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Review Article

Prospective Assessment Model of End Users for Artificial Intelligence Applications: A Systematic Review

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Abstract

Background: End-user opinions are crucial for the success of health applications, particularly in the emerging field of artificial intelligence (AI) in medicine. Understanding the perspectives of end users is essential for the acceptance and effectiveness of AI.

Objectives: This systematic review aimed to comprehensively analyze existing literature on the perspectives and acceptance models of end users for AI applications. By synthesizing and critically evaluating research, this review seeks to identify key themes, methodologies, and knowledge gaps.

Methods: A systematic review was conducted in PubMed in 2023 to identify relevant peer-reviewed articles written in English. Inclusion criteria focused on original studies that validated assessment AI models from the perspectives of users. The extracted information included publication details, countries of research, participant characteristics, data collection and analysis methods, and attributes of the proposed models.

Results: In total, 19 papers out of 3714 records that were published between 2019 and 2022 were included in this study. Participants belonged to six categories, namely physicians, medical students, nurses, patients, and the general public. The most important assessed factors in identified papers were "ethical issues, trust, and anxiety", "usability", "self-efficacy and knowledge", "social", "benefits", "quality of the AI products and service support", "AI acceptance, resistance of AI, attitude, and satisfaction". In addition, the commonly examined several moderating variables, including perceived ease of use, perceived usefulness, and perceived risks were explored.

Conclusion: The findings contribute to understanding current trends and practices in the perspective research of end users. Future studies should continue exploring end users' perspectives to enhance the development and implementation of effective AI systems in healthcare.

Keywords: Artificial intelligence, Evaluation frameworks, Evaluation models, Evaluation theory, Health informatics

1. Background

Artificial intelligence (AI) technologies are rapidly advancing and becoming integrated into various aspects of our daily lives. However, to ensure the successful development and deployment of AI products, it is crucial to consider the perspectives and needs of end users. Public acceptance and adoption of AI will depend on the perception of the benefits as meaningful and the risks as manageable through measures, such as risk management and redress (1).

For intelligent systems to be truly effective, end users must actively engage with them and trust their recommendations. Understanding the expectations of users and identifying the factors that influence the successful acceptance of these systems is essential for their optimal utilization and adoption (2). Moreover, user satisfaction with AI-enabled technology can lead to greater acceptance and positive outcomes, such as increased productivity and more efficient work processes (3).

However, certain studies have indicated dissatisfaction or mistrust among medical users regarding the use of AI products in healthcare. For instance, a survey by Santos et al. revealed that while many medical physicists believe AI will bring about changes in medical physics practices, there is also a certain level of mistrust towards AI, likely stemming from a lack of knowledge about the technology (4). Similarly, a national survey among Canadian vascular surgeons found that although they had positive views about AI and its potential to enhance patient care, research, and education, their self-reported knowledge about AI was generally poor (5).

2. Objectives

This systematic review aimed to comprehensively analyze the existing literature on prospective assenting models of end users for AI products. By synthesizing and critically evaluating the available research, this review sought to identify key themes, methodologies, and gaps in knowledge. Furthermore, it aimed to provide insights and recommendations for future research and the development of effective assenting models that promote user-centric AI product design.

By addressing these objectives, this review can contribute to a better understanding of the perspectives and needs of end users in relation to AI products, ultimately facilitating their successful implementation and adoption.

3. Methods

The current systematic review was conducted on October 8, 2023, in PubMed based on Cochrane guidelines. A comprehensive search was performed on the PubMed and Medline databases to identify peer-reviewed articles written in English. The search strategy utilized specific terms to ensure the retrieval of relevant articles. The PubMed search strategy included terms, such as "technology acceptance theor*," "influencing factors," "effective factors," "attitudes," "behavioral intentions," "perception," "acceptance," "perspectives," "point of views," "usage intention," "evaluation framework," "intention to adopt," "usage," "technology acceptance model," "technology readiness," "satisfaction," and "success." Additionally, the search incorporated terms related to "artificial intelligent," "artificial intelligence," "Intelligent products," and "automated monitoring system." To enhance the precision of the search, systematic reviews and general reviews were excluded from the results.

During the title and abstract screening phase, studies that were identified as non-English, protocol, editorial, or systematic review papers were excluded from the study. These exclusion criteria were applied to ensure that only relevant studies meeting the inclusion criteria were included in the final analysis.

The inclusion criteria for the studies in this review were as follows: original studies that specifically focused on the development and validation of an assessment model from the perspective of users. This assessment model aimed to measure the success, acceptance, usage, and satisfactoriness of AI products. To be included in the review, the questionnaire used in the study needed to have undergone validation to ensure its reliability and validity. Additionally, the questionnaire needed to encompass assessment dimensions related to success, acceptance, usage, usage intention, and satisfaction with AI products.

Additionally, the exclusion criteria for this review were as follows:

1. Papers that assessed the viewpoint of end users using qualitative methods, such as semi-structured or structured interviews, were excluded. The focus of this review was on studies that developed and validated assessment models, rather than solely relying on qualitative data collection methods.

2. Papers that explored the opinions of end-users using questionnaires without performing validation of the research instrument were also excluded.

To test the data extraction process, a random sample of six papers (one-third of the total included papers) that focused on the development of prospective assessment models of end users for AI applications was selected and data was extracted using a separate spreadsheet file.

Throughout the study, the data extraction checklist was modified as needed. The following information was extracted from each included paper: authors, publication year, countries where the research took place, participants involved in the study, data collection methods, software used for analysis purposes, sampling technique employed in selection of participants, sample size of participants included in the study, validation methods used to ensure accuracy and reliability of the assessment of proposed model along with values obtained from these methods. Additionally, information regarding construct validity model development basis (if any), whether a causal model was utilized in the analysis of relationships between variables (yes/no), and evaluation variables, such as independent variables that influence outcomes of interest to researchers, as well as moderating and dependent variables were also extracted during this process.

4. Results

After importing the records retrieved from PubMed into EndNote, a total of 3,714 records were obtained. The initial screening process involved reviewing the titles and abstracts of these records, resulting in 103 potentially relevant papers (Figure 1).

Next, the full text of these 103 papers was assessed to determine their suitability for inclusion in the review. Among these, 73 papers were excluded as they fell outside the scope of the review, including qualitative interview studies and surveys that utilized non-valid questionnaires. Additionally, records published in languages other than English (n=2), protocol papers (n=3), and editorial papers (n=4) were also excluded.

After the exclusion process, 19 papers remained for further analysis. Data extraction was conducted on these selected papers to gather relevant information for the review. Table 1 shows characteristics of the identified studies related to prospective assessment models of end users for AI applications.

Years and countries

The results showed that the identified papers were published in 2019 (n=1), 2020 (n=4), 2021 (n=4), 2022 (n=7), and 2022 (n=3) and were from several countries, namely China (n=6), USA (n=2), and Germany (n=2) as well as Romania, Bangladesh, Scotland, New Zealand, India, Thailand, Caucasian Americans, Korea, and Japan, each with one paper.

Sampling technique and sample size

In the 19 papers analyzed, convenience sampling was the most commonly used method of sampling, as reported in 13 of the papers. Purposive sampling and random sampling were each used in two papers. Criterion-based sampling and snowball sampling were each used in one paper. The means and 95% confidence intervals for sample size in each of the different validation methods were as follows: Exploratory Factor Analysis (EFA): Mean = 399 (SD=±152.88), Confirmatory Factor Analysis (CFA): Mean = 507.66 (SD=±159.09), Structural Equation

Modeling (SEM): Mean = 343.71 (SD=±51.10), Regression: Mean 145= (SD=±44).

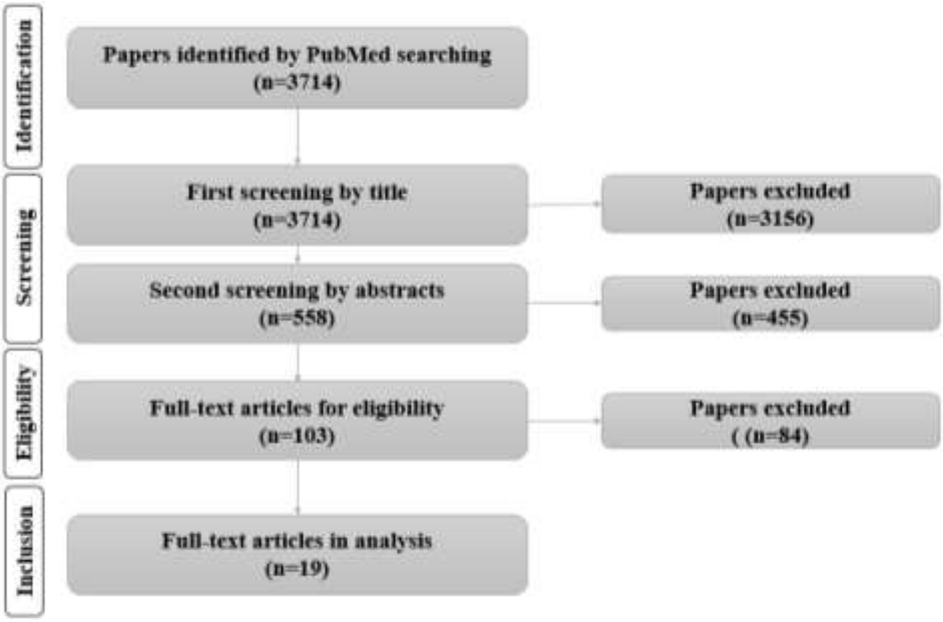

Figure 1. Flow chart of the selection process of studies in PubMed

Table 1. Characteristics of the identified studies related to prospective assessment models of end users for AI applications

Column	Authors	Publication year	Countries	Participants	Data collection methods	Software	Sampling technique	Sample Size
1	**Yang et al. (6)**	2022	China	Customers	Online	Not reported	Simple sampling	419
2	**Fujimori et al. (7)**	2020	Japan	Physicians	Face to face	Not reported	Simple sampling	14
3	**Grassini et al. (8)**	2023	US	Customers	Online	Not reported	Simple sampling	300
4	**Jussupow et al. (9)**	2022	Germany	Medical professionals\ students	Online	SATA-SPSS	Simple sampling	206
5	**Iancu and Iancu (10)**	2022	Romania	Customers	Was not reported	SPSS	Simple sampling	235
6	**Ye et al. (11)**	2019	China	Potential end users of ophthalmic AI devices	Was not reported	SPSS	Random sampled	474
7	**Sisk et al. (12)**	2020	US	Customers	Online	SPSS	Criterion-based sampling	804
8	**Tran et al. (13)**	2021	China	Medical students	Online	Partial least squares	Snowball sampling	223
9	**Esmaeilzadeh (14)**	2020	US	Customers	Online	SPSS-AMOS	Simple sampling	307
10	**Uzir et al. (15)**	2021	Bangladesh	Smartwatch users	Face to face	Partial least squares	Purposive sampling	206
11	**Aw et al. (16)**	2023	Scotland	Patients attending intravitreal treatment	MS Excel	SAS software	Simple sampling	177
12	**Huo et al. (17)**	2023	China	Medical staff	Was not reported	Partial least squares	Simple sampling	288
13	**Mugabe (18)**	2021	New Zealand	Medical staff	Online	Not reported	Simple sampling	101
14	**Holdener et al. (19)**	2020	German	Customers	Online	SPSS	Simple sampling	73
15	**Pal et al. (20)**	2022	India and Thailand	Customers	Online	Partial least squares	Simple sampling	675
16	**Zhai et al. (21)**	2021	China	Radiation oncologists\medical students	Online	SPSS	Simple sampling	307
17	**Li et al. (22)**	2022	China	Medical students	Online	Not reported	Simple sampling	247
18	**Choudhury [23)**	2022	Caucasian Americans	Physician residents, attending physicians, nurses	email- Online	SPSS	Simple sampling	121
19	**Kwak et al. [24)**	2022	Korea	Nursing students	Online	SPSS	G*Power software\random sampled	189

Scope of the identified papers

In the current review, the studies were focused on 10 scopes: General (n=4), AI-based decision support systems (n=3), ophthalmic AI devices (n=2), healthcare scenario in Amazon Mechanical Turk (n=2), AI in radiation therapy (n=2), traveling website experience (n=1), Chabot in COVID-19 (n=1), AI for independent diagnosis and treatment (n=1), AI mobile application for personalized health guide (n=1), and voice-based consumer electronic devices (n=1).

Participants

In the current review, six user categories were identified that participated in the studies evaluating artificial intelligence:

1. Physicians (n=7): including radiologists, ophthalmologists, and other medical doctors.

2. Medical students (n=4): students studying medicine.

3. Nurses (n=2): including participating nurses.

5. Patients (n=2): Individuals with ophthalmological conditions and patients attending intravitreal treatment who participated in the studies.

6. General public (n=7): Members of the general population who also participated in the studies.

Analysis software

Among the papers that disclosed their used software, SPSS was the most commonly utilized one, being used in nine papers. In one of these papers, AMOS was also used in conjunction with SPSS. Another article reported the use of both SATA and SPSS. Besides, SAS software was used in one paper, while Partial Least Squares was used in four papers.

Theoretical basis models and the evaluation variables

Based on the findings, 13 out of the 19 papers analyzed developed a causal model that incorporated independent, moderating, and dependent variables, while the remaining six papers proposed a non-causal model for the assessment of AI.

The identified articles commonly examined several moderating variables, including perceived ease of use, perceived usefulness, and perceived risks. Other moderating variables that were observed, although less frequently, included flow experience, self-efficacy, speciesism, anxiety, perceived competence, trust in perceived benefits, attitude toward using technology, behavioral intention, and intention to use (Table 2). When it comes to the dependent variables, the most frequently studied ones were behavioral intention and acceptance. Other dependent variables that were investigated, but to a lesser extent, were actual learning, use behavior, switch intention, and resistance to AI.

Table 2. Evaluation items in prospective assessment models of end users for AI applications

Column	Authors	Development basis	Casual model	Independent	Moderating	Dependent
1	Yang et al. (6)	UTAUT	Yes	Utilitarian motivation, interaction convenience, task-technology fit	Perceived competence, flow experience	Switch intention
2	Fujimori et al. (7)	UTAUT	Yes	Effort expectancy, performance expectancy, social influence, facilitating environment	Attitude toward using technology	Behavioral intention
3	Grassini et al. (8)	TAM, UTAUT	No	-	-	-
4	Jussupow et al. (9)	Literature review	Yes	Threats to professional capabilities, perceived temporal distance of AI, familiarity with AI	Temporal distance	Resistance to AI, self-threat from AI
5	Iancu and Iancu (10)	Literature review	Yes	Age, gender, having heard of chat-bots, knowledge of chat-bots, used chat-bots, inclination towards chat-bots, enjoyment, satisfaction/output quality, effort/objective usability, competence/self-efficacy on using chat-bots, pressure, perception of external control, subjective norms	Perceived ease of use, perceived usefulness	Behavioral intention
6	Ye et al. (11)	UTAUT, TAM, TPB	Yes	Perceived behavioral control, subjective norms, trust, resistance bias, eye health consciousness, perceived risks	Perceived usefulness, perceived ease of use	Intention to use
7	Sisk et al. (12)	Literature review	No	Quality/accuracy, privacy, shared decision-making, convenience, cost, human element of care, and social justice	Not reported	Not reported
8	Tran et al. (13)	UTAUT	Yes	Task complexity, perceived innovativeness in IT, technology characteristics	Performance expectancy, effort expectancy, social	Behavioral intention

					influence, perceived substitution crisis, initial trust	
9	Esmaeilzadeh (14)	Literature review	Yes	Perceived performance anxiety, perceived social biases, perceived privacy concerns, perceived mistrust in AI mechanisms, perceived communication barriers, perceived unregulated standards, perceived liability issues	Perceived benefits, perceived risks	Intention to use AI-based tools
10	Uzir et al. (15)	Literature review	Yes	Product quality, service quality, perceived ease of use, perceived convenience	Customer experience, AI-Trust	Customer satisfaction
11	Aw et al. (16)	Literature review		Anxiety, presence of a doctor and a virtual clinic		
12	Huo et al. (17)	Literature review	Yes	Medical staff participation	AI Self-efficacy, AI anxiety, speciesism	Acceptance of medical AI-IDT
13	Mugabe (18)	Literature review	No	Innovation (fit for purpose, inconvenience factor, perceived benefits)\ Organization (AI usage, expertise, change experience)\provider	Do not have	Do not have
14	Holdener et al. (19)	Literature review	No	Focused attention, perceived usability, aesthetic appeal, reward	Do not have	Do not have
15	Pal et al. (20)	UTAUT, TAM	yes	Functional aspects (performance expectancy, effort expectancy positively, hedonic motivation), social aspects (perceived social, perceived humanness, social cognition)	User trust	behavioral intention
16	Zhai et al. (21)	UTAUT	Yes	Performance expectancy, effort expectancy, social influence, facilitating conditions	Behavioral intention, perceived risk, resistance bias	Use behavior
17	Li et al. (22)	TPB	Yes	Personal relevance of medical AI, subjective norm related to learning medical AI, self-efficacy in learning medical AI, basic knowledge of medical AI	Behavioral intention to learn medical AI	Actual learning of medical
18	Choudhury (23)	UTAUT	Yes	Expectancy (effort expectancy, performance expectancy), perception of AI	Patient risk	System adoption
19	Kwak et al. (24)	TAM3	NO	AI ethics awareness, Positive attitude toward AI, Negative attitude toward AI, Anxiety, Self-efficacy	Do not have	Do not have

UTAUT: Unified Theory of Acceptance and Use of Technology model, TAM: Technology Acceptance Model, TPB: Theory of Planned Behavior

Eight studies used the Unified Theory of Acceptance and Use of Technology model to develop the AI evaluation model (6-8, 11, 13, 20, 21, 23), while the Technology Acceptance Model was used in four papers (8, 11, 20, 24). Other studies used literature review to develop AI assessment models.

This study identified several key variables related to "***ethical issues, trust, and anxiety in AI products***". The most frequent variables found were AI ethics awareness and trust or mistrust (11, 13, 14, 20), perceived risks (11, 14, 23), anxiety (14, 17, 24), and privacy (12, 14). Other variables that were assessed in this study included threats to professional capabilities (9), perceived humanness (20), perceived communication barriers (14), pressure (10), perceived unregulated standards (14), perceived liability issues (14), threats to professional capabilities (9), perceived substitution crisis (13), and speciesism (17). In the identified studies, the variables of anxiety, trust, perceived risks, and speciesism were considered both independent and moderate variables. However, the variable of speciesism was only considered a moderate variable. The other variables in the identified studies were classified as independent variables within the framework.

The present study highlighted the importance of AI ethics awareness and user trust in AI studies. For example, in the study conducted by Esmaeilzadeh, several factors were examined to understand their impact on perceived mistrust in AI. These factors included AI ethics awareness, trust, perceived performance anxiety, perceived communication barriers, perceived unregulated standards, perceived liability issues, and perceived privacy concerns (14). Anxiety emerged as another significant variable in the present study. For example, the impact of self-efficacy, anxiety, and speciesism as moderate variables on the acceptance of AI was specifically explored (17).

Additionally, the review identified related ***"usability factors"***, such as perceived ease of use (10, 11, 15), effort expectancy (7, 19, 20, 23), convenience (6, 12, 15), inconvenience (18), aesthetic appeal (19), perceived usability (19), effort/objective usability (10), inclination towards Chat-bots (10), enjoyment (10). In the identified studies, the ease of use variables were considered moderate variables. The other variables in the identified studies were classified as independent variables within the proposed models.

This systematic review also explored "***social factors"*** including subjective norms (10, 11, 13, 22), the human element of care (12), social justice (12), social influence (22), social cognition (20), perceived social biases (14), and social influence (7).

"Self-efficacy and knowledge factors" encompass various variables, such as competence and self-efficacy in using chat-bots (10, 17, 22, 24), knowledge of chat-bots (10, 22), customer experience (18), flow experience (6), perceived competence (6), perception of AI (17, 23), personal relevance of medical AI (22), having heard of chat-bots (10), perceived temporal distance of AI (9), and familiarity with AI (9).

"Benefits factors" were perceived as usefulness (10, 11), performance expectancy (7, 14, 19, 20, 23), utilitarian motivation (6), and perceived benefits (14, 18).

The "***quality of the AI products and service support factors"*** were being fit for purpose (18), technological characteristics (13), task complexity (13), task-technology fit (6), product quality (12, 15), service quality (15), accuracy (12), perceived innovativeness in information technology (13), perception of external control (10), and environment facilitation (7, 19).

Furthermore, in this review, factors related to "***AI acceptance, resistance of AI, attitude, and satisfaction"*** were determined, which were explored in some studies to assess user acceptance and resistance towards AI. Three variables were explored about attitudes that were positive attitude toward AI (24), negative attitude toward AI (24), and attitude toward using technology (7). In use behavior, variables were often response variables in the frameworks. These variables were behavioral intention (7, 10, 20, 22), perceived behavioral control (11, 13), intention to use (11, 13, 14, 21), learning medical sciences (22), use behavior (21), switch intention (6), and perceived behavioral control (11, 13). In two studies, satisfaction and output quality (14, 18) were determined. In addition, AI acceptance (17, 23) as well as resistance to AI (9, 11, 13) were explored in some studies. Table 2 shows evaluation items in prospective assessment models of end users for AI applications.

Statistical validation methods

In the 19 papers that reported the validation methods used, the most commonly utilized technique was SEM, which was employed in 14 papers. In three papers, SEM was combined with EFA and CFA. Regression analysis was used in two articles, while EFA was used in one paper.

Reliability assessment methods and values

Cronbach's alpha was calculated in 11 articles, and in three of those articles, it was used in conjunction with the Composite Reliability (CR) measure. The CR measure was calculated in eight of the articles. Two papers did not report any reliability values.

The range of CR values in the identified studies was from 0.673 to 0.98, indicating a high level of internal consistency. Similarly, the range for Cronbach's alpha was from 0.673 to 0.977, further demonstrating the reliability of the measures used in these studies.

Statistics criteria in the Structural Equation Modeling approach

The Root Mean Square Error of Approximation variable was measured in seven papers. The minimum value observed was 0.029, while the maximum value was 0.078. The mean value was calculated to be 0.05350, with a standard deviation of 0.014756.

The Standardized Root Mean Square Residual variable was measured in five papers. The minimum value observed was 0.032, while the maximum value was 0.060. The mean value was calculated to be 0.04694, with a standard deviation of 0.010309.

The Chi-square ($\chi 2$) variable was measured in four papers. The minimum value observed was 1.956, while the maximum value was 360.350. The mean value was calculated to be 91.66475, with a standard deviation of 179.123535.

The Goodness-of-Fit Index variable was measured in three papers. The mean value was calculated to be 0.88, with a standard deviation of 0.019. Additionally, the Adjusted Goodness-of-Fit Index was measured in three papers. The mean value was calculated to be 0.84, with a standard deviation of 0.026.

The values of the Normed Fit Index and Relative Fit Index were calculated in the study conducted by Esmaeilzadeh (14). The Root Mean Square Residual value was observed at 0.069 in the study performed by Sisk et al. (12). Table 3 shows the validation models and values in the identified studies.

Table 3. Validation models and values in identified studies

Column	Authors	Validation value	Construct validity
1	Yang et al. (6)	KMO=0.941\ AVE >0.05	CR=0.7 C_α: 0.925
2	Fujimori et al. (7)	Not reported	C_α: 0.499 to 0.760
3	Grassini et al. (8)	KMO=0.827, CFI=0.999, TLI=0.998, χ2(2)=2.49, RMSEA=0.0285	C_α: 0.496 to 0.892
4	Jussupow et al. (9)	CFI=0.94, NFI=0.90, GFI=0.87, AGFI=0.83, TLI=0.93. CFA values=χ2: 360.35, CFI=0.95, TLI=0.95, RMSEA=0.06, SRMR=0.06, AVE=0.45.	C_α: 0.71 to > 0.85
5	Iancu and Iancu (10)	Factor loading of CB-SEM=0.67 to 0.923	C_α: 0.745 to 0.964
6	Ye et al. (11)	AVE=0.408-0.524, χ2 0.629, df=356.00, Chi-square (χ2/df)=2.123, RMSEA=0.049, SRMR=0.057, CFI=0.915, GFI=0.896, AGFI=0.873	CR: 0.673-0.837
7	Sisk et al. (12)	KMO=0.92/x 2 P<0.001, CFI=0.91, RMR=0.069, RMSEA=0.053	C_α: 0.84 to 0.90
8	Tran et al. (13)	AVE >0.5	C_α: 0.738 to 0.909
9	Esmaeilzadeh (14)	AVE=0.670 to 0.767, (χ2/df)=2.23, CFI=0.91, NFI=0.90, RFI=0.93, and TLI=0.90, SRMR=0.05, RMSEA=0.06.	CR: 0.910 to 0.952
10	Uzir et al. (15)	AVE=0.730-0.846	CR: 0.915 to 0.962
11	Aw et al. (16)	Not reported	Not reported
12	Huo et al. (17)	AVE=0.66-0.85	CR: 0.88-0.96 C_α: 0.83-0.94
13	Mugabe (18)	Multiple regression	Not reported
14	Holdener et al. (19)	KMO=0.858, factor loading 0.585 to 0.891	C_α: 0.693 to 0.912
15	Pal et al. (20)	AVE=0.667 to 0.919	CR: 0.870 to 0.971 C_α: 0.816-0.908
16	Zhai et al. (21)	Chi-square=692.543, df=354, Normed Chi-square value (χ2/df)=1.956, RMSEA=0.056, SRMR=0.0317, CFI=0.968, CFI=0.859, AGFI=0.827	CR: 0.93
17	Li et al. (22)	AVE=0.77, χ2=490.388, df=215, χ2/df=2.281, P<0.001, CFI=0.950, TLI=0.941, RMSEA=0.078, SRMR=0.044	CR:0.820 to 0.980 C_α: 0.544-0.942 C_α: 0.824-0.977
18	Choudhury (23)	Chi-square=23.56, CFI=0.99, TLI=0.98, RMSEA=0.05	CR: 0.89 to 0.91
19	Kwak et al. (24)	Pearson's correlation coefficient	C_α: 0.75

Note: AGFI: Adjusted Goodness of Fit Index, AVE: Average Variance Extracted, CB-SEM: Covariance-Based Structural Equation Modeling, C_α: Cronbach's alpha CFI: Comparative Fit Index, CFA: Confirmatory Factor Analysis, CR: Composite Reliability, df: Degrees of Freedom, GFI: Goodness of Fit Index, KMO: Kaiser-Meyer-Olkin, NFI: Normed Fit Index, RMSEA: Root Mean Square Error of Approximation, SRMR: Standardized Root Mean Square Residual, TLI: Tucker-Lewis Index, χ2: Chi-Square

5. Discussion

This review provided a comprehensive overview of the research on the perspective of users within AI healthcare settings and highlighted key findings related to sampling techniques, validation methods, scope, participant categories, and analysis software used. These insights contribute to our understanding of current trends and practices in research on the perspective of users.

First, the results of this review indicated a consistent and increasing trend in the publication of papers on AI, in line with previous studies (25, 26). This trend was particularly observed in the field of AI applications for decision support systems. It shows that AI applications could provide effective decision support in certain contexts (27). It can be indicated by the application and potential of AI in improving healthcare outcomes.

Second, the findings revealed that identified papers were conducted across different domains of health settings. From general AI applications to specific areas, like ophthalmic AI devices (11, 16) or AI use in radiation therapy (18, 21). In addition to these findings, one study specifically focused on COVID-19 (10), demonstrating the relevance of AI in addressing challenges related to the pandemic.

Third, a diverse range of participants in the identified studies was observed, including medical professionals, patients, general public ensuring a comprehensive evaluation from different perspectives, bringing together expertise from various healthcare domains. It is noteworthy that some articles explored the opinions of public users by examining their experiences with AI applications outside healthcare settings, such as during travel or via artificial intelligent watches and the Amazon website. This may be attributed to the fact that many users are still unfamiliar with AI applications in healthcare, prompting researchers to explore more general domains and gather insights from various perspectives.

Findings of a study carried out by Ali et al. align with the idea that AI studies in healthcare consider multiple levels of analysis, including individual, organizational, and industry perspectives. They also highlight the extensive benefits of AI in healthcare, such as improved outcomes for individuals and increased efficiency for medical staff and organizations. This suggests that AI has the potential to greatly impact and transform the healthcare sector (28).

Fourth, it was observed that a significant portion of the articles were from developed economies, with China and the United States being prominent contributors, suggesting that these countries are leading the way in healthcare AI development and deployment. This finding is consistent with those of previous studies that have also identified developed countries as key players in advancing AI technologies in healthcare (27, 29).

The prominence of research and development activities in developed economies can be attributed to various factors, such as their well-established healthcare systems, advanced technological infrastructure, and significant investments in AI research. These countries also have access to abundant data for training and testing AI algorithms. Gonzales and Julius Tan reported a direct relationship between modern science and information and communication technology developments and economic growth (30). However, it is worth noting that the present analysis also identified an article from Bangladesh, indicating that AI advancements are not limited to developed countries but are growing globally.

Fifth, in this review, various variables related to ethical issues, ease of use and usability, social factors, self-efficacy and knowledge, usefulness and benefits, attitude and use behavior, and satisfaction/output quality concerning AI acceptance and user perceptions were identified. The results underscore the complex interplay between various factors influencing trust in AI. For example, in a study performed by Iancu and Iancu, relationships between independent, moderating, and dependent variables in the context of AI were assessed. They found that both perceived ease of use and perceived usefulness influence the intention of users to continue using AI applications. This suggests that if users find AI applications easy to use and perceive them as useful, they are more likely to continue using them in the future (10).

Finally, our findings revealed the importance of addressing issues, such as mistrust, ethics awareness, anxiety, humanness perception, and communication barriers in the development and implementation of AI systems, emphasizing the need to foster greater trust and acceptance of AI technology. For example, in the field of nursing care, care users place a great deal of importance on the presence of empathy and compassion in their care managers. They also look for care managers who can comprehend intricate situations and understand the personalities and motivations of involved individuals. This has led to hesitance in accepting AI machines that are seen as lacking the capacity to make sound judgments in complex situations (31).

6. Conclusion

This systematic review provided valuable insights into the research on the perspective of users towards AI in healthcare settings. It highlights the increasing trend of AI publications in healthcare, indicating the potential of AI applications in improving healthcare outcomes. The diverse range of participants ensures a comprehensive evaluation from different perspectives, and the prominence of research and development activities in developed economies suggests their leadership in health

Overall, this systematic review provides valuable insights into the perceptions of end users regarding AI applications in healthcare. These findings contribute to our understanding of current trends and practices in research on the perspectives of users. Future studies should continue to explore the perspectives of end users to enhance the development and implementation of effective AI systems in healthcare.

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Conflicts of interest

The authors declare no conflict of interest.

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