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Psychometric Evaluation of the Artificial Intelligence Perception Scale for Cancer Patients: A Structural Equation Modeling Approach

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ABSTRACT

Rationale, Aims and Objectives: Artificial intelligence (AI) is increasingly integrated into oncology care, with oncology nurses playing a key role in patient education, communication, and trust in these technologies. Although artificial intelligence is increasingly integrated into healthcare, existing AI perception and technology acceptance scales have largely been developed for general healthcare settings and do not adequately capture the unique clinical, ethical, and workflow-related aspects of oncology practice. This study aimed to develop and psychometrically validate a scale measuring oncology patients' perceptions of artificial intelligence. The study focused on instrument development rather than testing a theoretical model of technology acceptance.

Methods: A methodological, cross-sectional scale development study. The scale was developed according to established nursing research guidelines. An initial item pool was generated using the Technology Acceptance Model, literature review and expert opinions from oncology nursing and interdisciplinary healthcare professionals. Content validity was assessed using the Davis technique and Lawshe method. Data were collected from 382 adult cancer patients receiving nursing care. Construct validity was examined using exploratory and confirmatory factor analyses. Reliability was evaluated using Cronbach's α, split-half reliability and composite reliability. Structural equation modeling with bootstrapping tested the theoretical model.

Results: The final scale included 33 items across three factors: knowledge, awareness, and trust; perceived benefit; and acceptance and use tendencies. Exploratory factor analysis explained 82.37% of the total variance. Confirmatory factor analysis demonstrated good model fit (CFI = 0.99, RMSEA = 0.079, SRMR = 0.038). Internal consistency was excellent for the total scale ($\alpha = 0.97$) and subscales ($\alpha = 0.97$–0.98). Perceived benefit partially mediated the relationship between knowledge and acceptance, explaining 52% of the variance.

Conclusions: The scale is a valid and reliable instrument for assessing cancer patients' perceptions and acceptance of AI in oncology nursing practice. This scale provides oncology nurses and nurse researchers with a standardized tool to support nursing-led patient education, shared decision-making and the integration of AI into patient-centred oncology nursing care.

1 | Introduction

Artificial intelligence (AI) has emerged as one of the most prominent technologies driving the digital transformation of healthcare over the past decade. Particularly in the field of oncology, AI-based applications have been increasingly integrated into clinical nursing practice, including diagnostic support, treatment planning, symptom monitoring and prognostic prediction [1]. From a nursing perspective, AI technologies have the potential to accelerate early cancer detection through large-scale data analysis, reduce diagnostic and care-related errors, and support nurses' clinical decision-making processes, thereby enhancing the quality and safety of nursing care. Alongside the digitalization of healthcare systems, the transition towards AI-based applications in oncology nursing has gained momentum, and various AI-supported algorithms have been developed, particularly for the early diagnosis, follow-up and symptom management of patients with cancer [2]. However, technological advancement alone is not sufficient. The sustainable integration of AI-driven innovations into nursing practice and their ability to generate meaningful clinical outcomes are closely related to patients' perceptions, trust and acceptance of such technologies within the context of nursing care. Compared with patients in many other clinical specialties, individuals with cancer often experience prolonged treatment trajectories, greater prognostic uncertainty, repeated interactions with oncology professionals and higher levels of psychological distress. These characteristics make trust, transparency, empathy and shared decision-making particularly important when AI-supported technologies are introduced into oncology care. Consequently, cancer patients may evaluate AI not only according to its technical performance but also according to whether it preserves human communication, supports emotional needs, and complements rather than replaces healthcare professionals. Recent studies have consistently reported that concerns regarding trust, explainability, and the role of clinicians are more prominent among oncology patients than in several other healthcare contexts [3, 4]. In this context, patient trust in AI-supported nursing interventions is emphasized as being shaped by perceived benefits that align with patients' values, expectations, and experiences of nurse–patient interaction [5]. Unlike many other clinical disciplines, oncology nursing involves continuous patient interaction throughout diagnosis, treatment, symptom management, survivorship and palliative care. Consequently, oncology nurses play a central role in explaining AI-assisted technologies, addressing patients' concerns, promoting digital health literacy, and supporting informed decision-making. Understanding patients' perceptions of AI is therefore essential for the successful integration of AI into oncology nursing practice [4, 6–8].

Recent studies indicate that patients experience a dual emotional response towards AI-based applications, characterized by both curiosity and hope, as well as concern and mistrust. For instance, research conducted among cancer patients has revealed that a substantial proportion of individuals express apprehension that AI-driven diagnostic systems may produce erroneous decisions or potentially replace the physician's role in clinical care [9]. From an ethical perspective, the use of AI has introduced new debates concerning patient autonomy, informed consent, and data privacy. In populations experiencing high levels of uncertainty and stress, such as cancer patients, the degree of trust in technology can directly influence engagement with treatment and care processes [10]. These inconsistent findings suggest that cancer patients' perceptions of AI are multidimensional and context-dependent, highlighting the need for standardized psychometrically sound instruments capable of capturing these complex attitudes.

Within the context of AI, perception encompasses individuals' beliefs, expectations, perceived benefits, and concerns regarding AI technologies. Trust refers to confidence that AI systems are reliable, safe, and capable of supporting appropriate clinical care, whereas acceptance reflects patients' willingness or behavioural intention to use AI-assisted healthcare technologies. Although these constructs are closely related, they represent conceptually distinct dimensions of patients' responses to AI [11–13].

Although several instruments have been developed to assess attitudes toward artificial intelligence or technology acceptance, most have been designed for healthcare professionals, healthcare students or members of the general public and primarily assess perceived usefulness, perceived ease of use, attitudes and behavioural intention within the Technology Acceptance Model framework [14–16]. Recent instruments, including the Artificial Intelligence Attitude Scale developed for nurses and questionnaires assessing AI use in academic settings, were not designed to capture patients' experiences of AI in clinical care. Furthermore, evidence from recent systematic reviews indicates that patients' perceptions of AI encompass broader dimensions—including trust, transparency, communication, clinician involvement and ethical concerns—that are not comprehensively addressed by conventional technology acceptance measures [5, 11, 17]. To our knowledge, no psychometrically validated instrument has been specifically developed to comprehensively assess cancer patients' perceptions of AI in oncology care by integrating these multidimensional constructs. Consequently, an oncology-specific measurement instrument is warranted. A review of the existing literature highlights a notable lack of standardized measurement instruments capable of systematically and quantitatively assessing cancer patients' attitudes toward AI. The available studies are largely limited to researcher-developed questionnaires designed for specific studies, many of which lack fully established psychometric properties [5]. This situation complicates the comparison of findings across studies and hinders the establishment of a standardized assessment of patient perceptions. Therefore, there is a clear need to develop a valid and reliable scale capable of evaluating patients' perceptions of AI in a multidimensional manner, including perceived benefits, risks, trust and ethical concerns.

Against this background, the present study aimed to develop and psychometrically validate the Artificial Intelligence Perception Scale for Cancer Patients. Rather than testing a theoretical model of technology acceptance, the study focused on the development and psychometric evaluation of a multidimensional instrument designed to assess cancer patients' perceptions of AI in oncology care. The resulting scale is expected to facilitate the systematic assessment of patients' perceptions, including perceived benefits, perceived risks, trust, ethical concerns and acceptance of AI technologies. Such evidence may support the patient-centred implementation of AI applications in oncology care and inform future research and clinical practice. A better understanding of cancer patients' perceptions of AI may enable oncology nurses to tailor patient education, improve communication regarding AI-supported care, strengthen patient trust and facilitate the ethical integration of AI into routine oncology nursing practice.

2 | Methods

2.1 | Design

This study aimed to develop and psychometrically validate a scale measuring cancer patients' perceptions of artificial intelligence properties between December 2025 and January 2026. This study was primarily designed as a methodological psychometric scale development study. A cross-sectional design was adopted, as all psychometric assessments, including exploratory factor analysis, confirmatory factor analysis (CFA) and reliability analyses, were performed using data collected from participants over a specific time period; this is consistent with established recommendations for instrument development research. The study process was structured in two main phases in accordance with established scale development guidelines [18]; (1) generation of the item pool and assessment of content validity; and (2) evaluation of construct validity and reliability analyses. The reporting of this study followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) checklist.

2.2 | Questionnaire Development

The item pool of the scale was generated based on a comprehensive literature review and patient experiences, and consisted of draft items covering the dimensions of knowledge, awareness, trust, perceived benefits, perceived risks and acceptance. Thirty-six preliminary items were generated from the literature review and theoretical frameworks, whereas 12 additional items were derived from recurring themes identified during informal interviews conducted with 10 cancer patients regarding their expectations, concerns, and experiences with AI-supported healthcare technologies. The content relevance of the item pool was evaluated using the Davis Technique and the Lawshe Method in line with expert opinions. Content Validity Ratio (CVR) and Content Validity Index (CVI) were calculated according to the experts' ratings of item relevance. Items with a CVR value ≤ 0.80 were planned to be excluded from the scale [19, 20]. The threshold of 0.80 was selected based on recommendations by Polit et al. and Davis for expert panels of similar size, ensuring that only items demonstrating a high level of content relevance were retained. To assess content validity, the opinions of an expert panel consisting of 11 specialists in oncology and psychometrics were obtained. Based on expert evaluations, the Content Validity Index (CVI) was calculated as 0.862, and three items with index values below 0.80 were removed. The overall CVI score of the scale was 0.862, indicating adequate content validity. Following linguistic and content revisions made in accordance with expert recommendations, the scale proceeded to the construct validity phase. Item-level CVR values ranged from 0.82 to 1.00, while item-level CVI values ranged from 0.84 to 1.00.

2.3 | Content

In determining the content domains of the scale, the Technology Acceptance Model (TAM), which constitutes a foundational framework for explaining technology acceptance [21], and the World Health Organization's guidelines on the ethics and governance of artificial intelligence in health [22] were adopted as the theoretical basis. The item pool was developed through the synthesis of these theoretical frameworks with evidence from recent qualitative literature examining oncology patients' perceptions of AI systems [23–25]. The initial five-factor model was developed to reflect the multidimensional nature of AI perception. Knowledge represents cognitive understanding of AI; Trust reflects confidence in the safety and reliability of AI systems; Perceived Benefit captures expected clinical advantages; Fear and Concern represent perceived risks and ethical uncertainty; and Acceptance reflects the behavioural intention to use AI-supported healthcare. Together, these dimensions are consistent with the Technology Acceptance Model and recent evidence regarding patients' perceptions of AI (Figure 1a). This model is grounded in the assumption that technology perception among oncology patients represents a multidimensional process encompassing cognitive components based on knowledge, affective components shaped by trust and fear, and behavioural components reflecting intention to use.

This figure depicts the hypothesized relationships among the cognitive (Knowledge and Awareness), affective (Trust, Fear, and Concern), and behavioural (Acceptance and Intention to Use) components conceptualized to explain artificial intelligence acceptance among oncology patients. The symbols displayed on the arrows represent the expected direction of the relationships, with (+) indicating a positive association and (−) indicating a negative association. The model posits that the

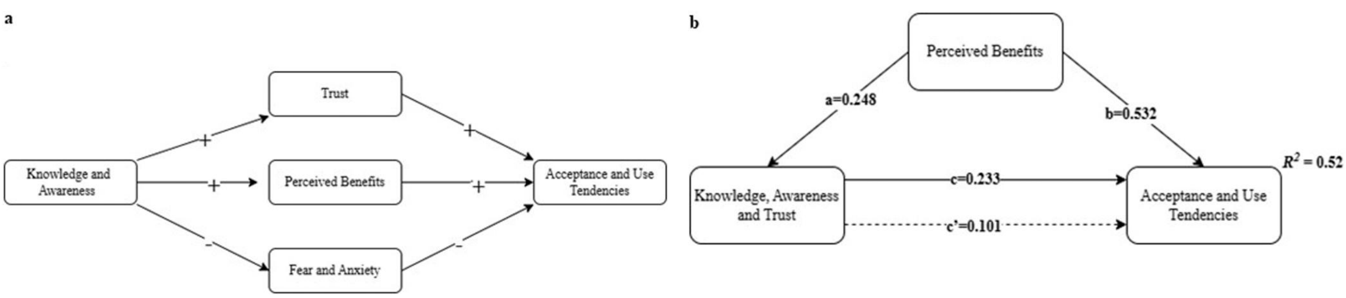

FIGURE 1 | (a) Initial conceptual model for the development of the Artificial Intelligence Perception Scale for Cancer Patients. (b) Structural model of the perceived artificial intelligence (AI) scale for cancer patients. All paths are significant at the $p < 0.001$ level. B values represent standardized regression coefficients. R^2 indicates the explained variance.

"Perceived Benefit" and "Trust" dimensions increase acceptance intention, whereas the "Fear and Concern" dimension exerts an inhibiting effect on acceptance.

2.4 | Format

Given the high symptom burden commonly experienced by patients undergoing cancer treatment (e.g., fatigue and physical weakness), the scale was intentionally designed to be concise, linguistically clear, and easy to complete within a short time frame [5]. To achieve this, the initial item pool consisting of 48 items was refined based on expert feedback and pilot study findings, with the aim of minimizing respondent burden. Data were collected using a 5-point Likert-type response format (1 = *Strongly Disagree* to 5 = *Strongly Agree*), which has demonstrated high psychometric stability in attitude and perception research. Likert-type scales are well recognized for their validity in capturing subjective constructs in sensitive populations such as oncology patients and are known to provide more nuanced data compared with visual analogue scales [18]. The reduction from 48 to the final set of items followed a sequential process involving expert review for content validity, pilot testing for clarity and comprehensibility, item-total correlation analysis, and exploratory factor analysis. Items demonstrating poor psychometric performance or conceptual redundancy were removed.

2.5 | Participants and Sampling

The study was conducted in the medical oncology inpatient wards and outpatient chemotherapy units of Izmir City Hospital, a large public hospital in western Izmir/Turkey. The hospital provides comprehensive oncology services, including systemic chemotherapy, immunotherapy, supportive care, and palliative care, and serves patients referred from the surrounding region. The study sample consisted of adult cancer patients receiving active cancer treatment in these units between December 2025 and January 2026.

In determining the sample size, established recommendations for exploratory factor analysis (EFA) and CFA in scale development studies were taken into account, including the criteria of "a minimum of 200 participants per analysis" or "10–20 participants per item" [26, 27]. In line with the literature suggesting that a sample size between 301 and 500 is considered "very good" for psychometric analyses, a target sample of 400 cancer patients was planned. Upon completion of data collection, the study was finalized with 382 cancer patients who met the inclusion criteria and provided complete data.

Participants were recruited using convenience sampling among individuals who met the inclusion criteria and voluntarily agreed to participate in the study. Inclusion criteria were: being 18 years of age or older; having a medically confirmed cancer diagnosis; being aware of the diagnosis; possessing the ability to use a computer or smartphone; currently receiving active treatment (chemotherapy, radiotherapy, or immunotherapy) or palliative care; and having sufficient physical and cognitive capacity to complete the questionnaire. Digital literacy was included as an eligibility criterion because the scale evaluates perceptions of AI-based healthcare technologies. A minimum ability to use digital devices was therefore considered necessary to ensure that participants could meaningfully interpret AI-related concepts. Patients in the terminal stage of illness, those with advanced cognitive impairment, or individuals who declined to provide informed consent were excluded from the study.

2.6 | Data Collection

The data collection process was conducted in two phases in accordance with methodological standards. In the first phase, a pilot study was carried out with a group of 30 patients to evaluate the linguistic coherence between items, clarity of wording, and average completion time of the draft version of the scale. Thirty patients meeting the inclusion criteria were recruited using convenience sampling. Preliminary internal consistency analysis yielded satisfactory reliability. Based on participant feedback, minor wording revisions were made to improve clarity and readability, while no items required deletion at this stage. Based on the feedback obtained from the pilot application, the final version of the instrument was revised and subsequently administered to the main sample of 382 participants. Data were collected through face-to-face interviews using a 21-item Participant Information Form developed by the researcher and the draft scale formatted with a 5-point Likert-type response system. The Participant Information Form consisted of 21 researcher-developed questions addressing sociodemographic characteristics, clinical variables, digital technology use, internet habits, previous experience with AI applications, and perceived familiarity with artificial intelligence. Interviews were conducted in clinical waiting areas in a manner that did not interfere with patients' treatment routines.

2.7 | Data Analysis

The data obtained in the study were analyzed using SPSS version 26.0 and LISREL version 8.7 statistical software packages. Descriptive statistics were used to summarize the demographic characteristics of the participants in the sample of 382 individuals. Given the methodological nature of the study as a scale development research, the validity of the instrument was evaluated through exploratory factor analysis (EFA), CFA, item discrimination analyses, and average variance extracted (AVE) methods. To provide independent evidence for construct validity, the total sample was randomly divided into two subsamples. EFA was conducted using the first subsample, whereas CFA was subsequently performed on the second subsample to validate the factor structure identified by the EFA. Item discrimination was assessed using corrected item–total correlation coefficients and Cronbach's α if item deleted statistics. Items with corrected item–total correlation coefficients below 0.30 or showing negative correlations were considered to have inadequate discriminative ability and were removed prior to exploratory factor analysis. Subsequently, the reliability of the scale was assessed using Cronbach's α coefficient, split-half reliability, and composite reliability analyses.

Univariate normality of the scale items was examined using the Shapiro–Wilk test, while multivariate normality was assessed using the Henze–Zirkler test. Based on the results of the normality assessments, nonparametric statistical methods were employed for comparisons involving variables that did not exhibit a normal distribution. Relationships among variables were analyzed using Spearman's rho correlation coefficient. Statistical significance was evaluated at the 95% and 99% confidence levels, with p values of < 0.05 and < 0.01 considered statistically significant.

Furthermore, Structural Equation Modeling (SEM) was applied to test the theoretical model of the scale. Direct and indirect effects among variables were analyzed using the Maximum Likelihood estimation method in conjunction with bootstrapping techniques.

2.8 | Ethical Considerations

This study was approved by the Izmir City Hospital Non-Interventional Clinical Research Ethics Committee (Decision No: 2025/576; Date: March 19, 2025).

3 | Results

3.1 | Descriptive Characteristics and Artificial Intelligence Usage Habits of the Participants

The mean age of the participants was 54.93 ± 12.99 years (range: 21–86). Of the participants, 50.3% were female and 49.7% were male. The majority were married (78.8%). Regarding educational level, 29.8% had completed primary school, followed by high school graduates (27.7%), while 16.2% had a university degree or higher. In terms of employment status, 34.6% were employed, 33.5% were retired, and 30.4% were housewives. Most participants reported a moderate income level (58.9%). More than half of the participants were current smokers (54.7%), while 27.7% were former smokers. Alcohol use was reported by 73.8% of the participants. The most common cancer types were genitourinary and gynecological cancers (25.9%) and gastrointestinal system cancers (25.1%), followed by breast cancer (20.9%). Regarding treatment modalities, 73.8% received chemotherapy, 52.4% underwent surgical treatment, and 15.7% received chemoradiotherapy (Table 1).

The mean daily internet usage time of the participants was 4.99 ± 3.37 h (range: 1–16). A majority of the participants (69.1%) reported using the internet to access health-related information, and 50.5% reported using artificial intelligence applications. The most common purposes of AI use were health-related information seeking (30.4%) and general information seeking (29.8%). The primary device used to access the internet was smartphones (90.6%). When searching for health-related information online, participants most frequently used forums and social media (48.4%), followed by official health websites (23.6%). Regarding digital skills, 38.7% reported a moderate level, while 36.1% reported poor digital device use skills. Awareness of the concept of artificial intelligence was reported as partial by 45.5%, while 36.1% reported being aware. Additionally, 66.0% of the participants believed that artificial intelligence would have a positive impact on patient care (Table 1).

3.2 | Results of Item Analysis

Item analysis was conducted to calculate the item reliability of the items included in the designed Artificial Intelligence Perception Scale for Cancer Patients and to identify items exhibiting low correlations with the overall scale for potential removal. The results of the item analysis are presented in Table 2.

As a result of the analysis, item–total score correlations and Cronbach's α values if items were deleted were examined for the designed scale. Twelve items with item–total correlation values below 0.30 or exhibiting negative correlations were identified. Accordingly, items *ITEM_12, ITEM_14, ITEM_23, ITEM_30, ITEM_31, ITEM_32, ITEM_33, ITEM_34, ITEM_35, ITEM_36, ITEM_37*, and *ITEM_38* were removed from the scale. For the remaining 33 items, item–total correlation coefficients ranged from $r = 0.666$ to 0.860.

The overall internal consistency of the scale was assessed using Cronbach's α coefficient, which was calculated as 0.95, indicating excellent reliability. The removal of the identified items did not result in a substantial change in the internal consistency of the scale. Furthermore, anti-image correlation values obtained from the Exploratory Factor Analysis ranged between 0.87 and 0.98, suggesting a high level of sampling adequacy and strong inter-item suitability. These findings indicate that the scale items demonstrate a very good level of compatibility for factor analysis.

The Artificial Intelligence Perception Scale for Cancer Patients consisted of 33 items, and factor analysis was conducted using the Principal Axis Factoring extraction method. Based on factor eigenvalues obtained from the analysis of the 33 items, three underlying dimensions were identified. According to the results presented in Table 3, the scale comprised three subdimensions: knowledge, awareness, and trust; perceived benefit; and acceptance and intention to use. Given the presence of correlations among the factors, an oblique rotation method *(PROMAX)* was applied. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was calculated as 0.971, and Bartlett's Test of Sphericity yielded a value of $\chi^2 = 20{,}202.75$ ($p < 0.001$), indicating that the data were suitable for factor analysis. The three-factor solution accounted for 82.37% of the total variance, suggesting that the identified factors jointly explained a substantial proportion of the variance in the items and the overall scale. In factor analysis, initial eigenvalues greater than 1.0 are generally considered acceptable, and all three factors in the present analysis met this criterion. Examination of the scree plot (Figure 2) revealed a clear inflection point after the third factor, further confirming the three-factor structure of the scale.

3.3 | CFA Results

Table 4 presents the results of the CFA, discriminant validity analysis, Cronbach's α, and composite reliability of the Artificial Intelligence Perception Scale for cancer patients.

The Henze–Zirkler multivariate normality test indicated that the items of the Artificial Intelligence Perception Scale for Cancer Patients did not conform to a normal distribution ($p < 0.001$). Therefore, in the CFA, regression coefficients were estimated using the *Diagonally Weighted Least Squares* (DWLS)

TABLE 1 | Sociodemographic data of the participants ($n = 382$).

Characteristics	**Mean ± SD**	**Minimum-maximum**	
Age (years)	54.93 ± 12.99	21–86	
Parameters		***n***	**%**
Gender	Male	190	49.7
	Female	192	50.3
Marital status	Married	301	78.8
	Single	81	21.2
Educational level	Illiterate	14	3.7
	Literate	24	6.3
	Primary school	114	29.8
	Secondary school	62	16.2
	High school	106	27.7
	University and above	62	16.2
Employment status	Employed	132	34.6
	Housewife	116	30.4
	Student	2	.5
	Retired	128	33.5
	Unemployed	4	1.0
Income level	Good	50	13.1
	Moderate	225	58.9
	Low	107	28.0
Smoking status	Yes	209	54.7
	No	67	17.5
	Former smoker (quit smoking)	106	27.7
Alcohol use	Yes	282	73.8
	No	32	8.4
	Former (Stopped drinking alcohol)	68	17.8
Diagnosis			
Genitourinary and gynecological cancers	Cervix, endometrium, ovary, prostate, bladder, kidney, testis, penis	99	25.9
Breast cancer	Breast Cancer	80	20.9
Gastrointestinal system cancers	Esophagus, stomach, colon, rectum, rectosigmoid, liver, pancreas, peritoneal carcinomatosis	96	25.1
Respiratory and head–neck cancers	Lung, larynx, oropharynx, thyroid	62	16.2
Hematological malignancies	Leukemia, lymphoma, multiple myeloma, bone marrow malignancies	39	10.2
Central nervous system and other rare tumours	Brain, neuroendocrine tumour, osteosarcoma, skin cancer, meningomyelocele	6	1.6
Metastasis	Present		
	Absent		
Treatment*	Surgical treatment	200	52.4
	Radiotherapy	20	5.2
	Chemotherapy	282	73.8
	Chemoradiotherapy	60	15.7
	Mean ± SD	**Minimum-maximum**	
Daily internet usage time (hours)	4.99 ± 3.37	1–16	
Parameters		***n***	**%**
Use of the internet to access health-related information	Yes	264	69.1
	No	118	30.9

(Continues)

TABLE 1 | (Continued)

Parameters		n	%
Use of artificial intelligence applications	Yes	193	50.5
	No	189	49.5
Purpose of artificial intelligence use*	Health-related information seeking	116	30.4
	Homework/academic work preparation	20	5.2
	General information seeking	114	29.8
	Entertainment/chat	50	13.1
Primary device used for internet access	Computer	21	5.5
	Smartphone	346	90.6
	Tablet	15	3.9
Sources used for seeking health-related information on the internet*	Official health websites (e.g., Ministry of Health, WHO)	90	23.6
	Forums and social media	185	48.4
	Academic articles	14	3.7
	Artificial intelligence applications	12	3.1
	Other	22	5.8
Level of digital device use skills	Poor	138	36.1
	Moderate	148	38.7
	Good	71	18.6
	Very good	25	6.5
Awareness of the concept of artificial intelligence	Yes	138	36.1
	No	70	18.3
	Partially	174	45.5
Perceived impact of artificial intelligence on patient care	Yes	252	66.0
	No	130	34.0

*Multiple answers possible.

estimation method. The standardized factor loadings of the scale items ranged between 0.82 and 0.97, and all items were found to be statistically significant ($p < 0.01$).

The overall Cronbach's α coefficient of the scale was calculated as 0.986, indicating a very high level of internal consistency and demonstrating that responses to the Artificial Intelligence Perception Scale for cancer patients were highly consistent.

For the Knowledge, Awareness, and Trust subscale, the Average Variance Extracted (AVE) value was 0.826 (≥ 0.50), indicating adequate convergent validity. Reliability results further demonstrated very high internal consistency, with Composite Reliability (CR) = 0.989 (≥ 0.70) and Cronbach's α = 0.98 (≥ 0.80).

Similarly, the Perceived Benefit subscale demonstrated sufficient convergent validity, with an AVE value of 0.902 (≥ 0.50). Reliability analyses revealed a CR value of 0.928 (≥ 0.70) and a Cronbach's α coefficient of 0.97 (≥ 0.80), indicating a very high level of reliability.

For the Acceptance and Intention to Use subscale, the AVE value was calculated as 0.873 (≥ 0.50), supporting adequate convergent validity. Reliability indices showed CR = 0.979 (≥ 0.70) and Cronbach's α = 0.97 (≥ 0.80), confirming a very high level of internal consistency.

The CFA model fit indices for the Artificial Intelligence Perception Scale for Cancer Patients were as follows: chi-square/df (CMIN/*df*) = 3.40, NNFI = 0.99, NFI = 0.98, CFI = 0.99, IFI = 0.99, GFI = 1.00, SRMR = 0.038, and RMSEA = 0.079. As all fit indices fell within acceptable or good fit thresholds, the model was considered to demonstrate adequate construct validity. The path diagram of the model is presented in Figure 3.

3.4 | Split-Half Reliability Analysis

To determine the internal consistency of the Artificial Intelligence Perception Scale for Cancer Patients, a split-half reliability analysis was conducted, and the consistency of the scale items was examined as presented in Table 5. The correlation coefficient between the two halves of the scale was found to be 0.829, indicating a strong relationship between the split sets of items.

The Cronbach's α coefficient for the first half of the scale (first 17 items) was 0.98, while the α coefficient for the second half (last 16 items) was 0.97, demonstrating a high level of internal consistency for each half independently. In addition, the Spearman–Brown reliability coefficient was calculated as 0.907, and the Guttman split-half reliability coefficient was 0.901. As all reliability coefficients exceeded the recommended threshold of 0.70, the scale items were considered to exhibit a high level of reliability.

TABLE 2 | Item analysis results of the Artificial Intelligence Perception Scale for cancer patients ($n = 382$).

ITEMS	Mean ± S.D.	Median (minimum–maximum)	Anti-image correlation	Item–total correlation (r)	Cronbach's alpha if item deleted (α)
ITEM_1	3.3 ± 1.4	4 (1–5)	0.967	0.834	0.947
ITEM_2	3.2 ± 1.4	4 (1–5)	0.960	0.826	0.947
ITEM_3	3.3 ± 1.4	4 (1–5)	0.978	0.835	0.947
ITEM_4	3.2 ± 1.4	4 (1–5)	0.976	0.827	0.947
ITEM_5	3.3 ± 1.4	4 (1–5)	0.980	0.853	0.947
ITEM_6	3.3 ± 1.4	4 (1–5)	0.963	0.828	0.947
ITEM_7	3.3 ± 1.4	4 (1–5)	0.972	0.837	0.947
ITEM_8	3.2 ± 1.4	4 (1–5)	0.976	0.840	0.947
ITEM_9	3.2 ± 1.4	4 (1–5)	0.953	0.783	0.948
ITEM_10	3.1 ± 1.4	3 (1–5)	0.954	0.767	0.948
ITEM_11	3.2 ± 1.4	3 (1–5)	0.966	0.836	0.947
ITEM_12	2.8 ± 1.4	3 (1–5)	0.880	-0.404	0.954
ITEM_13	3.2 ± 1.3	4 (1–5)	0.977	0.827	0.947
ITEM_14	2.7 ± 1.4	2 (1–5)	0.915	-0.484	0.955
ITEM_15	3.3 ± 1.4	4 (1–5)	0.979	0.851	0.947
ITEM_16	3.3 ± 1.3	4 (1–5)	0.973	0.86	0.947
ITEM_17	3.2 ± 1.3	3 (1–5)	0.976	0.829	0.947
ITEM_18	3.2 ± 1.3	4 (1–5)	0.972	0.837	0.947
ITEM_19	3.3 ± 1.4	4 (1–5)	0.960	0.783	0.948
ITEM_20	3.2 ± 1.4	4 (1–5)	0.973	0.839	0.947
ITEM_21	3.2 ± 1.4	4 (1–5)	0.964	0.841	0.947
ITEM_22	3.2 ± 1.4	4 (1–5)	0.976	0.724	0.948
ITEM_23	2.6 ± 1.4	2 (1–5)	0.928	-0.317	0.954
ITEM_24	3.2 ± 1.4	3 (1–5)	0.959	0.798	0.948
ITEM_25	3.3 ± 1.3	4 (1–5)	0.961	0.784	0.948
ITEM_26	3.2 ± 1.3	4 (1–5)	0.975	0.814	0.947
ITEM_27	3.3 ± 1.3	4 (1–5)	0.962	0.822	0.947
ITEM_28	3.2 ± 1.4	3 (1–5)	0.972	0.835	0.947
ITEM_29	3.2 ± 1.4	3 (1–5)	0.970	0.809	0.947
ITEM_30	3.3 ± 1.3	3 (1–5)	0.882	-0.108	0.953
ITEM_31	3.4 ± 1.3	4 (1–5)	0.899	-0.182	0.953
ITEM_32	3.3 ± 1.3	3 (1–5)	0.921	-0.243	0.953
ITEM_33	3.3 ± 1.3	3 (1–5)	0.914	-0.245	0.953
ITEM_34	3.3 ± 1.3	3 (1–5)	0.903	-0.210	0.953
ITEM_35	3.3 ± 1.3	3 (1–5)	0.936	-0.164	0.953
ITEM_36	3.3 ± 1.3	3 (1–5)	0.898	-0.030	0.952
ITEM_37	2.7 ± 1.3	3 (1–5)	0.869	-0.030	0.952
ITEM_38	2.7 ± 1.2	3 (1–5)	0.876	-0.019	0.952
ITEM_39	3.2 ± 1.3	3 (1–5)	0.963	0.666	0.948
ITEM_40	3.2 ± 1.3	3 (1–5)	0.974	0.739	0.948
ITEM_41	3.3 ± 1.3	4 (1–5)	0.966	0.751	0.948
ITEM_42	3.2 ± 1.3	3 (1–5)	0.961	0.733	0.948
ITEM_43	3.1 ± 1.3	3 (1–5)	0.966	0.716	0.948
ITEM_44	3.2 ± 1.3	3 (1–5)	0.966	0.741	0.948
ITEM_45	3.2 ± 1.3	3 (1–5)	0.965	0.765	0.948

TABLE 3 | Exploratory factor analysis results of the Artificial Intelligence Perception Scale for cancer patients ($n = 382$).

ITEMS	Knowledge, awareness and trust	Acceptance and intention to use	Perceived benefit	Initial eigenvalues	Initial variance explained (%)
ITEM_1	0.838			22.710	68.817
ITEM_2	0.842				
ITEM_3	0.85				
ITEM_4	0.882				
ITEM_5	0.896				
ITEM_6	0.938				
ITEM_7	0.953				
ITEM_8	0.926				
ITEM_9	0.839				
ITEM_10	0.844				
ITEM_11	0.671				
ITEM_13	0.606				
ITEM_15	0.683				
ITEM_16	0.659				
ITEM_17	0.574				
ITEM_18	0.597				
ITEM_19	0.586				
ITEM_20	0.549				
ITEM_21	0.608				
ITEM_22	0.555				
ITEM_24			0.807	2.906	8.807
ITEM_25			0.820		
ITEM_26			0.824		
ITEM_27			0.855		
ITEM_28			0.807		
ITEM_29			0.717		
ITEM_39		0.786		1.566	4.746
ITEM_40		0.825			
ITEM_41		0.889			
ITEM_42		0.903			
ITEM_43		0.881			
ITEM_44		0.889			
ITEM_45		0.846			
Total					82.370
Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy					0.971
Bartlett's test of sphericity (χ^2)					20,202.75
SD					528
p value					$p < 0.001$

3.5 | Results of Correlation Analysis

The relationships between the *Artificial Intelligence Perception Scale for Cancer Patients* and its subdimensions were examined using correlation analysis and are presented in Table 6. According to the results, the relationship between *Knowledge, Awareness, and Trust* and *Perceived Benefit* was found to be statistically significant ($p < 0.01$). This finding indicates a positive and strong correlation between the two variables ($0.60 < r < 0.79$), with a correlation coefficient of $r = 0.762$.

The relationship between Knowledge, Awareness, and Trust and Acceptance and Intention to Use was found to be statistically significant ($p < 0.01$), indicating a positive and strong correlation between these two variables ($0.60 < r < 0.79$, $r = 0.650$). A statistically significant relationship was also observed between Knowledge, Awareness, and Trust and the overall Artificial Intelligence Perception in cancer patients ($p < 0.01$), demonstrating a positive and very strong correlation ($0.80 < r < 1.00$, $r = 0.963$). The correlation between Perceived Benefit and Acceptance and Intention to Use was statistically

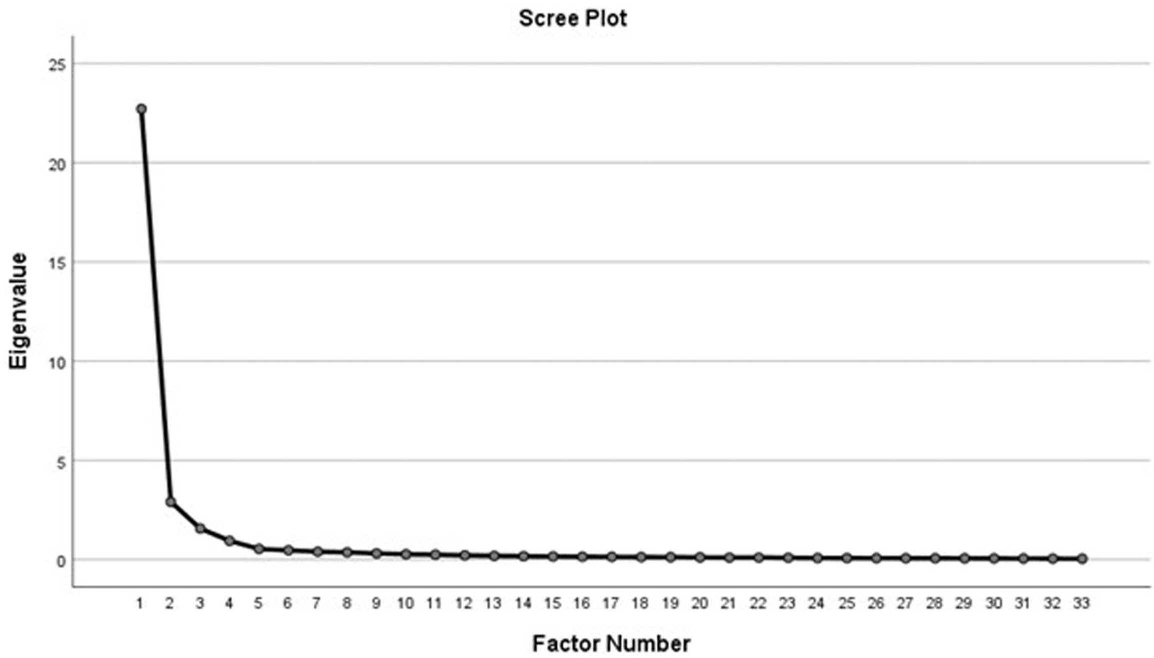

FIGURE 2 | Scree plot of the Artificial Intelligence Perception Scale for cancer patients.

significant ($p < 0.01$), reflecting a positive and strong association ($0.60 < r < 0.79$, $r = 0.654$). Similarly, a statistically significant and very strong positive relationship was found between Perceived Benefit and the overall Artificial Intelligence Perception in cancer patients ($p < 0.01$, $0.80 < r < 1.00$, $r = 0.856$). Finally, the correlation between Acceptance and Intention to Use and the overall Artificial Intelligence Perception was statistically significant ($p < 0.01$), indicating a positive and strong association ($0.60 < r < 0.79$, $r = 0.795$).

3.6 | Structural Model and Path Analysis

The draft version of the scale, initially designed as a five-dimensional instrument based on the theoretical framework and qualitative data (*Knowledge, Trust, Benefit, Fear, Acceptance*), was refined into a three-dimensional structure (*KAT: Knowledge, Awareness, and Trust; PB: Perceived Benefit; AUT: Acceptance and Intention to Use*) according to the factor loadings of the items and their theoretical alignment. The three-dimensional final form of the scale was subsequently tested using Structural Equation Modeling (SEM). The model demonstrated a high explanatory power, accounting for 52% of the variance in cancer patients' intention to accept and use AI ($R^2 = 0.520$). Standardized path coefficients and the overall model structure are presented in Figure 1b.

During the analysis, the mediating role of PB was examined in the relationship between KAT and AUT. The findings indicate that KAT had a significant direct effect on AUT, but this effect was notably strengthened when mediated through patients' perceived benefit. As shown in Table 7, the total effect (c) of *Knowledge, Awareness, and Trust* on AUT was significant ($\beta = 0.233$, $p < 0.001$). When PB was included as a mediating variable, the direct effect (c') remained significant, though its coefficient decreased ($\beta = 0.101$, $p < 0.001$), confirming the presence of a partial mediation structure in the model. The indirect effect of KAT on AUT via PB was also statistically significant ($\beta = 0.132$, $p < 0.001$). The 95% confidence interval [0.097; 0.167] did not include zero, indicating that perceived benefit serves as a robust and reliable mediator in the technology acceptance process among cancer patients.

4 | Discussion

In this study, the *Artificial Intelligence Perception Scale for Cancer Patients* was developed to evaluate cancer patients' perceptions of artificial intelligence (AI), and its psychometric properties were examined. Prior to developing a new measurement instrument, it is essential to determine whether existing tools assess similar constructs. A review of the literature indicates that most available scales evaluate perceptions of AI primarily among healthcare professionals or the general population [28, 29], and are insufficient for comprehensively capturing the perceptual, cognitive, and emotional dimensions specific to cancer patients. Therefore, there is a clear need for a valid and reliable instrument designed to assess AI perceptions in this patient population. Compared with previously published AI-related instruments, the present scale differs in both its conceptual focus and target population. Existing instruments, such as the AIAS-4 developed for nurses and the Artificial Intelligence and Academic Writing Questionnaire (AI-AWQ) developed for medical students, primarily assess attitudes toward AI, perceived usefulness, or behavioural intention in educational or professional contexts rather than patients' perceptions within clinical care [28, 29]. In contrast, the present instrument was specifically designed to capture cancer patients' perceptions of AI in oncology settings. This distinction is consistent with recent reviews showing that patients evaluate AI not only according to its usefulness but also in terms of trust, communication, transparency, clinician involvement and ethical considerations, dimensions that are often underrepresented in existing AI acceptance instruments [5, 30, 31]. While

TABLE 4 | Exploratory factor analysis results of the Artificial Intelligence Perception Scale for cancer patients ($n = 382$).

Subscales	Items	B	Standardized B	Standart deviation	t	p value	R^2	AVE	CR	α	Fit indices
Knowledge, awareness and trust	ITEM_1	2.66	0.94	0.027	97.14	$p < 0.001$	0.89	0.826	0.989	0.985	$\chi^2/df = 3.40$
	ITEM_2	2.09	0.94	0.026	81.01	$p < 0.001$	0.88				NNFI = 0.99
	ITEM_3	2.17	0.94	0.024	91.43	$p < 0.001$	0.88				NFI = 0.98
	ITEM_4	2.05	0.92	0.035	58.00	$p < 0.001$	0.85				CFI = 0.99
	ITEM_5	2.08	0.93	0.028	75.51	$p < 0.001$	0.87				IFI = 0.99
	ITEM_6	1.89	0.90	0.033	58.15	$p < 0.001$	0.81				GFI = 1.00
	ITEM_7	2.10	0.92	0.032	65.42	$p < 0.001$	0.84				SRMR = 0.038
	ITEM_8	1.79	0.94	0.024	74.57	$p < 0.001$	0.87				RMSEA = 0.079
	ITEM_9	1.85	0.88	0.045	41.34	$p < 0.001$	0.78				
	ITEM_10	1.99	0.87	0.044	45.50	$p < 0.001$	0.76				
	ITEM_11	2.41	0.91	0.038	64.14	$p < 0.001$	0.82				
	ITEM_13	1.92	0.90	0.042	46.25	$p < 0.001$	0.81				
	ITEM_15	2.20	0.93	0.027	80.45	$p < 0.001$	0.87				
	ITEM_16	2.55	0.93	0.033	77.49	$p < 0.001$	0.87				
	ITEM_17	2.00	0.91	0.035	57.83	$p < 0.001$	0.83				
	ITEM_18	1.80	0.90	0.034	52.60	$p < 0.001$	0.81				
	ITEM_19	2.24	0.86	0.061	36.98	$p < 0.001$	0.74				
	ITEM_20	1.99	0.91	0.040	49.78	$p < 0.001$	0.84				
	ITEM_21	2.40	0.92	0.041	58.14	$p < 0.001$	0.85				
	ITEM_22	2.22	0.82	0.084	26.29	$p < 0.001$	0.67				
Perceived benefit	ITEM_24	2.28	0.94	0.044	52.13	$p < 0.001$	0.88	0.902	0.928	0.975	
	ITEM_25	2.20	0.93	0.048	45.66	$p < 0.001$	0.86				
	ITEM_26	2.25	0.95	0.041	54.41	$p < 0.001$	0.91				
	ITEM_27	2.27	0.96	0.032	70.24	$p < 0.001$	0.92				
	ITEM_28	2.18	0.97	0.031	70.95	$p < 0.001$	0.95				
	ITEM_29	2.25	0.95	0.041	54.98	$p < 0.001$	0.90				
Acceptance and use tendencies	ITEM_39	2.20	0.86	0.075	29.26	$p < 0.001$	0.75	0.873	0.979	0.973	
	ITEM_40	2.40	0.94	0.053	45.52	$p < 0.001$	0.88				
	ITEM_41	3.12	0.95	0.052	60.22	$p < 0.001$	0.91				
	ITEM_42	2.96	0.95	0.050	59.72	$p < 0.001$	0.91				
	ITEM_43	2.86	0.93	0.056	50.85	$p < 0.001$	0.86				
	ITEM_44	3.04	0.95	0.045	67.84	$p < 0.001$	0.90				
	ITEM_45	2.91	0.96	0.040	72.37	$p < 0.001$	0.92				
Total											82.370
Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy											0.971
Bartlett's Test of Sphericity (χ^2)											20,202.75
SD											528
p value											$p < 0.001$

previous scales generally report multidimensional structures with high internal consistency, the three-factor structure identified in this study reflects a broader integration of cognitive, affective and behavioural aspects of AI perception that are particularly relevant to oncology care. These findings support the view that AI perception is context-dependent and varies according to the characteristics of the target population and clinical setting [5, 32–35].

In the first phase of the scale development process, a comprehensive item pool was generated. This phase involved a literature review, focusing on key concepts such as *artificial intelligence*, *AI in healthcare*, *cancer patients*, *technology perception*, *trust*, *ethical concerns* and *decision-making*. Based on this review, a draft scale comprising 48 items was created. To evaluate content validity, the draft scale was reviewed by experts in the field. For an item to be considered to have adequate

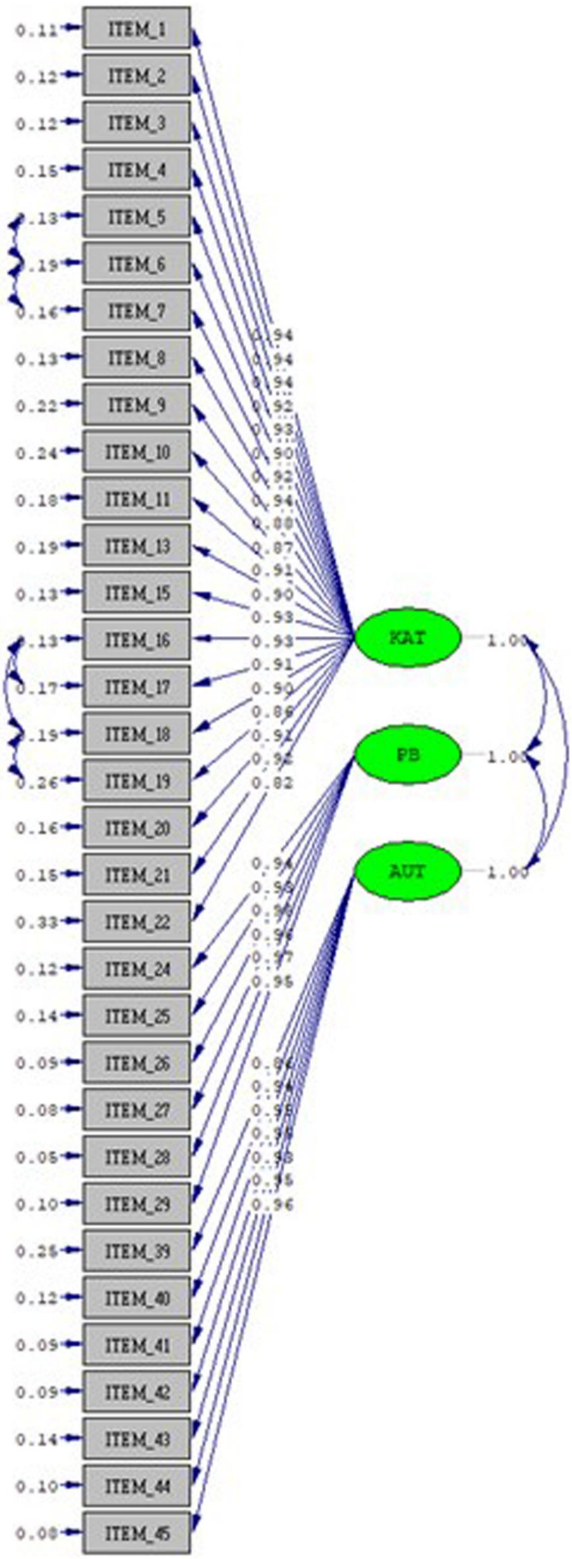

FIGURE 3 | CFA path diagram of the Artificial Intelligence Perception Scale for cancer patients.

content validity, an item-level content validity index (I-CVI) of at least 0.78 and a scale-level content validity index (S-CVI) of at least 0.80 are recommended [19, 20]. The results of the expert evaluations indicated that the scale demonstrated sufficient content validity. At this stage, three items with low item-level

TABLE 5 | Split-half reliability analysis results of the Artificial Intelligence Perception Scale for cancer patients.

Correlation coefficient between the two halves	0.829
Cronbach's α coefficient for the first half (first 17 items)	0.984
Cronbach's α coefficient for the second half (last 16 items)	0.972
Spearman–Brown reliability coefficient	0.907
Guttman Split-Half reliability coefficient	0.901

content validity scores were removed based on the consensus of the experts.

One of the most commonly employed methods for assessing the construct validity of a newly developed measurement instrument is factor analysis. Factor analysis allows researchers to determine which subdimensions the scale items cluster under, providing an empirical examination of the theoretical construct intended to be measured. In the scale development process, it is recommended to perform exploratory factor analysis (EFA) prior to conducting CFA [19, 20, 36].

Accordingly, to examine the factor structure of the *Artificial Intelligence Perception Scale for Cancer Patients*, the suitability of the dataset for factor analysis was first assessed. The analyses indicated that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeded the recommended threshold, and Bartlett's test of sphericity was statistically significant. These findings suggest that the dataset is appropriate for conducting exploratory factor analysis [37, 38].

In the exploratory factor analysis, the Principal Axis Factoring method was employed and considering the potential correlations among factors, the oblique rotation technique *Promax* was applied [39]. According to the literature, for newly developed scales, it is recommended that item factor loadings be at least 0.40 and item-total correlations be at least 0.30 [40]. Based on the initial analysis results, items that did not meet these criteria were removed, resulting in a scale with a more robust factor structure.

The number of factors was determined based on eigenvalues, with factors having an eigenvalue greater than 1.00 considered significant [40]. The analyses indicated that the scale exhibits a three-factor structure, encompassing *Knowledge/Awareness/Trust*, *Perceived Benefit* and *Acceptance/Intention to Use*. While it is recommended that multidimensional scales explain at least 40% of the total variance [40], the factor structure obtained in this study accounted for a substantial portion of the total variance (82.37%). Although the explained variance was considerably higher than the minimum recommended threshold, this finding should be interpreted cautiously, as very high values may also reflect conceptual overlap among some items or the relatively homogeneous characteristics of the study sample. Therefore, replication of the factor structure in independent and more diverse populations is warranted. Furthermore, the high factor loadings indicate that the items strongly represent the corresponding constructs. These EFA findings suggest that the *Artificial Intelligence Perception Scale for Cancer Patients* is a

TABLE 6 | Correlation results between the Artificial Intelligence Perception Scale and its subscales in cancer patients.

Scale variables	Mean ± SD	Median (minimum–maximum)	Spearman's rho	Perceived benefits (PB)	Acceptance and use tendencies (AUT)	Artificial Intelligence Perception Scale for cancer patients
Knowledge, awareness and trust (KAT)	3.2 ± 1.2	3.6 (1–5)	*r*	0.762	0.650	0.963
			p	$p < 0.001$	$p < 0.001$	$p < 0.001$
Perceived benefits (PB)	3.2 ± 1.3	3.5 (1–5)	*r*	1	0.654	0.856
			p		$p < 0.001$	$p < 0.001$
Acceptance and use tendencies (AUT)	3.2 ± 1.2	3.4 (1–5)	*r*		1	0.795
			p			$p < 0.001$

consistent, theoretically coherent, and construct-valid measurement tool. The scale is capable of evaluating cancer patients' perceptions and attitudes toward AI applications used in oncological care in a multidimensional manner. Overall, the EFA results demonstrate that the developed scale's factor structure is sufficient to comprehensively assess cancer patients' perceptions, attitudes, and acceptance of AI. Beyond its psychometric adequacy, the identified factor structure provides insight into how cancer patients conceptualize artificial intelligence in clinical care. Rather than perceiving AI as a purely technological innovation, participants appeared to evaluate it through an integrated perspective that combines cognitive understanding, emotional trust and perceived clinical value. This finding is consistent with the patient-centred nature of oncology care, where perceptions of new technologies are shaped not only by their technical capabilities but also by communication with healthcare professionals, previous healthcare experiences and expectations regarding treatment and safety. Therefore, the observed factor structure may reflect the way patients naturally organize their perceptions of AI within the context of oncology rather than representing isolated psychological constructs. The transition from the initially hypothesized five-domain framework to the empirically supported three-factor structure represents one of the novel contributions of this study, suggesting that cancer patients organize AI-related perceptions differently from the conceptual distinctions proposed in existing theoretical frameworks [11, 12, 41, 42]. A particularly noteworthy finding was that knowledge, awareness, and trust did not emerge as separate constructs but instead loaded onto a single factor. Although these dimensions are conceptually distinct in the literature [11–13], this finding suggests that cancer patients may develop trust in AI through their understanding and awareness of how AI is used in clinical care rather than viewing these as independent attributes. This pattern is broadly consistent with technology acceptance frameworks, which propose that cognitive evaluations influence attitudes and technology acceptance [12, 42]. However, unlike traditional technology acceptance models, where knowledge and trust are generally conceptualized as separate constructs, the present findings indicate that these perceptions become closely intertwined in the oncology context. This may be explained by the fact that most patients encounter AI indirectly through healthcare professionals rather than through direct interaction with AI systems, making knowledge, awareness and trust mutually reinforcing components of a single cognitive–affective dimension [5, 11–13, 31].

Testing the factor structure obtained through EFA using CFA is among the recommended standard approaches in scale development studies [43, 44]. Accordingly, CFA was conducted to examine whether the factor structure identified through EFA was supported by the proposed theoretical model. The resulting fit indices met or exceeded the recommended thresholds reported in the literature, providing further evidence for the adequacy of the measurement model [27, 45]. Accordingly, the extent to which the factor structure obtained from the EFA aligned with the theoretical model was evaluated using CFA. The analyses indicated that the fit indices achieved exceeded the minimum acceptable thresholds reported in the literatüre [46, 47]. In this study, the CFA results indicated that the model's RMSEA value was 0.079, and the chi-square/degrees of freedom ratio (χ^2/df) was 3.40. These values demonstrate that

TABLE 7 | Direct, indirect, and total effects.

Pathway	Effect (β)	SE	z	p	LLCI	ULCI
Total effect (c)	0.233	0.023	10.130	0.00	0.188	0.278
Direct effect (c')	0.101	0.021	4.929	0.00	0.061	0.141
a (KAT → PB)	0.248	0.032	7.750	0.00	0.185	0.311
b (PB → AUT)	0.532	0.066	8.104	0.00	0.403	0.661
Indirect effects						
Total indirect effects	0.132	0.018	7.330	0.01	0.097	0.167
Indirect 1 (KAT → PB → AUT)	0.132	0.018	7.330	0.01	0.097	0.167

Abbreviations: β = standardized regression coefficient, LLCI = lower-limit confidence interval, SE = standard error, ULCI = upper-limit confidence interval, z = critical ratio.

the model exhibits an acceptable level of fit. According to recent literature, fit indices above 0.85, a χ^2/df ratio below 5, and an RMSEA value less than 0.08 are considered indicative of adequate model fit [40, 48]. Overall, the CFA findings in this study are consistent with established fit criteria and strongly support the construct validity of the *Artificial Intelligence Perception Scale for Cancer Patients*. Beyond confirming the statistical adequacy of the measurement model, the CFA findings provide further evidence that cancer patients' perceptions of AI can be represented by a coherent multidimensional construct. The good model fit indicates that the relationships among the identified factors are conceptually meaningful and consistent with patients' experiences of AI in oncology care. This supports the assumption that perceptions of AI are not determined by a single attitude but arise from the interaction of cognitive, affective, and behavioural components. From a theoretical perspective, these findings are broadly compatible with technology acceptance frameworks, while also suggesting that, in oncology settings, patients' perceptions are shaped by the unique clinical context in which AI is introduced and explained by healthcare professionals.

To assess the internal consistency of the scale items, Cronbach's α coefficient was calculated. Cronbach's α is a key reliability indicator that reflects the degree to which scale items measure the same construct, with values approaching 1 indicating high internal consistency. According to the literature, Cronbach's α values between 0.60 and 1.00 are generally considered acceptable [27, 45, 46]. In this study, the Cronbach's α values obtained for both the overall scale and its subdimensions exceeded 0.80, indicating that the *Artificial Intelligence Perception Scale for Cancer Patients* demonstrates a high level of internal consistency and reliability. Although the Cronbach's α coefficients demonstrated excellent internal consistency, values exceeding 0.95 should be interpreted with caution, as they may indicate potential redundancy among items rather than solely reflecting high reliability. Nevertheless, the retained items were developed to capture different dimensions of cancer patients' perceptions of artificial intelligence and were supported by expert evaluation and factor analyses. Future studies should examine whether a shorter version of the scale can retain comparable psychometric performance while reducing potential item redundancy and preserving content validity.

To further support the reliability of the scale, the split-half method was also applied. In this approach, the Spearman-Brown and Guttman split-half coefficients, which reflect the consistency between the two halves of the scale, are expected to exceed 0.70 [48]. The analyses revealed that both coefficients were above 0.80, indicating a strong and statistically significant correlation between the two halves of the scale. These findings support the high measurement stability of the scale.

Item–total score correlations were examined to assess the extent to which the scale items represent the construct being measured. Item–total analysis is an important metric for evaluating the discriminative power of each item, as it reflects the relationship between individual items and the overall scale [47]. In the literature, item–total correlations above 0.30 and in the positive direction are generally considered acceptable. In the present study, 12 items with correlations below 0.30 or with negative values were identified and subsequently removed from the scale. The remaining items all demonstrated item–total correlations above 0.30 and in the positive direction, indicating that they adequately represent the overall construct measured by the scale.

Recent literature indicates that cancer patients' perceptions of AI-based healthcare applications have not been systematically or consistently evaluated. Uncertainties surrounding AI applications can influence patients' attitudes through psychosocial dimensions such as trust, ethical concerns, decision-making processes and perceived control [32–34]. These factors can directly affect not only treatment adherence but also patient satisfaction and quality of care [34, 35]. The *Artificial Intelligence Perception Scale for Cancer Patients* developed in this study allows for a comprehensive assessment of patients' knowledge, awareness and trust, as well as their perceived benefits and acceptance/usage tendencies regarding AI. The robust findings from validity and reliability analyses demonstrate that the scale can measure cancer patients' perceptions of AI accurately, consistently, and across multiple dimensions. In particular, the high internal consistency and strong factor structure suggest that the scale can be confidently applied in both clinical and research settings. Data obtained through this scale may provide valuable insights for planning patient education, enhancing digital health literacy, and shaping AI-supported care models in alignment with patient expectations. In conclusion, the *Artificial Intelligence Perception Scale for Cancer Patients* is expected to contribute to the development of patient-centred digital health applications and to fill a significant gap in the current literature.

5 | Strengths and Limitations

This study's main strength lies in the rigorous methodological approach used for scale development, including expert evaluation, exploratory and confirmatory factor analyses and multiple reliability tests. The scale addresses a timely and underexplored topic by assessing cancer patients' perceptions of artificial intelligence in healthcare.

However, the study has some limitations. Participants were recruited using convenience sampling from a single institution, which may limit the representativeness of the findings and their generalizability to broader oncology populations. Moreover, reliance on self-reported data may have introduced response bias, and despite efforts to minimize it, the possibility of selection and information bias cannot be entirely excluded and should be considered when interpreting the results. Future studies should validate the scale in larger and more diverse populations and across different cancer types and treatment stages. Importantly, the present study focused on the psychometric development and validation of a patient-reported measure and did not examine the post-deployment performance, safety or long-term effectiveness of specific AI-supported interventions. Therefore, the sustained effectiveness and accountability of AI applications in real-world oncology settings should be evaluated through continuous post-deployment surveillance. A practical framework may include the systematic collection of real-world performance indicators, such as accuracy, reliability, patient engagement, usability, patient satisfaction and clinically relevant outcomes, together with periodic assessment of patients' perceptions, trust, perceived benefits, and acceptance using the Artificial Intelligence Perception Scale for Cancer Patients. Monitoring should also include the identification of unexpected errors, safety concerns, inequitable effects or other unintended consequences. Periodic multidisciplinary reviews involving patients, nurses, physicians, data and AI specialists and institutional decision-makers could be used to identify performance gaps and determine whether modification, retraining, additional patient education, or changes in implementation procedures are required. Such an iterative surveillance and evaluation approach may support continuous quality improvement, accountability, and responsible integration of AI into patient-centred oncology care. Longitudinal and cross-cultural studies are also recommended to examine changes in perceptions over time and enhance the scale's applicability. Further research may explore associations between artificial intelligence perception and clinical or psychosocial outcomes. The validated scale offers a practical tool for assessing cancer patients' perceptions of artificial intelligence–based healthcare. In clinical practice, it can support patient-centred communication and education. From a policy perspective, incorporating patient perspectives may guide the ethical and acceptable implementation of artificial intelligence technologies in oncology care.

6 | Conclusion

This study presents the development and psychometric evaluation of a novel scale designed to assess cancer patients' perceptions of artificial intelligence in healthcare. The findings indicate that the scale has a clear factor structure and satisfactory reliability, supporting its use as a consistent measurement tool. By systematically capturing patients' views on artificial intelligence supported care, the scale contributes to patient-centred oncology research and practice. Its application may assist healthcare professionals and decision-makers in understanding patient expectations and concerns, thereby facilitating the responsible and ethical implementation of artificial intelligence in oncology settings. Further studies are recommended to expand its use across different populations and clinical contexts. Future studies should expand the use of the scale across diverse populations and clinical contexts and incorporate longitudinal and post-deployment evaluations to support continuous monitoring, accountability and quality improvement in the responsible implementation of AI in oncology care.

Author Contributions

Dilek Yildirim: conceptualization, data curation, formal analysis, writing – original draft, writing – review and editing, and visualization. **Vildan Kocatepe:** conceptualization, funding acquisition, investigation, writing – review and editing. **Sevda Tüzün Özdemi̇r:** data curation, funding acquisition, and investigation, resources, writing – review and editing. **Ayşegül Türkmenoğlu:** conceptualization, funding acquisition, investigation, writing – review and editing. **Ünal Önsüz:** conceptualization, funding acquisition, investigation, writing – review and editing. All authors read and approved the final manuscript.

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Funding

The authors have nothing to report.

Ethics Statement

This study was approved by the Non-Interventional Clinical Research Ethics Committee (Decision No: 2025/576; Date: March 19, 2025). Permission was obtained from the institution where the study was conducted. All procedures were carried out in accordance with the principles of the Declaration of Helsinki. In addition, all participants were provided with detailed information about the study and gave their voluntary verbal and written informed consent prior to participation.

Consent

The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Data are available from the corresponding author on reasonable request.

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

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.
Supporting File: jep70606-sup-0001-strobe-checklist.docx.