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Review Article

The Role of Artificial Intelligence in Palliative Care: A Scoping Review

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Abstract

Palliative care is a holistic, multidisciplinary approach aimed at improving the quality of life for patients with life-limiting illnesses and their families. Despite the global need for these services, many patients—especially in low-income countries—lack adequate access. Artificial Intelligence (AI) has emerged as a promising tool to enhance palliative care delivery by supporting early identification of patient needs, optimizing clinical decision-making, and improving patient outcomes. This scoping review examined the applications of AI in palliative care. A systematic search was conducted in PubMed, Scopus, and Web of Science up to June 2025, ultimately identifying 8 empirical studies that met the inclusion criteria. These studies were carried out across 5 countries and involved diverse patient populations, including advanced cancer, organ failure, dementia, and traumatic brain injury.

AI applications were categorized into five main areas: (1) evaluating chatbot responses (*e.g.*, ChatGPT, Gemini, Copilot), which revealed inadequate readability and quality; (2) identifying communication silences in patient-provider conversations using machine learning; (3) supporting clinical documentation and decision-making to reduce clinician workload; (4) analyzing inequalities in access to palliative care through predictive algorithms; and (5) predicting disease progression and patient status using longitudinal symptom data. The findings indicate that AI holds significant potential to improve symptom management, support clinical decisions, and enable data-driven interventions in palliative care. However, several challenges must be addressed for sustainable and effective implementation, including poor readability of AI-generated content, ethical concerns, patient privacy issues, and disparities in access to technology. Future research should focus on broader and more diverse populations, integrate survival prediction models, and carefully consider the ethical, regulatory, and organizational dimensions of AI integration into palliative care practice.

Keywords: Artificial intelligence, Decision support, Machine learning, Palliative care, Symptom management, Scoping review

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Introduction

Palliative care is a holistic and multidisciplinary approach with different specialties. Its goal is to improve the quality of life in patients who have life-changing or life-threatening illnesses, and their families (1,2). Palliative care is a human right based on individual dignity (3) and focuses on the early diagnosis and treatment of pain and other symptoms to prevent and alleviate suffering (4). Palliative care has various dimensions, such as physical, emotional, spiritual, and psychosocial care (1).

Palliative care can be used for conditions such as cancer, Serious Chronic Diseases (SCI), and disabilities with the goal of promoting independence and quality of life (5-7). Based on Mehr News Agency which interviewed the deputy of Nursing in the Ministry of Health of Iran (Dr. Abbas Ebadi) in 2023, 56 million people, in the world, annually need palliative care services, but only 14% receive them. This is while 78% of this population resides in low-income countries (8). Accurate statistics regarding the number of patients in Iran who require palliative care services are currently unavailable.

The complexity and increase in data and medical care have led to the use of Artificial Intelligence (AI) in the healthcare system (9); AI is a set of technologies that simulate human intelligence by using machines and computers (10). AI has transformed and strengthened healthcare by predicting, understanding, learning, and performing activities (11), and is used in imaging, diagnosis, and treatment, virtual patient care, patient engagement and adherence, rehabilitation, research and drug discovery, and administrative activities (9,12).

In recent decades, AI has played a significant and growing role in palliative care, similar to its role in other areas of medical science (13). Technology can be used to provide comprehensive and multidimensional palliative care services. Efforts have been made to integrate AI field with palliative care field in the clinical practice and research (14), some examples of which are briefly mentioned below. AI offers solutions for the early identification of those who need palliative care or are receiving inappropriate palliative care (15,16). AI tools and models such as Machine Learning (ML), Natural Language Processing (NLP), and algorithms can be used in palliative care (15,16) to perform timely and purposeful care interventions, reduce costs, and improve the quality of care and patient satisfaction in the areas of palliative care, chronic and life-limiting illnesses (13,15). Considering the mentioned content and the widespread of studies conducted on AI in palliative care, this article aims to provide a scoping review of the application of AI in palliative care.

Materials and Methods

Study design

This study design was a scoping review to examine the scope and nature of studies related to the application of AI in the field of palliative care, comprehensively. This framework was based on the methodology introduced by Arksey and O'Malley (2005) and revised by Levac *et al*, and the reporting process followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) guidelines.

The main goal of this study was to answer the following questions:

- What types of studies (observational, cross-sectional, cohort, retrospective, *etc.*) have been conducted in the field of AI and palliative care?
- Which groups of palliative care patients were the target population for these studies?
- Which AI technologies and tools were used in these studies?
- For what purpose has AI been used in these studies?
- What results have studies in the field of AI and palliative care achieved?

Search strategy

A systematic and comprehensive search strategy was developed in collaboration with a medical information science specialist, utilizing MeSH terms and relevant keywords. Searches were conducted in the PubMed, Scopus, and Web of Science databases (by proxy) without time limits until June 30, 2025.

Keywords included a combination of terms such as "palliative care", "artificial intelligence", "machine learning", "natural language processing", "decision support systems", and similar terms. The details of the search strategy and its results in each database, are presented in the attached table (Table 1).

Results of primary search:
- PubMed: 236 articles (limited to title and abstract);
- Scopus: 414 articles (limited to title, abstract, and keywords);
- Web of Science: 72 articles (limited by title).

Overall, 722 records were entered into the article management system (Rayyan.ai) to begin the process of removing duplicates and screening articles.

The process of selecting and screening articles

After removing duplicate entries, 442 unique records remained. These articles were independently and individually reviewed by two researchers based on inclusion and exclusion criteria. In case of disagreement, the opinion of the third reviewer was considered as the final authority.

Inclusion criteria:
- Original research articles with observational designs (longitudinal, cross-sectional, cohort, and retrospective);
- Studies with practical applications of AI in palliative care.

Exclusion criteria:
- Review studies, conference articles, letter to editor;
- Survival prediction articles that solely focus on predicting survival rates;
- Theoretical, ethical, or philosophical research lacking empirical data in the field of AI;
- Studies on child, infant, and neonate populations;
- Gray literature and non-peer-reviewed articles;

After screening the titles and abstracts, 9 articles were selected for full-text review. One article was excluded due to the lack of scientific peer review and its gray status, and finally, 8 articles were included in the final analysis.

The article selection process is illustrated in the PRISMA flow diagram (Figure 1).

Data extraction and analysis

The standardized data extraction form was designed based on the recommendations of the Joanna Briggs Institute and included items such as study type, target population, AI technologies used, AI application objectives, evaluation criteria, and key results.

The data was extracted independently by two researchers, and any difference in the data extraction was resolved after team discussion and agreement.

Table 1. Search strategy and search results in each database

Database	Search strategy	Filter	Date	Results
PubMed	(“Artificial Intelligence” OR AI OR “Computer Reasoning” OR “Machine Intelligence” OR “Computational Intelligence” OR “Computer Vision Systems” OR “Computer Vision System” OR “Intelligent Systems” OR “Machine Learning” OR “Deep Learning” OR “Transfer Learning” OR Chatbot OR Chatbots OR “Chat-GPT” OR “Chat GPT” OR ChatGPT OR ChatGPTs) AND (“Palliative Care” OR “Palliative Supportive Care” OR “Palliative Care Nursing”)	Title/ Abstract	2025/30/7	236
Scopus	(“Artificial Intelligence” OR AI OR “Computer Reasoning” OR “Machine Intelligence” OR “Computational Intelligence” OR “Computer Vision Systems” OR “Computer Vision System” OR “Intelligent Systems” OR “Machine Learning” OR “Deep Learning” OR “Transfer Learning” OR Chatbot OR Chatbots OR “Chat-GPT” OR “Chat GPT” OR ChatGPT OR ChatGPTs) AND (“Palliative Care” OR “Palliative Supportive Care” OR “Palliative Care Nursing”)	Article title, abstract, keywords	2025/30/7	414
Web of science (proxy)	(“Artificial Intelligence” OR AI OR “Computer Reasoning” OR “Machine Intelligence” OR “Computational Intelligence” OR “Computer Vision Systems” OR “Computer Vision System” OR “Intelligent Systems” OR “Machine Learning” OR “Deep Learning” OR “Transfer Learning” OR Chatbot OR Chatbots OR “Chat-GPT” OR “Chat GPT” OR ChatGPT OR ChatGPTs) AND (“Palliative Care” OR “Palliative Supportive Care” OR “Palliative Care Nursing”)	Title	2025/30/7	72

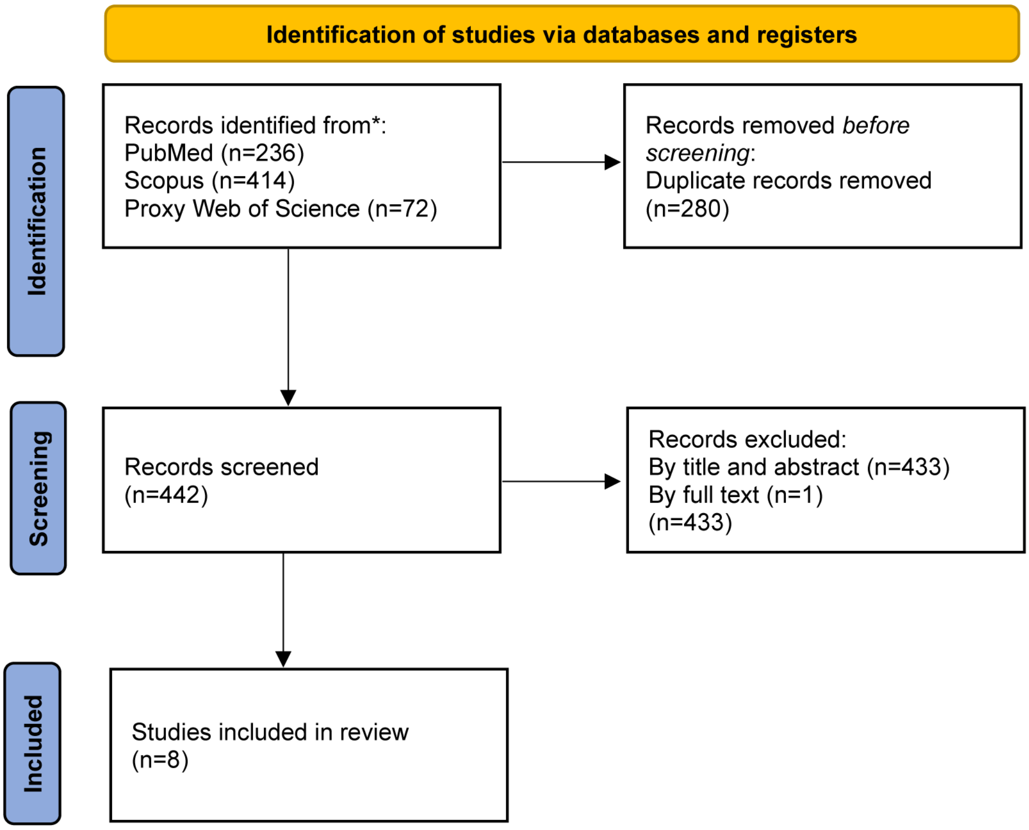

Figure 1. PRISMA flow diagram.

Ethical consideration

This study used published data without direct human intervention and did not require ethics committee approval. All authors actively participated equally in all stages of the study. Additionally, utilizing the Rayyan.ai artificial intelligence system in the process of article management led to reduce the probability of bias.

Results

Overall, eight studies were related to use of AI, were included. Their type of study was seven different types including observational and cross-sectional (17), cross-sectional only (18), cohort (19,20), retrospective observational (21), retrospective cohort (22), retrospective (23), and also a study with a mixed cross-sectional-longitudinal observational design (24). Cohort designs (19,20) and retrospective cohorts (22) were the highest frequency among these studies. It shows researchers' interest in examining longitudinal trends in patient-related data. Geographically, these studies were conducted in five different countries. The types of studies mentioned with their frequency can be seen in figure 2. The United States had four studies and it has the largest share (18-20,22). After that, Turkey had two studies (17,21), and each Germany (23) and New Zealand (24) had one study. The geographical distribution of these studies can be seen in the figure 3. This diversity in study design and geographical distribution shows the international and growing interest in using AI to improve the quality of palliative care. The study populations also include a diverse range of patients, including those with advanced cancer (18-20), metastatic breast cancer (23), oncological cancers, leukemia, organ failure, dementia (24), and traumatic brain injury (22).

The findings of these studies are categorized into five groups based on the application areas of AI in palliative care; also, article summaries are presented in the attached table 2.

Evaluating chatbot responses in providing palliative care information

In a study, the performance of five prominent chatbots (ChatGPT, Bard, Gemini, Copilot, and Perplexity) in answering 100 frequently asked questions

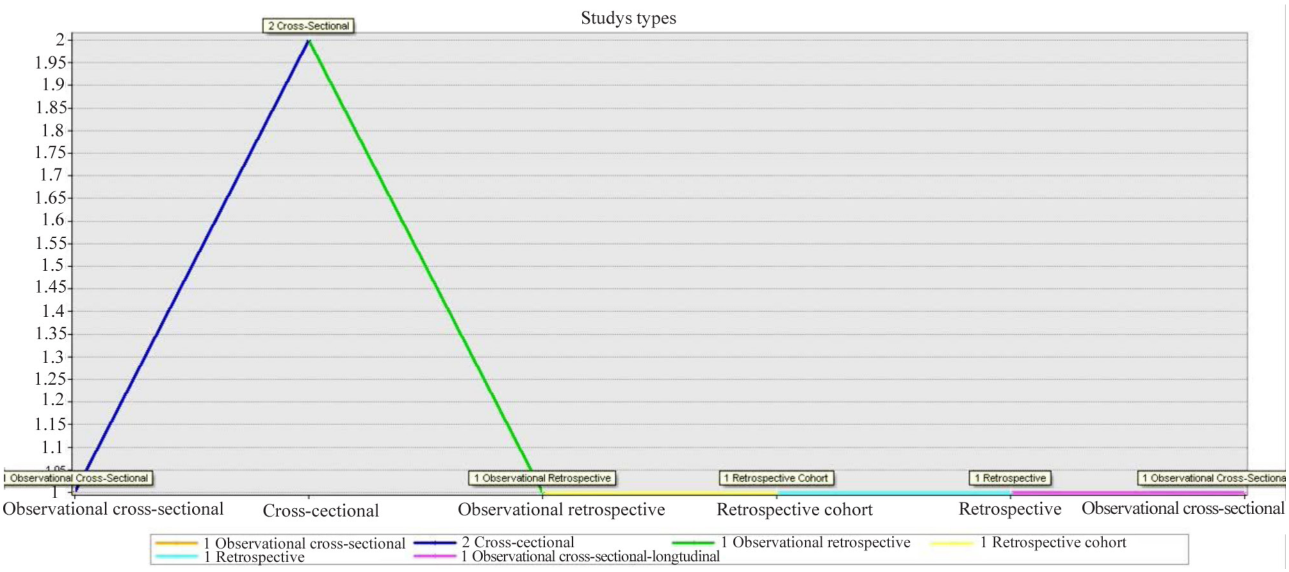

Figure 2. Types of included studies and their frequency.

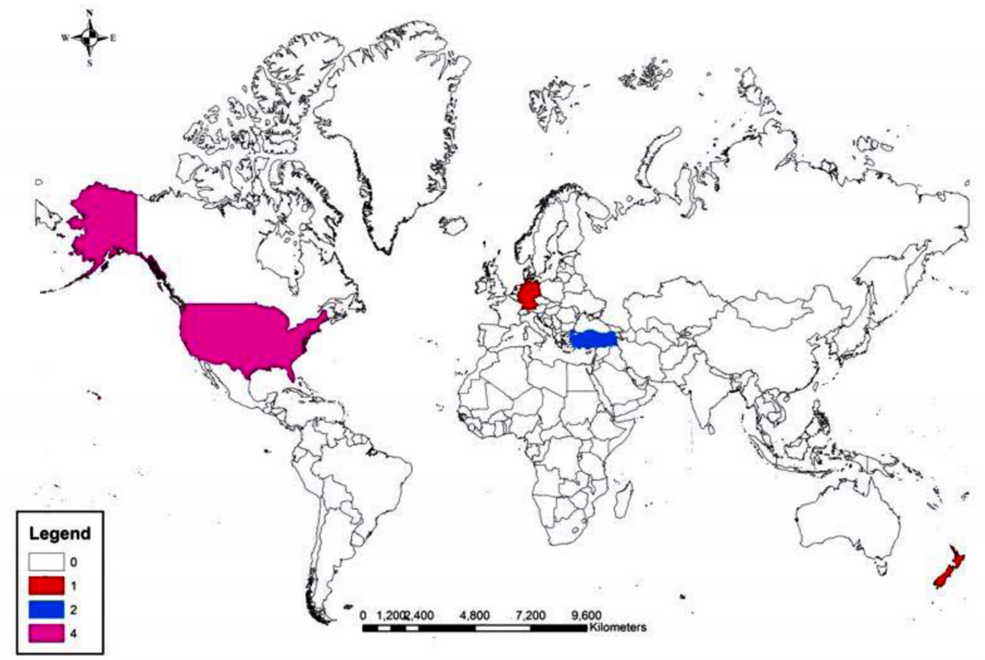

Figure 3. Geographical distribution of included studies.

from patients and families in the field of palliative care was evaluated. The results showed that their responses were difficult for patients with low health literacy to understand because their readability level in all chatbots weas higher than the recommended level (6th grade of school). The difficulty of readability was in order from easiest to hardest as Bard, Copilot, Perplexity, ChatGPT, and Gemini. Whereas Perplexity had the highest quality responses scientifically by using the modified DISCERN and Journal of American Medical Association (JAMA) tools, Gemini received the highest global quality scale. Overall, the quality and readability of these chatbots' responses for public use, especially in palliative care, were assessed as inadequate, and they need to improve (17).

Identifying communication silences in palliative care conversations with machine learning

Table 2. Summary of articles included in the study (n=8)

Title	First author	Year	Country	Type of study	Artificial intelligence used	Results
Assessment of readability, reliability, and quality of ChatGPT, BARD, gemini, copilot, perplexity responses on palliative care	Hancı	2024	Turkey	Observational and cross-sectional	Chatbots (ChatGPT, BARD, Gemini, Copilot, and Perplexity)	This article emphasizes that the current responses of these chatbots are not suitable in terms of quality and readability and need to be improved (17)
Identifying connectional silence in palliative care consultations: a tandem machine-learning and human coding method	Durieux	2018	America	Cross-sectional	A Tandem Machine-Learning and Human Coding Method	A tandem machine-learning and human coding method are reliable, efficient, and sensitive for identifying communication silences in serious illness conversations (18)
Automated detection of conversational pauses from audio recordings of serious illness conversations in natural hospital settings	Manukyan	2018	America	Cohort	Random forest machine learning algorithm	Machine learning automatically identified communication silences with a sensitivity of 90.5 and a specificity of 94.5, and is a valid method for automatically identifying communication silences in the natural environment of conversations of hospitalized patients with serious illnesses (19)
An acoustical and lexical machine-learning pipeline to identify connectional silences	Matt	2023	America	Cohort	An acoustical and lexical machine-learning pipeline	The machine learning pipeline detected communicative silence with an overall sensitivity of 84% and specificity of 92% and can be used to fully automate the detection of communication silences in natural hospital-based clinical conversations (20)
AI-supported documentation and clinical monitoring in palliative care: a real-world observational study	Gün	2025	Turkey	Retrospective observation	GPT-based al tools	These tools improve documentation efficiency and clinical awareness in palliative care settings and should be used under appropriate clinical supervision (21)
Machine learning reveals demographic disparities in palliative care timing among patients with traumatic brain injury receiving neurosurgical consultation	Aude	2025	America	Retrospective cohort	Machine learning methods	Three distinct clusters of patients based on age, gender, race, and severity of injury were identified with significant differences in the timing of receiving palliative care, demonstrating clear inequalities in access to palliative care (22)

Contd. table 2.

Machine learning and patient-reported outcomes for longitudinal monitoring of disease progression in metastatic breast cancer: a multicenter, retrospective analysis	Deutsch	2023	Germany	Retrospective	Regularized regression machine learning algorithm	The highly accurate AI algorithm predicts the risk of disease progression through patient self-reporting, earlier than testing and imaging, and identifies the need for palliative care at the right time (23)
Machine learning and patient-reported outcomes for longitudinal monitoring of disease progression in metastatic breast cancer: a multicenter, retrospective analysis	Sandham	2022	New Zealand	Cross-sectional-longitudinal observation	Six types of machine learning algorithms	Machine learning can predict disease stages in palliative care based on symptoms (24)

Three studies focused on the application of machine learning in analyzing conversations with patients in need of palliative care. These studies divided communication silences (pauses of two seconds or more), which play a significant role in conveying emotions, empathy, and sensitive information, into four categories:

- Emotional silence (after expressing strong emotions or bad news);
- Compassionate silence (for the affirmation or emotional support);
- Invitational silence (after deep questions about life goals or death);
- Non-connectional pauses (other pauses) (18-20).

The first study was able to identify these types of silences in videos of palliative care consultations for cancer patients by utilizing a tandem machine-learning and human coding method. This method was more efficient and just as sensitive as human coding alone (18).

The second study investigated the possibility of automatically detecting communication silences in a real hospital environment by using the random forest algorithm. This approach was evaluated as useful for analyzing participation, interaction, or distraction in conversations with patients who had the advanced cancer (19).

The third study also carefully classified different types of communication pauses by designing a machine learning pipeline. The results showed that using multilayer audio signals improves the accuracy of models in analyzing clinical conversations (20).

Using AI in documentation and supporting clinical decision-making

In one study, AI tools were used to automate clinical documentation, including daily notes, discharge summaries, and medication recommendations, in a palliative care setting. Doctors entered the data, and the intelligent system generated a draft of the documentation, which was reviewed and finalized by the physician. This intervention led to reduce significantly reduction in documentation time, to improve clarity of clinical records, and to increase engagement families by producing educational summaries. Using this tool reduced cognitive load and increased clinical awareness. Despite these benefits, the authors emphasized that this tool is not a substitute for professional medical judgment and should be used under close clinical supervision (21).

Analyzing inequality in access to palliative care with predictive algorithms

A study was conducted with the aim of analyzing

factors associated with the timing of receiving palliative care in patients with traumatic brain injury and it identified three distinct clusters of patients based on demographic and clinical characteristics:
- Older white women with mild damage and receiving early palliative care;
- Older white men with mild damage and receiving delayed care;
- Middle-aged non-white patients with severe damage and receiving care much later.

Based on the results, factors such as age, race, and gender had a greater impact on the time of receiving palliative care than the clinical severity of the injury. These findings highlight the overt inequality in access to care and emphasize the need for the development of standardized decision support tools (22).

Predicting changes in patient status by using longitudinal data

Two studies used machine learning algorithms to analyze frequent patient data to predict changes in disease status and the need for palliative care (23,24). In the first study, quality of life data from patients who had advanced breast cancer, were collected longitudinally (during six months). Then, changes in questionnaire scores were analyzed and patients who were progressing were identified by using a machine learning algorithm. This method made it possible to identify the need for palliative care early, even before imaging or clinical tests were confirmed (23).

In the second study, patient symptoms were analyzed and central symptoms (such as fatigue and decreased appetite) were identified by using network analysis and machine learning. These symptoms were related to other signs, and their changes predicted the stages of the disease, including stable, unstable, declining, and terminal. According to the results, this approach has moderate accuracy in diagnosing the stage of the disease and can be developed in the future by using applications and wearable devices (23).

Overall, while the first study focused more on early prediction of the need for palliative care, the second study focused on analyzing symptom patterns and improving clinical management (23,24).

Discussion

The eight studies reviewed in this review directly addressed the use of AI in palliative care and answered the research questions posed in the methodology section. The AI technologies and tools used in these studies have been diverse. These tools included ChatGPT, BARD, Gemini, Copilot, and Perplexity chatbots (17), machine learning algorithms and methods (22,24), a tandem machine-learning and human coding method (18), random forest algorithms (19), an acoustical and lexical machine-learning pipeline (20), GPT-based AI tools (21), and regularized regression machine learning algorithms (23).

Based on the findings of the reviewed studies, the quality and readability of existing chatbot responses are not adequate. It is essential to improve their performance (17). AI can be used to identify and classify communication silences in serious conversations. These methods were reliable, efficient, and sensitive (18-20). The use of AI tools in palliative care units, has improved documentation efficiency and increased clinical awareness (21). These technologies have been able to identify and classify patients based on differences in the timing of receiving palliative care (22); they early predicted the risk of disease progression by patient self-reporting (23) and, finally, predicted disease stages based on symptoms in palliative care (24).

In a scoping review study conducted in 2025, the application of AI in palliative care for symptoms management and decision support was examined. This study was a mixed-method and limited to ten-year time. All included articles were peer-reviewed and empirical. The results showed that AI improves palliative nursing care by providing preventive and data-driven care. Ethical implementation, training, and validation are key to the sustainable adoption of these technologies (25).

Also, in another systematic review in 2025, the application of AI and machine learning models in identifying potential stakeholders of palliative care for patients with chronic and incurable diseases was examined. This review was conducted in four authoritative databases. The included studies used machine learning algorithms, natural language processing, and deep learning models. According to the results, these models provide solutions for the effective identification of palliative care stakeholders

(15).
Alongside these findings, some studies have addressed the technical, ethical, and regulatory challenges associated with using AI in healthcare. These challenges have included privacy, informed consent, patient autonomy, health equity, accountability, human error, and legal gaps in transparency and oversight. Therefore, the development of AI technologies in this field requires special attention to ethical, relational, and organizational dimensions to maintain the quality of the patient-physician relationship (16,26).
Unlike previous studies, the current study did not include a time limit, and the included articles were various observational study types (longitudinal, cross-sectional, cohort, and retrospective). Although an extensive search was conducted in the PubMed, Scopus, and Web of Science databases (accessed by proxy), it was not possible to search other databases due to access limitations. Therefore, it is suggested that future reviews also include searches in other databases and incorporate other types of studies. Additionally, this review only includes studies conducted on the adult population, and studies related to predicting survival rates or ethical issues were not included. Therefore, it is recommended that future reviews also exam the populations of newborns, infants, and children, and that studies addressing survival prediction and ethical considerations be included in the analysis.

Limitations and future research based on reviewed studies

In evaluating the quality of AI responses, the responses were reviewed in English and with limitation of time, whereas the responses may change after asking the questions again in subsequent days, or the questions from non-English speakers with different cultural, political, and geographical backgrounds may vary. In chatbots, it was not specified who asked the question (patient or specialist); also, questions and answers were not categorized by content. Finally, efforts should be made to ensure the readability level of chatbot responses is appropriate for individuals who have low health literacy skills (17).
In studies related to communication silences, although the capacity of machine learning technology is advancing, the authors of the article consider human interaction alongside the use of a tandem machine-learning and human coding method to be an important tool for clinical communication science in the future. Silence can have different interpretations in various cultures; recording audio or video is challenging and difficult from an economic, privacy, and resource (18); the recording environment, such as a hospital, is noisy, and there is a risk of missing important clinical moments of human communications (18,20); it is recommended to use directional or wearable microphones to minimize unnecessary background noise (20). The small sample size, the lack of linguistic resources, clinical scenarios, or sufficient cultural norms are other limitations of studying communication silences (18,20). The studies were conducted based on audio and text data, and inaudible communication moments such as brief eye contact and touch may be misclassified (20). The ability or inability of machine learning to distinguish between subgroups of silence remains unclear, and it is suggested in subsequent research that the sensitivity and specificity of the tool be improved (19).
In using AI for documentation and clinical support, the relatively small sample size, limitation to a single center, and lack of a control group or a reliable ranking scale for satisfaction or workload limited the generalizability of the findings. The AI tool in this study could not independently interpret clinical findings or interact with patients. It is recommended that in future research, these tools be validated across a wide range of palliative care settings (outpatient services and home care) and that patient or family satisfaction also be formally assessed. Providing these services requires joint collaboration between the healthcare system and technology (21).
Retrospective observational studies on traumatic brain injuries have limited causal conclusions, and there are likely unmeasured confounding factors in the research. The specific composition of the sample (primarily elderly individuals with an increased incidence of intracranial hemorrhage and a higher probability of comorbidities), demographic characteristics, and the single-center design led to biases in the study. Furthermore, this study's focus on patients with traumatic brain injury who received neurosurgical consultation limits the generalizability of the findings. It is recommended that future studies

be conducted in various healthcare settings with the aim of directly validating the findings (22).

In the longitudinal monitoring study of disease progression in metastatic breast cancer, as in previous studies, the sample size remained small, and despite the study being two centers, this still increased the risk of bias. Future studies are essential for prospective validation in larger, more diverse populations, and even remotely monitored settings. It is recommended that the actual clinical consequences and outcomes of such risk prediction tools be examined in future studies. This tool should be evaluated before clinical implementation to increase success (23). In the patient-reported outcomes study, the dataset is heterogeneous in terms of disease, with a predominance of oncological cancers, and the generalizability of the results to other studied diseases is challenging. Additionally, the number of patients in worsening and final stages could potentially bias the results and limit the prediction of patients with later stages. The number and intervals of patient examinations were different, and the data volume was low; overall, analyzing disease stage changes over time in a consistent and reliable manner was not possible. Therefore, it is suggested that future research be conducted with a larger sample size and the use of wearable devices (24).

Conclusion

In conclusion, AI has demonstrated significant potential to enhance palliative care by enabling early identification of patient needs, optimizing clinical decision-making, improving documentation efficiency, and supporting personalized care interventions. Despite these promising applications, challenges related to readability, ethical considerations, patient privacy, and equitable access remain critical barriers. Addressing these challenges through careful implementation, validation, and training is essential to ensure that AI technologies complement, rather than replace, the human-centered approach of palliative care. Future research should continue to explore diverse patient populations, integrate advanced predictive models, and establish ethical and regulatory frameworks to maximize the benefits of AI in improving quality of life for patients with life-limiting conditions.

Conflict of Interest

Authors declare no conflict of interest.

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