DOI: 10.5603/pmp.105709

Clinical applications of artificial intelligence in symptom management and decision making in oncologic palliative care: a systematic review

Sandra Marisel Botía Pinzón https://orcid.org/0009-0004-1055-9809, Fábian Alexander Leal Arenas https://orcid.org/0000-0003-0284-2423, Bilena Margarita Molina Arteta

Instituto Nacional de Cancerología, Bogotá, Colombia

Address for correspondence:

Sandra Marisel Botía Pinzón

Instituto Nacional de Cancerología, Bogotá, Colombia

e-mail: sandrammd1209@gmail.com

Received: 7.04.2025 Accepted: 9.06.2025 Early publication date: awaiting final publication date

Abstract

Introduction: Artificial intelligence (AI) is increasingly being integrated into healthcare, offering innovative tools to improve symptom management and support clinical decision-making in patients with advanced cancer receiving palliative care (PC). The study aimed to systematically evaluate recent evidence (2021–2024) on the clinical use of AI-based tools for symptom management, prognosis prediction, and clinical decision support in adult oncology patients in PC settings.

Methods: A systematic review was conducted following the PRISMA-P 2015 guidelines. Databases searched included PubMed, Scopus, Cochrane Library, BVS, Scielo, and

ScienceDirect, using MeSH terms related to AI, cancer, pain, and palliative care. Studies were included if they involved adult oncology patients using AI tools in PC and reported outcomes related to symptom control, clinical decisions, or mortality estimation. Two independent reviewers conducted the selection and methodological quality assessment using STROBE, PRISMA, and CONSORT guidelines. Only studies rated as medium or high quality were included.

Results: From an initial pool of 3,018 records, 20 studies were selected. AI applications were grouped into prognosis and mortality prediction (n = 9), symptom identification and monitoring (n = 5), clinical decision support (n = 4), and communication tools (n = 2). Models included neural networks, eXtreme Gradient Boosting (XGBoost), decision trees, natural language processing (NLP), and chatbots. Most studies demonstrated high accuracy in retrospective or real-world clinical settings.

Conclusions: AI has shown potential in the early identification of palliative needs, symptom control, and care planning. Prospective validation and implementation studies are needed to ensure ethical and safe integration into palliative care.

Keywords: cancer, pain, palliative care, artificial intelligence

Introduction

The World Health Organization (WHO) states that palliative care (PC) is an approach to improving the quality of life of patients at the end of life and their families, associated with life-threatening diseases. It includes the prevention and relief of suffering through early identification, assessment, and treatment of pain and other physical, psychosocial, and spiritual problems [1]. An estimated 40 million people worldwide need PC annually due to population aging and increased chronic and non-communicable diseases. PC is required in up to 60% of deaths worldwide, with cancer patients comprising up to 34% of cases, meaning an increase in the need for PC and pain management in the population [1]. In 2020, it was estimated that approximately 56.8 million patients experienced unnecessary suffering that could be addressed and treated through palliative care (PC). This number is expected to

increase in the coming decades, particularly in low- and middle-income countries, where the availability of PC remains limited worldwide, currently accessible in only 39% of countries [2]. This highlights a substantial gap in PC coverage and availability between countries, as well as an urgent need to expand PC services [2].

Palliative care involves a high symptom burden, which often leads to hospitalization. Therefore, access to these services should be provided early, ensuring continuous support from diagnosis to the end of life. This approach enables the timely identification of palliative needs that can be addressed through comprehensive early intervention. However, in healthcare institutions without access to a PC, it is essential to identify these needs to ensure early referral [3]. Over the past two decades, the recommendation for early PC in patients with advanced cancer has gained strong support from scientific evidence. Current guidelines suggest initiating PC within eight weeks of an advanced cancer diagnosis and emphasize the need for early referral [4]. Moreover, in patients with advanced cancer undergoing active chemotherapy, early PC can reduce symptom burden, improve quality of life, increase patient satisfaction, and potentially extend survival [5].

Despite the growing recognition of the importance of early PC, referrals to PC are often delayed, with some patients even dying without receiving these services. This is especially true in low- and middle-income countries, where a significant percentage of patients do not receive PC due to various barriers such as limited access, a shortage of trained personnel, and a lack of PC specialists [4]. In summary, PC is essential in end-of-life care [6, 7], with oncological patients having a particularly high need for these services [4] due to the clinical and pathological implications of their condition [8].

From another perspective, various studies are exploring the use of artificial intelligence (AI) as a supportive tool to reduce gaps in PC access and provide timely, comprehensive care. AI has been identified as a valuable aid in therapeutic decision–making, reducing workload, and enhancing patient care, ultimately improving overall treatment outcomes [5]. However, more evidence is needed to fully demonstrate the benefits AI can offer in PC, particularly in pain management and overall patient care.

Recognizing the advantages of AI in medicine [9], oncological patients receiving PC could also benefit from AI's role in comprehensive PC interventions, addressing the needs

of this highly vulnerable patient group. It is therefore essential to explore this topic further, as it will provide the most up-to-date evidence regarding PC in oncological patients at the end of life. This is particularly important for healthcare professionals, as both pain management and PC can lead to significant changes in medical strategies for treating these patients. Additionally, this research will strengthen the role of the medical team, ensuring they remain attentive to the needs of oncological patients requiring PC. Equally important is the consideration of AI's potential in medical decision-making, which could enhance therapeutic approaches, provide safer and more evidence-based treatment options, and improve the overall management of oncological patients receiving PC. AI's integration into PC has the potential to enhance the quality of life for patients at the end of life, as well as that of their families, by offering more effective pain relief and a more compassionate, human-centered approach.

From a PC perspective, AI will also help strengthen the competencies required by specialized personnel, as its holistic nature is closely tied to the critical thinking that can be developed through evidence-based practice. Applying AI-driven insights to palliative care will be highly valuable in addressing the needs of both patients and their families. For all these reasons, this document presents the latest advancements in AI applications for pain management and PC in oncological patients.

Methods

Study design

A systematic literature review was conducted following the PRISMA-P 2015 framework, aiming to identify, analyze, and synthesize available evidence on the use of artificial intelligence (AI) in pain management and palliative care for adult oncology patients. This methodology allowed for the exploration of the current state of knowledge, identification of clinical applications, and evaluation of the methodological quality of the included studies.

Information sources and search strategy

The literature search was performed between May and June 2024 in the databases PubMed/Medline, Scopus, Cochrane Library, BVS, Scielo, and ScienceDirect, using MeSH terms and Boolean operators. The search strategy was structured using the PICO model:

- **P (Population):** adult oncology patients;
- **I (Intervention):** artificial intelligence applications ;
- **C (Comparison):** not applicable;
- **O** (Outcomes): pain management, symptom or mortality prediction, clinical decision support, communication and education tools.

Specific strategies for each database and the filters applied (language, population type, and publication period 2021–2024) are detailed in Table 1, which presents the search combinations and results obtained per database.

Inclusion and exclusion criteria

Included articles were in English or Spanish, published between January 2021 and June 2024, and met the following criteria:

- evaluated the use of AI in adult oncology patients receiving palliative care;
- applied AI to predict symptoms, estimate prognosis, or support clinical decision-making;
- presented a structured methodological design (observational study, clinical trial, or systematic review);
- full-text availability.

Articles were excluded if they were duplicates, not directly related to AI or palliative care, lacked a concrete clinical application, or had low methodological quality.

Study selection process

The selection process involved three stages:

1) **duplicate removal** using Rayyan.ai® software;
2) **title and abstract screening** by two independent reviewers, applying the inclusion and exclusion criteria;
3) **full-text review** of preselected articles and critical content analysis, prioritizing clinical applicability, type of AI used, and relevant outcomes.

This process is summarized in the PRISMA flow diagram (Table 2) [10–29], which outlines the number of records identified, selected, and excluded at each stage.

Methodological quality assessment

An adapted assessment tool was used based on the STROBE guidelines (for observational studies), PRISMA (for reviews), and CONSORT (for clinical trials). Each article was evaluated according to compliance with key methodological criteria. The results of this assessment are summarized in Table 3 [10–29], where studies are classified as high quality (≥ 80%), medium quality (≥ 60% and < 80%), or low quality (< 60%). Only articles rated as medium or high quality were included. No study was rated as low quality.

Data synthesis

A synthesis matrix was used to identify common patterns, clinical application categories, and types of AI tools employed. This information is presented in Table 4 [10–29], which groups the studies according to their main function: mortality prediction, symptom identification, clinical decision support, and communication tools. A meta-analysis was not conducted due to the heterogeneity in study designs, populations, and outcomes.

Results

From a total of 3,018 articles identified, 20 studies met the eligibility criteria and were selected. These investigations, published between 2021 and 2024, reflect the growing interest in integrating artificial intelligence (AI) into the context of oncologic palliative care. The results of this assessment are summarized in Table 2, where studies are classified as high quality (≥ 80%), medium quality (≥ 60% and < 80%), or low quality (< 60%). Only articles rated as medium or high quality were included. No study was rated as low quality. The majority of studies were observational (65%). The remainder included thematic reviews, a randomized controlled trial, a mixed-methods study, a systematic review, and a scoping review. The geographic distribution was diverse, with a predominance of studies conducted in the United States (25%) and contributions from countries in Asia, Europe, and Latin America. Additionally, 20% of the studies involved international collaboration, highlighting a global effort to explore AI applications in palliative care.

Collectively, the studies analyzed more than 34,000 patients and 37,000 clinical records. They involved clinical experts (oncologists, palliative care specialists, and mental health professionals), language models such as ChatGPT and Bard, and even immersive experiences in pediatric palliative care. To facilitate analysis and interpretation, the findings were organized into four main clinical categories: prognosis and mortality prediction, symptom identification and monitoring, clinical decision support, and communication and education tools. Below are the main contributions within each of these areas.

Prognosis and mortality prediction

Zhuang et al. [16] developed a deep learning model to predict 365-day survival with an area under the receiver operating characteristic curve (AUROC) of 0.861 and an area under the precision-recall curve (AUPRC) of 0.771. The model, based on electronic health records, slightly overestimated risk and used Shapley additive explanations (SHAP) plots for interpretability. Kawashima et al. [26] applied XGBoost to predict palliative care needs in chemotherapy patients, achieving an area under the curve (AUC) of 0.89, 95.8% sensitivity, and 71.9% specificity. Gajra et al. [21], using Jvion CORE, reported an increase in referrals to palliative care after implementing AI tools in clinical settings. Wilson et al. [17] developed a Bayesian model in R (JAGS, Just Another Gibbs Sampler) to predict palliative care needs, resulting in higher referral rates and lower hospital readmissions at 60 and 90 days. Soltani et al. [27] used Seasonal Autoregressive Integrated Moving Average (SARIMA), convolutional neural network (CNN), and long short-term memory (LSTM) models to optimize home-based palliative care demand management, achieving 69.75% accuracy. DiMartino et al. [20], with the Clinical Annotation Research Kit (CLARK) system, identified uncontrolled symptoms with 61% accuracy for pain, 68% for nausea/vomiting, and 80% for dyspnea. Kim et al. [22] employed XGBoost, Random Forest, and other models to predict delirium, reaching an AUC of 74.55% and a balanced accuracy of 69.84%. Limsomwong et al. [19] implemented a rule-based algorithm using LexTo to identify key predictors in the Supportive and Palliative Care Indicators Tool — Low Income Settings (SPICT-LIS) tool, achieving 95% agreement and a Cohen’s kappa of 0.83.

Symptom identification and monitoring

Mallick et al. [24] developed a remote monitoring tool using wearable sensors and a Raspberry Pi to measure respiratory and heart rate parameters, anticipating dyspnea episodes in advanced cancer patients. DiMartino et al. [20] applied natural language processing (NLP) to detect uncontrolled symptoms in the electronic medical records of hospitalized patients with advanced disease. Shimada and Tsuneto [25], using RapidMiner, predicted multiple symptoms including pain, dyspnea, fatigue, anxiety, and spiritual distress, with accuracy ranging from 55% to 88%. Sandham et al. [14] used the Integrated Palliative Care Outcome Scale (IPOS) and various AI techniques (including neural networks and decision trees) to identify key symptoms in phase transitions, such as loss of energy and appetite. **Huang et al. (2021) [ref. No. ??]** identified patterns of undocumented pain using an AI algorithm applied to clinical notes. DiMartino et al. [20], with the CLARK system, identified uncontrolled symptoms with 61% accuracy for pain, 68% for nausea/vomiting, and 80% for dyspnea. Kim et al. [22] employed XGBoost, Random Forest, and other models to predict delirium, reaching an AUC of 74.55% and a balanced accuracy of 69.84%.

Clinical decision support

Wilson et al. [17] implemented a clinical prediction tool in community hospitals, improving early access to palliative care and reducing hospital admissions. Kawashima et al. [26] developed a model to define predictive characteristics that could replace conventional screening tools. Soltani et al. [27] strengthened home care systems in high-demand settings using LSTM models and deep learning. Limsomwong et al. [19] applied a rule-based system with LexTo that accurately identified candidates for palliative care.

Communication and education tools

Van Bussel et al. [10] analyzed factors influencing acceptance of a virtual assistant, highlighting the role of performance expectancy, effort expectancy, and trust in user intention. Srivastava and Srivastava [29] evaluated ChatGPT-3 in therapeutic communication in palliative care, noting realistic human-like responses but thematic redundancy regarding spirituality and death. Yücel et al. [28] compared ChatGPT-4, Bard, and other platforms, finding that ChatGPT-4 showed the highest accuracy (96%), while Google Bard had the lowest (86%), with variability in readability and response stability.

Discussion

The findings of this systematic review reaffirm the transformative potential of artificial intelligence (AI) in oncologic palliative care. The integration of predictive algorithms, natural language processing tools, and machine learning models has proven to be an effective strategy for anticipating clinical needs, improving care planning, and strengthening patient–centered decision-making.

Firstly, AI has demonstrated strong capabilities in predicting prognosis and mortality, particularly through models such as XGBoost, LSTM, and SARIMA. These tools not only achieved high sensitivity and specificity but also offered clinical interpretability through SHAP plots or cross-validation techniques [16, 19, 22, 26, 27]. These models represent a crucial step toward personalized medicine, especially in identifying the optimal timing for palliative care referrals, as shown by Gajra et al. [21] and Wilson et al. [17].

Regarding symptom monitoring, the use of NLP applied to electronic health records allowed for the detection of unreported or uncontrolled symptoms, optimizing the multidimensional approach to suffering in palliative care [20, 24]. Moreover, sensor-based tools and platforms like RapidMiner enabled remote monitoring of respiratory or psychological symptoms, which is particularly valuable in home care or limited-access settings [25].

Another key contribution was the use of AI in clinical decision support. Studies by Kawashima et al. [26] and Soltani et al. [27] demonstrated how AI can complement — or even replace — traditional screening methods, dynamically adapting to high-demand contexts or resource-constrained environments. These findings pave the way for hybrid care models in which artificial intelligence and clinical judgment coexist to enhance the efficiency and timeliness of palliative care delivery.

Finally, AI-based communication and education tools, including virtual assistants and chatbots, have shown significant improvements in accuracy, stability, and readability. Although limitations remain — particularly in conveying emotional depth or addressing sensitive topics such as death or spirituality — their progressive implementation suggests a promising future for patient education and the humanization of care [10, 28, 29].

Despite these advances, important challenges persist: the limited prospective validation of models, potential biases in datasets trained on small or unrepresentative cohorts, and the need for ethical, person-centered integration of AI tools. Furthermore, most studies were conducted in hospital settings in high-income countries, which restricts the generalizability of findings to lower-resource healthcare systems. Overall, this review not only provides a critical synthesis of clinical AI applications in oncologic palliative care but also highlights emerging opportunities to transform care through a more anticipatory, precise, and compassionate approach.

Study limitations

This review presents several important limitations. First, the methodological heterogeneity of the included studies prevented the performance of a quantitative meta-analysis. Additionally, many of the AI models analyzed have not yet been prospectively validated, limiting the generalizability of their results to real-world clinical settings. Most of the research was conducted in high-income countries, so their applicability in low-resource settings still requires evaluation. Furthermore, the studies showed variability in the metrics used, the type of AI applied, and the reported outcomes, making direct comparisons between them difficult.

Conclusions

1) Artificial intelligence is emerging as a promising tool in oncologic palliative care. Its applications in clinical prediction, symptom monitoring, clinical decision support, and communication demonstrate encouraging results in terms of accuracy, timeliness, and clinical utility. This systematic review provides solid and up-to-date evidence that supports the progressive implementation of AI, while highlighting the need for prospective validation, ethical integration, and contextual adaptability.
2) It is essential to recognize that palliative care patients require far more than algorithmic precision. From direct clinical experience, it is clear that emotional support, physical presence, an empathetic gaze, or an explanation tailored to the patient's sociocultural background provide comfort and trust that even the most advanced AI cannot replicate. The human value of compassionate care remains irreplaceable. In this regard, AI does

not substitute clinical judgment or interpersonal connection — it complements them, offering opportunities for more anticipatory and personalized care, always grounded in human presence and the dignity of the patient.

Article information and declarations

Acknowledgments

The author would like to express deepest gratitude to Dr. Fabián Leal Arenas for his invaluable guidance throughout the author's academic training; to the librarian at the National Cancer Institute of Colombia for her support in the search and organization of scientific database information; and to the epidemiologist who provided methodological guidance and assistance with statistical analysis. The author also extends heartfelt thanks to the patients, whose experiences have given meaning and purpose to this work, and the author's family, for their unwavering understanding, patience, and support throughout this academic and personal journey.

Ethics statement

This study is a systematic review based solely on previously published data and did not involve primary data collection or direct participation of human subjects; therefore, ethical approval was not required.

Author contributions

The author declares having conceived the study design, conducted the literature review, collected and analyzed the data, drafted the manuscript, and completed the final revision.

Conflict of interest

The authors declare no conflicts of interest regarding this publication.

Funding

The authors declare that they received no external or institutional funding of any kind.

Supplementary material

None.

References

1. OPS. Planificación e implantación de servicios de cuidados paliativos: Guía para directores de programa [Internet]. Organización Panamericana de la Salud; 2020. Planificación e implantación de servicios de cuidados paliativos: Guía para directores de programa (26.09.2024).
2. WHO. Assessing the development of palliative care worldwide: a set of actionable indicators;
   2021. https://iris.who.int/bitstream/handle/10665/345532/9789240033351-eng.pdf?sequence=1 (26.09.2024).
3. Sánchez-Cárdenas M, León M, Rodriguez-Campos L. Estado actual de los cuidados paliativos en Colombia. Observatorio Colombiano de Cuidados Paliativos, Bogotá 2022: Feb.
4. Kawashima A, Furukawa T, Imaizumi T, et al. Predictive models for palliative care needs of advanced cancer patients receiving chemotherapy. J Pain Symptom Manage. 2024; 67(4): 306–316.e6, doi: 10.1016/j.jpainsymman.2024.01.009, indexed in Pubmed: 38218414.
5. Reddy V, Nafees A, Raman S. Recent advances in artificial intelligence applications for supportive and palliative care in cancer patients. Curr Opin Support Palliat Care. 2023; 17(2): 125–134, doi: 10.1097/SPC.0000000000000645, indexed in Pubmed: 37039590.
6. Warraich HJ, Wolf SP, Mentz RJ, et al. Characteristics and trends among patients with cardiovascular disease referred to palliative care. JAMA Netw Open. 2019; 2(5): e192375–e192379, doi: 10.1001/jamanetworkopen.2019.2375, indexed in Pubmed: 31050773.
7. Sorenson HM. Palliative care for lung disease: start early, stay late. Lancet Respir Med. 2013; 1(4): 279–280, doi: 10.1016/S2213-2600(13)70083-3, indexed in Pubmed: 24429141.
8. Hui D, Bruera E. Integrating palliative care into the trajectory of cancer care. Nat Rev Clin Oncol. 2016; 13(3): 159–171, doi: 10.1038/nrclinonc.2015.201, indexed in Pubmed: 26598947.
9. Lanzagorta-Ortega D, Carrillo-Pérez D, Carrillo-Esper R. Artificial intelligence in medicine: present and future. Gaceta Médica de México. 2023; 158(91), doi: 10.24875/gmm.m22000688.
10. van Bussel MJP, Odekerken-Schröder GJ, Ou C, et al. Analyzing the determinants to accept a virtual assistant and use cases among cancer patients: a mixed methods study.

BMC Health Serv Res. 2022; 22(1): 890, doi: 10.1186/s12913-022-08189-7, indexed in Pubmed: 35804356.

11. Vu E, Steinmann N, Schröder C, et al. Applications of machine learning in palliative care: a systematic review. Cancers (Basel). 2023; 15(5), doi: 10.3390/cancers15051596, indexed in Pubmed: 36900387.
12. Kim MJi, Admane S, Chang YK, et al. Chatbot performance in defining and differentiating palliative care, supportive care, hospice care. J Pain Symptom Manage. 2024; 67(5): e381–e391, doi: 10.1016/j.jpainsymman.2024.01.008, indexed in Pubmed: 38219964.
13. Garani-Papadatos T, Natsiavas P, Meyerheim M, et al. Ethical principles in digital palliative care for children: the mypal project and experiences made in designing a trustworthy approach. Front Digit Health. 2022; 4: 730430, doi: 10.3389/fdgth.2022.730430, indexed in Pubmed: 35373180.
14. Sandham MH, Hedgecock EA, Siegert RJ, et al. Intelligent palliative care based on patient-reported outcome measures. J Pain Symptom Manage. 2022; 63(5): 747–757, doi: 10.1016/j.jpainsymman.2021.11.008, indexed in Pubmed: 35026384.
15. Braun EM, Juhasz-Böss I, Solomayer EF, et al. Will I soon be out of my job? Quality and guideline conformity of ChatGPT therapy suggestions to patient inquiries with gynecologic symptoms in a palliative setting. Arch Gynecol Obstet. 2024; 309(4): 1543–1549, doi: 10.1007/s00404-023-07272-6, indexed in Pubmed: 37975899.
16. Zhuang Q, Zhang AY, Cong RS, et al. Towards proactive palliative care in oncology: developing an explainable EHR-based machine learning model for mortality risk prediction. BMC Palliat Care. 2024; 23(1): 124, doi: 10.1186/s12904-024-01457-9, indexed in Pubmed: 38769564.
17. Wilson PM, Ramar P, Philpot LM, et al. Effect of an artificial intelligence decision support tool on palliative care referral in hospitalized patients: a randomized clinical trial. J Pain Symptom Manage. 2023; 66(1): 24–32, doi: 10.1016/j.jpainsymman.2023.02.317, indexed in Pubmed: 36842541.
18. Ben Shetrit S, Daghash J, Sperling D. The use of artificial intelligence-based technologies in palliative care: advancing patient well-being at the end-of-life and enhancing the implementation of the dying patient act. Isr Med Assoc J. 2024; 26(2): 126–129, indexed in Pubmed: 38420987.
19. Limsomwong P, Ingviya T, Fumaneeshoat O. Identifying cancer patients who received palliative care using the SPICT-LIS in medical records: a rule-based algorithm and text-mining technique. BMC Palliat Care. 2024; 23(1): 83, doi: 10.1186/s12904-024-01419-1, indexed in Pubmed: 38556869.
20. DiMartino L, Miano T, Wessell K, et al. Identification of uncontrolled symptoms in cancer patients using natural language processing. J Pain Symptom Manage. 2022; 63(4): 610–617, doi: 10.1016/j.jpainsymman.2021.10.014, indexed in Pubmed: 34743011.

21. Gajra A, Zettler ME, Miller KA, et al. Impact of augmented intelligence on utilization of palliative care services in a real-world oncology setting. JCO Oncol Pract. 2022; 18(1): e80–e88, doi: 10.1200/OP.21.00179, indexed in Pubmed: 34506215.

22. Kim YuJ, Lee H, Woo HoG, et al. Machine learning-based model to predict delirium in patients with advanced cancer treated with palliative care: a multicenter, patient-based registry cohort. Sci Rep. 2024; 14(1): 11503, doi: 10.1038/s41598-024-61627-w, indexed in Pubmed: 38769382.

23. Sarmet M, Kabani A, Coelho L, et al. The use of natural language processing in palliative care research: a scoping review. Palliat Med. 2023; 37(2): 275–290, doi: 10.1177/02692163221141969, indexed in Pubmed: 36495082.

24. Mallick MK, Biser S, Haridas A, et al. Improving dyspnoea symptom control of patients in palliative care using a smart patch — a proof of concept study. Front Digit Health. 2021; 29(3): 765867, doi: 10.3389/fdgth.2021.765867, indexed in Pubmed: 34913047.

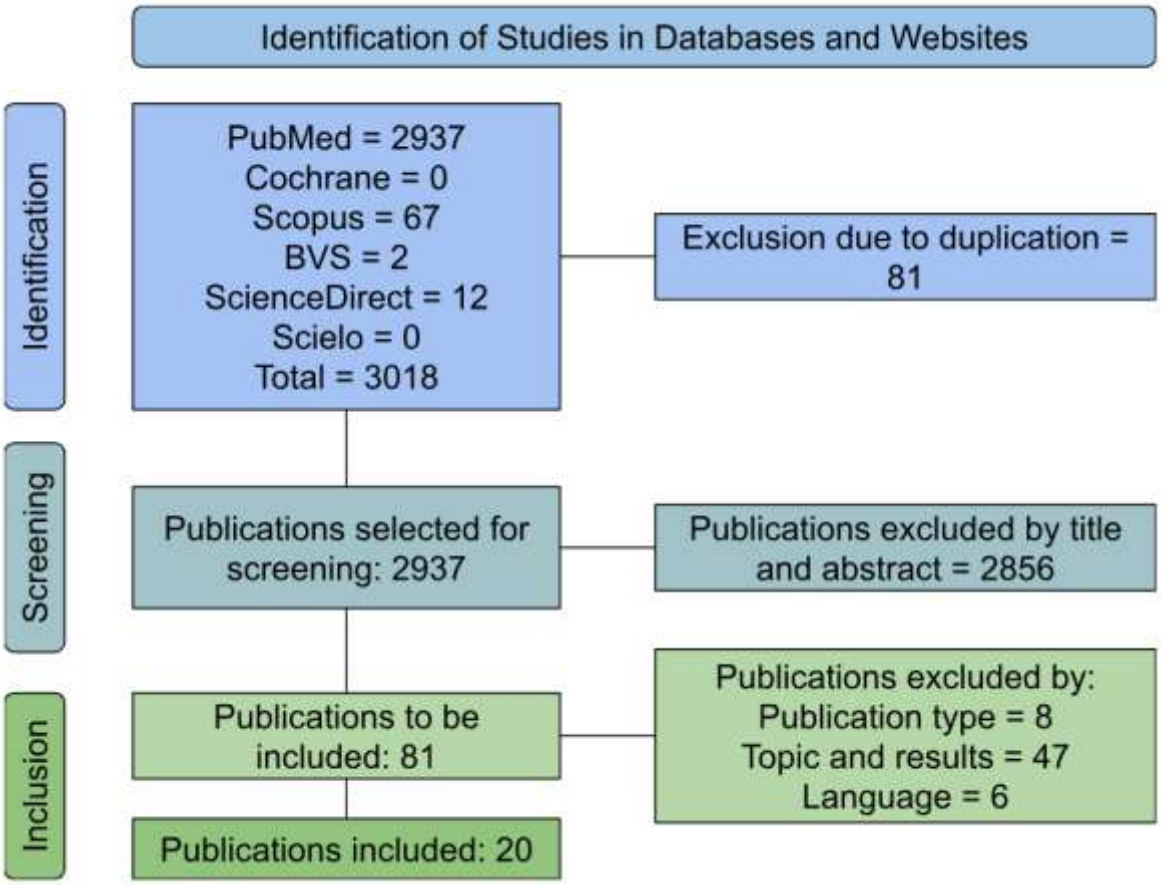
25. Shimada K, Tsuneto S. Novel method for predicting nonvisible symptoms using machine learning in cancer palliative care. Sci Rep. 2023; 13(1): 12088, doi: 10.1038/s41598-023-39119-0, indexed in Pubmed: 37495739.

26. Kawashima A, Furukawa T, Imaizumi T, et al. Predictive models for palliative care needs of advanced cancer patients receiving chemotherapy. J Pain Symptom Manage. 2024; 67(4): 306–316.e6, doi: 10.1016/j.jpainsymman.2024.01.009, indexed in Pubmed: 38218414.

27. Soltani M, Farahmand M, Pourghaderi AR. Machine learning-based demand forecasting in cancer palliative care home hospitalization. J Biomed Inform. 2022; 130: 104075, doi: 10.1016/j.jbi.2022.104075, indexed in Pubmed: 35490963.

28. Yücel KB, Sutcuoglu O, Yazıcı O, et al. Can artificial intelligence provide accurate and reliable answers to cancer patients' questions about cancer pain? Comparison of chatbots based on ESMO cancer pain guideline. Memo Mag Europ Med Oncol. 2024; 17(4): 302–306, doi: 10.1007/s12254-023-00954-6.

29. Srivastava R, Srivastava S. Can artificial intelligence aid communication? Considering the possibilities of GPT-3 in palliative care. Indian J Palliat Care. 2023; 29(4): 418–425, doi: 10.25259/IJPC_155_2023, indexed in Pubmed: 38058478.


Identification of Studies in Databases and Websites
Identification
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Cochrane = 0
Scopus = 67
BVS = 2
ScienceDirect = 12
Scielo = 0
Total = 3018
Exclusion due to duplication = 81
Screening
Publications selected for screening: 2937
Publications excluded by title and abstract = 2856
Inclusion
Publications to be included: 81
Publications excluded by:
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Topic and results = 47
Language = 6
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