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An overview of the role of artificial intelligence in palliative care: a quasi-systematic review

Abstract

Background: Recently, there has been a dramatic increase in research on the use of artificial intelligence (AI) in medicine, uncovering new areas for its application. However, palliative care continues to make limited use of these tools, despite promising results from various models that could significantly improve the quality of palliative care and optimize health resources. This review aims to summarize the current literature on applying AI techniques, with particular focus on machine learning (ML), in palliative care practice, and to analyze their performance rates and usability.

Methods: Quasi-systematic review; PubMed and Scopus databases were searched utilizing selected MeSH terms.

Results: A total of 17 sources were included in the review. The literature used ML for mortality forecast (n = 8), predicting demands, nonvisible symptoms, and delirium (n = 3), identification of phases in palliative care status (n = 1), communication and information supply (n = 4), clinical decision support system (n = 1). Most analyzed techniques achieved good performance rates, however, communication skills and providing reliable information in the field of palliative care were still insufficient.

Conclusions: Machine learning in palliative care is mainly used to predict mortality, however, other forecasts are gradually being introduced. AI-based models are used as clinical decision support and in the assessment of a patient's palliative care status. Another potentially important future role of AI is in communication and presenting information to patients, provided certain improvements are made to existing models.

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Keywords: artificial intelligence, machine learning, palliative care, palliative medicine

Introduction

Artificial intelligence (AI) refers to the development of computer systems that can perform tasks that would typically require human intelligence; therefore, it mimics cognitive functions such as problem-solving or learning. Machine learning (ML), a subset of AI, focuses on systems that analyze data, adjust the parameters

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of a model to achieve the best approximation, and subsequently extrapolate new information based on those studied insights. ML has been the dominant paradigm in AI, nevertheless, it is worth highlighting that ML is only a subset of the broader category of AI and it encompasses a range of statistical algorithms performing tasks without explicit instructions thanks to the process of extracting knowledge from data [1]. One popular method used for ML is modeling the decision process as artificial neural networks, which are inspired by the way neurons are activated in the brain.

Although the number of studies in medicine utilizing machine learning techniques has surged in recent years, this growth appears uneven across various medical disciplines. Thus far, the research has been primarily concentrated on new methods for image analysis, benefiting fields such as radiology and pathology where images constitute a significant portion of the data [2]. Policymakers and healthcare leaders are allocating resources towards artificial intelligence solutions to enhance operational efficiency, reduce healthcare expenses, and improve patient care; however, underinvestment is being observed, especially in the supporting infrastructure, crucial for the effective deployment of AI [3].

Palliative care has seen minimal impact from ML advancements, despite several scenarios where contemporary models could be beneficial, such as predicting survival rates, assessing responses to and quality of life during palliative treatments, or assisting in image-guided radiotherapy [4, 5]. The limited use of AI in palliative care practice contrasts with the vast potential it holds and with the high acceptance among palliative care patients of digital health technologies based on ML models [6]. This review aimed to explore the literature for studies that explicitly use ML techniques to enhance palliative care practice. The objective was to create a resource for healthcare professionals interested in the implementation of AI in their clinical practice, as well as in research in palliative care, and to highlight noteworthy developments and challenges that future researchers should address.

Methods

A quasi-systematic review was performed, which has some components of a systematic review, namely pre-defined criteria of selection, however, it does not evaluate critically the quality of studies. Selected articles were all original articles and addressed subjects related to applications of AI techniques in palliative care practice. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were not fully applied to the literature, which was acquired from electronic databases: PubMed and Scopus [7].

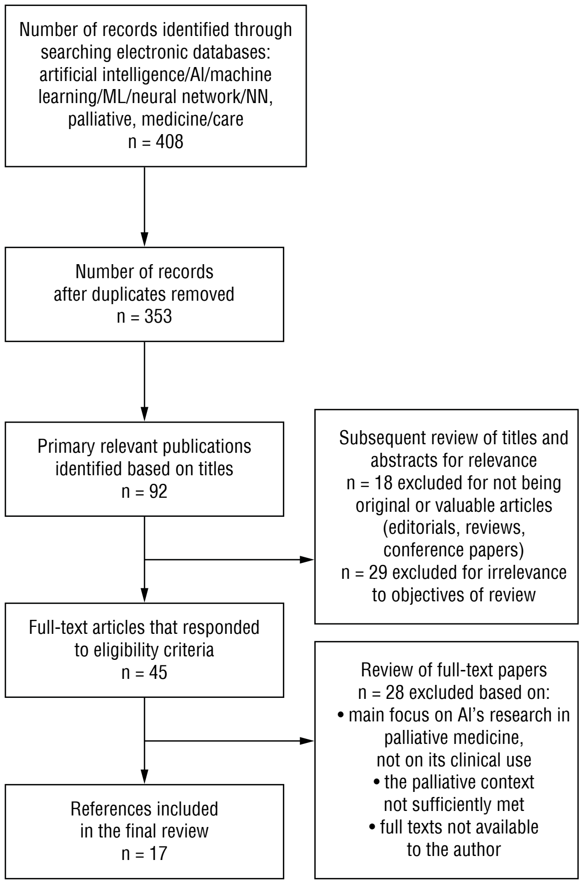

Figure 1. Search strategy

Search strategy and study selection

A search strategy was conducted using the following Medical Subject Headings (MeSH) headings/ /keywords in titles or abstracts: artificial intelligence/ /AI/machine learning/ML/neural network/NN, palliative, care/medicine. The operator 'AND' was used to combine these terms (Figure 1).

The pre-defined selection criteria for the searches limited them to the following: (i) original research articles (ii) with the application of machine learning tools in palliative care practice (iii) written in the English language. After the removal of duplicates, the titles were screened, and subsequently evaluated for their content. Due to the rapid technological development of artificial intelligence in many countries, a date limit was fixed, therefore, only the articles published in the last 10 years, that is, 2014–2024, were considered.

Results

From the quasi-systematic review of literature, seventeen studies published between 2019 and 2024 were thoroughly analyzed (Table 1 [8–24]). Eight publications contained data from patients with

Table 1. Summary of extracted study parameters

Title	Author	Year	Disease	Function
Responsive and minimalist app based on explainable AI to assess palliative care needs during bedside consultations on older patients	Blanes-Selva et al. [8]	2021	Not applicable — older patients	1-year mortality forecast model during hospital admission (a bedside web app)
Complementary frailty and mortality prediction models on older patients as a tool for assessing palliative care needs	Blanes-Selva et al. [9]	2022	Not applicable — older patients	1-year mortality, survival estimation, and 1-year frailty classification forecast model for older patients (≥ 65 years old)
Development and validation of a deep learning algorithm for mortality prediction in selecting patients with dementia for earlier palliative care interventions	Wang et al. [10]	2019	Alzheimer's disease and related dementias	6-month, 1-year, and 2-year mortality forecast model in patients with dementias
Predicting potential palliative care beneficiaries for health plans: a generalized machine learning pipeline	Zhang et al. [11]	2021	12 chronic health conditions	1-year mortality forecast model based on administrative data
Intelligent palliative care based on patient-reported outcome measures	Sandham et al. [12]	2022	Different types	Identification of phases in patient palliative status through symptoms
Diagnostic models for impending death in terminally ill cancer patients: a multicenter cohort study	Mori et al. [13]	2021	Cancer	≤ 3 days mortality forecast model in inpatient hospices
Impact of augmented intelligence on utilization of palliative care services in a real-world oncology setting	Gajra et al. [14]	2022	Cancer	30-day mortality forecast model at a hematology-oncology practice
Evaluating the potential of machine learning and wearable devices in end-of-life care in predicting 7-day death events among patients with terminal cancer: cohort study	Liu et al. [15]	2023	Cancer	7-day mortality forecast model based on continuous monitoring through smartwatches
Towards proactive palliative care in oncology: developing an explainable EHR-based machine learning model for mortality risk prediction	Zhuang et al. [16]	2024	Cancer	365-day mortality forecast model for patients with advanced cancer within an outpatient setting
Machine learning-based demand forecasting in cancer palliative care home hospitalization	Soltani et al. [17]	2022	Cancer	Demand forecast model (predicting the type and time of the next service required)
Novel method for predicting nonvisible symptoms using machine learning in cancer palliative care	Shimada et al. [18]	2023	Cancer	Nonvisible symptoms forecast model based on patient background data and visible symptoms
Machine learning-based model to predict delirium in patients with advanced cancer treated with palliative care: a multicenter, patient-based registry cohort	Kim et al. [19]	2024	Cancer	Delirium forecast model for patients with advanced cancer
Can Artificial Intelligence aid communication? Considering the possibilities of GPT-3 in palliative care	Srivastava et al. [20]	2023	Not applicable	AI-assisted communication in palliative care
Debunking palliative care myths: assessing the performance of artificial intelligence chatbots (ChatGPT *vs.* Google Gemini)	Gondode et al. [21]	2024	Not applicable	Debunking palliative care myths by chatbots: improving patient education and awareness
Assessment of readability, reliability, and quality of ChatGPT®, BARD®, Gemini®, Copilot®, Perplexity® responses on palliative care	Hanci et al. [22]	2024	Not applicable	Providing information on palliative care by artificial intelligence chatbots
AI-generated content in cancer symptom management: a comparative analysis between ChatGPT and NCCN	Lazris et al. [23]	2024	Cancer	Recommendations for cancer-related symptoms by artificial intelligence-driven tools like ChatGPT
User-centered design of a clinical decision support system for palliative care: Insights from healthcare professionals	Blanes-Selva et al. [24]	2023	Not applicable	The Aleph PC CDSS-user-centred validation

AI — artificial intelligence; CDSS — clinical decision support system; EHR — electronic health records; NCCN — National Comprehensive Cancer Network; PC — palliative care cancer, two publications from older patients [8, 9], one publication from patients with dementia [10], one publication from patients with determined 12 health conditions with palliative care [11], one publication from patients enrolled in a palliative care service with various diseases [12]. The remaining four publications focused more on the assessment of AI in palliative care for different purposes, therefore a type of disease was of no significance or not mentioned. The most repeated function of ML-based tools was mortality prediction (n = 8). Other predictions regarded: demands for services in cancer palliative care homes (n = 1), nonvisible symptoms (n = 1), and delirium (n = 1). Four papers analyzed AI-based communication or its informative function for patients (n = 4). One paper focused on the identification of the current palliative care status of patients (n = 1), while another publication assessed the clinical decision support system (CDSS) in palliative care from the perspective of healthcare professionals (n = 1).

Machine learning

Within machine learning, a subset of AI, there are two main approaches: supervised and unsupervised learning, primarily differing in the type of training data used. Supervised learning employs examples containing both the input and the expected output, whereas unsupervised learning operates only on the input data. Articles used various supervised and unsupervised models with heterogeneous outcome metrics, including the area under the receiver operating characteristic curve, accuracy, sensitivity, and specificity.

Receiver operating characteristic (ROC) is a graphical representation used in statistics and machine learning to evaluate the classification performance of a system. In a model with continuous output values, the classes are differentiated according to a chosen threshold. The ROC curve plots the true positive rate (sensitivity) against the false positive rate (1 — specificity) across threshold settings. The area under the ROC curve (AUC ROC) is a measure of the model's ability to distinguish between classes, with a higher AUC indicating better performance. AUC ROC value of 1 indicates a perfect classifier, 0.5 is equivalent to a random guess. Any values below 0.5 have a worse predictive value than a random guess, which makes them inviable. AUC ROC is regarded as a reliable indicator of the intrinsic validity of a diagnostic test, and therefore widespread in medical research [25, 26]. F1 score is another metric used by the authors to assess the models. It is defined as the harmonic mean of true positive rate and precision.

Application: machine learning for mortality prediction

Blanes-Selva et al. [8] developed a responsive and minimalist web application with a 1-year mortality model based on the dataset from electronic health records (EHRs). The predictive model obtained an area under the receiver operating characteristic curve of 0.83 [95% confidence interval (CI): 0.82–0.84]. The same dataset was used for another publication where Blanes-Selva et al. [9] created predictive models based on gradient boosting machines (GBM) and deep neural networks (DNN) for binary 1-year mortality, survival estimation, and 1-year frailty. The 1-year mortality classifier achieved an area under the curve receiver operating characteristic of 0.87 (95% CI: 0.86–0.87), whereas, the 1-year frailty classifier obtained an AUC ROC of 0.89 (95% CI: 0.88–0.90).

Wang et al. [10] created a 2-year, 1-year, and 6-month mortality neural network-based forecast model in patients with Alzheimer's disease and related dementias. Along with standard demographic criteria, natural language processing (NLP) was used for the extraction of information from medical notes for better predictions. The model achieved an area under the receiver operating characteristic curve of 0.943 (95% CI: 0.942–0.944), 0.956 (95% CI: 0.955–0.956), and 0.978 (95% CI: 0.977–0.978) for 2-year, 1-year, and 6-month mortality, respectively.

Zhang et al. [11] prepared a general machine learning pipeline (GMLP) for the identification of patients with high 1-year mortality prediction in a population with some chronic conditions. Data for the prediction was obtained not from electronic health records (EHRs), but from administrative records: ICD codes, utilization cost, and demographic parameters. The algorithm AdaBoost had the best performance rate, with an area under the receiver operating characteristic curve of 0.73.

Mori et al. [13] created diagnostic models for $\leq$ 3 days mortality for patients of hospices: one with a decision tree and one with a system-based score. The first approach involved a recursive partitioning analysis and 10-fold cross-validation, while the second one was based on the categorization of bedside signs and developing a scoring system. The diagnostic accuracy was respectively: 68.3% and 65.5% with a high specificity of over 90% when using proper cutoff points.

Gajra et al. [14] assessed the impact of a commercially available AI tool to predict 30-day mortality, The Jvion CORE, on palliative care service. Data used by the CORE includes elements from the electronic health record (EHR) and professional billing information, which allows for generating an n-dimensional space with patients mapped along vectors, creating relevant clusters of similar patients. The integration of this AI tool into the workflow of a large oncology practice resulted in significant increases in both palliative care consults and hospice referrals: from 17.3 to 29.1 per 1,000 patients per month (PPM) and from 0.2 to 1.6 per 1,000 PPM, respectively.

Liu et al. [15] investigated the potential of the application of smartwatches collecting physiological data and ML-based classifiers for a 7-day mortality prediction. The best performance was by the model of extreme gradient boost (XGBoost) with an area under the receiver operating characteristic curve of 0.96, F1 score of 78.5%, accuracy of 93%, and specificity of 97% on the testing set.

Zhuang et al. [16] developed an explainable ML-based model predicting a 365-day mortality risk among patients with advanced cancer. Data was collected from electronic health records (EHRs). The model achieved an area under the receiver operating characteristic curve of 0.861 (95% CI: 0.856–0.867).

Application: machine learning for identification of palliative status phases

Six ML techniques presented moderately successful results in being able to correctly predict patients falling within phases of their palliative care status, with an average area under the receiver operating characteristic curve of 0.639, 0.60, 0.627, and 0.724 for the four stages of stable, unstable, deteriorating and terminal, respectively, according to Sandham et al. [12].

Application: machine learning for demands, invisible symptoms, and delirium prediction

Soltani et al. [17] created a novel management information system with predictive models for demand forecasting in the palliative care setting. Deep learning models were effective at both individual and population levels: the individual-based had an average accuracy of 69.75% and an F1 score of 66.8% in predicting the types of services needed.

Good results were also achieved in predicting nonvisible symptoms in cancer palliative care by decision tree analysis-based model, which was proven by Shimada et al., with the highest values for prediction accuracy, sensitivity, and specificity: 88%, 84.9%, and 96.7%, respectively [18]. Delirium was also successfully predicted in patients with advanced cancer by the combination of extreme gradient boosting and random forest obtaining the accuracy metrics: 68.83% sensitivity, 70.85% specificity, 69.84% balanced accuracy, and 74.55% area under the receiver operating characteristic curve [19].

Application: machine learning as a communicative and informative tool

Four studies focused on the application of AI not in prediction models, but as a tool for obtaining valuable information by patients or as a communication aid in palliative care settings. Srivastava et al. [20] pointed out that the GPT-3 large language model cannot at this moment substitute for a human being in conversations with patients, although it seems to be very promising in the future as a training tool or therapeutic intervention. Gondode et al. [21] showed that ChatGPT and Google Gemini chatbots demonstrate high accuracy in debunking palliative myths. Therefore, they might raise awareness and education levels among patients in palliative care. Oppositely, Hanci et al. [22] evaluated five AI-based chatbots that were answering questions about palliative care, finding a mediocre level of readability and a low score of text content quality, both still not sufficient, especially for patients with low health literacy skills. Lazris et al. [23] analyzed ChatGPT responses regarding cancer symptom management in comparison to guidelines from the National Comprehensive Cancer Network (NCCN), showing that the AI tool provides more readable recommendations but without the proper specificity and evidence-based information.

Application: machine learning in clinical decision support system (CDSS)

Blanes-Selva et al. [24] designed and validated the Aleph palliative care (PC) clinical decision support system (CDSS) through a user-centered method, achieving a good user experience score and modest but acceptable performance regarding usability.

Discussion

The most frequent use case of ML found in palliative care is mortality prediction. The sources of data for models differed, ranging from electronic health records to administrative claims, which makes them difficult to compare to each other. However, the idea of a practical tool helping recognize the need to either refer patients to palliative services (consults or admission to hospices) or to prepare patients and their families for an impending death, seems to be valuable. Automated techniques based on AI achieve a good performance rate, becoming an attractive alternative to standard prognostic scores demanding time-consuming face-to-face consultations [27]. Moreover, it is worth emphasizing that developers provide convenient forms of these tools, for instance as a minimalist web application for bedside use, and data is always collected in a way that is non-intrusive for patients, from their electronic records or through smartwatches.

Nevertheless, it is important to distinguish between mortality prediction and the need for palliative care due to clinical deterioration. There is evidence that early referral to palliative care is beneficial [28] and therefore Gajra et al. [14] found their results of significant increases in both palliative care consults and hospice referrals satisfactory. However, a relatively subjective threshold achieved by AI models does not always aim to forecast the timing of clinical decline, which is typically the more pertinent factor in deciding when palliative care is necessary. Sandham et al. [12] focused more on ML-driven identification of patient phases (stable, unstable, deteriorating, terminal) thanks to palliative-specific data instead of general electronic health records, which seems to have the potential to enhance the clinical decision process, possibly better than sole mortality rates.

Soltani et al. [17] attempted to predict the type and timing of demands of patients in palliative home care, obtaining good performance rates both individually and on the population level, which is a great example of resource optimization in a palliative care environment. Similarly, when delirium or different nonvisible symptoms of patients with advanced disease can be successfully forecast by ML-based models, physician workload becomes reduced due to better resource planning. Since delirium or nonvisible symptoms are often inadequately identified and managed, modern technological tools could evolve into medical aids, significantly improving patients' quality of life [29, 30].

Another promising use of ML in palliative care is its potential to educate and communicate with patients. Conversations about death and the dying process are extremely difficult and daunting for health professionals, which is why the use of AI seems to be a helpful solution [31]. Nevertheless, GPT-3 analyzed by Srivastava et al. [20] was found to have limitations such as unnatural synthetic empathy level, vagueness, redundancy at times, insensitivity to individual beliefs, values, and traditions, and lack of human intuition in nonstandard situations. Still, it is proposed to make use of AI-assisted communication in a simulation setting as part of training for professionals, as well as enhance its scope to make it a therapeutic assistant.

The informative and educative function of currently available AI-based chatbots was assessed yielding diverse results: Gondode et al. [21] proved high accuracy in debunking palliative care myths, while Hanci et al. [22] demonstrated insufficient readability and content quality of AI answers to palliative care questions if patients with low health literacy skills were concerned. A discrepancy between guidelines from the National Comprehensive Cancer Network (NCCN) and answers by ChatGPT to cancer symptoms management questions was observed by Lazris et al. [23], which might indicate the inadequate specificity of the chatbot responses. All these results do not contradict the convenience of using an online tool such as a chatbot for obtaining information and educating patients. However, they highlight the flaws and shortcomings that need to be addressed to use it safely.

Aleph palliative care clinical decision support system was evaluated by Blanes-Selva et al. [24] through a user-centered method, allowing for the understanding of the perspectives of users — healthcare professionals. Due to good user experience quality and favorable performance of predictive models, it is an argument for broader acceptance of such AI-based tools in clinical practice.

Potential constraints at the review include the limitation that only articles featuring "palliative" in their title or abstract were selected by the query. This might have resulted in the exclusion of articles aiming to predict short-term mortality but not using this specific keyword. Nonetheless, it is reasonable to assume that any study aimed at enhancing palliative care practice would likely incorporate this term in either the title or abstract. The same holds for publications employing ML models without explicitly mentioning them in the title or abstract.

Conclusions

To sum up, ML in palliative care is predominantly used to forecast mortality. However, recent literature suggests its promise in novel applications like predicting demands and various symptoms of patients with advanced disease. Moreover, AI has found application as a source of information in the field of palliative care for patients, enhancing their level of awareness and knowledge, although the quality of generated data should be thoroughly evaluated and frequently improved. The role of AI in communication with people should continue to be developed further, since at the moment its empathy level leaves much to be desired. Available ML-based tools are being validated for their use in clinical practice, achieving satisfactory results, nonetheless, there is still room for developing models to improve their usability and user experience. Meanwhile, the added value of ML and particularly its capability to generalize across data from various institutions continues to be challenging to evaluate.

Article information and declarations

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Author contributions
Jaśmina Bork-Zalewska is the sole author and is responsible for the whole review.

Conflict of interest
The author declares that she has no conflicts of interest relevant to the content of this manuscript.

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