

Women's knowledge and attitude scale toward ai-based chatbot systems in preconception counseling: A scale development study

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Abstract

Background

This study aimed to develop and validate a psychometrically sound scale to assess women's knowledge and attitudes toward artificial intelligence (AI)-based chatbot systems in the context of preconception counseling.

Methods

A methodological scale development study was conducted between February and April 2026 with 474 women aged 18 years and older. Data were collected online using a structured questionnaire including a descriptive information form, the newly developed scale, and the Digital Health Literacy Scale. The sample was randomly divided into two independent groups for exploratory factor analysis (EFA; $n = 237$) and confirmatory factor analysis (CFA; $n = 237$). Content validity was assessed using expert evaluation and the Lawshe technique. Construct validity was examined through EFA and CFA. Reliability was evaluated using Cronbach's alpha, McDonald's omega, and parallel test reliability. Criterion validity was assessed by examining the relationship between the developed scale and digital health literacy.

Results

The final scale consisted of 19 items and three subdimensions: Acceptance and Intention to Use, Knowledge and Awareness, and Critical Evaluation and Trust. The three-factor structure explained 63.16% of the total variance. CFA results indicated acceptable model fit ($\chi^2/df = 2.668$; RMSEA = 0.084; CFI = 0.928; TLI = 0.914). The scale demonstrated high internal consistency (Cronbach's $\alpha = 0.942$; McDonald's $\omega = 0.946$). A statistically significant positive correlation was found between the scale and digital health literacy ($r = 0.265$, $p < 0.01$), supporting criterion validity.

Conclusion

The developed scale is a valid and reliable instrument for assessing women's knowledge and attitudes toward AI-based chatbot systems in preconception counseling. It enables a multidimensional evaluation of user perspectives, including acceptance, knowledge, and trust-related components.

Background

The preconception stage is a crucial period during which biological, behavioral, and environmental risk factors can be modified in advance of conception. It is considered a critical factor in facilitating improved maternal and neonatal outcomes. Research has demonstrated that care provided during this period not only impacts pregnancy and birth outcomes, but also intergenerational health via epigenetic

processes and life-course health trajectories [1]. Nonetheless, global service delivery of preconception counseling services is neither universal, organized, nor equitable. According to WHO (2022), the effectiveness of health services is substantially weakened due to inequalities in access to them, time and workforce capacity constraints, and low health literacy, particularly in low- and middle-income countries [2]. This emphasizes the need for scalable and sustainable solutions beyond current care models.

Digital health technologies are changing quickly and may offer new solutions. Artificial Intelligence (AI)-based chatbot systems have emerged as highly attractive and interactive tools that enable users to interact with them through natural language. These applications provide a real-time feedback mechanism and personalized health information by harnessing large language models. Recent systematic reviews and meta-analyses by Gaffney et al. (2021) and Tudor Car et al. (2020) determined that these systems can produce significant changes in health behaviors, levels of knowledge, and user engagement [3, 4]. Due to the ability of these technologies to reach significant numbers of populations at low marginal cost in preventive health services, they are of strategic importance for health systems.

Although there are potential opportunities to be gained, the use of AI-based systems in the healthcare sector can also present many risks as well as uncertainties. According to Ayers et al. (2023), large language model-based systems may sometimes generate inaccurate, incomplete, or out-of-context information. Using this for health-related decision-making is harmful to patient safety. Issues such as data privacy, algorithmic bias, limited explainability, and ethical responsibility are also central to trust in these technologies [5]. Thus, the introduction of such systems to the health services should not only be evaluated in terms of technical accuracy, but also the respective users' perception levels, levels of trust, and ethical judgments.

The theoretical models regarding technology acceptance suggest that users adopt digital systems, which involves various cognitive and affective processes. The revised technology acceptance models suggest that trust, perceived risk, ethical acceptability, and others have become important determinants of technology acceptance, particularly in health-related contexts, besides the classical determinants such as perceived usefulness and ease of use [6]. In the case of AI, user-developed trust is not only linked to performance but also dynamically shaped by the perception of accuracy, transparency, explainability, and human-likeness [7]. This multidimensional framework becomes even more pronounced in such areas as preconception counseling, which is sensitive and has a considerable decision-making burden.

Although there are quite a number of scales measuring general attitudes towards digital health technologies in the literature, measurement tools assessing AI-based chatbot systems, adapted to the context of preconception counseling, are highly limited. The existing scales appear to address technology acceptance in a broad sense and do not incorporate sufficient contextual determinants such as ethical sensitivities regarding reproductive health, as well as risk perceptions, privacy expectations,

and broader cultural values [8]. The measurement tools in the field today are not really tailored to be used in these settings, which brings up some relevant methodological issues.

In this context, the measurement of knowledge and attitude towards an AI-based chatbot system needs to be done accurately and reliably for research and practical purposes. A comprehensive measurement tool would allow knowledge, perceived benefits and risks, trust, ethical sensitivity, and intention to use such systems to be assessed within an integrated framework. The effective development of this instrument will also assist with designing targeted education and intervention programs, segmentation of the users of technology, and developing evidence-led digital health policy.

This study focused on first developing a scale that would measure people's knowledge and attitude toward AI-based chatbot systems used for preconception counseling. Within this context, nurses and midwives play a central role in delivering preconception care, supporting digital health integration, and guiding women in the safe use of AI-based systems.

Methods

Study procedure

This methodological study was developed in three stages.

Phase 1. Evaluation of content clarity and validity: item generation and selection

The scale was developed following the stages of scale development described by DeVellis (2021) [9]. The construct to be measured was first defined with input from field specialists and relevant literature, and a 30-item draft form was then generated. This draft was reviewed by 13 midwifery and nursing experts who had doctoral-level training and experience in scale development. Each item was rated on a four-point relevance scale (1 = should be removed, 2 = somewhat appropriate, 3 = quite appropriate, 4 = appropriate). Content validity was evaluated from these expert ratings using the Lawshe technique. Following the expert review, seven items with predominantly unfavorable ratings were excluded, and the retained items were refined for wording and clarity according to expert feedback.

To evaluate the applicability of the draft PC-AICBS-KAS, the 23-item draft scale was administered to a group of 10 women who had characteristics similar to those of the target sample. Based on participant feedback, the items were found to be understandable, and no comprehension problems were reported for any item. Accordingly, the draft PC-AICBS-KAS was considered suitable for use in the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) stages.

Phase 2. Population and sample selection for administering the draft scale

The required sample size for scale development studies remains debated. Although Nunnally (1978) suggested that a sample size of approximately 300 would be sufficient, the more widely accepted view in the literature is that the sample size should be 5 to 10 times the number of scale items [10, 11]. In the present study, approximately 10 times the number of items in the 23-item scale was used. The draft scale was completed by 474 women in total, divided equally between the two analytic phases (237 for EFA and 237 for CFA). Eligible participants were reproductive-age women aged 18 years or older who provided consent to take part in the study.

EFA and CFA were performed on two different sample sets. The data collection process took place from February to April 2026. Recruitment notices for the study were circulated through social media channels, specifically Instagram, Facebook, and Twitter. Participants were further encouraged to share the study invitation with eligible women in their personal networks, adding a snowball component to the recruitment process; this approach has been described as useful for reaching groups that are otherwise difficult to access [12]. The survey opened with an information page explaining the study purpose, voluntary participation, and data confidentiality, and electronic consent was obtained before participants could access the questionnaire. Several screening procedures were applied before analysis to preserve the quality and completeness of the dataset. The online form was restricted to a single submission per user account, and the dataset was later screened for repeated IP addresses and unusually brief completion times; 11 survey forms considered likely to include careless or invalid responses were excluded from the evaluation. In addition, three surveys containing a substantial amount of missing data were not included in the final analyses.

Phase 3. Evaluation of construct validity, reliability, and factor structure

Instruments

Data were collected using a Descriptive Information Form and the Knowledge and Attitude Scale Toward AI-Based Chatbot Systems in Preconception Counseling.

Descriptive Information Form

This form was developed by the researchers on the basis of the relevant literature [7, 8, 13]. It consists of six questions addressing variables such as participants' age, marital status, educational level, history of receiving preconception care, and plans for having children in the future.

Knowledge and Attitude Scale Toward AI-Based Chatbot Systems in Preconception Counseling (PC-AICBS-KAS)

The final form of the scale measuring knowledge and attitudes toward AI-based chatbot systems within the context of preconception counseling consists of 19 items. The scale includes three subdimensions: Acceptance and Intention to Use, Knowledge and Awareness, and Critical Evaluation and Trust. It is a five-point Likert-type scale (1 = Strongly Disagree, 2 = Disagree, 3 = Undecided, 4 = Agree, 5 = Strongly Agree). The scale contains no reverse-coded items. The minimum possible score is 19, and the maximum possible score is 95.

Digital Health Literacy Scale (DHLS)

This instrument measures individuals' ability to adapt to new technological developments [14]. The adapted version of the scale has demonstrated adequate validity and reliability in previous studies. The scale consists of 18 items and six dimensions: Information Searching, Evaluating Reliability, Determining Relevance, Adding Content, Navigational Skills, and Protecting Privacy. A four-point Likert rating is used (1 = very difficult, 2 = difficult, 3 = easy, 4 = very easy). The Navigational Skills and Protecting Privacy subdimensions are reverse-coded—total scoring and interpretation of the scale range from 1 to 4. Scores below 2 indicate low digital health literacy, scores between 2 and 3 indicate moderate digital health literacy, and scores above 3 indicate high digital health literacy. The total Cronbach's alpha coefficient of the scale is 0.896 [15].

Evaluation of items

After the item pool was created, item evaluation focused on whether the scale items showed sufficient relationships with one another [9]. EFA and CFA were performed for construct validity, while Cronbach's alpha internal consistency, McDonald's omega, and parallel test analysis were used during the reliability stage.

Construct validity: Factor analysis may be used to obtain evidence regarding the construct validity of a scale. To determine whether the data were suitable for factor analysis, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity, which indicates correlations among the items, were performed. After the data were judged suitable, EFA was performed with Varimax rotation, and CFA was then used to verify the factor structure. Reliability analysis: To evaluate the internal consistency of the scale, reliability coefficients were calculated using Cronbach's alpha, McDonald's omega, and the parallel scale.

Data analysis

The data obtained were analyzed using SPSS (Statistical Package for Social Sciences) for Windows, version 26.0, and AMOS 24.0. Data obtained from sociodemographic variables in the participant information form were analyzed using descriptive statistics, including number, percentage, mean, and standard deviation. EFA and CFA were also performed to examine the construct validity of the scale. To establish construct validity, the following criteria were used: Comparative Fit Index ($0.90 \leq CFI \leq 0.95$), Goodness of Fit Index ($0.90 \leq GFI \leq 0.95$), Incremental Fit Index ($0.90 \leq IFI \leq 0.95$), Standardized Root

Mean Square Residual ($0.05 \leq \text{SRMR} \leq 0.10$), Root Mean Square Error of Approximation ($0.05 \leq \text{RMSEA} \leq 0.10$), and $0 \leq \chi^2/\text{df} \leq 3$ [9, 16, 17]. Scale reliability was assessed through Cronbach's alpha, McDonald's omega, and parallel scale analysis. Internal consistency was determined using Cronbach's alpha for both the subdimensions and the overall scale, with $\alpha > 0.87$ considered acceptable. A p-value of ≤ 0.05 was accepted as statistically significant.

Results

The mean age of the participants was 25.45 ± 4.62 in Sample 1 and 24.12 ± 3.78 in Sample 2; in both samples, the age range was 18 to 45 years. In Sample 1, 67.1% of the participants were married, as were 70.5% of those in Sample 2. In terms of educational status, 76.4% of participants in Sample 1 and 66.7% of participants in Sample 2 had a university degree or higher level of education. Regarding employment status, the large majority of participants in both samples were not employed (Sample 1: 90.3%; Sample 2: 92.4%) (Table 1).

In sample 1, 70.8% of participants had not received information about preconception health, while this proportion was 76.7% in Sample 2. When sources of information were examined, the most frequently reported source among participants who had received information in both groups was the internet and social media (Sample 1: 27.0%; Sample 2: 27.8%). This was followed by education programs and information obtained from friends, neighbors, and relatives. Health professionals (Sample 1: 19.0%; Sample 2: 22.8%) and traditional communication channels such as television/radio (Sample 1: 8.0%; Sample 2: 13.1%) were reported at lower rates (Table 1).

Regarding intentions to have children in the future, a substantial proportion of participants stated that they planned to have children within the next 5–10 years (Sample 1: 48.5%; Sample 2: 53.6%). Smaller proportions of participants reported that they intended to have children within the next five years, did not intend to have children, or were undecided on this issue (Table 1).

Table 1
Sociodemographic characteristics of the participants

Variables	Sample 1 (N:237)	Sample 2 (N:237)
Age, M (SD)	25.45 (4.62)	24.12 (3.78)
	(Min:18, Max:45)	(Min: 18, Max: 45)
	n (%)	n (%)
Marital status		
Single	159 (67.1)	167 (70.5)
Married	78 (32.9)	70 (29.5)
Educational status		
High school	56 (23.6)	79 (33.3)
University and above	181 (76.4)	158 (66.7)
Employment status		
Employed	23 (9.7)	18 (7.6)
Unemployed	214 (90.3)	219 (92.4)
Pre-pregnancy health information status		
Yes	35 (29.2)	35 (23.3)
No	85 (70.8)	115 (76.7)
Source of this information*		
Educational programs (school education, courses, seminars, etc.)	66 (27.8)	58 (24.5)
Internet and social media (Instagram, Facebook, etc.)	64 (27.0)	66 (27.8)
Friends, neighbors, relatives	56 (23.6)	55 (23.2)
Healthcare professionals (nurses, midwives, physicians)	45 (19.0)	54 (22.8)
AI tools	27 (10.4)	27 (11.4)
Communication channels such as TV/radio	19 (8.0)	31 (13.1)
Intention to have children		
Within the next five years	33 (14.0)	27 (11.4)
Within the next 5–10 years	115 (48.5)	127 (53.6)
N = sample size; n = number of observations; % = percentage; Min = minimum; Max = maximum; M = mean; SD = standard deviation. *Multiple responses were allowed.		

Variables	Sample 1 (N:237)	Sample 2 (N:237)
Do not intend to have children	32 (13.5)	23 (9.7)
Undecided	57 (24.1)	60 (25.3)
N = sample size; n = number of observations; % = percentage; Min = minimum; Max = maximum; M = mean; SD = standard deviation. *Multiple responses were allowed.		

The mean and standard deviation values for the total scores of the PC-AICBS-KAS and the DHLI were 69.63 ± 12.51 and 46.49 ± 5.80 , respectively (Table 2). The mean and standard deviation values for the DHLI subdimensions were 7.60 ± 1.51 , 6.62 ± 1.73 , 7.62 ± 1.50 , 8.35 ± 1.68 , 8.03 ± 1.84 , and 8.25 ± 1.39 , respectively. For each variable, the skewness and kurtosis coefficients fell within the accepted range (skewness = -0.883 to 0.086 ; kurtosis = -0.349 to 0.866).

Table 2
Descriptive statistics of the total scores of pc-aicbs-kas and dhls and their subdimensions

Scales	M (SD)	Skewness	Kurtosis
PC-AICBS-KAS Total Score	69.63 (12.51)	– .594	.552
DHLS Total Score	46.49 (5.80)	– .012	.030
Information seeking subdimension	7.60 (1.51)	– .248	.145
Evaluating reliability subdimension	6.62 (1.73)	.086	.190
Determining relevance subdimension	7.62 (1.50)	– .136	– .168
Navigation skills subdimension	8.35 (1.68)	– .161	– .349
Content creation subdimension	8.03 (1.84)	– .576	.521
Protecting privacy subdimension	8.25 (1.39)	– .883	.866
PC-AICBS-KAS: Knowledge and Attitude Scale Toward AI-Based Chatbot Systems in Preconception Counseling; DHLS: Digital Health Literacy Scale; M = Mean; SD = standard deviation.			

Content validity

Content validity was evaluated using the Lawshe technique, and the Content Validity Ratio (CVR) and Content Validity Index (CVI) were calculated based on expert opinions [18]. The CVR values of the items were found to be above 0.80, and the CVI value of the scale was 0.95. When the number of experts is 13, the minimum acceptable CVR value at the 0.05 significance level has been reported as 0.53 [19]. The fact that the CVI value exceeded this threshold indicated that the content validity of the scale was statistically adequate. At this stage, seven items were excluded from the item pool.

Construct validity

To assess the suitability of the data for factor analysis, KMO and Bartlett's test of sphericity were performed. KMO values were found to be above 0.50, and Bartlett's tests were significant (Table 3). These findings indicate that the data were suitable for factor analysis.

Table 3. Kaiser–Meyer–Olkin (KMO) and Bartlett's test of sphericity values of the sample

Algorithms	Indicators	Values	
		AFA	DFA
		All participants	All participants
KMO	KMO	.916	.924
Bartlett's Test of Sphericity	Approx. Chi-Square	3183.234	3388.092
	df	276	171
	p	.000	.000

Exploratory factor analysis

Prior to Exploratory Factor Analysis (EFA), the distributional properties of the scale scores were checked through skewness and kurtosis coefficients. As all coefficients remained between -1.5 and $+1.5$, the data were considered to meet the assumption of approximate normality [20]. Principal Component Analysis (PCA) and the Varimax rotation method were used in the EFA [21]. In the initial analysis, several items were found to have high loadings on more than one factor and to exhibit cross-loading. Considering the criterion that the difference between factor loadings should be less than 0.10, Items 8, 9, and 12 were removed from the scale, and the analysis was repeated. In the repeated analysis, item factor loadings were evaluated, and Item 20, which had a factor loading below 0.40, was removed from the scale. As a result, a final structure consisting of 19 items and three subdimensions was obtained. This structure explained 63.16% of the total variance. The eigenvalues and explained variance ratios of the factors were 7.928 (41.73%) for Factor 1, 2.650 (13.95%) for Factor 2, and 1.422 (7.48%) for Factor 3, respectively. The factor loadings of the subdimensions of the scale were found to be at acceptable levels. Item loadings were 0.694–0.818 for Factor 1, 0.562–0.814 for Factor 2, and 0.626–0.829 for Factor 3. These findings indicate that the construct validity of the scale was adequate (Table 4).

Table 4
Data on exploratory factor analysis of the PC-AICBS-KAS (n = 237)

New number	Items	Factor 1	Factor 2	Factor 3
1	1. I know that artificial intelligence can provide information about preconception daily lifestyle habits.		.562	
2	2. I know that artificial intelligence can provide information about preconception exercise.		.610	
3	3. I know that artificial intelligence can provide information about preconception healthy nutrition.		.678	
4	4. I know that artificial intelligence can provide information about preconception weight management.		.712	
5	5. I know that artificial intelligence can provide information about the risks of smoking, alcohol, and other harmful habits in the preconception period.		.659	
6	6. I know that artificial intelligence can provide information about medication side effects in the preconception period.		.734	
7	7. I know that artificial intelligence can provide information about environmental risk factors (e.g., radiation, chemical exposure) in the preconception period.		.814	
8	10. I know that information obtained from artificial intelligence does not replace the recommendations of healthcare professionals.			.814
9	11. I know that preconception information obtained from artificial intelligence should be verified from reliable sources.			.829
10	13. Preconception health-related decisions should not be made solely based on artificial intelligence.			.626
11	14. I have a positive attitude toward using artificial intelligence for preconception health-related issues.	.765		
12	15. I would like to benefit from artificial intelligence for preconception nutrition recommendations.	.809		
13	16. I would like to receive support from artificial intelligence for preconception weight control.	.793		
14	17. I do not feel uncomfortable asking artificial intelligence questions about preconception health.	.742		
15	18. Receiving recommendations from artificial intelligence during the preconception period makes me feel reassured.	.818		

New number	Items	Factor 1	Factor 2	Factor 3
16	19. I think artificial intelligence can serve as a guide for women during the preconception period.	.742		
17	21. I consider artificial intelligence as a supportive resource in my preconception health-related decisions.	.803		
18	22. I believe that using artificial intelligence will increase my control over managing my preconception health process.	.791		
19	23. I support the use of AI-based systems as a standard tool in preconception counseling.	.694		
Eigenvalue		7.928	2.650	1.422
Variance Explained Total (63.16%)		41.73	13.95	7.48
Cronbach's Alpha (0.912)		0.93	0.87	0.79

Confirmatory factor analysis

The three-subdimension structure obtained through EFA was tested using CFA with the Maximum Likelihood method in AMOS. The initial fit indices of the model established with 19 items were examined, and no cross-loading items that weakened model fit were identified. In line with the literature, covariance links were established between error terms that belonged to the same subfactor and showed high relationships in the modification indices, such as e1–e2, e2–e3, e10–e11, e10–e12, and e15–e16. Following these modifications, no items were removed, and the final 19-item model was obtained.

First-order confirmatory factor analysis

To confirm the three-factor structure obtained as a result of EFA, first-order CFA was performed on an independent sample. Examination of the model fit indices showed that the χ^2/df value was below 3, CFI and IFI values were close to 0.90, and the RMSEA value was close to 0.08, indicating that the model demonstrated an acceptable level of fit ($N = 237$; $p < 0.001$; $\chi^2/\text{df} = 2.668$; RMSEA = 0.084; CFI = 0.928; GFI = 0.855; TLI = 0.914; IFI = 0.928) (Fig. 1). These values show that the 19-item, three-subdimension PC-AICBS-KAS fitted the collected data at an adequate and acceptable level and that the construct validity of the scale was confirmed (Fig. 1).

Reliability analysis

Cronbach's alpha and McDonald's omega reliability coefficients were used to evaluate the reliability of the scale [22, 23]. McDonald's omega was reported together with Cronbach's alpha (α), as both coefficients are commonly used to evaluate internal consistency and often produce comparable estimates [24]. For the three subdimensions, Cronbach's alpha coefficients were 0.925, 0.925, and 0.770; the coefficient for the total scale was 0.942. McDonald's ω coefficients were 0.926, 0.928, and 0.801 for

the subdimensions and 0.946 for the overall scale. The interpretation of Cronbach's alpha may vary across studies, and Taber (2018) emphasizes that reliability coefficients should be considered in relation to the measurement context rather than by relying on a single rigid cut-off [25]. In the present study, the alpha and omega coefficients obtained for the subdimensions and the total scale were within acceptable to high ranges, supporting the internal consistency of the PC-AICBS-KAS.

Relationship between PC-AICBS-KAS and DHLI scores

As shown in Table 5, a positive and statistically significant relationship was found between the total PC-AICBS-KAS score and the total DHLI score ($r = 0.265$, $p < 0.01$). When the subdimensions were examined, positive and significant relationships were found between the PC-AICBS-KAS and the DHLI subdimensions of information searching ($r = 0.147$, $p < 0.05$), evaluating reliability ($r = 0.179$, $p < 0.01$), determining relevance ($r = 0.212$, $p < 0.01$), adding content ($r = 0.200$, $p < 0.01$), and protecting privacy ($r = 0.129$, $p < 0.05$). By contrast, the relationship with the navigational skills subdimension was not statistically significant ($r = 0.081$, $p > 0.05$) (Table 5).

Table 5
The relationship between PC-AICBS-KAS and DHLS

Scales	1	2	3	4	5	6	7	8
1. PC-AICBS-KAS Total	1	.265**	.147*	.179**	.212**	.081	.200**	.129*
2. DHLS total	-	1	.693**	.680**	.724**	.456**	.643**	.381**
3. Information Seeking Subdimension	-	-	1	.548**	.513**	.141*	.269**	.033
4. Evaluating Reliability Subdimension	-	-	-	1	.531**	.043	.262**	.018
5. Determining Relevance Subdimension	-	-	-	-	1	.161*	.388**	.010
6. Navigation Skills Subdimension	-	-	-	-	-	1	.089	.194**
7. Content Creation Subdimension	-	-	-	-	-	-	1	.212**
8. Protecting Privacy Subdimension	-	-	-	-	-	-	-	1

PC-AICBS-KAS: Knowledge and Attitude Scale Toward AI-Based Chatbot Systems in Preconception Counseling; DHLS: Digital Health Literacy Scale; * $p < 0.05$ ** $p < 0.01$

Discussion

This study examined the psychometric properties of the PC-AICBS-KAS, which was developed to assess knowledge and attitudes toward AI-based chatbot systems in preconception counseling. The findings

support the validity and reliability of the scale. The scale's three-dimensional structure appears to be meaningful and adequate when the content validity findings, EFA and CFA results, and internal consistency coefficients are considered collectively. Nonetheless, these findings should be validated in different samples.

The three-factor structure of acceptance and intention to use, knowledge and awareness, and critical evaluation and trust is consistent with contemporary theoretical approaches explaining AI acceptance in health care. According to recent studies, the use of AI in health is not just determined by perceived usefulness and ease of use. Several other multidimensional factors are involved. Among them are trust, perceived risk, data privacy, and ethical evaluations [6, 7]. It has been reported that trust in medical AI in particular is closely related to system accuracy, transparency, and human oversight [5, 26]. The emergence of "critical evaluation and trust" as a separate factor suggests that the scale has a conceptually valid structure.

The generally moderate-to-positive attitudes of participants toward AI-based systems suggest that these technologies may have the potential to be accepted in health care. In agreement with previous literature, this finding lends credence to the idea that health behavior and knowledge levels may be improved with the support of AI chatbots [3, 4]. Still, interpreting this positive tendency as direct acceptance of clinical use requires caution. The current literature suggests that users' attitudes toward AI systems are context-sensitive and that users take a more cautious approach when serious health-related decision making is involved [13].

The establishment of "knowledge and awareness" as an independent factor in the present study indicates that individuals' attitudes towards AI are associated with cognitive components. Familiarity with the competencies and limitations of AI systems has been found to be decisive in the correct and safe use of these systems [26]. The implication is that it is not simply access to technology that matters, but also the amount of critical knowledge about that technology.

One of the significant findings of the study is that the PC-AICBS-KAS correlates positively and significantly with digital health literacy. This finding aligns with prior studies indicating that digital health literacy is an essential factor influencing individuals' uptake and effective engagement with digital health technologies [14]. Current literature reveals that digital health literacy directly affects an individual's ability to access, evaluate, and use digital health-related information and impacts the acceptance and continued use of digital health applications [27–29].

In the current study, items indicating that information obtained from AI would not replace health professionals and should be verified showed high factor loadings. This indicates that AI is regarded not as a substitute for health professionals, but as a supportive tool. This finding is consistent with evidence showing that AI-based systems may sometimes generate inaccurate or incomplete information [13], as well as with approaches emphasizing that AI in health care should be positioned as a supportive technology [30].

Implications for Practice and Policy

The findings of this study have important implications for clinical practice and digital health policy. The developed scale provides nurses, midwives, and healthcare professionals with a valid and practical tool to assess women's knowledge, attitudes, trust, and acceptance regarding AI-based chatbot systems in preconception counseling. The scale may help identify educational needs and support the development of targeted interventions aimed at improving digital health awareness and informed use of AI-supported reproductive health services.

The findings also emphasize that AI-based systems should be implemented as supportive tools rather than replacements for healthcare professionals. In this context, nurses and midwives have an important role in guiding women toward the safe, ethical, and critical use of AI-generated health information.

At the policy level, the study highlights the need for guidelines and educational frameworks addressing ethical use, transparency, privacy, and patient safety in AI-supported healthcare applications. Integrating AI literacy and digital health competencies into healthcare education programs may further support the responsible adoption of emerging digital health technologies.

Limitations

The study has many strengths to note. To start with, the internal validity of the structure obtained is well-established by virtue of the fact that both EFA and CFA were performed on independent samples. By offering both Cronbach's alpha and McDonald's omega coefficients, these outcomes help support the reliability of the scale through different methods. It is especially interesting that the scale focuses on a precise and clinically sensitive area such as preconception counseling, indicating the gap that exists in the literature. The analysis of relations to digital health literacy further indicates that the scale is not only descriptive but also capable of generating substantively meaningful associations.

Despite these strengths, several limitations should be noted. Initially, social media was used to recruit the sample, which, given the snowball sampling mode of recruitment, means that the participants were more likely to be familiar with digital technology. The inclusion of sampling strategies may have introduced a bias that compromised the generalizability of the findings. Secondly, since the research only included women, the scale's validity needs to be tested among men as well. Self-reported data may involve an element of social desirability and response bias. Due to the cross-sectional nature of the study, causation between the variables cannot be inferred. The absence of test-retest reliability analysis for temporal stability and measurement invariance analysis across groups may be considered additional methodological limitations. Future research should revisit the scale in varied cultures, heterogeneous samples, and over time for more robust results.

Conclusion

This study provides a valid and reliable measurement tool for the multidimensional evaluation of knowledge and attitudes toward AI-based chatbot systems in the context of preconception counseling. The results show that people's attitudes toward AI are shaped not only by perceived benefit but also by a number of factors that are all interconnected and include level of knowledge, critical evaluation, trust, and digital health literacy.

The integration of AI-based systems into health services involves much more than the performance of technology alone. In addition, it must be addressed in a user-centered manner, with variables such as trust, ethical acceptability, and cognitive competence. The tool developed in this study may be useful for understanding AI-related user profiles in research and for designing relevant education and intervention strategies in practice. However, it is still important to re-evaluate the scale on different populations and cultural contexts in order to strengthen the generalizability of the findings.

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with ethical principles and received approval from the Social and Human Sciences Ethics Committee of Bartın University (date: 26.01.2026; Protocol No: 2026-SBB-0050). Participants also approved the informed consent page before beginning the survey. They were informed about anonymity, their right to withdraw, and the voluntary nature of the study. The study was carried out in accordance with the Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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Authors' Contributions

ECE,GA: Study conception, ECE,GA: Data collection, ECE,GA: Study design, ECE,GA: Data analysis, drafting the manuscript, ECE,GA: Critical revisions for intellectual content, supervision.

Data Availability Statement

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

Clinical Trial Number: Not applicable.

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Figures

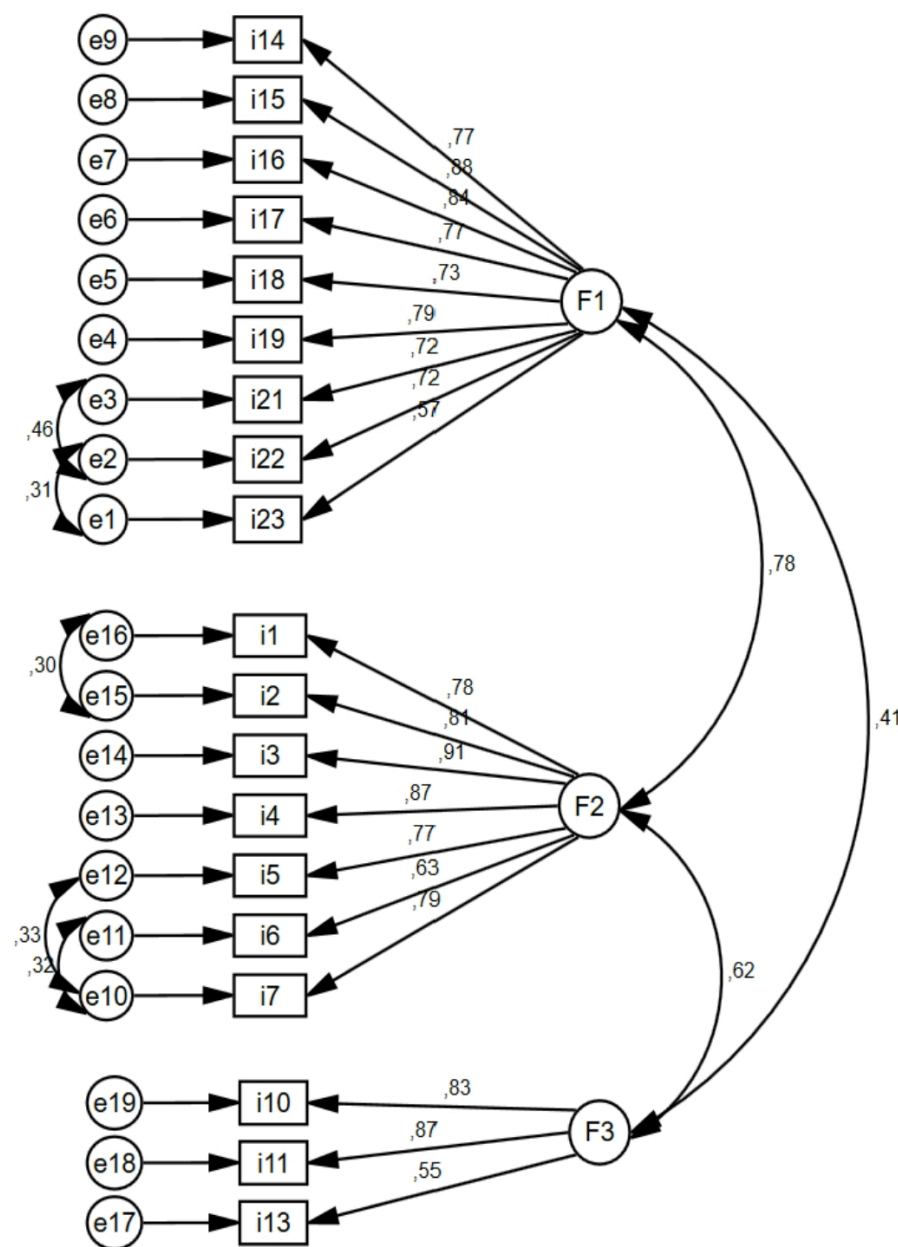


Figure 1

First-order confirmatory factor analysis