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THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE-BASED CANCER DIAGNOSTIC AND THERAPEUTIC TECHNOLOGIES: MEDICAL EFFECTIVENESS, LEGAL CHALLENGES, AND MARKETING STRATEGIES

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ABSTRACT

The global cancer burden is increasing rapidly, and adoption of Artificial Intelligence (AI) technology for diagnosis and therapy may improve accuracy and efficiency. However, gaps in implementation, regulation, and marketing still hinder clinical adoption, alongside limited measurable real-world evidence. This study synthesized evidence on medical effectiveness, legal challenges, and marketing strategies for oncology AI, recommending a practical, measurable, multidisciplinary implementation framework. A mixed-methods systematic literature review followed PRISMA guidelines using a Scopus search (2020–2025). Inclusion/exclusion criteria were defined; quality appraisal used the MMT with two independent reviewers, standardized extraction, and quantitative–thematic synthesis. Thirty-eight studies identified three themes: medical effectiveness, legal challenges, and marketing/change management strategies. Evidence showed diagnostic accuracy increased up to 94.7%, diagnosis time decreased by 7.4 hours, adverse events decreased up to 44%, and therapy recommendation accuracy increased up to 87.27%. The literature highlighted issues of explainability, liability, clinician collaboration, training, and geographical bias, supporting regulatory harmonization, longitudinal studies, multicenter randomized controlled trials, and patient-oriented research. AI clinical decision support systems improve oncology effectiveness, but regulation and liability require multidisciplinary harmonization research.

KEYWORDS: Artificial Intelligence in Oncology; Clinical Decision Support Systems; Cancer Diagnosis; Healthcare Regulation; Systematic Literature Review.

1 INTRODUCTION

Cancer is one of the biggest global health challenges, with the number of cases continuing to rise. In 2022, there were nearly 20 million new cases and 9.7 million deaths, with 35 million new cases projected by 2050 (Bray et al., 2024). Of the 5.28 million premature deaths from cancer in 2020, approximately 3.63 million could have been prevented through timely intervention (Frick et al., 2023). With the growing burden of cancer, Artificial Intelligence (AI) applications have huge potential. The drug prediction model response in cancer patients exhibited a sensitivity of 0.82, a specificity of 0.84, and an AUC of 0.83 (Abdeldjouad et al., 2023). These results demonstrate the role of AI in enhancing diagnostic accuracy and drug efficacy.

In addition to the high prevalence of cancer, cancer is also a leading cause of death worldwide, with more than 20 million new cases and 9.7 million deaths in 2022 (Sung et al., 2021). Diagnostic delays are suffered by 40% of cancer patients (Rony et al., 2024), the absence of oncology professionals results in up to 2.3 million in 2030 (Bray et al., 2024), and heterogeneity of therapy protocols results in up to 67% worse clinic outcomes. Treatment costs are estimated to reach up to USD 458 billion in 2030 (World Health Organization International Agency for Research on Cancer, 2020). Although AI has the potential to accelerate diagnosis and personalize therapy, its implementation is still hampered by regulatory and privacy issues, with 65% of patients concerned about the security of their medical data (Rony et al., 2024).

Advances in AI diagnostic technology are evident in the Vision Transformer (ViT) model, which achieved 99.8% accuracy in histopathology classification (Abimouloud et al., 2024). Meanwhile, graph neural networks (GNNs) are becoming increasingly important for discovering new drugs through molecular graph representations (Zhang et al., 2025). ViT strengthens medical diagnostics, while GNN advances therapeutic innovation, requiring attention to legal issues and marketing strategies to ensure widespread adoption in healthcare systems.

In the field of therapy, AI also supports the development of CAR-T cell therapy. The integration of AI with CRISPR-Cas9 has been shown to improve gRNA design accuracy, reduce the risk of off-target effects, and lower production costs (Boretti, 2024). The CURATE.AI 'digital twin' platform enhances therapy personalisation with 97.2% clinical acceptance and a 20% reduction in chemotherapy doses (Blasiak et al., 2025). Furthermore, AI in multi-stage CRISPR-Cas9 accelerates the development of precision cancer therapies but also poses legal challenges and evidence-based marketing opportunities (Abbasi et al., 2025).

Despite its promise, AI in oncology still faces gaps. Technical challenges include a lack of decision transparency (reported by 67% of clinicians), a 15–30% decline in performance in different populations, and barriers to integration with electronic medical records. Regulations are also inconsistent across 34 countries, with limited long-term safety data and unclear medical liability. Clinical implementation is further hindered by 73% of institutions struggling with AI integration, low healthcare literacy, and insufficient cost-benefit evaluations and patient acceptance.

The post-pandemic context has accelerated the transformation of healthcare services, marked by a 340% increase in cancer telemedicine and USD 350 billion in digital health investment. The 156% growth in AI-based patient monitoring systems further emphasises the urgency of smart solutions. Global regulations such as the EU AI Act 2024, FDA AI Action Plan 2024, and ISO/IEC 23053:2024 provide a comprehensive legal framework. The market also shows strong support with the expansion of big tech, 2,847 health AI startups (32% focused on oncology), and public-private collaborations worth USD 45 billion.

Against this backdrop, this study aims to systematically review the medical effectiveness, legal challenges, and marketing strategies of AI implementation in oncology. Key contributions include a multi-stakeholder analysis from the perspectives of doctors, patients, regulators, and industry, as well as the development of an evidence-based implementation roadmap. Using a systematic review method with a mixed-methods approach that combines quantitative meta-analysis and qualitative thematic synthesis grounded in real-world evidence, this study is expected to strengthen the academic foundation, support evidence-based policies, and provide strategic guidance for integrating AI into clinical practice. The study is guided by three research questions (RQ). RQ1 examines how the implementation of AI technology in clinical oncology workflows affects diagnosis times, treatment decisions, and patient outcomes for cancer patients. RQ2 explores how legal liability is distributed among doctors, healthcare institutions, and technology developers in the use of AI systems for cancer diagnosis and treatment. RQ3 investigates effective marketing and change management strategies for increasing the adoption of AI technology among oncology healthcare professionals.

2 RESEARCH METHOD

This study employed a systematic literature review design following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to identify, evaluate, and synthesize empirical evidence on AI-based technologies for cancer diagnosis and treatment. The review was structured using the PICO framework, encompassing cancer patients, healthcare institutions, and relevant stakeholders as the population; AI-based technologies (e.g., machine learning, deep learning, clinical decision support systems) as the intervention; conventional diagnostic and clinical workflows as the comparison; and outcomes including medical effectiveness, regulatory challenges, and implementation impact. A comprehensive search was conducted across PubMed/MEDLINE, Scopus, IEEE Xplore, ACM Digital Library, Cochrane Library, and Google Scholar using controlled vocabulary and keyword combinations related to AI and oncology, limited to publications from 2018 to 2024. Eligible studies included original research articles published from 2020 to 2025, while non-clinical and non-empirical studies were excluded.

Study quality was assessed using the MMAT (2018), with independent evaluation by two reviewers and consensus resolution procedures. Data extraction was conducted using a standardized form to capture study characteristics, interventions, outcomes, and key findings, followed by analysis using a mixed-methods approach. Quantitative data were synthesized descriptively, with meta-analysis conducted where appropriate, while qualitative findings were analyzed thematically, ensuring high inter-rater reliability. The review process was conducted collaboratively among three researchers to ensure rigor and consistency. From 1,000 identified records, 960 were screened after deduplication, 495 full-text articles were assessed, and 38 studies met the inclusion criteria and were included in the final analysis.

3 RESULTS AND DISCUSSION

Results

Based on the comprehensive research table compiled, there are three main interrelated dimensions in the development of AI-based cancer diagnostic and therapeutic technologies: medical effectiveness, legal challenges, and marketing strategies. The implementation of AI in clinical decision support systems (CDSS) has significantly improved diagnostic accuracy and therapeutic efficiency. However, it still faces complex legal and liability issues among doctors, technology developers, and health institutions. Meanwhile, adopting this technology requires a mature change management strategy, including user training, seamless integration with existing clinical workflows, and building trust through algorithm transparency and active stakeholder involvement in the development process. The studies compiled in Table 1 provide deep insights into how these three aspects must be managed holistically to ensure the successful and sustainable implementation of AI in modern oncology practice.

Table 1: Comprehensive Summary of Included Research Studies and Citations.

No	Title	Author	Year	Excerpt	Citation
1	Effect of an AI clinical decision support system on treatment decisions for complex breast cancer	Xu et al.	2020	Use of an AI–based CDSS had a significant impact on treatment decisions and on adherence to NCCN guidelines in HR-positive breast cancers.	(Xu et al., 2020)
2	Prediction system for prostate cancer recurrence using machine learning	Lee et al.	2020	If we could predict prostate cancer BCR by analyzing data on the progress and recurrence patterns of prostate cancers, it would help clinicians to make better decisions about future treatment options. In addition, depending on the predicted BCR probability, the recurrence rate could be reduced by providing patients with physical examinations or related medications.	(Lee et al., 2020)
3	CarePre: An intelligent clinical decision assistance system	Jin et al.	2020	The system extends a state-of-the-art deep learning model to predict upcoming diagnostic events for a focal patient based on their historical medical records. The system includes an interactive framework and intuitive visualizations designed to support diagnosis, treatment, and analysis of treatment outcomes.	(Jin et al., 2020)
4	Radiomics-based prediction of long-term treatment response of vestibular schwannomas following stereotactic radiosurgery	Langenhuizen et al.	2020	The ability to a priori predict such a treatment response can significantly impact treatment selection and may improve overall treatment outcome.	(Langenhuiz et al., 2020)
5	Machine learning for dose-volume histogram-based clinical decision-making support system in	Siciarz et al.	2021	The proposed ML classifier and model explainability work together to provide additional value to the clinical processes. After the plan is created and the algorithm	(Siciarz et al., 2021)

No	Title	Author	Year	Excerpt	Citation
	radiation therapy plans for brain tumors			classifies the treatment plan, the model's explainability analysis (performed instantly) identifies the attributes underlying the classification (i.e., which plan and patient-related attributes led the plan to require a trade-off).	
6	How clinicians perceive AI-assisted technologies in diagnostic decision making	Hah & Goldin	2021	The developers of AI need to consider clinicians' current levels of exposure to technology in practice and simulation, and then design clinician-centered algorithms and interfaces. To achieve the goal of human-AI collaboration in health care, beyond involving clinicians in the development of clinical AI algorithms, these algorithms and their interfaces should be more human-centered.	(Hah & Goldin, 2021)
7	Development and implementation of a clinical decision support-based initiative to drive intravenous fluid prescribing	Spiegel et al.	2021	Pre-intervention (3/2019–9/2019), balanced fluids comprised 33% of isotonic fluid orders, with a gradual increase (1.4%/month) in balanced fluid prescribing. Clinician education (10/2019–2/2020) yielded a modest (4.4%/month, 95% CI 1.6–7.2, p =0.01) proportional increase in balanced fluid prescribing, while CPOE redesign (3/2020) yielded an immediate (20.7%, 95% CI 17.7–23.6, p < 0.0001) and sustained increase (72% of fluid orders in 12/2020).	(Spiegel et al., 2021)
8	Coronavirus disease 2019 (COVID-19) diagnostic clinical decision support	Dugdale et al.	2021	CORAL significantly reduced average time to PUI status discontinuation (adjusted difference [standard error], −7.4 [0.8] hours per patient), total duration of PUI status (−19.5 [1.9] hours per patient), and average ID physician work-hours (−57.4 [2.0] hours per day) (all P < .01). No patients had a positive NAAT result within 7 days after discontinuation of precautions via CORAL.	(Dugdale et al., 2021)
9	Acceptance, barriers, and facilitators to implementing AI–based decision support systems in emergency departments	Fujimori et al.	2022	Although concerns about system failure and overreliance on the system could be barriers to implementation, the system's local presence and an intuitive user interface are likely to facilitate the use of optimal AI-based CDSS.	(Fujimori et al., 2022)
10	i-Net: a deep CNN model for white blood cancer segmentation and classification	Agughasi & Murali	2022	Compared with other pre-trained deep learning models, such as the standard VGG-19 and ResNet-50, we achieved better performance on a test dataset of about 630 microscopic images, suggesting that the CNN can be used in clinical decision support systems (CDSS) for leukemia detection.	(Agughasi & Murali, 2022)
11	Machine learning-based prediction model for late recurrence after surgery in patients with renal cell carcinoma	Kim et al.	2022	This algorithm may be used by clinicians to identify patients at high risk of late recurrence who require long-term follow-up and to establish patient-specific treatment strategies.	(Kim et al., 2022)
12	AI-assisted discrimination between pulmonary tuberculous nodules and solid lung cancer nodules	Zeng et al.	2022	Deep learning-based AI assisted diagnosis of lung nodules has covered lung nodule detection, pathological diagnosis, and postoperative prediction, among other areas, enabling quick and accurate localization, reducing reading time, and greatly improving doctors' analysis efficiency and diagnostic accuracy.	(Zeng et al., 2022)
13	CURATE.AI-AI-driven personalized tacrolimus dosing for pediatric liver transplant	Tan et al.	2022	Using CURATE.AI added two steps to the clinical workflow: involving the CURATE.AI team and informing the patient (via verbal communication and a written dosing calendar) of the dose adjustment before the next cycle.	(Tan et al., 2022)
14	Expectations and attitudes towards medical AI: A qualitative study in the field of stroke	Amann et al.	2023	There was wide agreement that the responsibility for medical decisions, alongside the Decision-making authority, presently rests with the healthcare professional or care team. While some participants argued that at least a rudimentary understanding of the AI system would be necessary to ensure quality and patient safety, others noted that the lack of explainability was not unique to medical AI.	(Amann et al., 2023)
15	Usability of the IDDEAS prototype in child and adolescent mental health services	Clausen et al.	2023	Because of the challenge of juxtaposing normative clinical guidelines with empirical evidence in the form of care patterns, developing a CDSS requires collaborative, multidisciplinary interventions to achieve an equitable balance between technological advancement and the clinical workflow.	(Clausen et al., 2023)
16	Advancing acceptance: assessing acceptance of the ESR iGuide clinical decision support system	Singer et al.	2023	The user acceptance theory suggests that understanding the interaction between end users and technology determines the level of adoption. In particular, the technology acceptance theory emphasizes user expectations and suggests that perceived usefulness and ease of use are key	(Singer et al., 2023)

No	Title	Author	Year	Excerpt	Citation
				factors in adoption.	
17	Physicians' perspectives on AI in clinical decision support systems	Vijayakumar et al.	2023	Evidence, patient safety, data availability, awareness, and collaborative functioning are the most important dimensions that characterize physicians' technology adoption. Even though these dimensions capture the broad contours of technology adoption, studies have also outlined the nuances that comprise them.	(Vijayakuma r et al., 2023)
18	Expectation of clinical decision support systems: a survey study among nephrologist end-users	Kotsis et al.	2023	CDSS and the application of machine learning methods will have a significant impact on healthcare. That, also, raises several ethical issues, because high-quality patient care relies not just on accurate prediction, prevention, or enhanced decision-making by CDSS with a better set of individualized treatments, but also on experience, empathy, and concrete judgment by doctors. This may be because both patients and doctors believe that the final decision-making lies in the hands of the human players.	(Kotsis et al., 2023)
19	Analysis of Watson for oncology and clinicians' treatment recommendations for patients with breast cancer in Korea	Park et al.	2023	WFO provided the same treatment option recommendations as clinicians in 74 cases (40.4%). According to the logistic regression, the difference in recommendation concordance between stage I and stage III was statistically significant (P = 0.004).	(Park et al., 2023)
20	A mixed-methods feasibility study of a novel AI-enabled, web-based, clinical decision support system for the treatment of major depression in adults	Qassim et al.	2023	As this platform is intended for decision support, the physician remains in control of clinical decisions and may choose not to act in accordance with either the guidelines or the AI-based predictions. This is fundamentally how the system is intended to be used. Rather than physicians abdicating responsibility and simply following AI recommendations, they are meant to incorporate the model's predictions while still considering their own expertise and collaborating with the patient.	(Qassim et al., 2023)
21	Implementing a machine learning screening tool for malnutrition	Besculides et al.	2023	Our findings highlight that ML tools will not replace clinicians but augment their capabilities; therefore, the active involvement of clinicians at all stages of ML tool development and implementation is critical.	(Besculides et al., 2023)
22	Early experiences of integrating an AI-based diagnostic decision support system into radiology settings	Faric et al.	2024	Clinicians consistently emphasized that the final clinical decision rested with them. I mean, you know it can only do relatively binary tasks at the moment, and those tasks are generally tasks that help radiologists.	(Faric et al., 2024)
23	Natural language processing to automate a web-based model of care and modernize skin cancer, a multidisciplinary team meeting	Ali et al.	2024	The vSMDT with human involvement would likely be classified as a class 1 device. Class 1 devices typically include non-invasive devices, such as a clinical decision support system, which support rather than dictate clinical decisions.	(Ali et al., 2024)
24	The facilitators and barriers of the implementation of a clinical decision support system for breast cancer multidisciplinary team meetings	Kočo et al.	2024	Furthermore, participants welcome the involvement of end-users during the development and implementation phases of CDSSs to specifically develop functionality that aligns with actual expectations, needs, and current clinical practice workflows.	(Kočo et al., 2024)
25	Expectations and requirements of surgical staff for an AI-supported clinical decision support system for older patients	Uihlein et al.	2024	This is evident in the current legislation, which states that, even when using an AI-CDSS, medical professionals remain responsible for the decisions.	(Uihlein et al., 2024)
26	Risk perception, acceptance, and trust of using AI in gastroenterology practice in the Asia-Pacific Region	Goh et al.	2024	One intriguing finding is that participants with more (years of) experience appear to accept the risk and would trust the use of AI more than those who are less experienced. This probably indicates that they see AI as an option or recommendation rather than an obligation or necessity.	(Goh et al., 2024)
27	CLARUS: An interactive explainable AI platform for manual counterfactuals in graph neural networks	Metsch et al.	2024	Lack of trust in artificial intelligence AI models in medicine is still the key blockage for the use of AI in clinical decision support systems (CDSS). Although AI models are already performing excellently in systems medicine, their black-box nature makes patient-specific decisions incomprehensible to physicians.	(Metsch et al., 2024)
28	Theory of radiologist interaction with instant messaging decision support tools	Burns et al.	2024	However, the future radiologist concept will not come to fruition if tools are poorly integrated and have cumbersome human-computer interfaces. Deliberate and sustained effort, drawing on interdisciplinary knowledge from human-centered	(Burns et al., 2024)

No	Title	Author	Year	Excerpt	Citation
				computing, psychology, cognitive sciences, and medicine, is required to build CDSS for the future radiologist.	
29	Personalized dose selection for the first Waldenström macroglobulinemia patient on the PRECISE CURATE.AI trial	Blasiak et al.	2024	Stakeholder inclusion and patient-centered care are emerging as best practices in digital health innovation and implementation. The co-creation with physicians was highlighted as foundational for bridging AI fairness with meaningful clinical benefits.	(Blasiak et al., 2024)
30	Barriers to adoption of a child-abuse clinical decision support system in emergency departments	Peterson et al.	2024	Before going live at each site, training was provided to both ED nurses and practitioners. Nurses completed an interactive online learning module, which remains part of the onboarding process for ED nurses and has become an education requirement every two years.	(Peterson et al., 2024)
31	Clinical decision making in prostate cancer care—evaluation of EAU-guidelines use and novel decision support software	Engesser et al.	2024	Here, we also demonstrate the potential of CDSS to improve decision-making quality. Using the software, the rate of incomplete and incorrect decisions decreased from 33% to 0%, and the rate of incomplete decisions decreased from 39% to 0% compared to the first setting with no guidelines.	(Engesser et al., 2024)
32	Machine learning-based clinical decision support system for treatment recommendation and overall survival prediction of hepatocellular carcinoma	Lee et al.	2024	The proposed system can assist physicians by providing data-driven predictions for reference from other larger institutions or from other physicians within the same institution when making treatment decisions.	(Lee et al., 2024)
33	Responsibility and decision-making authority in using clinical decision support systems	Funer et al.	2024	Interviewees generally mention the following areas of responsibility: developers/providers, regulatory control bodies, healthcare institutions/supervisors, and clinical professionals. There is consensus that ML-CDSS cannot be held responsible. Instead, interviewees are concerned that colleagues could invoke ML-CDSS as an excuse and 'shift responsibility to the system'.	(Funer et al., 2024)
34	A deep learning-based clinical decision support system for glioma grading using ensemble learning and knowledge distillation	Liu et al.	2025	The CDSS enhances clinical acceptance by providing interpretable features that influence classification decisions and by automatically generating standardized diagnostic reports. This advancement substantially improves diagnostic workflow efficiency and demonstrates superior clinical deployability.	(Liu et al., 2025)
35	Rad4XCNN: A new agnostic method for post-hoc global explanation of CNN-derived features by means of Radiomics	Prinzi et al.	2025	From a practical point of view, the lack of transparency makes both doctors and patients skeptical about these new technologies. Opaque AI systems can impair the doctor-patient relationship and jeopardize patient trust.	(Prinzi et al., 2025)
36	Improving AI-based clinical decision support systems and their integration into care from the perspective of experts	Giebel et al.	2025	'Training/education' might lead to more openness to AI-based CDSS. Therefore, information on AI should be a part of both medical training and further staff training. Staff training should include educational courses or workshops on AI, its threats and limitations, and its impact on existing care pathways.	(Giebel et al., 2025)
37	Problems and barriers related to the use of AI-based clinical decision support systems	Giebel et al.	2025	Furthermore, experts saw problems with 'liability.' There were concerns that physicians were always liable for decisions, even if the errors stemmed from AI-based CDSSs. It was stated that the issue of liability is a difficult one and that, in some cases, responsibility remains unclear or is not regulated at all.	(Giebel et al., 2025)
38	Investigating clinicians' intentions and influencing factors for using an intelligence-enabled diagnostic clinical decision support system	Zheng et al.	2025	Drawing on the unique characteristics and requirements of clinical tasks, a CDSS can be tailored and optimized to align with clinicians' operational routines and bolster their decision-making processes.	(Zheng et al., 2025)

RQ1: The implementation of AI technology in clinical oncology workflows affects diagnosis times, treatment decisions, and patient outcomes for cancer patients.

The implementation of AI in clinical decision support systems (AI-CDSS) demonstrates significant effectiveness across multiple medical domains, particularly in improving diagnostic accuracy, efficiency, and transparency. In radiation therapy, machine learning models for dose-volume histograms enable real-time, explainable classification of treatment plans, enhancing clinical interpretability (Siciarz et al., 2021). Deep learning systems for lung nodule detection improve

diagnostic accuracy and efficiency, while CORAL reduces processing time without compromising safety (Zeng et al., 2022; Dugdale et al., 2021). In oncology, AI-CDSS shows strong potential in supporting therapeutic decision-making, with machine learning models for hepatocellular carcinoma achieving high recommendation accuracy across internal and external datasets (K. H. Lee et al., 2024). Additionally, AI-assisted decision systems in breast cancer management have improved adherence to clinical guidelines and influenced treatment decisions following clinician review (Xu et al., 2020).

RQ2: Legal liability in the use of AI systems for cancer diagnosis and treatment is distributed among doctors, healthcare institutions, and technology developers.

Legal responsibility in AI-CDSS remains a complex issue spanning legal, ethical, and practical dimensions, with consensus that clinical decision-making authority and liability continue to rest with healthcare professionals, as AI functions only as a supportive tool (Amann et al., 2023). This reliance on clinician oversight highlights the importance of maintaining human judgment in AI-assisted healthcare decisions. This becomes more complicated in cases of system errors, where clinicians may still bear responsibility despite limitations in current regulatory frameworks, creating uncertainty in liability attribution (Giebel et al., 2025a; Giebel et al., 2025b). The distribution of responsibility involves multiple stakeholders—including developers, regulators, healthcare institutions, and clinicians—yet AI systems themselves cannot be held legally accountable, raising concerns about potential misuse or shifting of responsibility (Funer et al., 2024). Although AI-CDSS is generally regulated as a medical device under strict safety and efficacy standards, its classification as a low-risk, human-in-the-loop system underscores the need for clearer, more adaptive regulatory frameworks to address emerging legal challenges (Ali et al., 2024).

RQ3: Effective marketing and change management strategies can increase the adoption of AI technology among oncology healthcare professionals.

Effective change management in AI-CDSS implementation requires a participatory and user-centered approach grounded in technology acceptance theory, where perceived usefulness and ease of use drive adoption among healthcare professionals (Singer et al., 2023). Key adoption factors include demonstrated clinical effectiveness, patient safety, data quality, technological awareness, and system interoperability, with more experienced clinicians showing higher trust and acceptance of AI as a supportive tool (Vijayakumar et al., 2023; Goh et al., 2024). Successful implementation further depends on active involvement of end-users in system development and deployment to ensure alignment with clinical workflows and user needs, while also supporting fairness and clinical relevance (Kočo et al., 2024; Blasiak et al., 2024). Additionally, continuous education and structured training programs—integrated into medical curricula and professional development—are essential to improve AI literacy, address risks and limitations, and ensure sustainable adoption in clinical practice (Giebel et al., 2025a; Peterson et al., 2024).

Strategic Implications and Recommendations

A synthesis of the reviewed literature highlights the augmentation paradigm as the central strategic foundation for AI-CDSS implementation, where these systems enhance rather than replace clinicians' capabilities (Besculides et al., 2023). Effective adoption requires human-centered design, ensuring that clinicians retain full decision authority while using AI as a supportive tool (Qassim et al., 2023), alongside interdisciplinary collaboration integrating medicine, cognitive science, and human-computer interaction to align technological innovation with clinical workflows (Burns et al., 2024; Clausen et al., 2023). Additionally, transparent and adaptive regulatory frameworks are essential to ensure explainability, fairness, and compliance with standards such as GDPR, thereby maintaining trust between clinicians and patients (Prinzi et al., 2025). Empirical evidence from 38 studies (2020–2025) confirms that AI-CDSS delivers measurable clinical benefits, including reductions in adverse events, faster diagnosis, and high treatment recommendation accuracy (Dugdale et al., 2021; Hah & Goldin, 2021; S. J. Lee et al., 2020). However, its implementation is constrained by challenges related to explainability, legal liability ambiguity, and user acceptance (Funer et al., 2024; Giebel et al., 2025a; Metsch et al., 2024; Prinzi et al., 2025). Addressing these issues requires structured change management, continuous education, and active user involvement in system development (Burns et al., 2024; Kočo et al., 2024). Overall, successful integration depends on a balanced approach that combines technological advancement with ethical, regulatory, and human-centered considerations to ensure optimal human–AI collaboration in healthcare (Kotsis et al., 2023; Qassim et al., 2023).

4 DISCUSSION

A systematic review of 38 studies (2020–2025) demonstrates substantial advancement in AI-CDSS for oncology, particularly in improving diagnostic accuracy and efficiency. Deep learning models have enhanced lung cancer detection by enabling faster, more precise nodule localization, while CNN-based systems such as i-Net outperform conventional models in leukemia classification, confirming the strong potential of AI for diagnostic support (Zeng et al., 2022; Ikechukwu & Murali, 2022). In therapeutic applications, AI-CDSS shows high reliability, with machine learning models for hepatocellular carcinoma achieving strong accuracy in treatment recommendations (K. H. Lee et al., 2024). Additionally, collaborative use of AI in breast cancer imaging improves clinicians' diagnostic sensitivity, underscoring AI's complementary role in clinical decision-making (Li et al., 2021). Overall, these findings reinforce a paradigm shift toward more accurate, efficient, and AI-assisted cancer care aligned with the PICO framework.

Legal responsibility in AI-based cancer diagnosis and treatment remains a multidimensional challenge, as clinical decision-making authority and liability continue to rest primarily with healthcare professionals despite the increasing use of AI-CDSS (Amann et al., 2023). This issue is particularly critical in oncology because of the high-stakes nature of treatment decisions, while existing regulations still create uncertainty regarding accountability for errors originating from AI systems, revealing significant gaps in current legal frameworks (Giebel et al., 2025a; Giebel et al., 2025b; Uihlein et al., 2024). The responsibility landscape involves multiple stakeholders—including developers, regulators, healthcare institutions, and clinicians—but AI systems themselves cannot assume legal accountability, raising concerns about potential misuse or shifting of responsibility (Funer et al., 2024). Although AI-CDSS is regulated as a medical device under strict standards, its classification as a supportive, human-in-the-loop system underscores the need for clearer, more adaptive regulatory frameworks in oncology practice (Ali et al., 2024). The successful implementation of AI-based cancer diagnostic and therapeutic technologies depends on integrated marketing and change management strategies, where user acceptance plays a central role in adoption (Singer et al., 2023). Key determinants include patient safety, data quality, technological awareness, and collaborative system functionality. More experienced physicians also tend to place greater trust in AI, viewing it as a supportive rather than mandatory tool, which highlights the importance of targeted adoption strategies (Vijayakumar et al., 2023; Goh et al., 2024). Adoption can be further strengthened through end-user involvement in system development to ensure alignment with clinical workflows and needs, reflecting a co-creation approach (Kočo et al., 2024). In addition, continuous education and training improve AI readiness among healthcare professionals, while broader stakeholder engagement and patient-centered approaches support fairness, clinical relevance, and the sustainable integration of AI into oncology practice (Giebel et al., 2025a; Blasiak et al., 2024).

5 CONCLUSION

This systematic review of 38 studies (2020–2025) demonstrates a clear paradigm shift in AI-based cancer diagnosis and therapy, showing high medical effectiveness, with diagnostic accuracy reaching 94.7%, significant reductions in diagnostic time, and improved therapeutic outcomes, such as enhanced survival rates and reduced treatment toxicity. The findings support an augmentation paradigm, where AI enhances—rather than replaces—clinical decision-making, emphasizing the need for human-centered implementation, continuous professional training, and clinician involvement. However, AI adoption in oncology remains constrained by regulatory uncertainty, unclear liability frameworks, limited transparency, and technical challenges, including reduced model performance across diverse populations and integration issues with clinical systems. Despite growing global investment and rapid market expansion, these barriers highlight the need for adaptive regulatory policies, standardized evaluation frameworks, and collaborative international research to ensure safe, effective, and scalable implementation of AI in cancer care.

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