Review Article

Integrating Artificial Intelligence in Multidisciplinary Tumor Boards: A Scoping Review of its Impact and Potential

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Abstract: Multidisciplinary Tumor Boards (MDTs) are meetings where experts get together to decide what the best treatment for cancer patients is. But we could make even better treatment decisions by adding Artificial Intelligence (AI) to these teams. In this review, we examine how AI can contribute to selecting the appropriate treatments for MDTs. While there is still some work to be done, AI has certainly already shown that it can help us better diagnose and treat cancer. It reviewed 22 studies from 2016 to 2024 that looked at how often AI's suggestions matched with what MDTs decided. In most cases, AI and MDT agreed, and rates of concordance ranged from 48.9 to 99.1 percent, mostly 72 to 87 percent. Concordance rates in the other studies were somewhat lower, but were not that significantly different from ours. In at least one study, agreement varied based on patient age, possible treatment side effects or lack of financial resources. AI, although a few hurdles, is proving to be an invaluable tool for MDTs. Yet in order to make it work in more rapid and more precise fashion, we need to keep working at improving the technology, to get doctors comfortable with how to use it, and to scrub out the same legal and access barriers that we've always had with other forms of commerce that have been somewhat slower to come to medicine.

Keywords: Multidisciplinary Tumor Boards (MDTs), Artificial Intelligence (AI), Cancer treatment, AI-assisted diagnosis, Oncology care, Decision support systems.

INTRODUCTION

In the era of molecular genetics and advanced technology, prompt diagnosis of various cancers has not only become simple enough but has been bountiful when it comes to anticipated cancer progression yet the therapeutic armamentarium is still a major challenge worldwide because of increasingly available therapeutic regimens and patients' preference [1].

The time elapsed since the initiation of cancer or patient presentation to diagnosis and ultimate treatment decision is the most important factor in the prognosis and survival of patients; along with the delivery of proper medical care, for which, a multidisciplinary approach system was initiated, which included experts from different fields of medicine, called Multidisciplinary Tumor Boards (MDTs) [2, 3].

Over the last decade, scientific evidence has shown that MDTs have significantly improved the clinical and survival outcomes of cancer patients by delivering timely-accurate diagnosis [3, 4].

During the time of COVID-19, the transition from face-to-face MDTs to virtual MDTs assisted in broadening the local cancer treatment-decision meetings into worldwide networks with timely discussion. It is a cost-effective means of facilitating easier access to clinical trial opportunities [5]. However, it has also put ample workload on the experts which may exhaust the team or lead to decreased efficiency in the meetings' outcomes.

The creation of Artificial Intelligence (AI) in healthcare has revolutionized almost the complete process of diagnosis, treatment and treatment outcomes by offering pertinent meaningful diagnosis and treatment streamlined regimens [6]. AI has demonstrated valuable results in different treatment regimens including surgery, chemotherapy, radiotherapy, immunotherapy, targeted therapy and nanotechnology [7].

In this review, the authors aimed to evaluate the assistance of AI in Multidisciplinary Tumor Board meetings by examining the concordance rate (level of agreement) between treatment decisions predicted by AI and MDT experts.

METHODOLOGY

This study uses a scoping review approach to see how AI and MDTs work together in cancer treatment. The main goals are to assess AI's role in treatment, compare its recommendations with MDTs recommendations, and gather studies about AI and MDTs in cancer care.

We included original research focused on cancer and tumors that specifically examined AI and MDTs. We excluded review articles, studies with only abstracts, or research not related to cancer, AI, or MDTs.

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Literature Search Strategy

Under the above keywords, Boolean operators, such as “Artificial Intelligence,” “Multidisciplinary Tumor Board,” “cancer treatment,” “tumor management,” we did a detailed search on PubMed. Only articles in English were included, and abstracts were checked to see if they met the criteria for inclusion or exclusion (Fig. **1**).

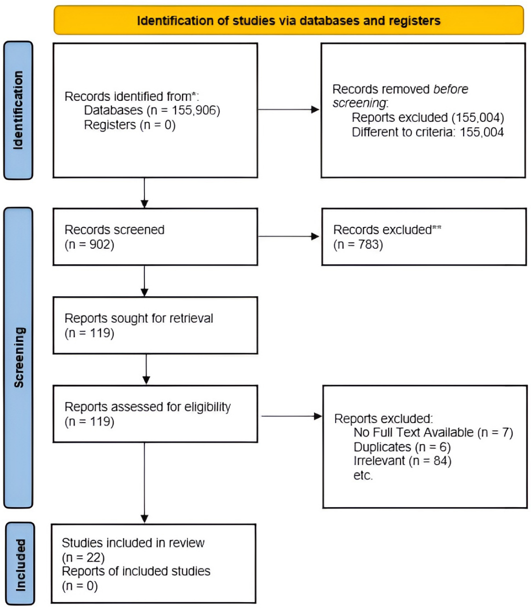

Fig. (1): PRISMA 2020 Flow Diagram for New Systematic Reviews which Included Searches of Databases and Registers.

RESULT

Demographics

A scoping review of 22 studies published in 2016 – 2024, almost all of which were retrospective, was carried out. Six studies covered breast, five gastric, four lung, four colon, three recto, and one esophageal cancer. A majority of the research focused on lung, breast, and colon cancer. The majority of studies geographically were carried out in Germany, Korea and China. The ages of participants ranged from 35 to 89 years of age (mean age of about 60 years; (Figs. **2, 3**).

In Table **1**, each study is summarized and includes the type of study, study objectives, sample size, cancer type’s studied as well as key findings [8-29].

Alignment of AI and MDT Decisions

Some studies compared AI and MDT treatment decisions by grouping them as "recommended," "for consideration," and "not recommended" [12, 19, 23, 26]. In Suwanvecho’s study, decisions were counted as matching if they were "identical" or considered "alternatives" [18]. For instance, other studies used scoring and interviews to understand extent to which AI and MDT decisions matched [20]. With GPT employed, cases were supplied to evaluators as they are supplied in MDTs [8, 9, 11].

Agreement between AI and MDT decisions ranged from 48.9% to 99.1%, with most studies reporting 72% to 87%. However, Stefan Lukac's study showed only 16.05% agreement, possibly because ChatGPT didn’t take neoadjuvant treatments and ongoing studies into account, or interpreted Her2 positivity mathe-

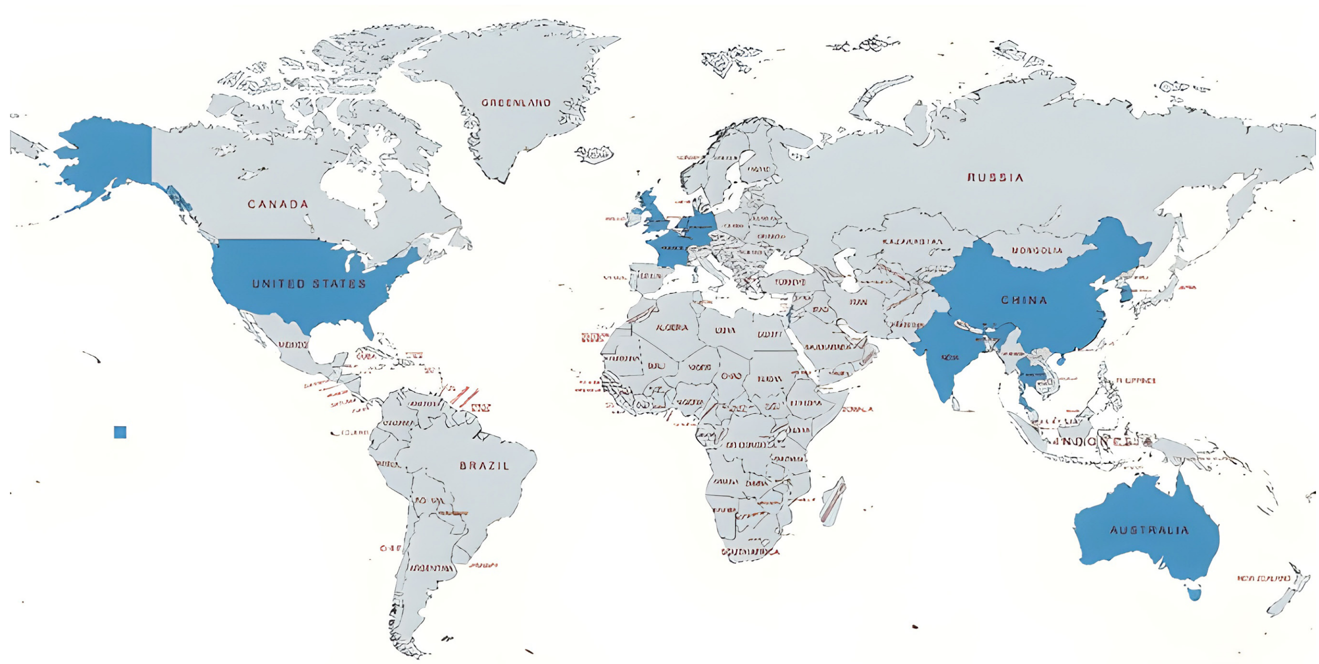

Fig. (2). Map Diagram of the Countries Studies.

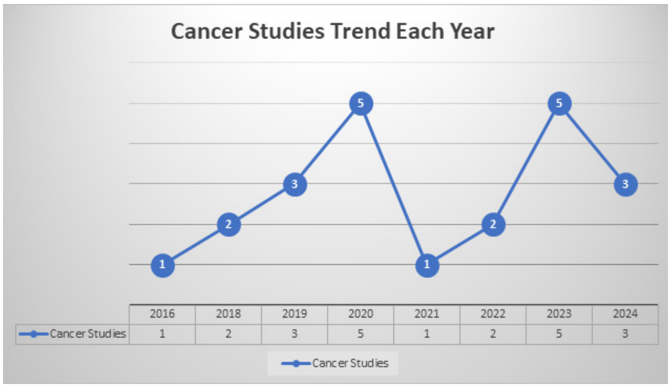

Fig. (3). Cancer Studies Trend Each Year.

matically rather than considering overexpression. ChatGPT did adjust treatment options based on age for older patients, suggesting personalized care [11].

Several studies also examined the influence of factors such as patient's age, type of treatment and their genetic profile on agreement rates. We didn't find any compelling data regarding these factors after reviewing multiple studies, but generally, agreement was lower for older patients. Rates dropped from 63.8% to 20.2% for those over 70, as noted in Won Suk Lee's study [27]. Similar findings are presented by Park Young's and Somashekhar's studies showing that age influences the alignment of AI with MDT [12, 26].

Factors Responsible for Discordance between AI and MDT Decisions

Differences between AI models and MDT decisions were affected by several factors. For instance, older patients (70 years or older) were less likely to receive chemotherapy or intensive treatment. Lower agreement rates were reported for use of biologic agents due to lack of AI system suggestion in such patient populations [27].

Table 1. Key Findings.

Author	Objective	Study Design	Cancer Type	AI Model	Key Findings
Schmidl *et al.* (2024) [8]	To assess ChatGPT 3.5 and 4.0's recommendations for primary head and neck cancer, comparing them to MDT decisions.	Pilot Study (20)	Head and Neck	ChatGPT 3.5 & 4.0	ChatGPT 3.5 surgery recommendation: 90% (18/20). Text summarization: (κ value) ChatGPT 4.0 = 0.612, ChatGPT 3.5 = 0.459 ChatGPT 3.5 suggested more treatment options (avg. 4.85).
Schmidl *et al.* (2024) [9]	To compare Claude 3 and ChatGPT 4.0 as MDT support tools for head and neck cancer treatment.	Retrospective (50)	Primary Head and Neck Cancer	ChatGPT-4 & Claude 3	Claude: 16.3/17 (Reviewer 1), 15.2/17 (Reviewer 2), ChatGPT: 15.1/17, 13.6/17. Treatment summarization score: ChatGPT 4.5/6, Claude 4.37/6.
Daye *et al.* (2024) [10]	To evaluate AI's ability to predict initial MDT treatment recommendations.	Retrospective (140)	Hepatocellular Carcinoma	XGBoost	Model performance: >72% for ablation, chemotherapy, surgery, transplant, palliative.
Lukac *et al.* (2023) [11]	To evaluate ChatGPT's recommendations for early-stage breast cancer compared to MDT decisions.	Pilot Study (10)	Breast Cancer	ChatGPT 3.5 (ChatGPT Feb 13 Version)	Overall Concordance: 16.05% (64.2/400). Anti-hormonal treatment requiring patients: 100% identified.
Park & Chae (2023) [12]	To analyze concordance between AI and MDT treatment recommendations.	Retrospective (322)	Gastric Cancer	WFO	Overall Concordance: 86.96% (280/322).
Ural *et al.* (2023) [13]	To develop a smartphone-based decision support system for first-line urological cancer therapy.	Retrospective (1873)	Prostrate Cancer	Algorithm-driven decision support system	Overall Concordance: 99.1% (1856/1873).

Thavanesan *et al.* (2023) [14]	To develop ML models with the ability to predict curative Esophagus Cancer MDT treatment decisions	Retrospective (399)	Oesophageal Cancer	MLR, RF, XGB, Decision Tree	AUC values: MLR = 0.793, RF = 0.757, XGB = 0.740, DT = 0.709.
Sorin *et al.* (2023) [15]	To assess ChatGPT's recommendations for breast tumor treatment based on summarization.	Retrospective (10)	Breast Cancer	ChatGPT 3.5	70% agreement between AI and Reviewers Scores: Reviewer 1: Summarization: 3.7, Recommendations: 4.3, Explanation: 4.6. Reviewer 2: Summarization: 4.3, Recommendations: 4.0, Explanation: 4.3.
Redjdal *et al.* (2022) [16]	To test ML models for predicting treatment decisions in complex breast cancer cases where CDSS recommendations were not followed.	Retrospective (298)	Breast Cancer	Decision Trees, Random Forests, XGBoost	XGBoost, MLP: F1 score = 83%.
Andrew *et al.* (2022) [17]	To develop ML models predicting MDT recommendations for MMS vs concentional surgery or radiotherapy in nasal BCC.	Retrospective (304)	Basal Cell Carcinoma (BCC) Nasal	Machine Learning Model	Overall Concordance: 45.1%.
Suwanvecho *et al.* (2021) [18]	To analyze concordance between WFO and MDT decisions	Prospective (276)	Breast Cancer Colon Cancer Lung Cancer Rectal Cancer	WFO v18.8	Overall Concordance: 70%.
Zou *et al.* (2020)[19]	To explore consistency between WFO and expert panel treatment recommendations for cervical cancer patients.	Retrospective (246)	Cervical Cancer	WFO v18.1R	Overall Concordance: 72.8%.
Pluyter *et al.* (2020) [20]	To evaluate the impact of CDSS on MDT lung cancer decisions.	Case based (8)	Lung Cancer	CDSS	Median values: (by reviewers) Information relevance, readability, understandability: 4 (min: 4, max: 5). Confidence in decisions: 3 (min: 2.5, max: 4). Improved team performance: 6 better, 2 Neutral.
Tian *et al.* (2020) [21]	To analyze concordance between WFO and MDT in gastric cancer and its prognostic impact.	Retrospective (235)	Gastric Cancer	WFO v18.3	Overall Concordance: 54.5%.
Kim *et al.* (2020) [22]	To analyze concordance between AI and MDT treatment recommendations.	Retrospective (405)	Lung Cancer	WFO	Overall Concordance: 92.4%, higher in metastatic cases.
Kim *et al.* (2019) [23]	To analyze concordance between Watson for Oncology (WFO) and MDT in breast cancer treatment options.	Retrospective (170)	Breast Cancer	WFO	Concordance: Radiotherapy: 99% (143/144). Chemotherapy: 93% (136/147).

Choi *et al.* (2019) [24]	To analyze concordance between WFO and MDT decisions in advanced gastric cancer.	Retrospective (65)	Gastric Cancer	WFO	Recommended treatment: 41.5%. For consideration: 87.7%.
Kim *et al.* (2019) [25]	To analyze concordance between WFO and MDT for chemotherapy options.	Retrospective (69)	Colon Cancer Rectal Cancer	WFO v16.9	Overall concordance: 87%.
Somashekhar *et al.* (2018) [26]	To analyze concordance between AI and MDT treatment recommendations.	Retrospective (638)	Breast Cancer	WFO v16.4	Overall Concordance: 93%.
Lee *et al.* (2018) [27]	To analyze concordance between WFO and MDT in colon cancer.	Retrospective (656)	Colon Cancer	WFO v16.9	Overall Concordance: 48.9%.
Zhou *et al.* (2018) [28]	To analyze concordance between WFO and MDT decisions.	Retrospective (362)	Lung Cancer Breast Cancer Gastric Cancer Colon Cancer Rectal Cancer Cervical Cancer Ovarian Cancer	WFO	Highest concordance: 95.83% (Ovarian). Lowest: 11.9% (Gastric).
Lin *et al.* (2016) [29]	To design an ML model that predicts MDT decisions for adjuvant breast cancer treatments.	Retrospective (1065)	Breast Cancer	Naïve Bayes, SVM (poly & RBF), Multivariate LR, Nearest Neighbors, Ripple Down Rules, J48, AD Trees	Concordance rate with respect to treatment modality: MDT & NCCN/ESMO (endocrine) =85% MDT & NCCN/ESMO (trastuzumab) = 96% MDT & NCCN/ESMO (adjuvant chemo) = 47% and 57% resp

Treatment toxicity, particularly in older patients, financial limitations, treatment availability, case complexity, and specific (driven by financial conditions or intolerance for some therapies) treatment preference were also factors. These differences were also influenced by treatments choices: for example, patients choosing surgery over radiation; variations in national guidelines; insurance coverage; and treatment access [16, 18, 19, 24]. These limitations are revealed by these findings on the effectiveness of AI in fully matching MDT recommendations, particularly in complex or financially challenging cases.

DISCUSSION

Using its advanced algorithms, Deep Learning (DL) and Natural Language Processing (NLP), AI has transformed medicine mostly in the area of oncology. In case AI can't match doctors, AI has a huge role to play in decision making, to search and analyze large datasets, to derive information from clinical trials and to serve them personalized treatment plans with patient treatment profiles. ChatsGPT, XGBoost, and Watson for Oncology are found helping oncologists in their work. ChatGPT can assist in suggesting treatments, forecasting decisions of Multidisciplinary Team (MDT), personalized care and smoothing the Multidisciplinary Team (MDT) workflows [6,9,30], supporting the oncologist in making more informed decisions by virtue of the model as an assistant [31, 32]. A known machine learning (ML) algorithm called XGBoost has shown record in learning from large dataset of clinical specimen classified into many classes; it has also been reported to assist in very complex clinical cases such as in breast and hepatocellular carcinoma [17,21].

For example, the other AI model, Watson for Oncology, has high concordance with MDT's decisions across different types of cancer, and provides expert clinical insights [8,14] through its algorithms. Together, we've seen these AI tools help increase treatment accuracy, personalize medicine, and optimize clinical decisions more accurately. It promises us that we will give our patients faster, evidence based care. In addition to identifying these optimal therapeutic strategies, these models also play a large part in detecting cancer early thus improving the prognosis of the patient [20,21] and improving the performance of the healthcare practitioner [33-35]. Furthermore, It enables quality improvement in radiology via assuring that the reports have a readable, accurate, and useful content for use in oncological care [36, 37].

We observe that the findings we have from all the studies prove the effectiveness of AI in clinical settings, showcasing the concordance between expert opinion from oncologists and AI recommendations that may vary by cancer type and treatment modality. For instance, we found studies have shown a high concordance rate in the treatment of breast cancer in radiation therapy and in the chemotherapy domain [9, 14]. However, it's not always effective and discordance has also been noticed in some specific demographics, particularly in older patients as AI suggests not to give any aggressive treatment to old age groups, this can limit the treatment for this age group and results may be dangerous. This attempt has raised many questions about the applicability of AI recommendations in populations with unique health profiles and demographics. Factors such as incorporation of biological agents have further decreased the concordance as AI systems often don't allow these therapies, this highlights the need for continuous refinement and training of AI algorithms to solve these problems [25]. The problem of treatment toxicity, especially in elderly patients and financial barriers both collectively make the decision more complicated and restrict access to optimal care [16, 22]. After all these findings we can say that implementing AI can improve cancer care and increase the prognosis of patients after addressing the problems in treatment accessibility.

We've noticed the advancements AI brings to oncology with its integration with MTDs and hinted at difficulties with the usage of AI as well. In subsequent sections, we will further explore the barriers to AI becoming a standard of practice in oncology. Physician's inexperience using AI is one of the root causes. The underuse of AI features and its implications for handling cases [37] is a result of lack of understanding. Moving case details and nuances in a physician's record to an AI system is hard. A primary challenge is also bias and class imbalance due to patient number restrictions, data sharing costs, privacy and security concerns and the generated data complexity [38-40]. Not only that, there are legal risks when working with AI, which cannot be stressed enough. They admit that after all, there should be knowledge and data transfer if anything is going to happen and then the hospital as well as the oncologist should be bound legally [37]. Thus, the shift of human oncologists to AI only feels theoretical.

LIMITATIONS

A major limitation in our study pertains to the lack of research in many fields of oncology namely, dermatology, ophthalmology and neuro-oncology. We saw robust literature on colorectal and breast cancer. Research on gastric cancer was also appreciable. We included an almost equal amount of Eastern and Western studies, 12 and 11 respectively. In Eastern studies, the data set was more concentrated in the East-Asian population and only one of the South-Asian population (India). Similarly, a lack of research was noted in the European population in the Western studies. This restricts the generalizability of our results. Another noticeable limitation was time constraints for this scoping review.

CONCLUSION

The great potential of applying AI in the area of oncology, including in aiding MDT, has been shown in this review which also streamlined patient care and significantly reduced the burden of work of an expert. We perceived the concordance rates extracted from our studies to be substantively consequential, ranging from 48.9 – 99.1%, and falling primarily in the 72 – 87% band. They studied a host of algorithms, with Watson for Oncology and Chat GPT 3.5/4.0 being the major ones. Factors including Age, Financial Issues, National Guidelines and biological agents produced Discordance. Moreover, the studies were concentrated in high income countries. The potential of AI in oncological medicine is strong but one would hesitate to understand AI based on limited knowledge and ethical concerns. As such, more studies need to be done to answer these queries.

ABBREVIATIONS

AI: Artificial Intelligence.

ML: Machine Learning.

DL: Deep Learning.

NLP: Natural Language Processing.

MDTs: Multidisciplinary Tumor Boards.

AUTHORS' CONTRIBUTION

Anzalna Kamran: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

Iqra: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

Yasmeen Sufi: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

Anas Ali: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

Kanwar Arham: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

Fatima Shaukat: Conceptualization, Study Design, Methodology, Data analysis and interpretation, Writing Draft, Critical review and revision the manuscript, Final approval, final proof to be published.

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ETHICAL DECLARATIONS

Data Availability

All data which is collected and analysed during this review was derived from previously published sources and are sited within the manuscript.

Ethical Approval

Not applicable.

Consent to Participate

Not applicable.

Consent for Publication

Not applicable.

Conflict of Interest

Declared none.

Competing Interest/Funding

Declared none.

Use of AI-Assisted Technologies

The authors declare that no generative artificial intelligence (AI) or AI-assisted technologies were utilized in the writing of this manuscript, in the creation of images/graphics/tables/captions, or in any other aspect of its preparation.

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