Benefit	**I1**	0.799	1.000	-	12.75	***	**0.570**	**0.837**
	I2	0.912	1.150	0.064	18.08	***		
	I3	0.601	0.759	0.063	11.96	***		
	I4	0.668	0.771	0.057	13,54	***		
Perceived Risk	**I6**	0.612	1.000	-	8.04	***	**0.502**	**0.720**
	I7	0.712	1.276	0.141	9.06	***		
	I8	0.712	1.130	0.125	9.06	***		
Health Information Verification Behavior	**I9**	0.778	1.000	-	9.24	***	**0.506**	**0.701**
	I10	0.598	0.814	0.093	8.76	***		
	I11	0.534	0.578	0.071	8.15	***		
Usage Inclination	**I5**	0.691	1.000	-	11.12	***	**0.504**	**0.821**
	I12	0.561	0.926	0.094	9.83	***		
	I13	0.579	0.936	0.092	10.13	***		
	I14	0.806	1.383	0.102	13.49	***		
	I15	0.801	1.403	0.104	13.43	***		

Note. Standardized regression weights are shown. *** $p < .001$

The convergent validity of the measurement instrument was examined within the scope of the validity and reliability analyses. In this context, standardized factor loadings obtained from the Confirmatory Factor Analysis (CFA) are expected to be at least 0.50. The findings demonstrate that these loadings range from 0.534 to 0.912. Accordingly, it is evaluated that the developed scale fulfills the requirements for convergent validity. Other criteria used to assess convergent validity, namely Average Variance Extracted (AVE) and Composite Reliability (CR), were also calculated. The acceptable threshold values are expected to be ≥ 0.50 for AVE and ≥ 0.70 for CR [30, 31]. Following the analysis, the AVE and CR values for all sub-dimensions were found to exceed the aforementioned thresholds. Based on these findings, it was determined that the scale possesses robust convergent validity (Table 5).

Regression coefficients indicate the extent to which observed variables explain the latent variables, representing the factor loadings. In the conducted analysis, the p-values obtained for each pairwise relationship were found to be below 0.001, indicating that the factor loadings are statistically significant.

Significant p-values serve as evidence that the items are correctly loaded onto their respective factors. Furthermore, the fact that standardized regression coefficients exceed 0.50 demonstrates a high level of predictability of the latent variables by the observed variables, confirming the strength of each item's factor loading (Table 5). These results collectively support the fit and validity of the structural model.

Correlations Between Variables

The results of the correlation analysis are presented in Table 6.

Table 6
Correlation matrix between scale dimensions

Dimensions	**1**	**2**	**3**	**4**
1. Perceived Benefit	1	.217**	.356**	.516**
2. Perceived Risk	.217**	1	.372**	.056
3. Health Information Verification Behavior	.356**	,.72**	1	.276**
4. Usage Inclination	.516**	.056	.276**	1
Note. ** p < 0.01.				

As presented in Table 6, the correlations between factors were examined to assess the collective applicability of the scale's dimensions. Pearson correlation analysis was conducted to investigate the relationships among the research variables. According to the analysis results, a low-level, statistically significant positive relationship was found between *Perceived Benefit* and *Perceived Risk* (r = .217, p < .01). This finding indicates that individuals who perceive AI-supported applications as more beneficial are also more cognizant of the potential risks associated with these applications.

A moderate positive relationship was identified between *Perceived Benefit* and *Health Information Verification Behavior* (r = .356, p < .01). Similarly, a moderate positive correlation was found between *Perceived Benefit* and *Usage Inclination* (r = .516, p < .01). Furthermore, a moderate positive relationship was observed between *Perceived Risk* and *Health Information Verification Behavior* (r = .372, p < .01). In contrast, no statistically significant relationship was detected between *Perceived Risk* and *Usage*

Inclination (r = .056, p > .05). Finally, a low-to-moderate positive correlation was found between *Health Information Verification Behavior* and *Usage Inclination* (r = .276, p < .01). In terms of construct validity, these results suggest that while the dimensions are interrelated (convergent validity), they also measure distinct concepts (discriminant validity), confirming the multidimensional structure of the scale.

Difference Analyses

The comparison of AI-HSBS scores and its sub-dimensions according to the descriptive characteristics of the participants is presented in Table 7.

Table 7

Comparison of AI health-seeking behavior scale scores according to descriptive characteristics

Demographic Variables	n	$\bar{x}$±sd	F/t		Demographic Variables	n	$\bar{x}$±sd	F/t	
Gender					**Marital Status**				
Female	254	3.18 ± 0.65	5.133	**0.024**	Married	154	3.08 ± 0.71	0.029	**0.004**
Male	134	3.25 ± 0.82			Single	234	3.29 ± 0.70		
Chronic Disease					**Generation**				
Yes	64	3.05 ± 0.68	0.001	0.060	Gen X[1]	71	2.86 ± 0.67	10.572	**0.000** 3 > 1
No	324	3.23 ± 0.71			Gen Y[2]	167	3.28 ± 0.75		2 > 1
					Gen Z[3]	150	3.29 ± 0.64		
Income Level					**Education level**				
22.000-32.000[1]	172	3.24 ± 0.74	0.548	0.740	Primary School [1]	6	2.93 ± 1.10	1.052	0.380
32.001-42.000[2]	33	3.24 ± 0.67			High School$_2$	61	3.06 ± 0.78		
42.001-52.000[3]	27	3.05 ± 0.72			Associate Degree[3]	90	3.21 ± 0.78		
52.001-62.000[4]	33	3.09 ± 0.62			Bachelor's Degree[4]	169	3.24 ± 0.65		
62.001 and above[5]	123	3.17 ± 0.62			Graduate Degree[5]	62	3.26 ± 0.65		
Note. * $p < 0.05$									

Statistically significant differences were identified using Independent Samples t-test and One-Way ANOVA. Post-hoc comparisons were performed using the Tukey HSD test.

As shown in Table 7, several differences were observed when the AI health-seeking behavior scores of the participants were compared according to their demographic characteristics. Regarding gender, the mean score of male participants (3.25 ± 0.82) was found to be statistically significantly higher than that of females (3.18 ± 0.65; t = 5.133, p = 0.024). A significant difference was also identified based on marital status (t = 0.029, p = 0.004), where single participants (3.29 ± 0.70) scored higher than married participants (3.08 ± 0.71).

The analysis according to generation revealed a significant difference (F = 10.572, p < 0.001). The AI health-seeking behavior scores of Gen Y (3.28 ± 0.75) and Gen Z (3.29 ± 0.64) individuals were significantly higher than those of Gen X (2.86 ± 0.67). In contrast, no significant differences were found regarding income level (F = 0.548, p = 0.740) or education level (F = 1.052, p = 0.380). Although a slight increase in scores was observed as income and education levels rose, these differences were not statistically significant. Similarly, no significant difference was observed in terms of chronic disease status (F = 0.001, p = 0.060). While the mean scores of participants without chronic diseases (3.23 ± 0.71) were slightly higher than those with chronic diseases (3.05 ± 0.68), this difference did not reach statistical significance.

Discussion

This study developed the Artificial Intelligence Health-Seeking Behavior Scale (AI-HSBS), a 15-item instrument designed to evaluate AI-supported health-seeking through a multidimensional lens. While existing literature predominantly examines "attitudes" [33, 34, 35, 36], this scale addresses a notable gap by directly focusing on "behavior." Our findings suggest that AI-HSBS is a holistic structure encompassing both cognitive and behavioral processes, providing insights into how individuals navigate health decisions in the digital age.

The identified four-factor structure—Perceived Benefit, Perceived Risk, Health Information Verification, and Usage Inclination—may represent a rational filtering process. Users tend to perceive AI as a facilitator for rapid information access (Benefit) but remain conscious of its inherent insecurities (Risk). Notably, information is not accepted unconditionally; users exhibit a strong tendency to cross-reference AI outputs with traditional medical authorities (Verification).

While conceptually aligned with the Technology Acceptance Model (TAM), the AI-HSBS seeks to extend beyond Davis's [26] focus on perceived usefulness and intention. In the high-stakes context of health, the inclusion of "risk" and "verification" factors aims to address the limitations of traditional models noted in previous research [37, 38]. Furthermore, the scale reflects the possibility that traditional internet searching is evolving from simple data collection into a more interactive and interrogative process [17, 39, 40].

CFA results confirmed excellent fit indices (> 0.90) and robust convergent validity (AVE > 0.70). The high internal consistency (0.839) supports the potential for the instrument to yield consistent results across different samples. Demographically, our sample—primarily healthy, highly educated Gen Y and Gen Z

women—possesses significant digital capital. Literature suggests these groups are naturally more active in digital health-seeking and more likely to consult healthcare professionals [41, 42]. Interestingly, since 83.5% of participants lacked chronic illnesses, their AI use appears more preventative or exploratory than condition-management oriented [43].

A key finding is the "cognitive balancing mechanism": as perceived benefit increases, so does the inclination to use AI, yet this is accompanied by an increased need for verification. Remarkably, in this specific sample, perceived risk does not directly inhibit usage inclination. Instead of abandonment, Turkish users appear to adopt a cautious, strategic approach, managing risk through comparative analysis. This discriminant validity is further confirmed by the low-to-moderate correlations ($r < 0.70$) between dimensions.

Conclusion

Rather than merely evaluating health-seeking behaviors via artificial intelligence based on frequency of use, this scale provides a perspective that measures how cognitive processes shape such behavior. It enables the assessment of the extent to which individuals perceive AI-generated health information as beneficial, their awareness of potential inaccuracies, their ability to cross-verify this information with traditional sources, and their overall usage inclinations. Thus, it demonstrates the complexity of the construct through a holistic lens. Within the context of health management, identifying how individuals maintain a balance between the concepts of benefit and risk while making health-related decisions offers valuable contributions to the development of health policies.

Practice Implications

Advancements in artificial intelligence have the potential to catalyze a fundamental transformation in the traditional patient-physician relationship. By recognizing that patients feel a necessity to verify AI-generated information, physicians can position artificial intelligence not as a competitor that disrupts information asymmetry, but as a resource capable of improving health outcomes. Furthermore, the willingness of participants to recommend AI to their social circles—despite perceived risks—points to a process of normalization of artificial intelligence within Turkish society. Consequently, given the ongoing global demographic shifts, this peer-to-peer dissemination should not be overlooked when designing health policy programs.

Limitations and Future Research

This study has several limitations that provide a roadmap for future inquiries. First, since the sample consists primarily of young and highly educated individuals residing in a specific urban context (Istanbul), the scale's applicability to digital immigrants, those with lower digital literacy, or diverse socioeconomic groups remains to be tested. Future research should target older populations and cross-cultural samples to help aging societies develop inclusive strategic health policies.

Additionally, the cross-sectional design of the study captures a current snapshot but does not allow for tracking longitudinal changes or causal relationships against rapid technological shifts over time. Since the data were collected through an online survey, a potential selection bias may exist, as individuals already comfortable with digital tools are more likely to participate. > Furthermore, while the scale measures self-reported behaviors which may be subject to social desirability bias, future studies could incorporate physician perspectives or objective usage logs to triangulate how AI-driven information is verified in clinical settings. Finally, testing the scale specifically on individuals with chronic illnesses and those in emergency medical situations will be crucial to understanding how AI-supported health-seeking evolves in more high-stakes medical contexts.

Declarations

Ethical Considerations: Ethical approval for this study was obtained from the Istanbul Yeni Yuzyil University Ethics Committee for Science, Social Sciences, and Non-Interventional Health Sciences Research (Date: 06.11.2025, Meeting No: 2025/11-1683). The procedures used in this study adhere to the tenets of the Declaration of Helsinki. Informed consent was obtained from all participants prior to their engagement with the survey. It was explicitly stated to participants that involvement was strictly voluntary and that all data would remain confidential.

Consent for Publication:

Not applicable.

Competing Interests:

The author declares that she has no competing interests.

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Author Contribution

MA , conceived the study, drafted the introduction and discussion sections, and conducted the data collection process. MA, performed the final proofreading of the manuscript and serves as the corresponding author. SŞ, developed the methodology, designed the "Artificial Intelligence Health-Seeking Behavior Scale (AI-HSBS)", and performed the statistical analyses, including EFA and CFA. SŞ also contributed significantly to the data collection and the interpretation of the findings. All authors read and approved the final manuscript.

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Data Availability

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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Figures

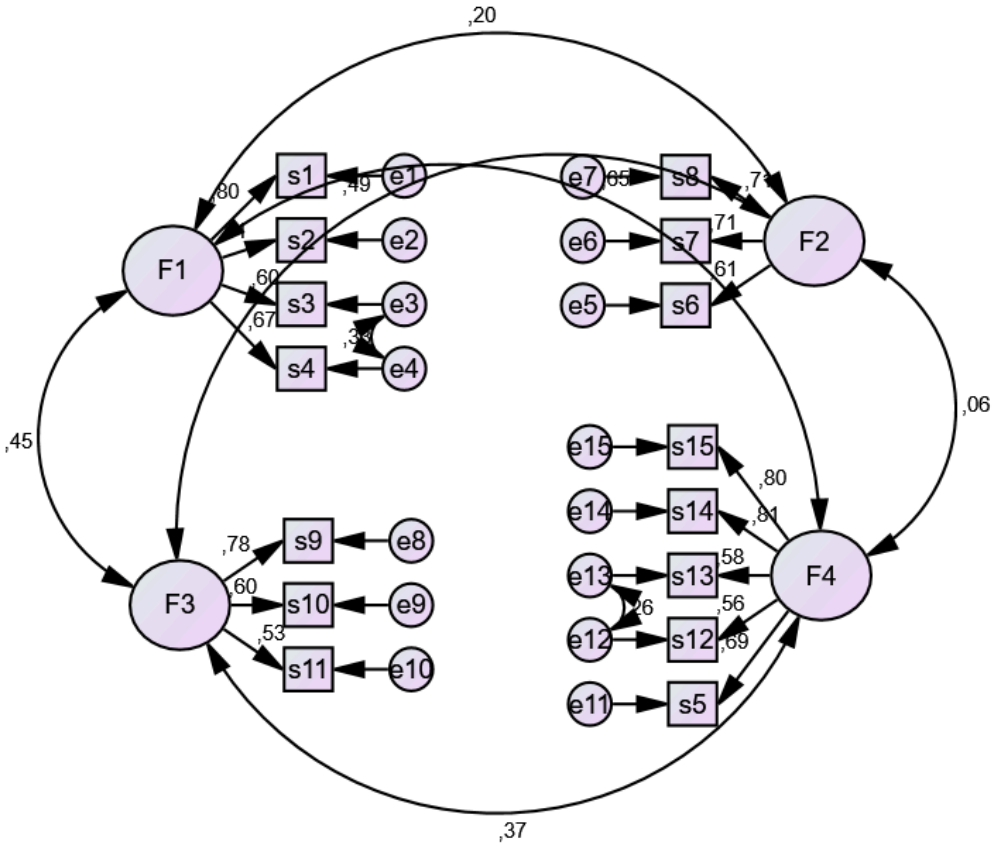


Figure 1

AMOS path diagram for the AI health-seeking behavior scale

Note. F1: Perceived Benefit; **F2:** Perceived Risk; **F3:** Health Information Verification Behavior; **F4:** Usage Inclination. **s1-s15:**Observed scale items; **e1-e15:** Measurement error terms. All path coefficients are statistically significant at the $p < .001$ level.

Supplementary Files

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