PeerJ Computer Science

Artificial intelligence-supported health counseling scale (AI-HCS): a reliability and validity study

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ABSTRACT

Background: This study aims to develop a valid and reliable scale for assessing individuals' attitudes towards, perceptions of, and tendencies to engage in artificial intelligence-supported health counseling (AI-HC) and to examine its psychometric properties.

Methods: The research was conducted using a methodological design with a two-stage data collection process. The initial item pool consisted of 55 items, which was reduced to 32 items based on expert opinions. In the first stage, exploratory factor analysis (EFA) was performed with 592 participants, and in the second stage, confirmatory factor analysis (CFA) was conducted with 663 participants. Composite reliability (CR), average variance extracted (AVE), and the Fornell–Larcker criterion were calculated. Internal consistency was assessed using Cronbach's Alpha and McDonald's Omega coefficients. Data were analyzed using SPSS 26.0 and AMOS 24.0.

Results: In both the EFA and CFA datasets, the majority of participants were female and aged between 18–24 years. Most were university graduates, and "doctor" was the most frequently preferred source of health information. Participants' knowledge levels regarding artificial intelligence technologies in health were generally reported as "low" or "moderate." The socio-demographic distributions of both datasets were largely similar. EFA yielded a four-factor, 24-item structure (Usage and Trust, Privacy Perception, Supportiveness Perception, and Medical Competence). The Kaiser–Meyer–Olkin (KMO) value was 0.955, and the total variance explained was 66.01%. In CFA, fit indices ($\chi^2/df = 2.957$, goodness of fit index (GFI) = 0.918, adjusted goodness of fit index (AGFI) = 0.900, comparative fit index (CFI) = 0.945, normalised fit index (NFI) = 0.938, Tucker–Lewis index (TLI) = 0.919, root mean square error of approximation (RMSEA) = 0.054, root mean square residual (RMR) = 0.045) supported the model's fit to the data. The four factors demonstrated convergent and discriminant validity, with CR and AVE values at acceptable levels, and inter-factor correlations supported discriminant validity. Cronbach's Alpha and McDonald's Omega coefficients ranged from 0.79 to 0.94 across all subscales, indicating high internal consistency. Based on the psychometric analyses, the scale was accepted as a valid and reliable 24-item, four-factor instrument.

Conclusion: The developed artificial intelligence-supported health counseling scale (AI-HCS) is a valid and reliable tool for measuring critical factors influencing the adoption of AI-HC. The scale can contribute to the development of AI integration strategies in health policies and the design of patient-centered digital solutions.

Submitted 1 November 2025
Accepted 21 April 2026
Published 2 June 2026

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Academic editor
Ankit Vishnoi

Additional Information and Declarations can be found on page 21

DOI 10.7717/peerj-cs.3937

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How to cite this article Göde A. 2026. Artificial intelligence-supported health counseling scale (AI-HCS): a reliability and validity study. PeerJ Comput. Sci. 12:e3937 DOI 10.7717/peerj-cs.3937

Subjects Human-Computer Interaction, Artificial Intelligence, Emerging Technologies, Social Computing
Keywords Artificial intelligence (AI), Health counseling, Scale development, Validity and reliability, Human–computer interaction

INTRODUCTION

Artificial intelligence (AI) systems are enabling changes in many fields today. These changes and transformations have also begun to play an active role in the field of healthcare services. They are evident in many areas of healthcare, from clinical decision support to patient monitoring, from public health initiatives to personalized health counseling (*Secinaro et al., 2021*). In addition, there has been a significant increase in individuals' behaviors toward seeking health-related information in digital environments. This shift, accompanied by a growing tendency to use digital health platforms, has led to an increasing importance of such platforms (*Kim et al., 2023*; *Rathore & Rathore, 2023*). Research has made it possible for people to receive health counseling through AI systems that assess, monitor, and interact regarding disease symptoms. Moreover, with ease of use and rapid accessibility, AI systems have been developed to be more adaptable to daily life, leading to significant advancements. In a study conducted by *Gould et al. (2023)*, it was noted that AI technological systems have begun to be used effectively in people's decision-making processes, especially regarding their health. In the study by *Quazi, Mohammed & Gorrepati (2024)*, it was indicated that AI-supported technological systems facilitate the monitoring of individuals' health conditions. *You et al. (2025)* stated that AI-supported mobile applications make it more sustainable and easier for patients to maintain personal oral health by reminding them of oral hygiene habits. The use of such AI-based digital applications provides a more trackable and organized structure for individuals to acquire healthy habits. Furthermore, these digital tools enable people to adopt a more conscious and active approach toward their health.

With the integration of AI-supported systems into healthcare services, significant progress has been made in recent years. The use of these systems, in harmony with processes such as treatment planning, data management, and patient information processing, makes healthcare services more practical and efficient (*Secinaro et al., 2021*). As a result of these processes, an important transformation is taking place, enabling people to obtain health information and advice directly from AI-supported systems. ChatGPT and similar conversation-based AI-supported systems facilitate access to health information, allowing people to communicate directly with AI regarding their health status (*Adigwe, Onavbavba & Sanyaolu, 2024*). As a result of these advancements, a perspective called "artificial intelligence-supported health counseling (AI-HC)" has emerged, representing a change in how people access information and make decisions about their health (*Rathore & Rathore, 2023*; *You et al., 2025*). AI-HC encompasses multidimensional interactions in which individuals can consult AI about health symptoms, have test results evaluated, or explore treatment alternatives before consulting a healthcare professional. In addition, this technological shift is expected to reshape people's habits of obtaining health

information and using health applications (*Young et al., 2021*; *Scott, Carter & Coiera, 2021*; *Adigwe, Onavbavba & Sanyaolu, 2024*).

Based on the literature, it can be concluded that people's perceptions and intentions are crucial determinants in the process of adopting technological innovations. Especially from the perspective of theoretical approaches such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), attitudes toward technological systems, along with perceived usefulness, ease of use, and behavioral intention, shape user behaviors (*Venkatesh & Davis, 2000*; *Holden & Karsh, 2010*). In this context, an examination of existing models in the healthcare field shows that various measurement tools have been developed for the use of e-health systems, mobile applications, and online health platforms (*Hsieh et al., 2016*). However, existing studies are generally limited to e-health applications. Moreover, they often focus on specific constructs such as usage intention or trust perception, and thus fall short of developing a more comprehensive approach (*Princi & Krämer, 2020*; *Beets et al., 2023*; *Kim, Ryan & Kim, 2025*). While the TAM and related frameworks primarily emphasize perceived usefulness, ease of use, and behavioral intention, these constructs alone are insufficient to capture individuals' engagement with AI-supported health counseling. Unlike general information technologies, AI-HC involves sensitive, high-risk health-related decisions, where users simultaneously evaluate not only usability and intention, but also trust in AI-generated recommendations, concerns about data privacy, and perceptions of the medical competence of AI systems. Therefore, extending beyond traditional acceptance models is necessary to adequately conceptualize and measure individuals' attitudes and tendencies toward AI-supported health counseling.

Although many measurement tools have been developed to address constructs such as digital health literacy, privacy awareness, and technology acceptance, the lack of a valid and reliable tool that examines the phenomenon of AI-HC from a multidimensional perspective stands out as an important gap in the literature. Existing scales primarily focus on user intentions or are adapted based on the perspectives of healthcare professionals. In this regard, the experiences of patients or individuals interacting with AI-based counseling systems are often neglected (*Princi & Krämer, 2020*; *Beets et al., 2023*; *Williamson & Prybutok, 2024*; *Santos & Nazaré, 2025*; *Kim, Ryan & Kim, 2025*). Evaluating the sustainability of AI-supported technological systems requires a comprehensive and multidimensional perspective on the psychosocial factors involved in users' interaction with AI-HC. The key issues in this perspective include individuals' tendencies to use the system, perceived accuracy and reliability, concerns about data security and privacy, usability experiences, and attitudes toward these systems compared to traditional healthcare providers (*Williamson & Prybutok, 2024*; *Arigbabu et al., 2024*). In this context, the need for a valid and reliable measurement tool that can evaluate people's perspectives on AI-HC from multiple dimensions is increasing. However, to date, no psychometrically tested and multidimensional scale specifically designed for this field has been developed. This deficiency makes it difficult to understand individual usage tendencies as well as to develop and disseminate digital health applications. Several existing instruments partially

address constructs related to AI-supported health interactions, such as trust in artificial intelligence, perceived AI competence, or digital health information seeking behaviors. However, these scales typically focus on single dimensions or isolated aspects of user interaction with AI systems. For example, AI trust scales primarily assess confidence in algorithmic outputs, while digital health information-seeking measures focus on access and usage behaviors rather than evaluative judgments in health decision-making contexts. In contrast, the AI-HCS integrates these related constructs within a unified, multidimensional framework specifically tailored to the context of AI-supported health counseling, thereby capturing the complex and interrelated evaluations individuals make when engaging with AI systems for health-related purposes.

AI-HC refers to a hybrid interaction process in which individuals engage with AI-based systems to obtain health-related information, guidance, and preliminary evaluations before or alongside professional medical consultation. Unlike general technology use or digital information seeking, AI-HC involves simultaneous evaluations of multiple interrelated dimensions, including the perceived usability of the system, trust in AI-generated health information, concerns regarding data privacy and security, perceived supportiveness in the decision-making process, and perceptions of the medical competence of AI systems. Due to the sensitive, high-stakes, and ethically complex nature of health-related decisions, individuals' engagement with AI-HC cannot be adequately captured by single-dimensional constructs such as usage intention or perceived usefulness alone. Therefore, AI-HC represents a fundamentally multidimensional phenomenon that requires an integrative measurement approach extending beyond traditional technology acceptance frameworks. To further ensure conceptual clarity, each dimension of AI-HC evaluated in this study is defined as theoretically distinct yet complementary. "Usage and trust" refers to the extent to which individuals are willing to engage with AI-based health counseling systems and the degree of confidence they place in the information provided. "Privacy perception" captures individuals' concerns and evaluations regarding the protection and security of personal health data within AI systems. "Supportiveness perception" reflects the extent to which AI systems are perceived as facilitating understanding, guiding decision-making, and enhancing the counseling process. In contrast, "medical competence" represents the perceived clinical accuracy, reliability, and adequacy of AI-generated health recommendations. While these dimensions may be interrelated in real-world use, each captures a distinct evaluative aspect of individuals' interaction with AI-supported health counseling systems.

This study aims to fill this gap by developing a multidimensional scale to assess individuals' perceptions, attitudes, and tendencies toward AI-HC. The "artificial intelligence-supported health counseling scale (AI-HCS)" developed in this study is intended to explain individuals' behaviors in using these systems and to contribute to the patient-centered design of AI applications in healthcare services. Accordingly, the aim of the study is to develop the AI-HCS and to evaluate its psychometric properties by conducting validity (content, construct, and criterion validity) and reliability (internal consistency) analyses.

MATERIALS AND METHODS

Research design

This methodological study aims to develop a scale to measure people's perceptions and attitudes towards AI-HC. The scale development process was planned in two main stages throughout the study, taking into account the systematic approaches recommended for scale development:

- identification of scale items and ensuring content validity,
- conducting psychometric analyses (structural validity, reliability analyses and criterion validity).

The multi-stage scale development principles proposed by *Lim (2024)*, *DeVellis (2017)*, *Boateng et al. (2018)* and *Netemeyer, Bearden & Sharma (2003)* were used as basic guidelines throughout the research.

Research group

This study's sample consists of Turkish adults who have obtained health information using AI-based systems. Participants were selected from individuals who had used AI-HC applications at least once. This selection criterion is essential to ensure the assessments are appropriate for the study's purpose.

The data collection process was organised into two stages. Different sample groups were used in each stage. In the first stage, data were collected from 592 participants *via* an online survey between 15 May and 15 June 2025. This stage was conducted for exploratory factor analysis (EFA). In the second stage, data were collected online between 1 July and 1 August 2025 from a group of 663 participants for the purpose of confirmatory factor analysis (CFA). Consequently, the psychometric analyses of the study used a large sample of 1,255 participants.

Participants were free to choose whether to take part in the study. The data collection process was conducted with anonymity in mind. Convenience sampling was used to select the sample. As the research was conducted on an online platform within a specific timeframe, the design is cross-sectional. When selecting participants, having previously used AI-based applications in a healthcare context was taken into account as a criterion. Anyone who met this criterion was eligible to participate in the study.

Regarding the sample size, it is generally recommended that it should be five to ten times the total number of scale items, particularly for factor analyses. This enables the validity and reliability of the developed scale to be analysed in a robust manner. In light of the standards recommended in the literature, this sample size provides a sufficiently robust foundation (*Şencan, 2005*; *Grove, Burns & Gray, 2012*; *Tabachnick & Fidell, 2013*; *Hair et al., 2014*).

Data collection tools

During the data collection process, two measurement tools were used: the 'personal information form' and the 'artificial intelligence-supported health counselling scale'. These

were used to determine the demographic characteristics of the participants and to measure the variables included in the study. These forms were used to obtain descriptive information and data related to the study's focus.

Personal information form

The first section of the survey included questions to determine the participants' demographics and characteristics, such as their age, gender, marital status, level of education, sources of health-related information, whether they had previously used AI-supported health applications, and their level of knowledge on the subject. This information was collected to assess the participants' profile prior to applying the scale.

The artificial intelligence-supported health counseling scale (AI-HCS)

The AI-HCS was developed as the primary data collection tool for the study and was utilised. The scale development process followed a structured multi-stage procedure to ensure methodological transparency and theoretical rigor. First, an extensive literature review was conducted to identify relevant constructs related to AI-supported health counseling, including technology acceptance, trust in AI, privacy concerns, and human–AI interaction in healthcare. Based on this review, an initial item pool of 55 items was generated. In the second stage, content validity was established through expert evaluation. A panel consisting of one measurement and evaluation specialist and five domain experts in health sciences reviewed the items in terms of conceptual relevance, clarity, and representativeness. Based on their feedback, items that were redundant, ambiguous, or not directly aligned with the AI-HC context were revised or removed, resulting in a 32-item draft scale. In the third stage, the refined item set was subjected to EFA to examine the underlying factor structure and to further eliminate items with low factor loadings or cross-loadings. Finally, CFA was conducted on an independent sample to validate the factor structure obtained from EFA. This sequential process ensured that the final scale structure was both theoretically grounded and empirically supported.

The scale aims to measure individuals' multidimensional perceptions of obtaining health-related information and counselling through AI-based systems, as well as their perceptions of trust, privacy, usability and physician–patient relationships in this process. A question pool consisting of 55 items was created by reviewing the literature and considering the AI-HC (*Shaw et al., 2019*; *Hatherley, 2020*; *Ronquillo et al., 2021*; *Secinaro et al., 2021*; *Shan et al., 2022*; *Beets et al., 2023*; *Rathore & Rathore, 2023*; *Gould et al., 2023*; *Stanley & Dorton, 2023*; *Adus, Macklin & Pinto, 2023*; *Alvarado, 2023*; *He, Zheng & Ding, 2023*; *Adigwe, Onavbavba & Sanyaolu, 2024*; *Quazi, Mohammed & Gorrepati, 2024*; *Santos & Nazaré, 2025*; *Stroud et al., 2025*; *Steerling et al., 2025*; *You et al., 2025*). This was then evaluated by a measurement and evaluation expert with experience in scale development in the field of health sciences, as well as five other experts. Following the evaluation, it was determined that the draft form should consist of 32 items.

Experts frequently recommended the removal or revision of items that were perceived as conceptually overlapping (*e.g.*, items simultaneously reflecting trust and usability),

insufficiently specific to AI-supported health counseling contexts, or ambiguously worded in terms of AI functionality. Items were retained when they were deemed to clearly and uniquely represent the theoretical scope of the proposed dimensions and to be directly relevant to AI-supported health counseling scenarios.

The item generation and refinement process was guided by established theoretical frameworks rather than being purely data-driven. Specifically, the initial item pool was informed by the literature on technology acceptance, trust in artificial intelligence, privacy calculus, and human–AI collaboration in healthcare contexts. Expert evaluations focused not only on statistical considerations but also on conceptual relevance, clarity, and theoretical alignment of each item with the proposed dimensions. EFA was subsequently employed as a confirmatory step to empirically refine the scale structure, ensuring that the final item set was both theoretically grounded and psychometrically robust. This approach enhanced the transparency of the scale development process by explicitly linking each stage of item generation, refinement, and factor validation to both theoretical and empirical criteria.

The scale, prepared in a 5-point Likert format, is rated as follows: "1—Strongly Disagree, 2—Disagree, 3—Somewhat Agree, 4—Agree, 5—Strongly Agree". As individuals' average scores approach 1, their propensity for AI-supported health counselling decreases; as they approach 5, their propensity increases. Based on the data obtained in the study, factor analysis resulted in the creation of a final scale consisting of 24 questions and four dimensions (see Appendix).

Data collection

The data collection process for this study was carried out in two stages. The first stage involved collecting the data necessary for the exploratory EFA between 15 May and 15 June 2025. The second stage involved obtaining the data required for the CFA between 1 July and 1 August 2025. Data was collected online *via* the Google Forms platform in both stages. At the beginning of the survey, participants were provided with clear and understandable information about the purpose, scope and conditions of participation in the research. The text stated that the study was conducted solely for scientific purposes, that participation was voluntary and that responses would be collected anonymously. Participants were also informed that they had the right to withdraw from the study at any time. Written informed consent was obtained electronically from all participants prior to data collection.

The prerequisites for participating in the study were set out in the survey as follows: being an adult and residing in Turkey, and having experience of obtaining health-related information using an AI-based system. A screening question was therefore included in the introductory section of the survey to determine whether participants met this requirement. This ensured that only those with the relevant experience were included in the study. Participants' privacy was fully protected throughout the data collection process. No personal or identifying data was requested. The data collected was analysed solely for the purposes of this research and was not shared with third parties under any circumstances.

Data analysis

The data collected in the study were analysed using the Statistical Package for the Social Sciences (SPSS) version 26.0 and the Analysis of Moment Structures (AMOS) version 24.0 software packages. Detailed statistical methods were employed to evaluate the psychometric properties of the scale in terms of validity and reliability.

First, EFA was applied to determine the scale's factor structure. Prior to this, the Kaiser–Meyer–Olkin (KMO) sample adequacy test and Bartlett's sphericity test were performed to assess the suitability of the data for factor analysis. Within the scope of EFA, the varimax rotation technique was used alongside the principal component analysis method. Items with factor loadings below 0.50, items showing high loadings on more than one factor and items causing problems in terms of item-total correlation were subsequently removed from the scale (*Coşkun et al., 2017*; *Kalaycı, 2017*; *Özdamar, 2017*).

Subsequently, CFA was performed to evaluate the validity of the factor structure obtained using EFA. This analysis examined the level of fit of the model with the data using various fit indices. The basic fit criteria considered included chi-square to degrees of freedom (χ^2/df), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), comparative fit index (CFI), normalised fit index (NFI), Tucker–Lewis index (TLI), root mean square residual (RMR) and root mean square error of approximation (RMSEA). These indices were used to determine how well the model fit the data. GFI, AGFI, CFI, NFI and TLI values between 0.95 and 1.00 indicate a good fit. Conversely, RMR and RMSEA values between 0 and 0.05 indicate a good model fit. Acceptable fit is indicated by GFI, AGFI, CFI, NFI and TLI values between 0.90 and 0.95 and RMR and RMSEA values between 0.05 and 0.08. Additionally, a chi-square/df value below two indicates a good fit, whereas a value between two and five indicates an acceptable fit (*Rose et al., 2004*; *Munro, 2005*; *Şimşek, 2007*; *Hooper, Coughlan & Mullen, 2008*; *Meydan & Şeşen, 2015*; *Kline, 2016*; *Wang & Wang, 2019*; *Gürbüz, 2021*). At the next stage, various statistical methods were employed to evaluate both convergent and divergent validity. Composite reliability (CR), average extracted variance (AVE) and Fornell–Larcker criteria were calculated in accordance with the established criteria.

First, the reliability of the scale was evaluated using Cronbach's alpha coefficient for the EFA and CFA datasets. Internal consistency analyses were reported separately for each sub-dimension. Item analyses were conducted in the EFA dataset in the first stage, considering statistics such as item-total correlation and the effect on Cronbach's Alpha value of deleting an item. Additionally, McDonald's omega coefficients were evaluated in the EFA and CFA datasets to support reliability (*Terwee et al., 2007*; *Kalaycı, 2017*; *Karagöz, 2019*; *Hayes & Coutts, 2020*). The statistical significance level was set at $p < 0.05$ for all analyses.

Ethical aspects of the research

This research was conducted in full compliance with the principles of scientific research and publication ethics. Ethical committee approval was obtained from the Scientific Research and Publication Ethics Committee of the Faculty of Social Sciences and Humanities at Hatay Mustafa Kemal University, with decision no. 02 dated 13/05/2025.

Participants were asked to provide written informed consent electronically prior to taking part in the survey, *via* the consent form included at the beginning of the questionnaire. Ethical principles were upheld throughout the research process, and the study was conducted in accordance with the provisions of the Helsinki Declaration.

RESULTS

Participants' characteristics

The study comprised a total of 1,255 adult participants. The sociodemographic characteristics of the participants are presented in Table 1 according to the EFA and CFA data sets.

As illustrated in Table 1, 60.6% of participants in the EFA dataset were female and 39.4% were male, while in the CFA dataset, these ratios were 59.9% and 40.1%, respectively. Upon examination of the age distribution, it was determined that 60.5% of participants in the EFA group and 58.5% of those in the CFA group fell within the 18–24 age range. Age was analyzed as a grouped variable to facilitate descriptive interpretation and to ensure comparability with previous scale development studies that commonly report age categories in demographic analyses. In addition, the mean age of participants was 24.2 years (standard deviation (SD) = 5.4) for the EFA dataset and 24.8 years (SD = 5.9) for the CFA dataset, indicating a relatively young but consistent sample across both stages. With respect to marital status, 74.5% of subjects in the EFA dataset were unmarried, whereas this proportion was 65.0% in the CFA dataset. With respect to educational attainment, a higher proportion of university graduates were observed in both data sets (EFA: 71.8%; CFA: 69.2%), followed by those with a high school education or below and those with a master's/doctorate degree. The most commonly used source for obtaining health information among participants was "doctor," with a rate of 49.2% in the EFA dataset and 49.5% in the CFA dataset. This is followed by the internet (EFA: 33.4%; CFA: 29.2%) and AI-based applications (EFA: 17.4%; CFA: 21.3%). With respect to the extent of knowledge concerning AI technologies in the health field, respondents who indicated a low level of knowledge (EFA: 40.2%; CFA: 41.3%) and a moderate level of knowledge (EFA: 38.5%; CFA: 37.7%) exhibited the highest rates in both datasets.

Structural validity

Exploratory factor analysis (EFA)

The structural validity of the AI-HCS was evaluated through the application of EFA. Prior to the analysis, the Kaiser–Meyer–Olkin (KMO) and Bartlett tests were performed to determine the suitability of the data for factor analysis. The KMO value obtained was 0.955, indicating an "excellent" level of sample adequacy for factor analysis. The result of Bartlett's sphericity test was found to be significant (X^2 = 9,135.15; $p < 0.001$), indicating that there is a meaningful relationship structure among the data suitable for factor analysis (*Kalaycı, 2017*). The EFA was conducted using the SPSS 26.0 program with the principal component analysis method and Varimax rotation technique. Following a thorough examination, it was determined that a number of items on the scale exhibited high loadings on multiple factors or demonstrated low item-total correlations (*Coşkun et al., 2017*;

Table 1 Socio-demographic characteristics of participants. A total of 60.6% of participants in the EFA dataset were female and 39.4% were male, while in the CFA dataset, these ratios were 59.9% and 40.1%, respectively. Upon examination of the age distribution, it was determined that 60.5% of participants in the EFA group and 58.5% of those in the CFA group fell within the 18–24 age range. With respect to marital status, 74.5% of subjects in the EFA dataset were unmarried, whereas this proportion was 65.0% in the CFA dataset. With respect to educational attainment, a higher proportion of university graduates were observed in both data sets (EFA: 71.8%; CFA: 69.2%), followed by those with a high school education or below and those with a master's/doctorate degree. The most commonly used source for obtaining health information among participants was "doctor," with a rate of 49.2% in the EFA dataset and 49.5% in the CFA dataset. This is followed by the internet (EFA: 33.4%; CFA: 29.2%) and AI-based applications (EFA: 17.4%; CFA: 21.3%). With respect to the extent of knowledge concerning AI technologies in the health field, respondents who indicated a low level of knowledge (EFA: 40.2%; CFA: 41.3%) and a moderate level of knowledge (EFA: 38.5%; CFA: 37.7%) exhibited the highest rates in both datasets.

Socio-demographic characteristics	Options	EFA data set		CFA data set	
		Number (N)	Percentage (%)	Number (N)	Percentage (%)
Gender	Female	359	60.6	397	59.9
	Male	233	39.4	266	40.1
Age	18–24 years old	358	60.5	388	58.5
	25–29 years old	113	19.1	118	17.8
	30 years old and above	121	20.4	157	23.7
Marital status	Single	441	74.5	431	65.0
	Married	151	25.5	232	35.0
Educational status	High school and below	94	15.9	103	15.5
	University	425	71.8	459	69.2
	Master's/doctorate	73	12.3	101	15.3
Which source do you use most often to obtain health information?	Doctor	291	49.2	328	49.5
	Internet	198	33.4	194	29.2
	AI-based applications	103	17.4	141	21.3
What is your level of knowledge about AI technologies in the field of health?	I don't know at all	29	4.9	32	4.8
	I know a little	238	40.2	274	41.3
	I know moderately well	228	38.5	250	37.7
	I know very well	97	16.4	107	16.2
Total		592	100.00	663	100.00

Note:
EFA, exploratory factor analysis; CFA, confirmatory factor analysis. Percentages are calculated within each dataset. Age is presented in grouped categories for descriptive comparability. N, number of participants.

Kalaycı, 2017; *Özdamar, 2017*). Consequently, eight items were excluded from the analysis. The final analysis was conducted on 592 participants, and 24 items were included in the analysis.

As demonstrated in Table 2, the EFA results indicated that AI-HCS exhibited a four-factor structure. Collectively, these four factors account for 66.01% of the total variance. The following table presents the eigenvalues and percentages of variance explained for the factors. The following percentages were obtained: 26.47% for usage and trust, 15.15% for the perception of privacy, 12.40% for the perception of supportiveness, and 12.00% for medical competence. The factor loadings of the items in the scale range from 0.543 to 0.841, and are all at an acceptable level. In addition, cross-loadings were examined for all items, and no item demonstrated problematic cross-loading values that would threaten the conceptual distinctiveness of the factors. The interpretation and naming of the factors were based on both statistical patterns and theoretical consistency.

Table 2 Exploratory factor analysis (EFA) results of the AI-HCS: factor loadings, item-total correlations, and reliability indicators (N = 592). AI-HCS exhibited a four-factor structure. Collectively, these four factors account for 66.01% of the total variance. The following table presents the eigenvalues and percentages of variance explained for the factors: The following percentages were obtained: 26.47% for usage and trust, 15.15% for the perception of privacy, 12.40% for the perception of supportiveness, and 12.00% for medical competence. The factor loadings of the items in the scale range from 0.543 to 0.841, and are all at an acceptable level. The bolded values indicate the highest factor loadings for each item and are used to highlight the primary factor structure.

Scale items	Factors				Adjusted total question correlation	Cronbach alpha when question is deleted
	Usage and trust	Privacy perception	Supportiveness perception	Medical competence		
1. I would consider consulting artificial intelligence about my symptoms.	**0.841**	0.163	0.078	0.187	0.722	0.940
2. I can obtain information from artificial intelligence about my health issues.	**0.810**	0.162	0.107	0.183	0.709	0.941
3. I find it useful to receive health recommendations from artificial intelligence.	**0.760**	0.273	0.229	0.093	0.754	0.940
4. Artificial intelligence can be a guide in health matters.	**0.745**	0.170	0.367	0.089	0.755	0.940
5. I take artificial intelligence's health recommendations into consideration.	**0.708**	0.310	0.306	0.138	0.785	0.940
6. I can have artificial intelligence interpret my test results.	**0.682**	0.281	0.177	0.176	0.708	0.941
7. I trust artificial intelligence's health information.	**0.680**	0.312	0.316	0.032	0.787	0.940
8. I consult artificial intelligence before going to the doctor.	**0.663**	0.255	0.202	0.009	0.635	0.942
9. I would like to use artificial intelligence for health monitoring.	**0.635**	0.209	0.310	0.129	0.681	0.941
10. Artificial intelligence can provide accurate health information.	**0.625**	0.252	0.308	0.142	0.747	0.940
11. Artificial intelligence keeps my information secure.	0.226	**0.796**	0.168	0.048	0.586	0.942
12. I can use artificial intelligence without privacy concerns.	0.235	**0.783**	0.206	−0.050	0.569	0.942
13. I am comfortable sharing my personal health information with artificial intelligence.	0.329	**0.725**	0.175	0.080	0.635	0.942
14. I trust platforms that use artificial intelligence in the healthcare field.	0.363	**0.627**	0.307	0.141	0.695	0.941
15. I can share my health information with artificial intelligence.	0.467	**0.593**	0.161	0.274	0.732	0.940
16. Artificial intelligence can be as important as doctors when it comes to healthcare.	0.300	0.264	**0.740**	−0.007	0.613	0.942
17. Artificial intelligence can reduce doctors' workload.	0.244	0.178	**0.703**	0.230	0.625	0.942
18. Artificial intelligence is faster than doctors in some healthcare matters.	0.353	0.207	**0.630**	0.231	0.653	0.941
19. Artificial intelligence can be as reliable as a doctor.	0.302	0.344	**0.603**	−0.217	0.525	0.943
20. Artificial intelligence can replace doctors.	0.042	−0.065	−0.113	**0.811**	0.572	0.947
21. Getting information from artificial intelligence does not prevent me from going to a doctor.	0.200	0.082	0.114	**0.767**	0.436	0.944
22. I do not feel the need to verify the information I get from artificial intelligence.	0.029	0.033	0.064	**0.734**	0.562	0.946

(Continued)

Table 2 (continued)

Scale items	Factors				Adjusted total question correlation	Cronbach alpha when question is deleted
	Usage and trust	Privacy perception	Supportiveness perception	Medical competence		
23. Artificial intelligence and doctors working together is better.	0.264	0.149	0.335	**0.558**	0.583	0.942
24. Artificial intelligence is fast at providing health information.	0.290	0.296	0.267	**0.543**	0.668	0.941
Initial eigenvalues	11.092	2.347	1.338	1.063		
Percentage of variance	26.466	15.148	12.396	12.003		
Total variance explained	66.01					
KMO = 0.955; Bartlett's X^2 = 9,135.15; $p < 0.001$.						

Notes:
EFA was conducted using principal component analysis with varimax rotation. Only factor loadings ≥0.50 are considered significant. Factor loadings represent the correlation between items and latent factors. Adjusted item-total correlations indicate item consistency within the scale. Cronbach's alpha values represent internal consistency when the item is deleted.
KMO = 0.955 indicates excellent sampling adequacy.
Bartlett's test of sphericity: χ^2 = 9,135.15, $p < 0.001$.
Total variance explained by the four-factor structure = 66.01%.
All statistical values required for independent interpretation of the factor structure are presented in Table 2, including factor loadings, item-total correlations, and reliability indicators.

Specifically, factor labels were assigned by examining the conceptual content of the items with the highest loadings within each factor and aligning them with established theoretical constructs in the literature. This approach ensured that factor interpretation was not solely data-driven but also theoretically meaningful.

Confirmatory factor analysis (CFA)

Construct validity was supported by CFA, and fit indices (χ^2/df, GFI, AGFI, CFI, NFI, TLI, RMSEA, RMR) were evaluated (*Yaşlıoğlu, 2017*; *Gürbüz, 2021*).

According to the CFA path analysis results shown in Fig. 1, standardized item loadings ranged from 0.64 to 0.84. Load values above 0.50 indicate good factor loading (*Çokluk, Şekercioğlu & Büyüköztürk, 2012*; *Özdamar, 2017*; *Gürbüz, 2021*). Therefore, no items were removed from the scale. Covariance was defined between some items to increase the model's fit level (*Şimşek, 2007*; *Meydan & Şeşen, 2015*; *Wang & Wang, 2019*; *Gürbüz, 2021*).

As demonstrated in Table 3, the developed AI-HCS fit indices are, in general, deemed to be acceptable. The χ^2/df value of 2.957 is less than 5, suggesting that the model provides a reasonable fit. The GFI and AGFI values are 0.918 and 0.900, respectively, and are within acceptable limits. The CFI value of 0.945 and the NFI value of 0.938 lend support to the model's adequate fit with the data. The TLI value of 0.919 is also deemed acceptable. The root mean square error of approximation (RMSEA) value associated with the model's error estimate is 0.054, and the RMR value is 0.045. The indices under consideration demonstrate a high degree of compatibility with the established criteria for an adequate fit. The results of this study indicate that the structural model of the developed scale is appropriate for the data and supports the validity of the factor structure (*Rose et al., 2004*; *Munro, 2005*; *Şimşek, 2007*; *Hooper, Coughlan & Mullen, 2008*; *Meydan & Şeşen, 2015*; *Wang & Wang, 2019*; *Gürbüz, 2021*).

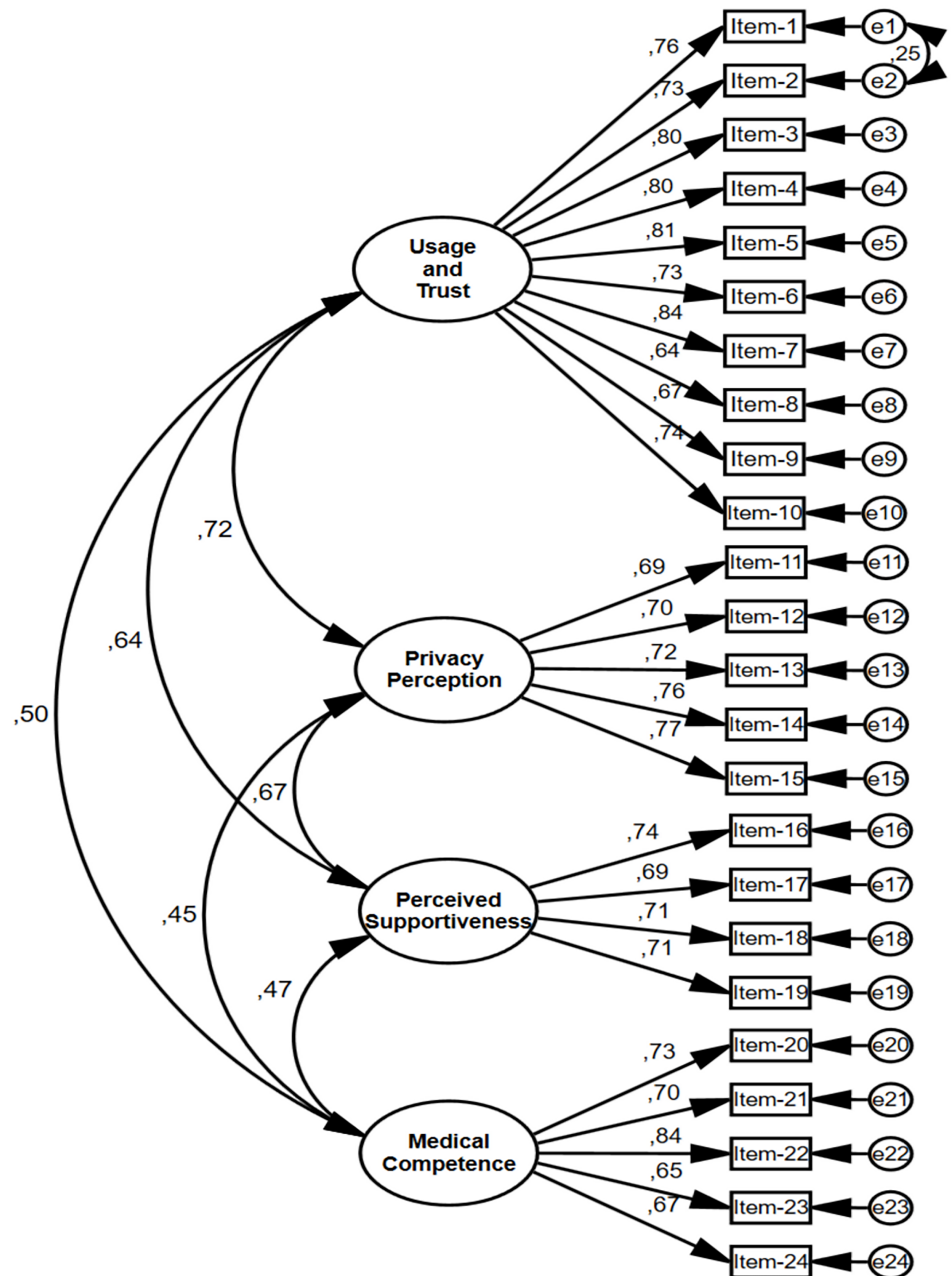

Figure 1 AI-HCS's CFA path diagram (N = 663). As demonstrated in Table 2, the EFA results indicated that AI-HCS exhibited a four-factor structure. Collectively, these four factors account for 66.01% of the total variance. The following table presents the eigenvalues and percentages of variance explained for the factors: The following percentages were obtained: 26.47% for usage and trust, 15.15% for the perception of privacy, 12.40% for the perception of supportiveness, and 12.00% for medical competence. The factor loadings of the items in the scale range from 0.543 to 0.841, and are all at an acceptable level.

Full-size DOI: 10.7717/peerj-cs.3937/fig-1

Table 3 Confirmatory factor analysis (CFA) fit indices and model fit evaluation for the AI-HCS (N = 663). The developed AI-HCS fit indices are, in general, deemed to be acceptable. The χ^2/df value of 2.957 is less than 5, suggesting that the model provides a reasonable fit. The GFI and AGFI values are 0.918 and 0.900, respectively, and are within acceptable limits. The CFI value of 0.945 and the NFI value of 0.938 lend support to the model's adequate fit with the data. The TLI value of 0.919 is also deemed acceptable. The root mean square error of approximation (RMSEA) value associated with the model's error estimate is 0.054, and the RMR value is 0.045. The indices under consideration demonstrate a high degree of compatibility with the established criteria for an adequate fit. The results of this study indicate that the structural model of the developed scale is appropriate for the data and supports the validity of the factor structure (*Rose et al., 2004*; *Munro, 2005*; *Şimşek, 2007*; *Hooper, Coughlan & Mullen, 2008*; *Meydan & Şeşen, 2015*; *Wang & Wang, 2019*; *Gürbüz, 2021*).

Fit indices	Good fit	Acceptable fit	AI-HCS
χ^2/df	<2	<5	2.957
GFI	>0.95	>0.90	0.918
AGFI	>0.95	>0.90	0.900
CFI	>0.95	>0.90	0.945
NFI	>0.95	>0.90	0.938
TLI	>0.95	>0.90	0.919
RMSEA	<0.05	<0.08	0.054
RMR	<0.05	<0.08	0.045

Note:
χ^2/df, chi-square/degrees of freedom; GFI, goodness of fit index; AGFI, adjusted goodness of fit index; CFI, comparative fit index; NFI, normed fit index; TLI, Tucker–Lewis index; RMSEA, root mean square error of approximation; RMR, root mean square residual. Values indicate acceptable to good model fit according to established thresholds in structural equation modeling literature.

Table 4 Convergent and discriminant validity results of the AI-HCS based on CR, AVE, and Fornell–Larcker criterion (N = 663). The scale's construct validity was evaluated based on convergent and divergent validity criteria. Upon examination of convergent validity, it was ascertained that the CR values were above 0.70 in all factors, thereby meeting the recommended threshold value. The AVE values were all above 0.50. The findings suggest that the items comprising the factors adequately explain the relevant structure and that the scale is appropriate in terms of convergent validity. Furthermore, in accordance with the Fornell–Larcker criterion, the AVE square root value of each factor was determined to exceed the correlation coefficients with other factors. However, it was observed that the correlation between the "usage and trust" and "privacy perception" factors (0.724) was relatively high, yet still met the discriminant validity criterion. The findings suggest that the scale provides adequate convergent and divergent validity in terms of construct validity.

Factors	CR	AVE	Usability and trust	Privacy perception	Supportiveness perception	Medical competence
Usability and trust	0.930	0.871	**0.756**			
Privacy perception	0.851	0.533	0.724	**0.730**		
Supportiveness perception	0.805	0.507	0.637	0.668	**0.712**	
Medical competence	0.843	0.519	0.496	0.452	0.473	**0.720**

Note:
CR, composite reliability; AVE, average variance extracted. Diagonal values (bold) represent the square root of AVE for each construct. Off-diagonal values represent inter-factor correlations. Discriminant validity is supported when the square root of AVE exceeds inter-factor correlations (Fornell–Larcker criterion).

As demonstrated in Table 4, the scale's construct validity was evaluated based on convergent and divergent validity criteria. Upon examination of convergent validity, it was ascertained that the CR values were above 0.70 in all factors, thereby meeting the

Table 5 Internal consistency reliability of the AI-HCS across EFA and CFA samples. Both Cronbach's Alpha and McDonald's Omega coefficients ranged between 0.79 and 0.94 across all subscales. The values obtained for the scale as a whole were all above 0.94. The findings suggest that the scale and its subscales exhibit a high degree of internal consistency and maintain consistent reliability across diverse samples. Furthermore, the close proximity of Cronbach's Alpha and McDonald's Omega coefficients lends support to the homogeneous structure of the scale. In the extant literature, values of 0.70 and above are considered acceptable reliability levels, while values of 0.80 and above are considered high reliability (*Terwee et al., 2007*; *Kalaycı, 2017*; *Karagöz, 2019*; *Hayes & Coutts, 2020*). In this context, it is evident that all sub-dimensions and the overall form of the AI-HCS possess a reliable structure that is in alignment with the measurement objective.

Factors	Number of items	EFA data set (N = 592)		CFA data set (N = 663)	
		Cronbach's α	McDonald's ω	Cronbach's α	McDonald's ω
Usability and trust	10	0.940	0.941	0.928	0.930
Privacy perception	5	0.871	0.872	0.850	0.852
Supportiveness perception	4	0.802	0.805	0.803	0.804
Medical competence	5	0.791	0.793	0.834	0.841
AI-HCS	24	0.944	0.947	0.939	0.941

Note:
α, Cronbach's alpha; ω, McDonald's omega. Values ≥0.70 indicate acceptable reliability, while values ≥0.80 indicate high reliability. Reliability coefficients are reported separately for each sub-dimension and the overall scale.

recommended threshold value. The AVE values were all above 0.50. The findings suggest that the items comprising the factors adequately explain the relevant structure and that the scale is appropriate in terms of convergent validity. Furthermore, in accordance with the Fornell–Larcker criterion, the AVE square root value of each factor was determined to exceed the correlation coefficients with other factors. However, it was observed that the correlation between the "usage and trust" and "privacy perception" factors (0.724) was relatively high, yet still met the discriminant validity criterion. The findings suggest that the scale provides adequate convergent and divergent validity in terms of construct validity. Although some inter-factor correlations were relatively high, particularly between "usage and trust" and "privacy perception," these constructs were theoretically grounded in distinct domains (behavioral engagement *vs*. risk evaluation), thereby supporting their conceptual separability despite empirical association.

Reliability

In order to evaluate the reliability of the scale, Cronbach's Alpha and McDonald's Omega coefficients were evaluated in the EFA and CFA data sets. As indicated in the relevant literature, the internal consistency analyses were reported separately for each sub-dimension.

An examination of Table 5 reveals that the results of the internal consistency analyses indicate that both Cronbach's Alpha and McDonald's Omega coefficients ranged between 0.79 and 0.94 across all subscales. The values obtained for the scale as a whole were all above 0.94. The findings suggest that the scale and its subscales exhibit a high degree of internal consistency and maintain consistent reliability across diverse samples. Furthermore, the close proximity of Cronbach's Alpha and McDonald's Omega coefficients lends support to the homogeneous structure of the scale. In the extant literature, values of 0.70 and above are considered acceptable reliability levels, while values of 0.80 and above are considered high reliability (*Terwee et al., 2007*; *Kalaycı, 2017*;

Karagöz, 2019; *Hayes & Coutts, 2020*). In this context, it is evident that all sub-dimensions and the overall form of the AI-HCS possess a reliable structure that is in alignment with the measurement objective.

DISCUSSION

The AI-HCS, which was developed in this study, has been added to the literature as a valid and reliable tool for measuring people's multidimensional perceptions, attitudes and tendencies towards receiving AI-based health counselling. The findings show that the four-dimensional structure of the scale (usage and trust, privacy perception, supportiveness perception and medical competence) was statistically strongly validated with both EFA and CFA. The scale's high internal consistency (Cronbach's $\alpha = 0.79$–0.94; McDonald's $\omega = 0.79$–0.94) and fit indices ($\chi^2/df = 2.957$, GFI = 0.918, AGFI = 0.900, CFI = 0.945, NFI = 0.938, TLI = 0.919, RMSEA = 0.054, RMR = 0.045) suggest it is a sound methodological measurement tool. According to the literature, the success of a scale depends on the variance adequately explained by its factors, and strong, well-defined structures form the basis of a quality psychometric evaluation (*Netemeyer, Bearden & Sharma, 2003*; *DeVellis, 2017*; *Boateng et al., 2018*; *Deveci et al., 2023*; *Lim, 2024*). Importantly, particular attention was given to ensuring conceptual distinctiveness among the identified dimensions. Although certain constructs (such as trust, usage intention, and perceived usefulness) may overlap in general technology acceptance literature, this study explicitly differentiates these dimensions within the context of AI-supported health counseling. Similarly, while both "supportiveness perception" and "medical competence" relate to evaluations of AI systems, the former focuses on the facilitative and process-oriented role of AI in guiding users, whereas the latter captures judgments regarding the clinical validity and reliability of AI-generated outputs. This distinction strengthens the theoretical robustness of the scale and supports its multidimensional structure.

Erlin et al. (2024) demonstrate that AI systems have made significant advances in online mental health counselling, positively impacting those who struggle to access traditional services. As AI increasingly interacts with human psychological processes, the critical role of psychology has come to the fore. Researchers also emphasise the importance of evaluating perceptions of such systems. Furthermore, *Fiske, Henningsen & Buyx (2019)* address the ethical dimensions of AI systems in mental healthcare, noting that, although this technology can aid therapy, it cannot replace the comprehensive services provided by mental health professionals. This emphasises the importance of factors such as medical expertise when examining the relationship between AI and healthcare services. It reveals users' perspectives on the effectiveness of AI tools in providing health recommendations. *Möllmann, Mirbabaie & Stieglitz (2021)* draw attention to the ethical issues surrounding the use of AI in digital health. They point out that tools such as the AI-HCS affect more than just user attitudes. They also emphasise the importance of examining the ethical frameworks associated with these technologies. *Fulmer (2019)* states that the use of AI systems in counselling applications requires a detailed understanding of users' reactions and attitudes towards such technologies. This suggests that validating AI-HCS could be

crucial in determining how AI initiatives can be effectively applied in healthcare counselling frameworks.

High factor loadings in the 'usage and trust' dimension support the idea that the 'perceived usefulness' and 'perceived reliability' variables emphasised in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks influence user behaviour (*Venkatesh & Davis, 2000*; *Holden & Karsh, 2010*). Although usage intention, perceived usefulness, and trust are conceptually distinct constructs in some technology acceptance models, prior research in high-risk and health-related AI contexts suggests that these perceptions often co-occur and form an integrated evaluative judgment. In AI-supported health counseling, individuals tend to evaluate system usefulness and usage intention through the lens of trust in AI-generated health information, which justifies their empirical convergence into a single dimension. This is important because it shapes users' trust in AI-HC systems and their intention to participate. *Potinteu, Renftle & Said (2023)* found that perceptions of trust significantly influence users' interactions with AI in various contexts. This finding is consistent with previous research indicating that trust is a critical factor in the 'usage and trust' dimension. Furthermore, *Nadarzynski et al. (2020)* observed that users are more inclined to adopt AI technologies when they perceive them as trustworthy. They further developed these insights, emphasising the fundamental role of trust in the user experience of health advisory systems. Similarly, studies by *Beets et al. (2023)* and *Young et al. (2021)* have revealed that trust in AI-based health technologies also plays a critical role in usage intent.

Findings in the 'privacy perception' dimension show that users' concerns about protecting their personal health data are a significant barrier to adopting AI-HC systems. As *Taitingfong et al. (2020)* noted, participants expressed concerns about the privacy of health data at both individual and societal levels. They indicated that these concerns hindered their willingness to participate in health research. This finding highlights the importance of addressing users' privacy concerns to facilitate acceptance of AI technologies. Consistent with this, the *Aldossari (2023)* study found that 41.3% of participants perceived a privacy risk related to health data when using AI technology. This statistic highlights the significant influence of privacy concerns on the adoption of these innovative systems, emphasising the urgent need for AI developers and healthcare providers to prioritise user privacy and implement robust data protection measures. This is also consistent with the 'privacy-acceptance balance' approach set out in the studies by *Williamson & Prybutok (2024)* and *Princi & Krämer (2020)*. Strengthening users' perception of privacy is a critical strategic priority for the widespread adoption of AI-HC systems.

In terms of the 'supportiveness perception' dimension, participants believe that AI-HC systems facilitate healthcare decision-making processes. In the context of the AI-HCS, "supportiveness perception" refers to users' perceptions that AI-based systems facilitate and guide the counseling process by improving understanding, providing reassurance, and supporting decision-making, rather than replacing clinical judgment or acting as the sole source of medical expertise. This aligns with the findings of *Scott, Carter & Coiera (2021)* and *Young et al. (2021)*, who documented the empowering effects of AI technologies on

patient engagement and health literacy. In addition, *Syed & Al-Rawi (2024)* reported that 68.7% of community pharmacists stated that AI systems facilitated healthcare professionals' access to information, while a large proportion also reported that AI systems contributed to healthcare professionals making more accurate decisions. A study by *Sauerbrei et al. (2023)* found that most patients have a positive attitude towards AI systems. Patients expressed a preference for AI tools to support human doctors rather than replace them entirely. *Larsson et al. (2025)* stated that AI systems are expected to improve the care environment by increasing patient safety and providing proactive support. Taken together, these results show that AI systems are seen as a complementary tool that improves decision-making processes and efficiency in healthcare, supporting the quality of care. Participants noted that AI-HC systems enhance healthcare workers' access to information, supporting informed decision-making and patient engagement. Importantly, supportiveness perception is conceptually distinct from the "medical competence" dimension. While medical competence reflects beliefs about the accuracy, reliability, and clinical adequacy of AI-generated health information, supportiveness captures the process- and relationship-oriented role of AI in counseling—namely, how the system assists users through guidance, reassurance, and facilitation during the counseling experience, rather than evaluating the medical correctness of the output. They also position themselves as a mechanism that fosters collaboration rather than replacing human decisions.

The items in the 'medical competence' dimension demonstrate that participants evaluated AI-HC systems in terms of both their potential to replace physicians and their ability to work in collaboration with physicians and provide support. This suggests that users do not perceive AI as a standalone replacement, but rather as a tool that can reduce the need for information verification under certain conditions, thereby providing quick and practical information. *Armansyah (2024)* supports this view, stating: "AI has the capacity to assist medical professionals in generating more precise diagnoses, delivering more personalised and effective care, and enhancing the efficiency of healthcare systems." This emphasis on the supportive role of AI systems aligns with the perspectives shared by participants regarding the function of AI systems and points to a consensus that AI technologies can enhance human capabilities in healthcare rather than replace them. *Harada et al. (2021)* conducted an analysis demonstrating that AI-supported diagnostic decision support systems enhance diagnostic accuracy for less experienced physicians. This finding is consistent with the prevailing research in the field, which suggests that users are more willing to accept AI systems as assistants rather than as replacements for human labour. The hypothesis is that collaboration between AI systems and physicians will lead to a more efficient healthcare process and better patient outcomes by empowering practitioners with advanced decision support tools. While consistent with the "acceptance of AI's potential for physician support and workload reduction" highlighted in the studies by *Gould et al. (2023)* and *You et al. (2025)*, it also demonstrates that some participants are open to the possibility of AI systems replacing physicians. Consequently, it can be posited that both complementary and, in select instances, substitutive functions must be contemplated in unison when situating AI-HC within the domain of healthcare services.

From a theoretical standpoint, the AI-HCS is distinguished by its ability to circumvent the constraints imposed by prevailing measurement instruments. Unlike existing scales that examine trust, competence, or information seeking in isolation, the AI-HCS offers an integrative measurement model that reflects the simultaneous cognitive, affective, and evaluative processes involved in AI-supported health counseling. This multidimensional structure enables a more comprehensive assessment of individuals' engagement with AI systems in health contexts, where trust, privacy, and perceived medical judgment are inherently intertwined. Whilst earlier research has chiefly concentrated on e-health or individual variables (*e.g.*, trust, intention to use) (*Hsieh et al., 2016*; *Kim, Ryan & Kim, 2025*), this study proposes a multidimensional measurement model that integrates psychosocial, technical and security dimensions. Consequently, the present study makes a methodological contribution to the development of technology acceptance theories in the AI-HC context. In terms of practical contributions, the AI-HCS will enable healthcare providers, policymakers, and technology developers to better understand user needs, trust expectations, and privacy sensitivities. The data obtained can contribute to the development of user-centred strategies in the design of AI-based health technologies, the strengthening of privacy policies, and the more effective planning of clinical integration processes. To further enhance the practical applicability of the AI-HCS, the scale can be used in both research and real-world healthcare settings in several ways. First, in research contexts, the scale can serve as a multidimensional measurement tool to assess individuals' readiness for AI-supported health counseling and to examine its relationship with outcomes such as behavioral intention, trust-based decision-making, adherence to recommendations, and digital health engagement. Second, in applied settings, healthcare providers and digital health developers can use the AI-HCS to identify user expectations, concerns, and barriers related to AI-based health counseling systems. For example, low scores in the "privacy perception" dimension may indicate a need for stronger data protection communication, whereas lower "usage and trust" scores may suggest the need to improve system transparency and user confidence. Third, policymakers and health system planners can utilize the scale to evaluate public acceptance of AI integration in healthcare services and to guide the development of patient-centered AI policies. The scale may also be used as a needs assessment tool prior to the implementation of AI-based health interventions. In terms of interpretation, higher scores across dimensions indicate greater acceptance and perceived effectiveness of AI-supported health counseling systems. However, each dimension should be interpreted independently, as they reflect distinct aspects of user evaluation. For instance, a user may perceive high medical competence but still report low usage intention due to privacy concerns. Therefore, multidimensional interpretation of the AI-HCS is essential for accurately understanding user attitudes and for designing targeted interventions.

In terms of future research and applied use, the AI-HCS can serve as a comprehensive assessment tool for examining individuals' readiness, engagement patterns, and evaluative orientations toward AI-supported health counseling. While the present study did not examine associations with outcome variables, the scale may be used in subsequent research

to explore its relationships with outcomes such as intention to continue using AI-based health counseling, adherence to AI-supported recommendations, trust-related behaviors, or acceptance of AI integration in healthcare services. Importantly, given that the AI-HCS includes usage-related perceptions as part of a broader evaluative framework, future predictive models should carefully distinguish between proximal perceptual dimensions (*e.g.*, usage and trust) and downstream behavioral outcomes. In this regard, the AI-HCS is best positioned as a multidimensional explanatory construct rather than a direct substitute for single-outcome measures, thereby minimizing conceptual overlap while enabling theoretically informed modeling of AI-HC adoption processes.

Limitations of the study

In terms of limitations and future research, the scale was tested only with adults living in Turkey who had experience with AI-based health counseling. Validation studies conducted in different cultural contexts and healthcare systems will strengthen the cross-cultural validity of the scale. Furthermore, as this study has a cross-sectional design, longitudinal research is needed to reveal changes in perception over time. Conducting validity analyses of the scale according to different age groups, health professions, and levels of digital health literacy will contribute to a deeper understanding of the determinants of attitudes toward AI-HC. In addition, the study sample was relatively young, with the majority of participants falling within the 18–24 age group. This age distribution may limit the generalizability of the findings to older populations, who may differ in their digital health literacy, trust in artificial intelligence, and health decision-making behaviors. Younger individuals are generally more familiar with digital technologies and AI-based systems, which may lead to more favorable perceptions of AI-supported health counseling. Therefore, future studies should validate the AI-HCS across more diverse age groups to examine potential age-related differences in perceptions and usage tendencies.

CONCLUSIONS

The present study saw the development of the Artificial Intelligence-Supported Health Counseling Scale (AI-HCS), the purpose of which was to measure people's perceptions, attitudes, and tendencies toward AI-SC. In this context, the validity and reliability characteristics of the scale were comprehensively evaluated. Psychometric analyses revealed that the scale consists of four dimensions (Usage and Trust, Privacy Perception, Supportiveness Perception, Medical Competence) and 24 items. The analysis of the EFA and CFA results indicated that the scale's factor structure was statistically significant and that the fit indices were at an acceptable level. Convergent and discriminant validity analyses were conducted to ascertain the adequacy of the scale in representing the theoretical structures. Furthermore, the reliability of Cronbach's Alpha and McDonald's Omega coefficients was confirmed to be at a high level for all sub-dimensions and the overall scale.

The findings indicate that the AI-HCS can be used as a valid and reliable tool for measuring individual tendencies, perceptions, and attitudes toward AI-HC. The scale

provides a methodologically sound and theoretically comprehensive contribution, which can be used as a reliable measurement tool in both academic research and the development of health technologies. Furthermore, it is hypothesised that the data obtained through this scale will contribute to the development of AI-based health technologies that align with user expectations and requirements.

The AI-HCS also provides a practical framework for assessing user readiness and guiding the implementation of AI-supported health counseling systems in real-world healthcare environments.

ABBREVIATIONS

AI	Artificial Intelligence
AI-HC	Artificial Intelligence-Supported Health Counseling
AI-HCS	Artificial Intelligence-Supported Health Counseling Scale
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
AVE	Average Variance Extracted
KMO	Kaiser–Meyer–Olkin
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology
χ^2/df	Chi-square/degrees of freedom
GFI	Goodness of Fit Index
AGFI	Adjusted Goodness of Fit Index
CFI	Comparative Fit Index
NFI	Normed Fit Index
TLI	Tucker–Lewis Index
RMSEA	Root Mean Square Error of Approximation
RMR	Root Mean Square Residual

ADDITIONAL INFORMATION AND DECLARATIONS

Funding

The authors received no funding for this work.

Competing Interests

The author declares that they have no competing interests.

Author Contributions

- Ali Göde conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.

Ethics

The following information was supplied relating to ethical approvals (*i.e.*, approving body and any reference numbers):

Ethical committee approval was obtained from the Scientific Research and Publication Ethics Committee of the Faculty of Social Sciences and Humanities at Hatay Mustafa Kemal University, with decision no. 02 dated 13/05/2025. Approval number: 2025/02.

Data Availability

The following information was supplied regarding data availability:

The data is available in the Supplemental Files.

The dataset is available at Zenodo:

- GÖDE, A. (2026). Artificial Intelligence-Supported Health Counseling Scale (AI-HCS): A Reliability and Validity Study [Data set]. Zenodo. https://doi.org/10.5281/zenodo.18850091.

Supplemental Information

Supplemental information for this article can be found online at http://dx.doi.org/10.7717/peerj-cs.3937#supplemental-information.

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