Title: Generative AI and Palliative Care

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Abstract

Context: AI advances are impacting healthcare and the possible impact of Generative AI on palliative care deserves special attention.

Objectives: The objective is to establish the literature trends in generative AI for palliative care and identify key opportunities.

Methods: A systematic and narrative literature review of PubMed entries from September 2023 till September 2024 establishes existing work and focuses on trends in generative AI for palliative care.

Results: The bulk of AI work in palliative care focuses on traditional tools for pattern analysis and attempts to better forecast mortality or characterize pain. Generative AI work tends to use ChatGPT-like systems to either answer predefined patient queries or summarize medical records. Work in other disciplines, such as radiation oncology, reveals the value of large-scale integration of Generative AI into the workflow.

Conclusion: A key opportunity for palliative care is to develop a hospice enterprise system that uses models of roles and functions to drive communication with patients and professionals intermediated by Generative AI.

Key Message: The literature on AI in palliative care indicates little opportunities for Generative AI, and a proposal for an intelligent hospice system highlights those opportunities.

Keywords: Artificial Intelligence, Large Language Models, Palliative Care, Narrative Literature Review, Hospice Care, PubMed

Running Title: Generative AI and Palliative Care

1 Introduction

A systematic literature review on PubMed will guide an iterative, concept-driven analysis of the field on Generative AI and palliative care. Hypotheses explored include that Generative AI opens new opportunities for engaging patients in palliative care and that the key to success of these applications is fitting them into the workflow.[1]

Part of this paper complies with the methodology "Enhancing transparency in reporting the synthesis of qualitative research (ENTREQ)".[2] Queries of Medical Subject Headings (MeSH) concepts will exploit the retrieval properties of PubMed.[3] The recent explosion of interest in AI in healthcare can be traced to ChatGPT's appearance in 2022,[4] and this paper focuses on the publications entered into PubMed between 2023/09/09 and 2024/09/09.

Since MeSH did not specifically represent the concept 'Generative AI', the search was broadened to its parent concept 'AI'. The European Commission's AI Act was the first to comprehensively regulate AI at a supranational level [5] and defines AI as:[6] "'... a machine-based system ... to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment, and that ... infers, from the input it receives, how to generate ... predictions, content, ... or decisions ....". Society has entered the 3rd epoch of AI where:[7] "AI 1.0 includes symbolic AI ... AI 3.0 is the era of ... generative AI". Text-based generative AI is the focus of this paper and uses hundreds of billions of digital neurons that were trained on the world's documents to manifests artificial general intelligence. Generative AI may be abbreviated as GenAI or referred to as Large Language Models (LLMs). GenAI uses machine learning which is the AI technology most discussed in the healthcare literature.[8]

Palliative care maximizes quality of life through alleviation of suffering and promotion of adaptive coping for those facing serious illnesses.[9] The timing of palliative care consultation varies based on an individual's evolving needs,[10] and only treatments consistent with patient preferences have positive outcomes.[11] Palliative nursing care addresses family dynamics, quality of life, psychological, physical, and cognitive comfort, safety, and physiological function.[12] Hospice care is a subset of palliative care. A Medicare patient qualifies for hospice care when her doctors certify that her life expectancy is no more than 6 months and she accepts comfort over curative care.[13]

2 Method

The US National Library of Medicine indexes PubMed articles with concepts from MeSH. Since 2023, indexing has been fully automatic with manual quality control.[14] MeSH includes hundreds of thousands of concepts connected in a hierarchy.[15] PubMed by default expands a query to include all the descendants of any query MeSH concept.

The part of the query for the palliative care literature was based on previously published literature reviews on palliative care[16] and on iterative fine-tuning based on following the citation trail and augmenting the query to cover missed, relevant articles. The query was designed for recall rather than precision. The query OR'ed together 21 MeSH concepts, 14 text keywords, and 23 journal titles, as detailed in Supplement "Query". The artificial intelligence query was guided by [8] but augmented iteratively to contain 5 MeSH concepts, 27 text words, and 7 journal titles (see "Supplement Query"). The preceding query components were each filtered by ANDing them with this query: (2023/09/09:2024/09/09[Date - Create] AND "hasabstract"[All Fields] AND "English"[Language]).

The retrieved citations constitute the Large Set and will be described numerically through the lens of the software tool "Anne O'Tate" abbreviated as "Tate". Tate is a free, public, web-based tool to support mining of search results from PubMed.[17] Additionally, the Large Set was placed through a text filter (see "Supplement Query") that focuses on GenAI to result in the Small Set. This Small Set was subsequently manually refined.

The Small Set will be narratively described after the numerical description of the Large and Small Sets. The narrative description is categorized into four parts addressing GenAI relationship to 1) Patients, 2) Professionals, 3) Systems, and 4) Ethics.

3 Results

3.1 Frequency Results

The Large Set contains 1,790 citations, and the Small Set, 100 citations. The number of citations retrieved per query component is summarized in Table 1: "Query Retrieval Counts".

Tate identified pairs of MeSH concepts that co-occur in individual articles of the Large Set and were relatively unique to the Large Set versus PubMed as a whole. The three most prominent MeSH pairs and a prototypical article characterized by that pair are:

- "Cost-Benefit Analysis" and "Quality-Adjusted Life Years".[18]
- "Analgesics, Opioid" and "Pain, Postoperative".[19]
- "Arthroplasty, Replacement, Knee" and "Osteoarthritis, Knee". [20, 21]

In each article the emphasis was on the relationship between the pair, such as opioid treatment of postoperative pain, and AI was only incidentally used, usually in data analysis. These three paired MeSH concepts are representative of the patterns in the Large Set.

Tate identified exactly one important MeSH pair in the Small Set, namely "Artificial Intelligence" and "Reproducibility of Results". Some of those articles examined how multiple LLMs responded to patient palliative care questions,[22, 23] and some, helping doctors via LLMs in treating specific problems, such as radicular pain [24] or bleeding risks.[25]

Tate identifies "Important Words" as those significantly over-represented in the retrieval set compared to all articles in PubMed and ranks them in order of the degree to which the word is over-represented. "Important Words" in the Small Set include SHAP and Roberta. SHAP explains the predictions of nonlinear models, such as factors predicting mortality risk.[26] Roberta refers to the LLM called "Robustly optimized BERT (RoBERTa)", and in a typical article was used to classify clinic notes.[27]

The journal frequency data from Tate show differences between the Large and Small Sets (see Table 2 "Journal Frequency"). The Large Set drew more heavily from voluminous publications, such as *Scientific Reports*. The Small Set drew more heavily from the relevant specialist journals *J Pain Symptom Manage* and *J Med Internet Res*.

Tate indicates the distribution of articles by country. The most salient difference between the Large Set and the Small Set is that China is second in the Large Set but does not appear in the top twenty of the Small Set. The GenAI cited in PubMed are trained largely on English-language documents.

3.2 GenAI supports Patients

A narrative, thematic analysis of articles in the Small Set reveals one grouping that focuses on generative AI interacting with patients and tends to show positive results but include ethical warnings. Examples of help offered follow. GPT-3 was presented patient prompts about palliative care, and GPT-3 responses were judged similar to human responses.[28] ChatGPT provided guideline-compliant therapy recommendations in response to queries from a library of palliative-care patient queries.[29] Parents were helped when GPT-4 advised them about pediatric emergencies.[30] GenAI can translate for underserved populations[31] or answer based on demographic characteristics of the patients.[32] Patients accepted chatbots for self-managing chronic illnesses,[33] and conversational agents support physical, mental, and social outcomes.[34]

Two papers emphasized weaknesses of ChatGPT responses to patients. In one, patients of different races and insurance status received biased responses.[32] In another, ChatGPT did not accurately answer diagnosis and treatment questions about cancer survivorship.[35]

Responses from GenAI depend on the prompt given [36] and whether fine-tuning or retrieval-augmented-generation were used. The following three papers evaluated GenAI systems and deemed the systems to have significant failings but did not address prompt engineering, fine tuning, or retrieval augmented generation. In three articles, questions about palliative care were posed to various LLMs, and responses either had the wrong readability level or deviated too far from expert answers.[22, 23, 37] The literature has well established that GenAI makes mistakes, hallucinates, and manifests bias.

3.3 GenAI supports Professionals

GenAI can support diagnosis by finding patterns that professionals have difficulty finding. It has

- facilitated diagnosis by detecting subtle differences in pain expression,[38]
- evaluated bleeding risk,[25] and
- translated billing administrative data into a narrative that facilitates palliative care clinical decision-making.[39]

GenAI can also support managing palliative care problems and can

- infer wishes of mentally incapacitated patients based on prior records,[40]
- anticipate cancer treatment side-effects,[41]
- predict recovery in cancer survivors,[42] or
- provides insights into the patient's emotional state.[43]

GenAI may also fail, as in one study on managing labor analgesia,[44] and in all cases GenAI may require fine-tuning and retrieval augmented generation.[45]

GenAI has been used to help write literature reviews. A series of literature reviews about osteoporosis in one journal were partially written by LLMs. One article said, "This review article is part of a series of multiple manuscripts designed to determine the utility of using artificial intelligence for writing scientific reviews",[46] and the other three papers had similar statements.[47-49]

3.4 GenAI supports Systems

A clinical information system relies on roles defined as functions with rules for passing messages among roles, but the challenge is the brittleness of the controlled vocabulary which can be side-stepped by relying on GenAI.[50] Historically an AI application focuses on one-tool-for-one-problem,[51] but GenAI supports a one-tool-many-problem approach.[52]

In a multi-agent system, each agent uses GenAI as a resource.[53] In a patient mental health system, one agent is a patient, and another agent is a counselor.[54, 55] GenAI is well suited to personalizing patient scheduling, improving clinical documentation, facilitating insurance prior authorization, increasing patient engagement, and decreasing barriers to access to healthcare.[56]

3.5 GenAI and Ethics

The AI techniques in the Large Set were largely well-established in the biostatistician's toolkit and might be called statistical techniques. In those papers the focus is typically an intervention independent of AI. For the Small Set the papers are often about GenAI and are far more tentative in their conclusions than in the Large Set. The cautions in the GenAI papers reflect those voiced in the burgeoning biomedical literature about ethical guidelines for GenAI.

The US National Academy of Medicine AI code of conduct says that AI should be engaged, safe, effective, equitable, efficient, accessible, transparent, accountable, secure, and adaptive.[57] A discourse analysis [58] of guidelines for healthcare AI concluded that the guidelines thematically say that AI is desirable and unavoidable, principles are the solution to guiding AI, and trust is key. The National Academy of Medicine has said [59], "There should be full transparency on the … quality of data used to develop AI tools. .. However, algorithmic transparency may not be required for all cases." How GenAI ethical concerns for palliative care might be unique remains to be explored.

4 Discussion

4.1 Limitations

Methodological limitations in this work include its focus on PubMed. Other document libraries, such as ACM Digital Library, CINAHL, Embase, IEEE Xplore, PsycINFO, Scopus, and Web of Science, could provide other relevant articles. Further tools to semi-automatically analyze patterns in retrieved document sets, such as CiteSpace, could offer other insights. Recruiting experts to interpret articles and to agree on their significance could increase confidence in the conclusions.

Benchmarks that measure GenAI's ability to answer standardized questions are less useful than those which address dynamics.[60] Developing dynamic palliative care clinical evaluations for GenAI remains a challenge.

4.2 Spectrum

Some cited papers described prompts to a publicly available LLM, while others present refinements to an LLM and embed it within a clinical information system. The interpretations of the results vary where at:

- one end, results are positive and have great potential but
- the other end, results are negative and regulation must constrain further work.

In some fields, such as radiation oncology, the enthusiasm about multi-agent generative AI is unbridled, as some radiation oncologists say that the required combination of information available with image, omic, and health record data is orders of magnitude beyond the cognitive capacity of a human.[58] Whether palliative care can show such GenAI magnification of ability remains to be shown.

The history of computer applications diffusing in healthcare shows that the first successes occur with numeric areas, such as billing, and the second successes in areas not highly dependent on patient-doctor interaction, such as pathology and radiology. Since GenAI is qualitatively different from the previous applications, does palliative care have a special opportunity?

4.3 Proposal

To recap, the review of the literature on Palliative Care and GenAI has shown trends, such as improving the forecasting of mortality or the monitoring of pain. However, each of these applications is stand-alone and unlikely to diffuse until incorporated in a clinical information system.[61] A palliative care specialist consulting in a cancer center uses the cancer information system. A special opportunity exists in hospice care.

In a GenAI-supported hospice information system the roles of the interdisciplinary team and the roles of patient and their family are represented. Patients could choose to assume their online role and interact with other roles. The implementation of the patient's role includes a soul that algorithmically-speaking is a scorecard which indicates the patient's objectives and the progress towards them. As an example of a function of a professional, an automated social worker could interact with patients to help them develop their dignity document.[41]

Historically a typical AI application focuses on one medical problem, such as coding medical problem statements[51] or diagnosing bacteremia. This one-tool-for-one-problem approach stymies integration. The flexibility of GenAI to reason across modalities and to be driven via prompt engineering to incorporate new information supports a one-tool-many-problem approach[52] and suits hospice care.[62, 63] However, getting support from the relevant stakeholders, including a hospice system, professionals, patients, payers, and regulators would be difficult. GenAI revolutionized AI by showed that a computer can sensibly communicate with anyone about anything, and the challenge is to exploit this capability to help hospice patients.

5 Disclosures

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