

ANALYZING DISCREPANCIES BETWEEN AI-GENERATED AND ONCOLOGIST-FINALIZED TREATMENT RECOMMENDATIONS IN VIRTUAL CANCER CARE: IMPACT ON CLINICAL WORKFLOW AND PATIENT OUTCOMES

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ABSTRACT

The application of AI to virtual cancer care has made a tremendous impact on the clinical decision-making process, as it has aided the process of diagnosis, treatment planning, and therapeutic advice, but the gap between the AI-based treatment advice and the finalized decision of the oncologist has become a crucial issue. Such discrepancies can influence clinical practice, drug safety, and patient outcomes especially in digitally mediated oncology environments. The objective of this narrative review is to examine the nature and degree of difference between AI-generated and oncologist-finalized treatment advice during virtual cancer care and to investigate their effect on clinical workflow, oncology pharmacotherapy, medication safety, and patient outcomes. The literature search involved PubMed, Scopus, and Google Scholar, including those that were published as early as 2018 to 2026 and assessed AI-aided oncology decision-making, clinician-AI discordance, workflow implications, and patient-related outcomes. The examined literature indicates that there is a general range of 60-80 percent AI-clinician concordance, but the discrepancies are caused by both quantitative (regimen selection and line of therapy) and qualitative (patient comorbidities, preferences, and contextual clinical judgment) factors. These inconsistencies frequently require extra verification procedures, augment cognition, and expand the multidisciplinary decision-making. Notably, oncology pharmacists can have the key role of reducing the risk of AI-based recommendations by validating chemotherapy regimens, making sure of adequate dose, potential drug-drug interactions, and medication safety. To sum up, although AI has a potential to improve efficiency and standardization in virtual oncology care, the ongoing discrepancies highlight the significance of human-in-the-loop models, explainable AI systems, and active participation of oncology pharmacists to streamline the workflow, protect the use of medications, and promote patient-centered outcomes.

KEYWORDS: Artificial Intelligence, Clinical Decision Support Systems, Oncology Pharmacotherapy, Virtual Cancer Care, Medication Safety.

1. INTRODUCTION

The integration of artificial intelligence (AI) into the field of oncology has led to a rapid increase in the development of the new field during the last ten years, especially the virtual cancer care, where online platforms are becoming more common for clinical appointments, treatment planning, and follow-up. Current AI systems such as machine learning (ML) based clinical decision support systems (CDSS) can process large amounts of clinical, genomic, and imaging data to aid in the diagnosis, prognosis, and treatment recommendations. Such tools are likely to enhance efficiency and standardization of complicated care pathways, such as multimodal planning of cancer therapy.^[1]

Although it has a huge potential, the aspect of AI in therapeutic decision-making also poses serious challenges. There is a postulation that AI tools have the potential to produce treatment options that are not the same as the ones that oncologists make final, which can be considered an issue of accuracy, clinical applicability, bias in data, and interpretation. Indicatively, research has discovered that AI reactions to cancer treatment questions may be not consistent with the clinical practice recommendations, and a great deal of inconsistency is present across AI products regarding the consistency and suitability of recommendations. These inconsistencies are not mere technical issues, but indicative of fundamental problems regarding the quality of data, model reliability, and situational clinical reasoning.

Clinician acceptance and trust is another factor that makes the issue more complex. The suggestions generated by AI can be overruled or adapted by human experts to consider some subtle clinical conditions, including comorbid conditions, patient preferences and tumor biology, which AI models might not reflect. The clinicians use the accountability issue, model transparency, and perceived reliability of AI outputs as some of the factors that determine their readiness to use or rely on AI recommendations.

In virtual oncology services, when face-to-face evaluation is reduced, and the use of digital technologies might have more importance, discordance between AI and clinician consultation could affect clinical practice, resource use, and eventual patient outcomes. Discordant AI recommendations may add new verification processes, create cognitive load among clinicians, and need detailed communication to the patient to avoid the loss of shared decision-making. Simultaneously, AI can also minimize variability in clinical decision-making and emphasize more obscure evidence-based choices as long as it is employed correctly.

2. METHODOLOGY

A qualitative literature search was performed on a number of major databases, such as PubMed, Scopus, and Google Scholar databases which are already reliable sources of peer-reviewed articles in the sphere of

healthcare and oncology. Keywords that were used in the search included AI in oncology, oncologist decision-making, AI treatment recommendations, cancer treatment discrepancies, and virtual cancer care. The restriction was set on the studies published between 2018 and 2026 to cover at least the recent developments in the field of AI implementation in oncology.

Searches were considered in the review provided that they concluded on the AI application in the cancer treatment recommendation, discussed the discrepancies of the AI generated and final decisions made by the oncologists and the effect that AI has on clinical workflow or patient outcomes when applied to virtual cancer care. Conversely, the studies were not included when they were not based on non-cancer uses or when they did not provide any analysis of the discrepancies in the AI and oncologist decision making, and they were not peer-reviewed articles or published in English.

The first stage involved the identification of 100 articles that were located in the chosen databases. Reviewing of the titles and abstracts of these articles were used to screen the articles and irrelevant studies were filtered out using the first screening. Following this process, 60 articles were picked to be fully reviewed. After the full-text screening, researches that failed to fulfill the inclusion criteria were eliminated and finally 18 researches appeared in the final review.

The most relevant parts of the chosen articles were identified (e.g., the tools of AI applied, cancer types, discrepancies, their effect on the clinical workflow, survival rates, success in treatment, and patient satisfaction). The thematic analysis of these data was performed, and the discrepancies were divided into quantitative (statistical discrepancies) and qualitative (e.g., patient preferences differences, ethical issues).

Though no specific quality analysis instrument (like PRISMA) was involved, the studies were critically evaluated in terms of methodology rigor, sample size and their applicability in practice. The quality and relevance of every study was assessed subjectively to identify the quality of the study. The limitations of the review were the possibility of publication bias as more positive results might be published and the geographic bias because a lot of the studies were carried out in the high-income countries with more developed healthcare infrastructure. Heterogeneity of AI models and outcome measures was the reason why this study was carried out as a narrative review.

3. Literature Review

The use of artificial intelligence (AI) in cancer has grown quickly, and now includes treatment decision support systems (CDSS), risk stratification, prognostication, and diagnostic imaging. Performance comparisons with doctors, disparities in treatment recommendations, clinician acceptance and trust, and consequences for

clinical workflow and patient outcomes are among the recurrent topics in this corpus of study.

3.1 AI Performance in Oncology Decision Support

Numerous researches have investigated the efficacy of AI systems in clinical oncology jobs relative to human expertise. AI models frequently exhibit performance levels akin to or marginally inferior than those of seasoned doctors in imaging and diagnostic scenarios. A recent study comparing AI interpretation of digital cervicography with gynecologic oncologist assessments found moderate agreement between the two, with clinicians achieving higher overall diagnostic accuracy. This highlights the current need for hybrid AI-human models rather than autonomous systems.^[2]

Evidence can be used to results regarding the possibility of AI tools to produce guideline-concordant choices on

decision support on treatment recommendations. When an oncology CDSS was compared to actual clinician decisions, it was revealed that in most treatment cases, AI suggested reasonable therapeutic options which aligned with clinical practice, but there were still significant differences where one of the options was considered insufficient according to the expert panels.^[3]

Moreover, in new perspective studies on the role of ChatGPT-4 as a CDSS in radiotherapy of neuro-oncology, overall agreement with a multidisciplinary tumor board was found in 76% of cases, and in cases of low complexity (or where AI had a tendency to overtreatment) the difference appeared. These results emphasize that although AI models can mimic the judgement of experts, subtle clinical reasoning and situation are difficult to compute by existing systems.^[4]

Table 1: AI Tools and Cancer Types Reviewed.

AI Tool / Model	Cancer Type	Study Design	Sample Size / Cases	Concordance with Clinician / MDT (%)
IBM Watson for Oncology	Breast cancer	Retrospective comparison with multidisciplinary tumour board	638 cases	93% concordance ^[5]
CSCO AI (Clinical Decision Support)	Breast cancer	Retrospective evaluation vs clinicians	4900 regimens	73.9% overall concordance ^[6]
ChatGPT-4 as CDSS	Neuro-oncology radiotherapy	Prospective comparative study	101 cases	76% concordance ^[7]
Other CDSS (various)	Multiple cancer types	Mixed evidence (meta-analysis)	~2463 patients (meta-analysis)	~81.5% average concordance across cancers ^[8]

3.2 Discrepancies Between AI and Oncologist Decisions

The discrepancies between the recommendations of AI and decisions made by clinicians are present both in the diagnostic and treatment-planning settings. Research indicates that such disparities may be caused by shortages of training data, on-the-job insensitivity, and the failure of AI to find nuances of individual cases of patients. A more comprehensive systematic review identifies technical and medical issues, including explainability, data representation, decision reasoning, and others, which cause discrepancy between AI output and multidisciplinary cancer care decisions.^[9]

Furthermore, assessments of AI applications identify transparency and reproducibility issues, particularly when chatbots and other generative models are used to offer therapeutic advice and they are not as much sensitive to contexts and do not always give consistent results, which should be verified by clinicians.^[10]

3.3 Clinician Perspectives, Trust, and Acceptance

There is a large body of literature that is dealing with the perception of AI decision support by clinicians. Most articles report that clinicians appreciate AI in enhancing data synthesis and workflow management but are also

apprehensive about giving up the decision-making power. The problems of trust, explainability, and liability are the most commonly mentioned obstacles to acceptance and adoption. Studies on the interaction of clinicians with AI highlights the fact that the trust does not remain constant but changes as the system performs, as the systems have explainability characteristics and conform to the knowledge systems already in place among the clinicians.^[11]

Similar to narrative reviews about clinician-AI interaction, it is important to note that AI recommendations are frequently overruled or modified by clinicians, especially when AI outputs are not transparent or they do not consider patient-specific variables like comorbidities, preferences, or psychosocial issues.^[12]

3.4 Workflow, Trust, and Patient Interaction

Research has started to investigate the impact of discrepancies on the clinical workflow and communication with patients. As an illustration, a study of patient attitudes towards AI-clinician discrepancies identified that patients can impose punishment on clinicians who cannot comply with AI recommendations in cancer screening settings, and that there can be

complicated interactions between patient expectations, clinician judgement, and AI influence.^[13]

Although the literature on the subject of workflow disruption in the oncology context in particular is still developing, the results of the more general research on CDSS imply that extensive cognitive workload, a possible delay, and additional verification steps can be the result of mismatching AI and clinician decision-making unless the systems are designed to integrate seamlessly and be understandable.^[14]

4. Types of Discrepancies

When discussing the AI-assisted oncology care, the differences between AI-generated treatment plans and the ones formulated by oncologists can be grouped into the quantitative and qualitative discrepancies, in general. These groups assist in understanding how and why AI suggestions do not align with expert clinical judgment and illuminate the implication of such a solution in the real-life practice.

4.1. Quantitative Discrepancies

Quantitative discrepancies are those that are measurable, numerical disparities between the recommendations that AI systems give and oncologists. These differences can take the form of differences in concordance rates i.e. the proportions of cases in which an AI suggestion is concordant with a clinician decision and are common in clinical decision support system (CDSS) and real-world clinician decision studies.

Indicatively, in a study conducted on the empirical evidence of comparison between AI CDSS output and clinician treatment decisions, moderate rates of agreement are indicated. In a major comparative study of IBM Watson in Oncology, a wide range of AI therapeutic options (around 60-70%), were identical or acceptable alternatives to clinician choices in various types of cancer (breast, colon and lung), whilst discordant of AI and human decisions were unacceptable in a third of the cases. In these articles, in cases where AI and clinician choices were both allowable, the preference was divided in a fairly balanced manner, which indicates the existence of calculable differences in choice of treatment that must be addressed by clinicians to fix.^[3]

Likewise, assessments of AI models such as CSCO AI in breast cancer cases have also documented concordance rates on the order of 73.9%, with increased agreement in the early-stage disease versus metastatic environments, and a great deal of variability in agreement across treatment stages (e.g. first-line therapy vs adjuvant therapies). These quantitative variations demonstrate that even highly trained AI systems cannot always recapitulate the pattern of clinical choices of clinicians, specifically in complicated clinical situations where the sequence of treatment and personalised judgement are essential.^[6]

Poor quantitative inconsistencies are also evident in environments that do not use formal CDSS tools, e.g., large language models used as clinical decision support. Future studies that evaluate AI models such as ChatGPT-4 at neuro-oncology radiotherapy showed that concordance with multidisciplinary tumor board decisions was between 76 and 79 percent, once again demonstrating that AI recommendation can be inconsistent with clinician judgment in a sizeable proportion of patients.^[4]

These numerical discrepancies underscore the importance of AI results and indicate that clinicians should perceive AI suggestions as auxiliary data instead of actual instructions especially when AI is more prone to under- or over-prescribe treatments compared to a human-made decision.

4.2. Qualitative Discrepancies

As opposed to quantitative discrepancies, qualitative discrepancies are differences between the nature, reasoning and context of AI and clinician treatment recommendations. Such differences are usually due to the inability of AI to utilize subtle clinical data and explain complex and situational factors that seasoned oncologists take into account in their decision-making.

A major way of difference in qualitative terms is the application of clinical guidelines in AI systems compared to the holistic thinking clinicians apply. AI devices often are based on a structured database of guidelines and recognition of patterns but do not necessarily provide the ability to incorporate patient preferences and psychosocial factors or clinical nuances. It may result in evidence-based recommendations that are clinically inappropriate in some specific situations. The studies of AI in oncology decision support also point out these interpretability and clinical contextualization issues as key sources of mismatch between AI outputs and clinician decisions.^[9]

The other cause of qualitative gap is the so-called black box character of most machine learning models, in which the decision pathways are not visible to users. This opaceness may lead to AI giving treatment recommendations with no apparent explanatory background, and thus clinicians are unwilling to fully use or implement such recommendations. Although the resulting final recommendations seem to agree numerically, AI outputs may also be based on very different reasoning logic than that of a clinician, leading to different final outcomes in situations where human expertise prevails over AI based on contextual knowledge.^[15]

The differences in the management of uncertainty also determine the qualitative discrepancies. AI models can tend to revert to guideline-based default recommendations but they cannot work across gray-area decisions when clinicians rely on experience and

judgement to make tradeoffs between risk, patient comorbidities and emerging evidence. An example of this is that, when clinicians were observed to interact with AI, qualitative analysis demonstrated that clinicians do not accept or reject AI suggestions at face value, instead, some selectively integrate, adapt or disregard AI suggestions based on their own determination of clinical value.^[16]

Quantitative and qualitative discrepancies collectively demonstrate that AI recommendations in oncology can be not merely different in a larger degree but tend to differ in a different kind of clinician decisions. The identification of such discrepancies can be useful in the development of AI that can not only work well in a statistical context but also in the context of the human thinking processes and subtle contextual thinking that clinicians apply when treating cancer in the real world.

Table 2: Quantitative vs Qualitative Discrepancies.

Type of Discrepancy	Description	Example from Literature	Implications for Clinical Workflow, Oncology Pharmacy, and Medication Safety
Quantitative	Numeric or measurable differences in AI vs oncologist recommendations; often reflected as concordance rates	IBM Watson for Oncology: 60–70% of AI treatment options matched clinician choices; 30% unacceptable mismatch	Oncology pharmacists and clinicians may need to verify AI-generated treatment plans, validate chemotherapy dosing and regimens, document deviations from AI recommendations, and ensure medication safety in virtual oncology care.
Quantitative	Differences in treatment choice based on cancer stage or line of therapy	CSCO AI breast cancer: 73.9% overall concordance; higher in early-stage vs metastatic disease	Oncology pharmacists support stage-specific pharmacotherapy decisions by reviewing regimen selection, preventing dosing errors, ensuring appropriate sequencing of therapies, and facilitating multidisciplinary coordination.
Qualitative	Differences in reasoning, context, or application of clinical judgment; AI may follow guidelines strictly but ignore patient-specific factors	AI ignores patient comorbidities or psychosocial preferences; clinicians override AI based on holistic judgement	Oncology pharmacists contribute to patient-centered care by reconciling AI recommendations with comorbidities, polypharmacy, toxicity risk, and patient preferences, supporting safe and individualized treatment planning.
Qualitative	Differences due to “black-box” AI models where decision rationale is unclear	ChatGPT-4 neuro-oncology: 76% concordance with tumor board, but reasoning pathways often opaque	Oncology pharmacists enhance medication safety by interpreting opaque AI outputs, identifying potential drug-related risks, and assisting clinicians in communicating safe, evidence-based treatment decisions to patients.

4.3 Implications for Oncology Pharmacists and Medication Safety

The difference between the treatment recommendations produced by AI and those produced by oncologists has direct consequences on oncology pharmacists and medication safety. Oncology pharmacologists have a significant role in the assessment of the AI-supported treatment plan especially checking the chemotherapy regimen, accuracy, dosage, drug-drug interactions, and contraindications depending on the individual factors of the patient e.g. renal condition, hepatic status, comorbidities. Where the AI-based systems come up with suggestions contrary to the way the clinician would decide, however, pharmacists tend to become a safety gateway to avoid medication errors, inadequate dosing, or unsafe regimen choices.

Also, AI models that are based mainly on guideline-based recommendations might be inadequate to consider individualized pharmacokinetic changes, polypharmacy, or toxicities related to previous treatment. In this case, AI

outputs must be reconciled with real-life medication safety concerns, and oncology pharmacists can provide the necessary clinical supervision. Incorporating pharmacists as part of the AI-assisted virtual oncology cycles can thus eliminate threats posed by the problems with algorithmic discrepancies and improve patient safety.

5. Impact on Clinical Workflow

The adoption of AI-based decision support systems into virtual cancer care has reformed the clinical practice in oncology. Although such technologies guarantee efficiency and standardization gains, the mismatch of AI-generated and oncologist-approved treatment recommendations presents novel workflow challenges. These issues are evidenced by delays in the treatment, a workload on clinicians, the changes in the dynamics in the multidisciplinary work, and adaptive workflow optimization strategies.

5.1. Treatment Delays and Workflow Disruptions

Mismatches between the AI and the oncologist decision can also lead to delays of treatment, especially in cases where the AI outputs are not in harmony with the concrete clinical judgment or even the practice of an institution. When this happens, clinicians usually go beyond the verification procedure which may involve guideline cross-checking, multidisciplinary consultations or revisiting data and completing the treatment plans. Experiments on the use of oncology clinical decision support systems have indicated that the concordant AI recommendations often need secondary review, thus, and not shortening the decision time-lines, but increasing them. In virtual cancer care environments where asynchronous communication and little physical examination is already a challenge the extra checks of verification may further break the workflow and slow down treatment initiation.^[17]

Further, AI software that is not connected to electronic health records (EHRs) may worsen the workflow. Manual data entry, irregular data structure, and a lack of interoperability have been listed as the primary factors that contribute to the workflow discontinuity in AI-supported oncology practices. Consequently, not only do the discrepancies slow down the treatment decisions but also affect the desired efficiency benefits of AI implementation.^[18]

5.2. Increased Workload for Oncologists

Instead of decreasing the workload of clinicians, differences in AI-generated and oncologist-finalized recommendations can augment both the cognitive and administrative workload of the oncologist. The clinicians need to read AI outputs, evaluate its clinical utility and explain why it should not be followed especially when AI suggestions are written or in places where the AI recommendations are visible to patients. This interpretation work weighs on an existing work-load pressure and may lead to decision fatigue. Studies conducted on the subject of automation bias suggest that clinicians can devote more resources to reviewing AI recommendations to prevent overdependence on potentially incorrect suggestions, which causes even greater cognitive load.^[19]

Also, clinicians commonly cite learning, validation, and troubleshooting AI costs in time, especially in initial phases of implementation. Qualitative research on AI implementation in oncology has identified that the oncologists often use selective adoption where AI results are applied selectively but highly contextualised, which may take even more time than conventional decision-making channels. Therefore, discrepancies do not only add to the workload but also increase the complexity of the clinical thinking processes.^[16] Besides oncologists, AI-generated and finalized treatment recommendations vary, which further burdens oncology pharmacists, who need to verify AI-influenced prescriptions, justify chemotherapy guidelines, and meet the institutional

medication safety regulations. Although this further verification procedure is necessary to eliminate adverse drug events, it can be a source of workflow complexity unless AI systems are developed with the involvement of pharmacists.

5.3. Impact on Multidisciplinary Collaboration

Cancer treatment is per se multidisciplinary and it requires oncologists, radiologists, pathologists, surgeons and healthcare professionals in support. AI-clinician discrepancies may affect the interactions of multidisciplinary team (MDT) meetings as they may bring more levels of discussions on algorithmic recommendations. Although the outputs of AI can be a valuable reference point, discordant recommendations usually involve the teams taking more time to align AI suggestions with the overall clinical experience. Research on tumor board decision-making has revealed that AI suggestions are often discussed and amended instead of implemented directing the ongoing central role of human consensus in complicated cancer care decisions.^[4]

The lack of synchronous communication and the chance to clarify in real-time may also complicate collaboration in real-life situations in virtual MDT because of the existence of discrepancies. Nonetheless, certain literature indicates that AI may also become a catalyst to more systematic discussion by bringing alternative evidence-based choices to the fore, in a situation when AI products are transparent and integrated into the team processes. Therefore, the effects of discrepancies on the multidisciplinary collaboration are two-fold, and they could either inhibit team deliberations or contribute to them based on system design and implementation.^[6]

5.4. Potential Solutions for Workflow Optimization

To address workflow breakdowns that might result due to AI-clinician discrepancies, a number of optimization strategies have been suggested in the literature. Models that use human-in-the-loop, making AI an assistant but not an independent decision-maker are popularly approved to provide clinician-level oversight and use computational efficiency. Improving AI recommendation explainability and transparency is also essential, and interpretable systems can provide clinicians with an opportunity to evaluate the reasoning behind AI outputs much faster and incorporate it into clinical reasoning.^[20]

Better integration of AI tools and EHR systems can even fewer administrative burdens and fragmentation of the workflow. Clinician training to get used to AI shortcomings and the proper use situations has also been demonstrated to enhance the levels of acceptance and minimize unnecessary verification cycles. the integration of AI suggestions within the clinical workflow at the best locations like during pre-consultation planning instead of making real-time decisions can assist in reducing delays and cognitive overload.^[21]

6. Impact on Patient Outcomes

The incorporation of AI into virtual care of cancer patients has serious patient outcomes implications, especially when there are anomalies between AI-generated and finalized oncologist recommendations. These effects are reflected in clinical performance, patient confidence and satisfaction, quality of patient-centered care. These effects are imperative to understand so that AI systems can be developed to improve, but not worsen patient outcomes.

6.1. Clinical Outcomes

Mismatches between AI and clinician advice have the potential to affect the safety and efficacy of cancer treatment. Where AI recommendations match clinical opinion, it can lead to a greater adherence to guidelines, standardization of care, and a decrease in omission errors, especially in low-risk or early cancer cases.^[17]

Nonetheless, when AI suggestions contradict the judgment of the oncologists, clinicians have to step in to mitigate incorrect therapy, including over- or under-treatment, which might jeopardize survival or augment the occurrence of bad events. Also delays related to verifying or reconciling discrepant AI recommendations are indirectly related to patient outcomes, as oncology requires timeliness, where delay in starting therapy is linked to worse prognosis in a variety of cancer types.^[22]

6.2. Patient Trust and Satisfaction

Disagreements also affect patient satisfaction with care. Patients are more and more exposed to AI-based decision support systems in the virtual platform or indirectly by communicating with clinicians. In cases where AI guidance is inconsistent with advisory services of the oncologist, the patients might feel confused or doubtful of the appropriateness of their care program, a factor that can adversely affect trust and satisfaction. On the other hand, trust may be enhanced through open sharing by clinicians of the reasoning behind any deviation of AI advice, boost patient interactions, and reassure patients that the decisions made in care delivery are still human and evidence-based.^[13]

6.3. Patient-Centered Care

Patient-centered care is the focus of the integration of personal preferences, values, and psychosocial context into the treatment. The AI systems, which are largely dependent on the data about the populations and uniform rules, might not be able to take into consideration such individual factors in their entirety and produce qualitative contradictions. The control of AI is essential because it would enable oncologists to adjust care plans based on patient objectives, comorbidities, and lifestyle changes.^[13] The inability to align AI results with patient needs may undermine compliance, patient satisfaction, and retention. Notably, patient-centered care can be facilitated with the help of AI systems that are designed to aid but not substitute the judgment of clinicians by offering evidence-based suggestions and allowing

clinicians to contextualize the results and engage patients in shared decision-making.^[20]

The misalignment of AI and oncologist recommendations influences the patient outcomes in various areas. Although such discrepancies are countered by clinician oversight to the risks of clinical safety, those discrepancies may affect the treatment timeliness, patient trust, patient satisfaction, and care delivery in line with patient preferences. The successful implementation of AI must be highly designed, transparent, and well-integrated clinician participation to maintain ideal patient outcomes during virtual oncology patient care.

7. Recommendations and Future Directions

As AI continues to advance as a tool for virtual cancer care, resolving the disparity between treatment recommendations made by AI and those issued by oncologists becomes crucial to achieving clinical efficacy and patient-centered outcomes. Recent research has shown that these differences may be managed and reduced with careful system design, physician training, and institutional rules, even if they are inevitable given the existing technical limitations.

It is suggested that human-in-the-loop frameworks should be adopted. The role of AI should be to act as a support system, but not as a decision-maker, and offer evidence-based suggestions in which the final decision is at the discretion of the clinician. By enabling oncologists to provide such frameworks with the context of patient characteristics, comorbidities, and personal preferences, the risk of overtreatment or under-treatment is minimized through the integration of AI output in such frameworks. Furthermore, the transparency can be increased by the implementation of explainable AI (XAI) methods that would enhance the trust of clinicians. Interpretable rationale behind recommendations such as the use of highlighted guideline references and reasoning channels enable faster verification and integration into workflow, reducing delays in decision-making and mental load.

The strategies that help in workflow integration are necessary in minimizing the disruptions. The electronic health records (EHRs) and, more importantly, AI tools need to be interoperable, and they should be implemented in places where they would be most useful in the clinical workflow, i.e., pre-consultation treatment planning or triage. Clinician training on proper use and limitations, and verification techniques can also facilitate smoother workflow adoption and minimize the number of errors that happen because of an incorrect interpretation of AI output.

AI development should be informed by focusing on patients in the future. Adding the patient preferences and psychosocial factors to AI algorithms either using structured patient-reported data or interactive interfaces can serve to decrease the qualitative discrepancies and assist with shared decision-making. The clinicians must

also be eager to discuss the role of AI in patient care with them, clarify any discrepancies, and underline the primary role of human judgment, thus improving their trust and compliance.

Standardization and evidence generation should become the research and regulatory priorities. Future multicentric research and evaluations in real-world settings are required to measure the clinical consequences of AI-clinician discrepancies on workflow and patient outcomes. Guidelines should be offered to the regulatory authorities and professional societies regarding validation, reporting, and monitoring of AI systems in oncology, which would guarantee that the technologies would comply with safety, equity, and performance criteria in different patient groups. Ethical aspects, such as data privacy, reducing bias, and the liability of AI-related mistakes, should be taken in advance to facilitate the responsible implementation of the AI.

8. CONCLUSION

The incorporation of artificial intelligence into virtual cancer care offers considerable prospects for augmenting decision-making, enhancing workflow efficiency, and optimizing patient outcomes; however, disparities between AI-generated and oncologist-finalized treatment recommendations continue to pose a significant challenge. These variances are evident both numerically, as seen in demonstrable variations in therapy selection or concordance rates, and qualitatively, via differences in clinical reasoning, contextual interpretation, and the consideration of patient preferences. These kinds of variations can affect workflow by making it harder to think, making interdisciplinary talks last longer and causing delays in treatment planning. They can also affect patient outcomes, such as how well the therapy works, how well patients follow the plan, how much they trust the doctor, and how satisfied they are. To solve these problems, we need to use human-in-the-loop frameworks, AI technologies that are easy to understand and explain, and patient-centered decision-making that is actively used in electronic health record processes. Furthermore, continuous research, prospective validation studies, and regulatory supervision are important to guarantee that AI technologies are safe, fair, and effective for various populations. In the end, the effective use of AI in oncology rests on finding a balance between what technologies can accomplish and the unique value of clinician judgment. This means creating collaborative human-AI processes that improve clinical accuracy, patient-centered care, and the overall quality of virtual cancer treatment.

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