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Artificial Intelligence for Clinical Prediction: Exploring Key Domains and Essential Functions

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ABSTRACT

Background: Clinical prediction is integral to modern healthcare, leveraging current and historical medical data to forecast health outcomes. The integration of Artificial Intelligence (AI) in this field significantly enhances diagnostic accuracy, treatment planning, disease prevention, and personalised care leading to better patient outcomes and healthcare efficiency.
Methods: This systematic review implemented a structured four-step methodology, including an extensive literature search in academic databases (PubMed, Embase, Google Scholar), applying specific inclusion and exclusion criteria, data extraction focusing on AI techniques and their applications in clinical prediction, and a thorough analysis of the collected information to understand AI's roles in enhancing clinical prediction.
Results: Through the analysis of 74 experimental studies, eight key domains, where AI significantly enhances clinical prediction, were identified: (1) Diagnosis and early detection of disease; (2) Prognosis of disease course and outcomes; (3) Risk assessment of future disease; (4) Treatment response for personalised medicine; (5) Disease progression; (6) Readmission risks; (7) Complication risks; and (8) Mortality prediction. Oncology and radiology come on top of the specialties benefiting from AI in clinical prediction.
Discussion: The review highlights AI's transformative impact across various clinical prediction domains, including its role in revolutionising diagnostics, improving prognosis accuracy, aiding in personalised medicine, and enhancing patient safety. AI-driven tools contribute significantly to the efficiency and effectiveness of healthcare delivery.
Conclusion and recommendations: AI's integration in clinical prediction marks a substantial advancement in healthcare. Recommendations include enhancing data quality and accessibility, promoting interdisciplinary collaboration, focusing on ethical AI practices, investing in AI education, expanding clinical trials, developing regulatory oversight, involving patients in the AI integration process, and continuous monitoring and improvement of AI systems.

Introduction

The field of clinical prediction is a cornerstone of modern healthcare. This process involves the use of current and historical medical data to forecast future health outcomes [1]. Clinical prediction helps in the early detection and prevention of diseases, enhancing the accuracy of diagnoses, and improving treatment planning. This results in better patient outcomes and improved efficiency of healthcare systems [2,3]. By processing extensive and complex medical data quickly and with high precision, Artificial intelligence (AI) algorithms can identify patterns and correlations that might be beyond the scope of human analysis. These algorithms are designed to continuously learn and improve from new data, which enhances their predictive accuracy over time [2,3]. By thoroughly analysing medical images, lab results, and patient histories, AI can identify signs of diseases such as cancer or cardiovascular disorders more accurately and at an earlier stage than traditional methods [4]. AI is instrumental in the advancement of personalised medicine. It helps doctors understand how different diseases progress in individual patients and predicts how they might respond to various treatments. This leads to more tailored treatment plans,

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maximising effectiveness while minimising potential side effects [5]. Furthermore, AI plays a vital role in risk assessment. It can identify patients who are at high risk of developing certain conditions based on genetic, lifestyle, and environmental factors. This enables the implementation of preventive measures delaying the onset of diseases [6].

AI also assists in predicting patient readmission risks and potential complications during medical and surgical procedures. This helps in planning and patient counselling, improving overall patient safety [7]. Moreover, AI's ability to predict mortality risks in critical and palliative care settings is invaluable. It helps in making crucial decisions regarding the intensity of treatment and end-of-life care, ensuring that patients receive appropriate and compassionate care tailored to their individual needs [8].Therefore, AI's integration into clinical prediction represents a significant leap forward in healthcare. Its ability to analyse and interpret vast amounts of medical data not only improves the accuracy of predictions but also personalizes patient care, enhances treatment effectiveness, and promotes preventive healthcare [9]. Accordingly, this systematic review seeks to extensively examine AI's role in enhancing clinical prediction functions. It focuses on identifying key areas, and clinical specialties, where AI enhances clinical prediction. This is essential for assessing AI's readiness for broader adoption, identifying research gaps, and guiding future research and development.

Methods

To conduct this systematic review, a structured four-step methodology was implemented to ensure a comprehensive and meticulous examination of relevant literature. The initial step included an extensive search across several academic databases including PubMed, Embase, and Google Scholar. The focus was on articles published in English from 2019 onwards, using keywords such as "artificial intelligence," "clinical prediction," "healthcare analytics," "predictive modelling," and "patient outcomes." This search aimed to gather peer-reviewed articles and primary studies that explored the use of AI in clinical prediction scenarios. The second step involved the development and application of specific inclusion and exclusion criteria. Studies were selected if they primarily investigated AI's role in enhancing clinical prediction, focusing on aspects like predictive accuracy, patient outcomes, and decision-making processes. Excluded were studies not centrally concerned with clinical prediction, those lacking empirical data, or with ambiguous methodologies. In the third step, relevant data were extracted from the selected studies, concentrating on the primary AI techniques used, significant findings, specific applications in clinical prediction, and the observed limitations and future recommendations. This data was then aggregated to highlight crucial areas where AI contributes to clinical prediction, identifying trends, barriers, and potential for further application in healthcare. The final step involved a thorough analysis of the collated information. This analysis aimed to clarify the roles of AI in enhancing

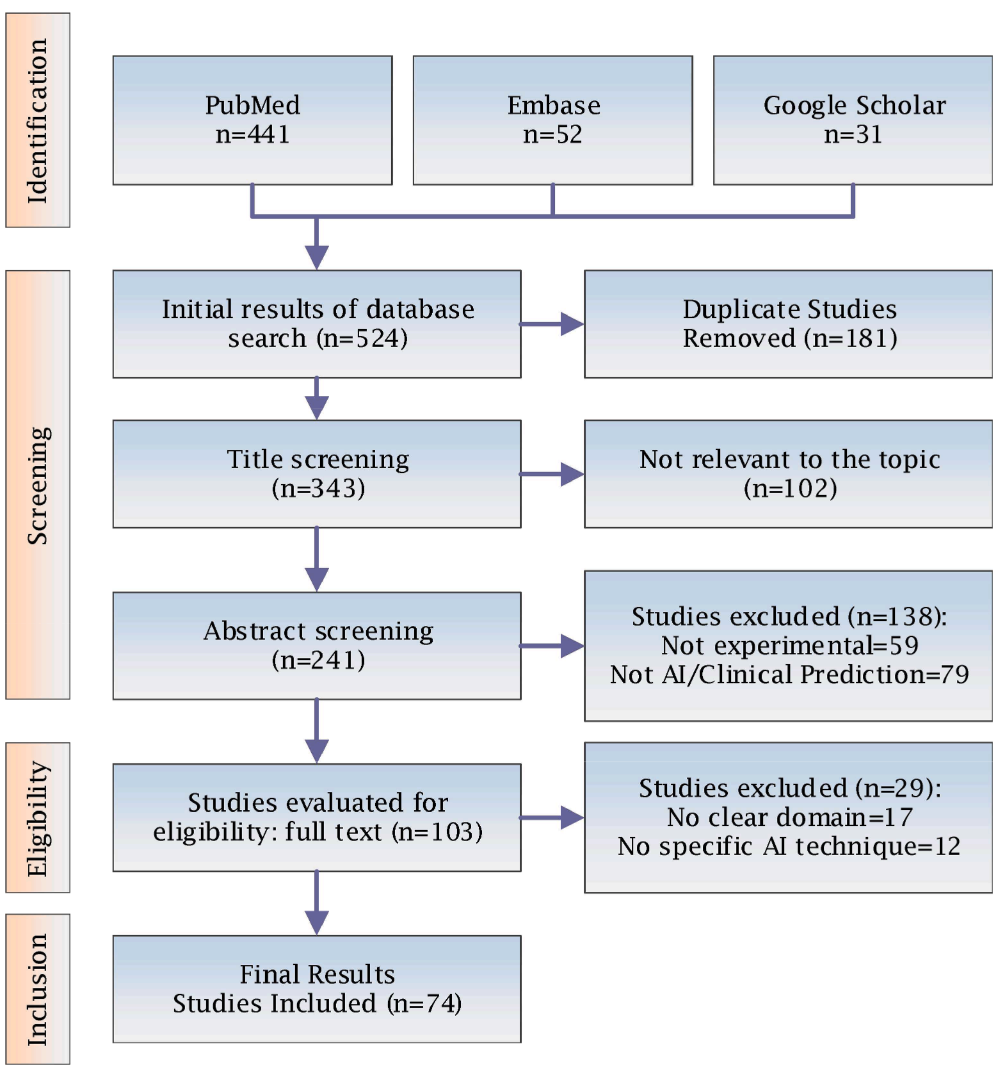

Fig. 1. PRISMA flowchart of study selection and inclusion process.

clinical prediction, noting the improvements in prediction accuracy, efficiency, and patient outcomes. Additionally, the analysis addressed the challenges in implementing AI in this field, including ethical implications, data security issues, and the integration with existing clinical workflows.

Results

Searching PubMed, Google Scholar, and Embase, 524 studies were found. After removing duplicates, 343 unique studies were identified. When inclusion and exclusion criteria were applied, 102 studies were excluded after title screening and another 138 were excluded after abstract screening. After full-text examination, 74 studies, out of 103, were included. Fig. 1 shows the study selection and inclusion processes.

Through careful qualitative analysis, this systematic review identified eight domains where AI has the potential to significantly enhance clinical prediction. The first domain, Diagnosis, involves a critical aspect of medical care; predicting the presence or absence of a disease or condition. This is done by analysing symptoms, clinical tests, and other patient data. Effective diagnostic predictions are crucial for early detection and timely treatment of diseases and medical conditions [9,10]. Among the included 74 studies, 24 discussed the role of AI-based clinical prediction for diagnosis. The second domain, Prognosis, is centred around predicting the likely course and outcomes of a disease or condition once diagnosed. This knowledge helps healthcare professionals in devising more effective treatment plans and providing patients with realistic expectations about their conditions [2,11]. This domain was discussed by 38 studies. In the third domain, Risk Assessment, the focus shifts to predicting the likelihood of a patient developing a disease or condition in the future. This prediction is based on various factors such as genetics, lifestyle, environmental exposures, and existing health conditions. Accurate risk assessment is pivotal in preventive medicine and health promotion, allowing for early interventions that can significantly alter a patient's health trajectory [12,13]. This domain was discussed by 14 studies. The fourth domain, Treatment Response, go deeper into the area of personalised medicine. Here, the aim is to predict how a patient will respond to a specific treatment or therapy. This is particularly important as it helps in tailoring treatments to individual patients, known also as personalised medicine, thereby enhancing the effectiveness of therapeutic interventions and reducing the likelihood of adverse reactions [14,15]. This domain was discussed by 22 studies.

Disease Progression, the fifth domain, is crucial for managing chronic diseases such as diabetes, heart disease, and neurological disorders. Predicting how a disease will progress over time assists healthcare professionals in planning long-term treatment strategies and anticipating future care needs, ultimately improving the quality of life for patients with chronic conditions [2,16]. This domain was discussed by nine studies. The sixth domain, Readmission Risks, utilizes predictive models to identify patients who are at high risk of being readmitted to the hospital after discharge. This knowledge enables healthcare providers to offer targeted interventions, aiming to reduce readmission rates, which is a key indicator of quality healthcare [17,18]. This domain was discussed by three studies. In the seventh domain, Complication Risks, the focus is on predicting the risk of complications, both during and after medical procedures or treatments [19,20]. This domain was discussed by nine studies. Finally, the eighth domain, Mortality Prediction, is particularly relevant in critical care and palliative care settings. Predicting the risk of mortality is important for decision-making regarding the intensity of treatment and end-of-life care planning [21,22]. This domain was discussed by 20 studies.

Table 1 and Fig. 2 show the eight domains where AI supports clinical prediction. Table 2 shows mapping of the 74 studies to the identified eight domains of AI-based clinical prediction. Accordingly, Fig. 3 shows the potential contribution of the AI to clinical prediction domains. Table 4 and 5, in the Appendix, show the detailed extracted information from the 74 studies, regarding their objectives, design, speciality, sample size,

Table 1
The AI eight domains for clinical prediction.

SN	Domains	Functions
1	Diagnosis	Predicting the presence or absence of a disease or condition based on symptoms, clinical tests, and other patient data. Diagnostic predictions are essential for early detection and timely treatment.
2	Prognosis	Predicting the likely course and outcome of a disease or condition once it has been diagnosed. Prognostic predictions help in understanding the disease's progression, potential complications, and the likely response to treatment.
3	Risk Assessment	Predicting the likelihood of a patient developing a disease or condition in the future based on various risk factors such as genetics, lifestyle, environmental exposures, and existing health conditions.
4	Treatment Response	Predicting how a patient will respond to a particular treatment or therapy. This is especially important in personalised medicine, where the goal is to tailor treatments to individual patients for maximum effectiveness.
5	Disease Progression	Predicting how a disease will progress over time is crucial for chronic diseases such as diabetes, heart disease, and neurological disorders. It helps in planning long-term treatment strategies and anticipating future care needs.
6	Readmission Risks	Hospitals and healthcare providers use predictive models to identify patients who are at high risk of being readmitted after discharge. This helps in providing targeted interventions to reduce readmission rates.
7	Complication Risks	Predicting the risk of complications, both during and after medical procedures or treatments, is vital for informed consent and for planning to mitigate those risks.
8	Mortality Prediction	In critical care and palliative care settings, predicting the risk of mortality is important for decision-making regarding treatment intensity and end-of-life care planning.

population and settings, intervention and exposure, outcome measures, AI or machine learning model used, key findings, limitations, and conclusions. n addition to the eight domains identified, the analysis of the 74 studies showed that Oncology and Radiology come on top of the specialties where AI enhances clinical prediction. Table 3 and Fig. 4 show the medical specialties discussed in the 74 studies.

Discussion

Domain one: diagnosis

Diagnosis is a vital aspect of medical care where the goal is to accurately predict the presence or absence of diseases or medical conditions [9,10]. AI algorithms, particularly those utilising machine learning and deep learning, can analyse complex and vast datasets more quickly and accurately than traditional methods. For instance, in medical imaging, AI can detect minor and complex patterns in X-rays, MRI, and CT scans that might be missed by the human eye. This capability is especially crucial in identifying early stages of diseases like cancer, where early intervention can substantially improve prognosis [4,97]. Moreover, AI-driven diagnostic tools are being integrated into primary care and telemedicine. These tools can assist healthcare professionals in making quick and accurate diagnoses by analysing symptoms reported by patients and comparing them with large medical datasets. This can make quality medical care more accessible, especially in remote or underserved areas [98]. AI in diagnostics also holds promise in personalised medicine, where it can help in identifying genetic markers and other specific factors that influence disease manifestation and progression [6,99].

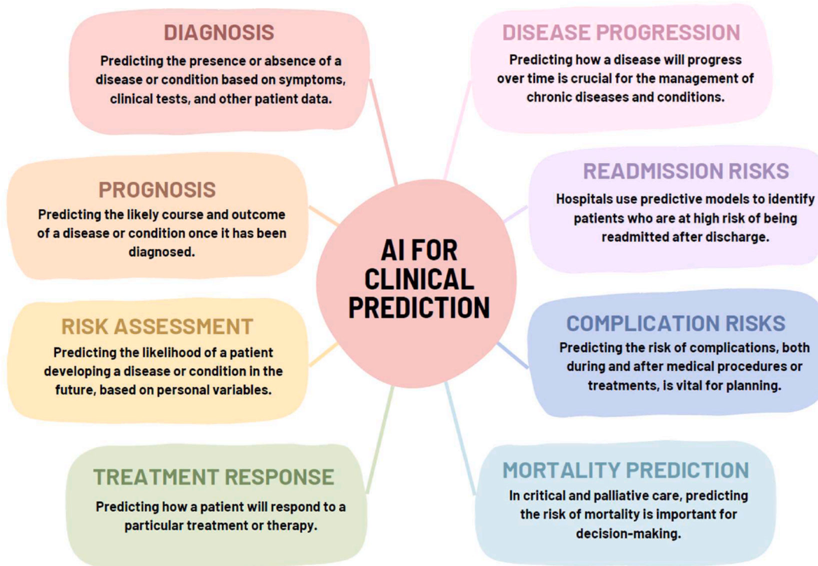

Fig. 2. AI supports eight domains of clinical prediction.

Domain two: prognosis

Prognosis involves predicting the future course and outcomes of a disease or condition after diagnosis [2,11]. In this domain, AI plays a transformative role. By leveraging large datasets and advanced algorithms, AI can identify patterns and correlations that may not be immediately apparent to human clinicians. This includes analysing progression trends of diseases, response rates to various treatments, and historical patient outcomes data. AI systems can also incorporate a wide range of variables, from genetic information to lifestyle factors, providing a more holistic and accurate prognosis [100]. For chronic and degenerative diseases like cancer, heart disease, and neurological disorders, AI-driven prognosis is particularly beneficial. It helps in understanding how these diseases are likely to progress over time, enabling healthcare providers to anticipate future complications and adjust treatment strategies accordingly. This proactive approach in managing chronic diseases can significantly improve patient quality of life and reduce long-term healthcare costs [101]. AI in prognosis also assists in personalised medicine. By understanding an individual patient's disease trajectory, treatments can be better tailored to their specific needs, improving efficacy and minimising adverse effects. This personalization is especially important in conditions with high variability in outcomes among patients [99].

Domain three: risk assessment

The risk assessment is a crucial domain in healthcare focusing on evaluating the probability of individuals developing a disease or condition in the future [12,13]. AI has become an indispensable tool in refining risk assessment. AI algorithms can process and analyse vast amounts of data, identifying risk factors and patterns that may not be immediately evident. For example, machine learning models can analyse genetic data alongside lifestyle and environmental factors to predict the risk of developing conditions like heart disease, diabetes, or certain types of cancer. This holistic approach provides a more comprehensive risk profile for each individual [4,9,102]. Moreover, AI-driven risk assessment is pivotal in public health initiatives. It aids in identifying populations at high risk for certain diseases, enabling targeted preventive measures and resource allocation. This approach is particularly effective in managing and preventing chronic diseases, which are a major challenge for global health systems [103]. AI in risk assessment also plays a role in personalised health recommendations. By understanding individual risk profiles, healthcare providers can offer tailored advice on lifestyle modifications, screening, and preventive measures. This personalised approach not only improves individual health outcomes but also contributes to more efficient and effective healthcare systems [104].

Domain four: treatment response

The treatment response is an essential facet of modern healthcare, focusing on predicting how patients will respond to specific treatments or therapies [14,15]. By leveraging advanced algorithms and large datasets, AI can analyse various factors that influence a patient's response to treatment. These factors include genetic makeup, biochemical parameters, lifestyle habits, and the presence of other health conditions. For instance, in oncology, AI models can predict how a cancer patient might respond to a particular chemotherapy regimen based on their genetic profile and the genetic characteristics of their tumour [105]. This predictive capability is not just limited to pharmacological treatments. AI systems are also being used to anticipate responses to surgical procedures, radiation therapy, and other medical interventions. This helps healthcare professionals in selecting the most appropriate treatment plan for each patient, maximising efficacy and reducing the risk of complications [106]. Furthermore, AI-driven treatment response prediction is instrumental in drug development. It enables researchers to identify which patient groups are most likely to benefit from new drugs, thereby facilitating more targeted and efficient clinical trials [107].

Domain five: disease progression

Disease Progression is a vital area in healthcare, especially for managing chronic conditions such as diabetes, heart disease, and neurological disorders [2,16]. AI has a significant impact in this area, offering advanced tools for monitoring and predicting disease progression. AI algorithms, particularly those using machine learning, can analyse large and complex datasets, including clinical records, patient histories, and biomedical data. This analysis helps in identifying patterns and markers that indicate the progression of a disease, sometimes even before clinical symptoms become apparent [108,109]. For instance, in the case of neurodegenerative diseases like Alzheimer's, AI can detect subtle changes in brain imaging or cognitive function tests that might predict the rate at which the disease will progress [110].

Table 2
Mapping the 74 studies to the eight clinical prediction domains.

SN	Study	Diagnosis	Prognosis	Risk Assessment	Treatment Response	Disease Progression	Readmission Risks	Complication Risks	Mortality Prediction
1	Wang et al., 2021 [23]	✓	✓						
2	Ma et al., 2022 [24]	✓			✓				
3	Huang et al., 2022 [25]	✓	✓						
4	Fremond et al., 2023 [26]	✓			✓				
5	Xu et al., 2021 [27]		✓						
6	Qin et al., 2021 [28]	✓	✓						
7	Salah et al., 2021 [29]				✓				
8	Shu et al., 2022 [30]	✓		✓					
9	Yue et al., 2022 [31]				✓				
10	Zhang et al., 2021 [32]	✓							
11	Groos et al., 2022 [33]	✓				✓			
12	Howell et al., 2021 [34]			✓	✓		✓		✓
13	Wen-Zhi et al., 2022 [35]	✓							
14	Cui et al., 2022 [36]		✓		✓				✓
15	Li et al., 2022 [37]		✓	✓					✓
16	Zhong et al., 2024 [38]		✓		✓	✓			
17	Liu et al., 2022 [39]			✓					
18	Feng et al., 2021 [40]	✓							✓
19	Yagi et al., 2022 [41]		✓			✓			
20	Min et al., 2021 [42]				✓				
21	El-Sappagh et al., 2021 [43]	✓							
22	Arabyarmohammadi et al., 2022 [44]			✓					✓
23	Liu et al., 2022 [45]		✓					✓	
24	Salari et al., 2023 [46]				✓				
25	Wen et al., 2023 [47]	✓	✓			✓			
26	Liu et al., 2021 [48]	✓							
27	Liu et al., 2023 [49]		✓						
28	Li et al., 2023 [50]		✓	✓	✓	✓			✓
29	Xia et al., 2023 [51]		✓			✓			✓
30	Vodencarevic et al., 2021 [52]		✓	✓			✓		
31	Li et al., 2022 [53]	✓	✓			✓			
32	Verma et al., 2022 [54]		✓	✓					
33	Hae et al., 2023 [55]			✓	✓				
34	Lee et al., 2022 [56]								✓

(continued on next page)

Table 2 (*continued*)

SN	Study	Diagnosis	Prognosis	Risk Assessment	Treatment Response	Disease Progression	Readmission Risks	Complication Risks	Mortality Prediction
35	Kong et al., 2023 [57]	✓							
36	Sundar et al., 2022 [58]		✓	✓	✓				
37	Sun et al., 2022 [59]	✓							
38	Zhang et al., 2022 [60]								✓
39	Fan et al., 2022 [61]	✓			✓				
40	Ou et al., 2022 [62]		✓					✓	
41	Luo Y et al., 2023 [63]		✓		✓				✓
42	Huang J et al., 2022 [64]	✓			✓			✓	
43	Yin P et al., 2023 [65]		✓			✓		✓	✓
44	Zhang Z et al., 2023 [66]								✓
45	Cheng M et al., 2023 [67]				✓				✓
46	Kao YT et al., 2023 [68]			✓					
47	Saux P et al., 2023 [69]		✓						
48	Li J et al., 2023 [70]		✓						
49	Faraone SV et al., 2022 [71]				✓				
50	Zhang K et al., 2023 [72]		✓						✓
51	Cai ZH et al., 2023 73]	✓							
52	Wang Y et al., 2023 74]			✓					
53	Bao Z et al., 2021 75]		✓		✓				
54	Li P et al., 2023 76]							✓	
55	Liu Y et al., 2023 77]		✓						
56	Xie N et al., 2023 78]		✓						
57	Chen X et al., 2023 79]			✓				✓	
58	Forrest LN et al., 2023 80]				✓				
59	Tan TH et al., 2021 81]	✓	✓						✓
60	Chandra RS et al., 2023 82]		✓		✓				
61	Jin Y et al., 2023 83]		✓		✓				
62	Su Z et al., 2023 84]			✓					
63	Liu Y et al., 2023 85]		✓					✓	✓
64	Wu Y et al., 2023 86]	✓							
65	Zhang K et al., 2022 87]	✓							
66	Tran QNN et al., 2023 88]		✓						✓
67	Zhang H et al., 2023 89]	✓	✓						
68	Ma X et al., 2023 90]	✓	✓						

(*continued on next page*)

Table 2 (*continued*)

SN	Study	Diagnosis	Prognosis	Risk Assessment	Treatment Response	Disease Progression	Readmission Risks	Complication Risks	Mortality Prediction
69	Li D et al., 2023 [91]		✓						✓
70	Le Y et al., 2023 [92]		✓			✓			✓
71	Zhang H et al., 2023 [93]		✓						✓
72	Etter JF et al., 2023 [94]						✓		
73	Lyu Z et al., 2023 [95]		✓					✓	
74	Huang J et al., 2023 [96]		✓						✓
Studies discussing each domain		24	38	14	22	9	3	9	20

✓ = Discussed domains in the 74 studies.

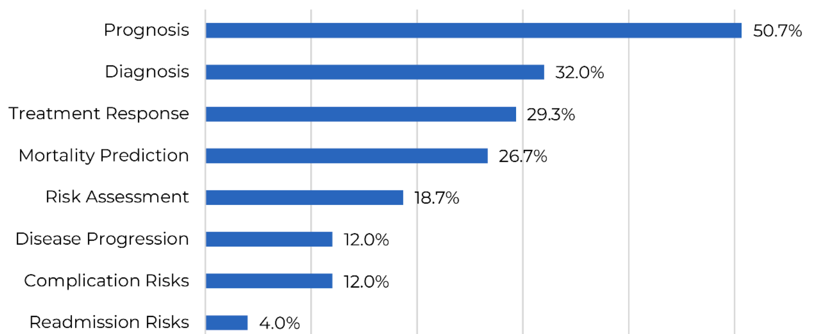

Fig. 3. AI contribution to clinical prediction domains, based on the 74 studies.

Similarly, in diabetes management, AI models can analyse blood sugar levels, lifestyle factors, and treatment responses to predict potential complications and guide adjustments in treatment plans [111,112]. AI's predictive capabilities in disease progression are not just limited to direct health outcomes. They also extend to predicting the impact of the disease on a patient's quality of life, daily functioning, and mental health. This comprehensive approach allows healthcare providers to offer more holistic and patient-centred care [113,114].

Domain six: readmission risks

Readmission Risks addresses a critical challenge in healthcare: identifying patients who are at high risk of being readmitted to the hospital shortly after discharge. This domain is particularly significant because high readmission rates are often indicators of suboptimal care and can lead to increased healthcare costs [17,18]. AI plays a pivotal role in assessing readmission risks. By analysing extensive datasets, including patient medical histories, treatment details, discharge conditions, and socio-demographic factors, AI algorithms can identify patterns and risk factors associated with higher chances of readmission. This information is crucial for healthcare providers to intervene proactively [115]. For example, AI can help in identifying patients who might need additional support post-discharge, such as those with chronic conditions like heart failure or diabetes, or elderly patients with multiple health issues. Accordingly, healthcare teams can implement targeted strategies such as arranging follow-up appointments, providing additional patient education, and ensuring proper medication management [116]. Moreover, AI-driven insights into readmission risks enable hospitals to allocate resources more efficiently, focusing on high-risk patients while optimising care for those with lower risks. This targeted approach not only improves patient care but also reduces unnecessary hospitalizations, thereby alleviating the financial strain on healthcare systems [117].

Domain seven: complication risks

Complication Risks is focused on predicting the likelihood of complications arising during or after medical procedures or treatments. This predictive capability is crucial for enhancing patient safety and improving care outcomes [19,20]. By analysing diverse data sets, including patient medical histories, the specifics of their current medical conditions, details of planned procedures, and even broader demographic data, AI algorithms can identify patterns and risk factors that might lead to complications. This could range from post-surgical infections to adverse reactions to medications or treatments [118,119]. For instance, in surgical settings, AI can evaluate a patient's risk of complications based on factors like age, underlying health conditions, and the nature of the surgery. This information is invaluable for surgeons and medical teams in planning and executing surgical interventions, allowing them to take preemptive measures to minimise risks [120]. Furthermore, AI-driven predictions are vital for informed consent processes. By providing more accurate information about potential risks, healthcare providers can ensure that patients are better informed about the procedures they are undergoing, leading to improved patient satisfaction and trust [121].

Domain eight: mortality prediction

Mortality Prediction is a sensitive yet crucial aspect of healthcare, particularly relevant in critical care and palliative care settings. This is essential for making informed decisions regarding treatment intensity and end-of-life care planning [21,22]. By analysing complex and comprehensive data sets, including patient medical histories, current health status, treatment responses, and even genetic information, AI

Table 3
Specialties where AI supports clinical prediction, based on the 74 studies.

Speciality	Number of studies
Oncology	32
Radiology	23
Neurology	11
Surgery	10
Cardiology	8
Pulmonology	5
Critical care medicine	4
Orthopaedics	4
Geriatrics	3
Psychiatry	3
Gerontology	3
Rheumatology	3
Gastroenterology	3
Urology	2
Infectious diseases	2
Pathology	2
Hepatology	2
Emergency medicine	2
Ophthalmology	2
Genetics	1
Psychology	1
Vascular medicine	1
Otolaryngology	1
Hospital management	1
Epidemiology	1
Public health	1
Addiction medicine	1
Diabetes	1
ADHD	1
Infectious disease	1
Dermatology	1
Bariatric surgery	1
Gynaecology	1
Trauma	1
Pain management	1
Endocrinology	1
Haematology	1
Neurosurgery	1
Clinical research	1
Paediatrics	1
Behavioural science	1

algorithms can identify patterns and indicators that may signify a higher risk of mortality. This predictive capability is particularly important in intensive care units, where rapid decision-making is often required [122]. AI's contribution to mortality prediction is not just about identifying those at highest risk; it also involves ensuring that patients receive appropriate levels of care. For instance, in cases where recovery is unlikely, such as patients with advanced stages of cancers, AI can help in recognising the need to shift from aggressive treatments to palliative care, focusing on the quality of life and comfort [123]. Moreover, AI-enabled mortality predictions are crucial for resource allocation in healthcare. Understanding which patients are most at risk helps in prioritising care and making critical decisions about the allocation of intensive care resources, especially in situations like pandemics or other health crises [124].

Technology landscape and innovations

The technology landscape associated with AI in clinical prediction spans various sophisticated techniques, notably Machine Learning (ML), Deep Learning (DL), and Natural Language Processing (NLP) [125]. Technological innovation in AI-supported clinical prediction, specifically through the application of Deep Learning Techniques and Large Language Models (LLMs), represents a significant leap forward in the medical field's capacity to diagnose diseases, predict outcomes, and tailor treatments to individual patients. Deep learning algorithms excel in analysing complex, large-scale datasets, including medical imaging,

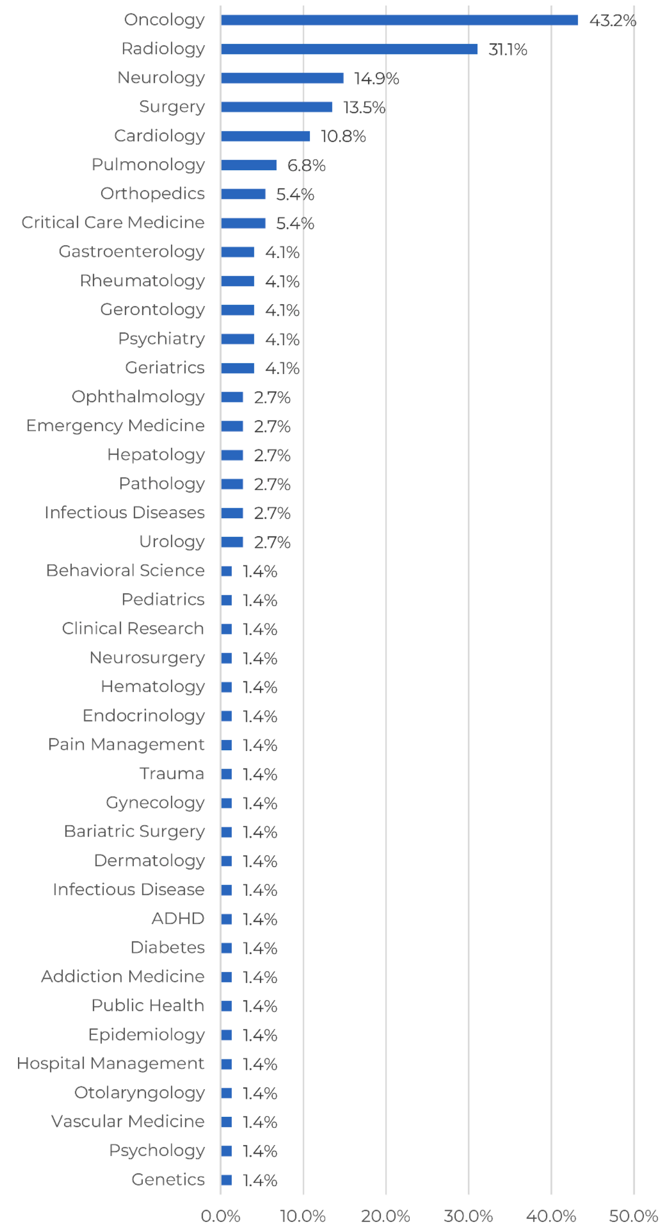

Fig. 4. Specialties where AI supports clinical prediction, based on the 74 studies.

genetic sequences, and electronic health records, uncovering patterns and anomalies that might be overlooked by traditional analytical methods [126]. This capability is crucial for early detection of diseases such as cancer, where timely intervention can dramatically improve prognosis. On the other hand, LLMs, such as GPT and BERT, have transformed the way medical professionals interpret vast amounts of unstructured text data, from clinical notes to medical research papers, enabling a deeper understanding of patient conditions and the medical landscape at large [127]. These advancements not only enhance diagnostic accuracy and prognostic predictions but also facilitate a more personalized approach to healthcare, aligning treatments with individual patient profiles for optimal outcomes. This synergy between AI technologies and medical expertise is paving the way for a future where healthcare is more efficient, effective, and patient-centred [6,9].

Conclusion and recommendations

AI has significantly advanced clinical prediction through its ability to process complex datasets. In diagnostics, AI enhances early disease detection accuracy, facilitating timely interventions. It aids in prognosis by predicting disease progression and outcomes, supporting more effective treatments. AI's analysis of various factors improves risk assessment for disease development, essential in preventive medicine. In personalised medicine, AI is key in predicting treatment responses, customising care to individual needs. It's also beneficial in managing chronic diseases, anticipating progression for proactive care. AI tools identify patients with high readmission risks, supporting targeted interventions, and improve complication risk predictions to enhance patient safety. Furthermore, AI offers critical insights in mortality prediction.

Based on the findings of this review, the following eight recommendations are proposed to optimise the integration of AI in clinical prediction. (1) Enhance Data Quality and Accessibility: Ensure the collection of high-quality, diverse, and comprehensive healthcare data to train AI models effectively. Improved data sharing protocols should be established to facilitate access to diverse datasets while maintaining patient privacy and data security. (2) Promote Interdisciplinary Collaboration: Encourage collaboration between AI experts, healthcare professionals, and researchers. This collaboration will foster the development of AI tools that are clinically relevant and user-friendly for healthcare providers. (3) Focus on Ethical and Transparent AI Practices: Develop AI systems with ethical considerations and transparency. This includes addressing biases in AI algorithms, ensuring equitable healthcare delivery, and maintaining transparency in AI decision-making processes. (4) Invest in AI Education and Training: Provide education and training for healthcare professionals on AI tools and their applications in clinical prediction. This will enhance their ability to interpret AI-generated predictions and integrate them into clinical practice. (5) Expand Clinical Trials and Research: Conduct extensive clinical trials to validate the efficacy and safety of AI applications in clinical prediction. Further research should also focus on exploring the potential of AI in unexplored areas of healthcare. (6) Regulatory Oversight and Guidelines: Develop and implement regulatory frameworks and guidelines to govern the use of AI in clinical prediction. This will ensure that AI tools meet quality and safety standards before their clinical implementation. (7) Patient Engagement and Consent: Involve patients in the AI integration process, ensuring they are informed about how AI is used in their care. Patient consent should be sought, especially in cases where AI influences critical healthcare decisions. (8) Continuous Monitoring and Improvement: Regularly monitor the performance of AI systems in clinical settings and make iterative improvements based on feedback from healthcare providers and patients.

Declaration on the use of AI in the writing process

The authors of this manuscript declare that in the writing process of this work, no generative artificial intelligence (AI) or AI-assisted technologies were used to generate content, ideas, or theories. We utilized AI solely for the purpose of enhancing readability and refining language. This use was under strict human oversight and control. After the application of AI technologies, the authors carefully reviewed and edited the manuscript to ensure its accuracy and coherence. The authors understand the potential of AI to generate content that may sound authoritative yet might be incorrect, incomplete, or biased. Considering this, the authors ensured that the manuscript was thoroughly revised by human eyes and judgement. In line with Elsevier's Authorship Policy, the authors confirm that no AI or AI-assisted technologies have been listed as an author or co-author of this manuscript. The authors fully comprehend that authorship comes with responsibilities and tasks that can only be attributed to and performed by humans, and authors have adhered to these guidelines in the preparation of this manuscript.

CRediT authorship contribution statement

Mohamed Khalifa: Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Mona Albadawy:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare no conflicting interests to declare regarding the publication of this manuscript.

Supplementary materials

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Appendix

Table 4: Objectives, Design, Specialties, Sample, and Population of the 74 Studies

SN	Study	Title	Study Objectives	Study Design	Specialty	Sample Size	Population/Setting
1	Wang et al., 2021 [23]	A Machine Learning Model for Accurate Prediction of Sepsis in ICU Patients.	To develop an AI algorithm for early prediction of sepsis	Secondary analysis of an observational cohort study	Critical Care Medicine, Informatics	4,449	ICU patients, First Affiliated Hospital of Zhengzhou University
2	Ma et al., 2022 [24]	Predicting the molecular subtype of breast cancer and identifying interpretable imaging features using machine learning algorithms.	Evaluate machine learning models in predicting breast cancer subtypes	Retrospective study	Oncology, Radiology	600	Patients with invasive breast carcinoma
3	Huang et al., 2022 [25]	Development and validation of a preoperative CT-based radiomic nomogram to predict pathology invasiveness in patients with a solitary pulmonary nodule: a machine learning approach, multicenter, diagnostic study.	Develop and validate a nomogram for preoperative CT-based prediction	Retrospective, multicenter, diagnostic study	Pulmonology, Radiology	373	Patients with a solitary pulmonary nodule
4	Fremond et al., 2023 [26]	Interpretable deep learning model to predict the molecular classification of endometrial cancer from haematoxylin and eosin-stained whole-slide images: a combined analysis of the PORTEC randomised trials and clinical cohorts.	Predict molecular classification of endometrial cancer from images	Combined analysis of randomised trials and cohorts	Oncology, Pathology	2,028	Patients with intermediate-to-high-risk endometrial cancer
5	Xu et al., 2021 [27]	Prognostic prediction of hypertensive intracerebral hemorrhage using CT radiomics and machine learning.	Establish outcome prediction models for hypertensive intracerebral hemorrhage	Retrospective study	Neurology, Radiology	270	Patients with hypertensive intracerebral hemorrhage (HICH)
6	Qin et al., 2021 [28]	Machine-learning radiomics to predict early recurrence in perihilar cholangiocarcinoma after curative resection.	Develop a model integrating clinicopathology, molecular pathology, and radiology to predict early recurrence in perihilar cholangiocarcinoma	Retrospective analysis at 2 institutions	Oncology, Gastroenterology	274	Patients with perihilar cholangiocarcinoma (PHC)
7	Salah et al., 2021 [29]	Prediction of treatment effect perception in cosmetics using machine learning.	Predict treatment effect perception using Random Forest classifier	Analysis of three randomised double-blind clinical studies	Dermatology, Clinical Research	50	Subjects in cosmetic clinical studies
8	Shu et al., 2022 [30]	Predicting Chronic Myocardial Ischemia Using CCTA-Based Radiomics Machine Learning Nomogram.	Develop a CT-based radiomics machine learning nomogram for predicting chronic myocardial ischemia (MIS)	Retrospective analysis of patients with CAD	Cardiology, Radiology	154	Patients with coronary artery disease (CAD)
9	Yue et al., 2022 [31]	Dose prediction via distance-guided deep learning: Initial development for nasopharyngeal carcinoma radiotherapy.	Develop a dose prediction method for nasopharyngeal carcinoma radiotherapy using distance information and mask information	Retrospective study including an external cohort	Oncology, Radiology	161	Patients with nasopharyngeal carcinoma
10	Zhang et al., 2021 [32]	Development and validation of MRI-based deep learning models for prediction of microsatellite instability in rectal cancer.	Develop and validate MRI-based deep learning models for prediction of microsatellite instability (MSI) in rectal cancer	Single-center retrospective study	Oncology, Radiology	491	Patients with rectal cancer

11	Groos et al., 2022 [33]	Development and Validation of a Deep Learning Method to Predict Cerebral Palsy From Spontaneous Movements in Infants at High Risk.	Develop a deep learning method to predict cerebral palsy (CP) based on infant movements at a corrected age of 12-89 months	Prognostic study involving multiple hospitals	Neurology, Pediatrics	557	Infants at high risk of perinatal brain injury
12	Howell et al., 2021 [34]	Using Machine-Learning for Prediction of the Response to Cardiac Resynchronization Therapy: The SMART-AV Study.	Develop a prediction model for short-term CRT response to identify CRT candidates for early multidisciplinary care	Analysis of the SMART-AV trial	Cardiology	741	Patients with heart failure (HF)
13	Wen-Zhi et al., 2022 [35]	Prediction of pathological staging and grading of renal clear cell carcinoma based on deep learning algorithms.	Develop a model to predict staging and grading of renal clear cell carcinoma using deep learning algorithms	Analysis of patients from the Department of Urology	Oncology, Urology	878	Patients with renal clear cell carcinoma
14	Cui et al., 2022 [36]	Machine learning models predict overall survival and progression free survival of non-surgical esophageal cancer patients with chemoradiotherapy based on CT image radiomics signatures.	Construct machine learning models for predicting progression free survival (PFS) and overall survival (OS) in esophageal squamous cell carcinoma (ESCC) patients	Analysis of 204 ESCC patients	Oncology, Radiology	204	ESCC patients receiving chemoradiotherapy
15	Li et al., 2022 [37]	Machine-learning based prediction of prognostic risk factors in patients with invasive candidiasis infection and bacterial bloodstream infection: a singled centered retrospective study.	Predict prognostic risk factors in patients with invasive candidiasis infection using machine learning	Retrospective study at a single center	Infectious Disease, Critical Care Medicine	246	Hospitalised patients with invasive candidiasis infection
16	Zhong et al., 2024 [38]	Deep Learning Radiomics Nomogram Based on Enhanced CT to Predict the Response of Metastatic Lymph Nodes to Neoadjuvant Chemotherapy in Locally Advanced Gastric Cancer.	Predict response of metastatic lymph nodes to NACT in LAGC using deep learning radiomics nomogram	Prospective study	Oncology, Radiology	112	Patients with LAGC receiving NACT
17	Liu et al., 2022 [39]	Predictive Models for Knee Pain in Middle-Aged and Elderly Individuals Based on Machine Learning Methods.	Develop prediction models for knee pain in middle-aged and elderly individuals using machine learning	Analysis of data from the National Health and Nutrition...	Orthopedics, Gerontology	5386	Middle-aged and elderly individuals
18	Feng et al., 2021 [40]	Machine learning algorithm outperforms fibrosis markers in predicting significant fibrosis in biopsy-confirmed NAFLD.	Develop a machine learning algorithm to predict fibrosis severity in NAFLD compared to non-invasive fibrosis biomarkers	Analysis of adults with biopsy-proven NAFLD	Gastroenterology, Hepatology	553	Adults with biopsy-proven NAFLD
19	Yagi et al., 2022 [41]	Development and validation of machine learning-based predictive model for clinical outcome of decompression surgery for lumbar spinal canal stenosis.	Develop a machine learning model to predict postoperative outcomes of decompression surgery for LSS	Multicentered retrospective study	Orthopedics, Neurosurgery	848	Patients undergoing decompression surgery for LSS
20	Min et al., 2021 [42]	Prediction of Coronary Stent Underexpansion by Pre-Procedural Intravascular Ultrasound-Based Deep Learning.	Develop IVUS-based models to predict the occurrence of stent underexpansion in coronary intervention	Analysis of 618 coronary lesions	Cardiology	618	Patients undergoing percutaneous coronary intervention
21	El-Sappagh et al., 2021 [43]	A multilayer multimodal detection and prediction model based on explainable artificial intelligence for Alzheimer's disease.	Develop an accurate and interpretable AD diagnosis and progression detection model	Analysis of data from Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset	Neurology, Gerontology	1048	294 cognitively normal, 254 stable MCI, 232 progressive MCI, 268 AD

22	Arabyarmohammadi et al., 2022 [44]	Machine Learning to Predict Risk of Relapse Using Cytologic Image Markers in Patients With Acute Myeloid Leukemia Posthematopoietic Cell Transplantation.	Predict relapse and prognosticate RFS after HCT in AML/MDS patients using myeloblasts' chromatin patterns	Study on Wright-Giemsa-stained post-HCT aspirate images	Hematology	92	Patients with AML/MDS undergoing HCT
23	Liu et al., 2022 [45]	Machine learning-based random forest for predicting decreased quality of life in thyroid cancer patients after thyroidectomy.	Predict decreased QoL in thyroid cancer patients post-thyroidectomy using machine learning	Prospective cross-sectional study	Endocrinology, Oncology	286	Thyroid cancer patients post-thyroidectomy
24	Salari et al., 2023 [46]	Using machine learning to predict gamma passing rate in volumetric-modulated arc therapy treatment plans.	Develop an algorithm to predict GPR in VMAT technique	Analysis of 118 clinical VMAT plans	Oncology, Radiation Therapy	118	Various cancer cases using VMAT technique
25	Wen et al., 2023 [47]	Deep learning-based postoperative visual acuity prediction in idiopathic epiretinal membrane.	Develop a DL model to predict postoperative visual outcomes in iERM patients based on preoperative OCT	Retrospective cohort study	Ophthalmology	442	Patients with idiopathic epiretinal membrane (iERM)
26	Liu et al., 2021 [48]	A deep learning model integrating mammography and clinical factors facilitates the malignancy prediction of BI-RADS 4 microcalcifications in breast cancer screening.	Improve malignancy prediction of BI-RADS 4 microcalcifications in breast cancer screening using DL model	Retrospective study	Radiology, Oncology	384	Patients with BI-RADS 4 microcalcifications
27	Liu et al., 2023 [49]	Construction and validation of machine learning models for sepsis prediction in patients with acute pancreatitis.	Construct predictive models for risk of sepsis in AP patients using machine learning methods	Retrospective cohort study	Gastroenterology, Critical Care Medicine	1672	Patients with Acute Pancreatitis (AP) from MIMIC III and IV databases
28	Li et al., 2023 [50]	Machine learning methods for accurately predicting survival and guiding treatment in stage I and II hepatocellular carcinoma.	Predict survival and guide treatment in early-stage HCC using machine learning models	Analysis of SEER database data	Oncology	1136	Patients with stage I and II hepatocellular carcinoma (HCC)
29	Xia et al., 2023 [51]	Prediction of lung papillary adenocarcinoma-specific survival using ensemble machine learning models.	Predict cancer-specific survival in LPADC using ensemble machine learning and Cox regression models	Study using SEER database	Oncology	3615	Patients diagnosed with LPADC
30	Vodencarevic et al., 2021 [52]	Advanced machine learning for predicting individual risk of flares in rheumatoid arthritis patients tapering biologic drugs.	Predict individual risk of flares in RA patients tapering biologic drugs using advanced machine learning	Analysis of data from a randomised controlled trial	Rheumatology	Data of 135 visits from 41 patients	RA patients on bDMARDs in sustained remission
31	Li et al., 2022 [53]	Combining machine learning with radiomics features in predicting outcomes after mechanical thrombectomy in patients with acute ischemic stroke.	Predict prognosis after mechanical thrombectomy in stroke patients	Retrospective	Neurology	260	Stroke patients receiving mechanical thrombectomy
32	Verma et al., 2022 [54]	Exploratory application of machine learning methods on patient reported data in the development of supervised models for predicting outcomes.	Explore ML methods to predict outcomes from PROMs in neck/back pain patients	Exploratory study	Orthopedics, Pain Management	PROMs from two datasets	Neck/back pain patients
33	Hae et al., 2023 [55]	Machine Learning-Based prediction of Post-Treatment ambulatory blood pressure in patients with hypertension.	Predict individual BP response to anti-hypertensive medication using ABPM data	Study with ABPM data	Cardiology	1129	Hypertension patients
34	Lee et al., 2022 [56]	A Machine Learning-Based Prognostic Model for the Prediction of Early Death After Traumatic Brain Injury: Comparison with the Corticosteroid Randomization After Significant Head Injury (CRASH) Model.	Develop ML models for early death prediction in traumatic brain injury	Retrospective review	Neurology, Trauma	423	Traumatic brain injury patients

35	Kong et al., 2023 [57]	Preoperative prediction and histological stratification of intracranial solitary fibrous tumours by machine-learning models.	Differentiate ISFT from AM and stratify ISFT histologically using ML models	Retrospective	Oncology, Neurology	268	Patients with ISFT or AM
36	Sundar et al., 2022 [58]	Machine-learning model derived gene signature predictive of paclitaxel survival benefit in gastric cancer: results from the randomised phase III SAMIT trial.	Identify gene signature predictive of paclitaxel benefit in GC patients	Analysis of SAMIT trial data	Oncology	499	Gastric cancer patients
37	Sun et al., 2022 [59]	Texture Features of Computed Tomography Image under the Artificial Intelligence Algorithm and Its Predictive Value for Colorectal Liver Metastasis.	Investigate CT image texture features' predictive role for CRLM	Research study	Oncology, Radiology	150	Colorectal cancer patients
38	Zhang et al., 2022 [60]	Construction and validation of nomograms combined with novel machine learning algorithms to predict early death of patients with metastatic colorectal cancer.	Develop prognostic models for early death in mCRC patients	Analysis of SEER database data	Oncology	35,639	Metastatic colorectal cancer patients
39	Fan et al., 2022 [61]	Machine learning analysis for the noninvasive prediction of lymphovascular invasion in gastric cancer using PET/CT and enhanced CT-based radiomics and clinical variables.	Develop predictive models for LVI in gastric cancer using PET/CT and CT radiomics	Retrospective study	Oncology, Radiology	101	Gastric cancer patients
40	Ou et al., 2022 [62]	Prediction of Postoperative Pathologic Risk Factors in Cervical Cancer Patients Treated with Radical Hysterectomy by Machine Learning.	Predict PRF in CC patients treated with RH using ML	Retrospective analysis	Oncology, Gynecology	1260	Early-stage cervical cancer patients
41	Luo Y et al., 2023 [63]	A DWI-based radiomics-clinical machine learning model to preoperatively predict the futile recanalization after endovascular treatment of acute basilar artery occlusion patients.	Develop an ML model to predict futile recanalization in ABAO patients with EVT	Retrospective analysis	Neurology, Radiology	132	Acute basilar artery occlusion patients
42	Huang J et al., 2022 [64]	Development and validation of a combined nomogram model based on deep learning contrast-enhanced ultrasound and clinical factors to predict preoperative aggressiveness in pancreatic neuroendocrine neoplasms.	Develop a model to predict preoperative aggressiveness in PNENs	Retrospective study	Oncology, Radiology	104	Patients with histologically proven PNENs
43	Yin P et al., 2023 [65]	Machine Learning Using Presentation CT Perfusion Imaging for Predicting Clinical Outcomes in Patients With Aneurysmal Subarachnoid Hemorrhage.	Evaluate ML models for predicting clinical outcomes in aSAH patients	Retrospective analysis	Neurology	242	Aneurysmal subarachnoid hemorrhage patients
44	Zhang Z et al., 2023 [66]	Using machine learning methods to predict 28-day mortality in patients with hepatic encephalopathy.	Develop ML models for predicting 28-day mortality in HE patients	Retrospective cohort	Hepatology	601	Patients with hepatic encephalopathy
45	Cheng M et al., 2023 [67]	Deep learning for predicting the risk of immune checkpoint inhibitor-related pneumonitis in lung cancer.	Develop a model for early prediction of ICI-related pneumonitis in lung cancer patients	Retrospective study	Oncology, Pulmonology	141	Lung cancer patients receiving ICI therapy
46	Kao YT et al., 2023 [68]	Machine Learning-Based Prediction of Atrial Fibrillation Risk Using Electronic Medical Records in Older Aged Patients.	Develop a model to predict 1-year new-onset AF risk in older patients using medical records	Retrospective study	Cardiology, Gerontology	10,690	Older aged patients without prior AF

47	Saux P et al., 2023 [69]	Development and validation of an interpretable machine learning-based calculator for predicting 5-year weight trajectories after bariatric surgery: a multinational retrospective cohort SOPHIA study.	Develop a model for individual preoperative prediction of 5-year weight loss trajectories after bariatric surgery	Multinational cohort	Bariatric Surgery	10,231	Adult patients undergoing bariatric surgery
48	Li J et al., 2023 [70]	Machine Learning-Based Development of Nomogram for Hepatocellular Carcinoma to Predict Acute Liver Function Deterioration After Drug-Eluting Beads Transarterial Chemoembolization.	Develop a nomogram to predict ALFD after DEB-TACE in patients with HCC	Retrospective study	Oncology	288	Patients with hepatocellular carcinoma (HCC) undergoing DEB-TACE
49	Faraone SV et al., 2022 [71]	Predicting efficacy of viloxazine extended-release treatment in adults with ADHD using an early change in ADHD symptoms: Machine learning Post Hoc analysis of a phase 3 clinical trial.	Determine if early response to viloxazine ER predicts efficacy outcome in adults with ADHD	Post-hoc analysis	Psychiatry, ADHD	354	Adults with ADHD participating in a clinical trial
50	Zhang K et al., 2023 [72]	Using deep learning to predict survival outcome in non-surgical cervical cancer patients based on pathological images.	Analyse clinical features and pathologic images to predict 5-year overall survival in non-surgical cervical cancer patients	Retrospective analysis	Oncology, Radiology, Pathology	238	Non-surgical cervical cancer patients treated with radiochemotherapy
51	Cai ZH et al., 2023 [73]	Magnetic resonance imaging-based deep learning model to predict multiple firings in double-stapled colorectal anastomosis.	Develop a model to predict the need for multiple linear stapler cartridges in DST anastomosis based on MRI	Retrospective study	Surgery, Radiology	328	Mid-low rectal cancer patients undergoing LAR with DST anastomosis
52	Wang Y et al., 2023 [74]	Development and validation of a prediction model based on machine learning algorithms for predicting the risk of heart failure in middle-aged and older US people with prediabetes or diabetes.	Develop and validate a ML model to predict the risk of heart failure in patients with prediabetes or diabetes	Analysis of survey data	Cardiology, Diabetes	3527	Middle-aged and older US people with prediabetes or diabetes
53	Bao Z et al., 2021 [75]	Prediction of repeated-dose intravenous ketamine response in major depressive disorder using the GWAS-based machine learning approach.	Predict treatment outcomes for repeated-dose intravenous ketamine in MDD patients using genotyping information	Retrospective analysis	Psychiatry, Genetics	83	Major depressive disorder patients receiving ketamine treatment
54	Li P et al., 2023 [76]	Prediction of postoperative infection in elderly using deep learning-based analysis: an observational cohort study.	Develop and validate deep learning models to predict postoperative infections in elderly undergoing surgery	Observational cohort	Surgery, Geriatrics	2014	Elderly patients who had elective surgery from 28 hospitals in China
55	Liu Y et al., 2023 [77]	Functional Outcome Prediction in Acute Ischemic Stroke Using a Fused Imaging and Clinical Deep Learning Model.	Predict the 90-day mRS score in acute ischemic stroke patients by fusing a deep learning model of diffusion-weighted imaging images and clinical information	Retrospective study	Neurology, Radiology	640	Acute ischemic stroke patients
56	Xie N et al., 2023 [78]	Preoperative Extrapancreatic Extension Prediction in Patients with Pancreatic Cancer Using Multiparameter MRI and Machine Learning-Based Radiomics Model.	Predict extrapancreatic extension (EPE) in patients with pancreatic cancer preoperatively based on multiparameter MRI and machine learning-based radiomics	Retrospective study	Oncology, Radiology, Surgery	156	Patients with pancreatic cancer

57	Chen X et al., 2023 [79]	Application of machine learning model in predicting the likelihood of blood transfusion after hip fracture surgery.	Develop machine learning models to predict the likelihood of postoperative blood transfusion in patients undergoing hip fracture surgery	Retrospective study	Orthopedics, Surgery	1355	Patients undergoing hip fracture surgery at the Affiliated Hospital of Qingdao University
58	Forrest LN et al., 2023 [80]	Machine learning v. traditional regression models predicting treatment outcomes for binge-eating disorder from a randomised controlled trial.	Compare the accuracy of traditional and machine-learning approaches in predicting BED treatment outcomes	Randomised controlled trial	Psychiatry, Psychology	191	Adults with binge-eating disorder (BED) in a treatment trial
59	Tan TH et al., 2021 [81]	Predicting outcomes in older ED patients with influenza in real time using a big data-driven and machine learning approach to the hospital information system.	Implement ML to predict outcomes in older ED patients with influenza	Retrospective study	Emergency Medicine, Geriatrics, Infectious Diseases	5508	Older emergency department (ED) patients with influenza in three hospitals
60	Chandra RS et al., 2023 [82]	Evaluation of Multiple Machine Learning Models for Predicting Number of Anti-VEGF Injections in the Comparison of AMD Treatment Trials (CATT).	Apply ML models to predict the number of PRN injections of anti-VEGF for neovascular AMD in two years	Retrospective analysis	Ophthalmology, Radiology, Otolaryngology	493	Participants with nAMD randomised to PRN treatment in the CATT trial
61	Jin Y et al., 2023 [83]	Development and testing of a random forest-based machine learning model for predicting events among breast cancer patients with a poor response to neoadjuvant chemotherapy.	Develop models to predict events in breast cancer patients with a poor response to neoadjuvant chemotherapy	Retrospective study	Oncology, Surgery	315	Breast cancer patients with stable disease or progressive disease after neoadjuvant chemotherapy
62	Su Z et al., 2023 [84]	Clinical model of pulmonary metastasis in patients with osteosarcoma: A new multiple machine learning-based risk prediction.	Construct a clinical prediction model for osteosarcoma patients to evaluate factors influencing the occurrence of pulmonary metastasis	Retrospective study	Oncology, Radiology, Surgery	612	Patients with osteosarcoma
63	Liu Y et al., 2023 [85]	Application of machine learning algorithms in electronic medical records to predict amputation-free survival after first revascularization in patients with peripheral artery disease.	Apply ML algorithms to develop a model predicting amputation-free survival (AFS) after first revascularization in peripheral artery disease (PAD) patients	Retrospective study	Cardiology, Vascular Medicine, Surgery	2130	Patients with peripheral artery disease undergoing revascularization
64	Wu Y et al., 2023 [86]	A retrospective study using machine learning to develop predictive model to identify urinary infection stones in vivo.	Develop a ML model for preoperative identification of infection stones in vivo	Retrospective study	Urology, Infectious Diseases	2565	Patients with urolithiasis who underwent surgery
65	Zhang K et al., 2022 [87]	The diagnostic value of machine-learning-based model for predicting the malignancy of solid nodules in multiple pulmonary nodules.	Examine the efficacy of a ML diagnostic model for solid nodules in multiple pulmonary nodules combining patient clinical information and CT features	Retrospective study	Radiology, Pulmonology	446	Patients with multiple pulmonary nodules
66	Tran QNN et al., 2023 [88]	A Machine Learning-Based Model to Predict In-Hospital Mortality of Lung Cancer Patients: A Population-Based Study of 523,959 Cases.	Stratify new lung cancer patients based on the risk of in-hospital mortality rate after diagnosis	Population-based study	Oncology, Epidemiology	523,959	Lung cancer cases from SEER database
67	Zhang H et al., 2023 [89]	Predicting N2 lymph node metastasis in presurgical stage I-II non-small cell lung cancer using multiview radiomics and deep learning method.	Develop a model to predict N2 lymph node metastasis in presurgical stage I-II non-small cell lung cancer (NSCLC) using multiview radiomics and deep learning method	Retrospective study	Oncology, Radiology, Surgery	140	NSCLC patients at stage I-II

68	Ma X et al., 2023 [90]	Development and validation of a deep learning signature for predicting lymph node metastasis in lung adenocarcinoma: comparison with radiomics signature and clinical-semantic model.	Develop a deep learning (DL) signature to predict lymph node metastasis in lung adenocarcinoma patients	Retrospective study	Oncology, Radiology, Surgery	612	Patients with lung adenocarcinoma
69	Li D et al., 2023 [91]	Prediction of mortality in pneumonia patients with connective tissue disease treated with glucocorticoids or/and immunosuppressants by machine learning.	Construct a nomogram for predicting 90-day mortality in pneumonia patients with connective tissue disease treated with glucocorticoids or/and immunosuppressants	Retrospective analysis	Pulmonology, Rheumatology	368	Pneumonia patients with connective tissue disease treated with glucocorticoids or/and immunosuppressants
70	Le Y et al., 2023 [92]	The Construction and Validation of a new Predictive Model for Overall Survival of Clear Cell Renal Cell Carcinoma Patients with Bone Metastasis Based on Machine Learning Algorithm.	Develop and validate ML-based predictive models for patients with bone metastases from clear cell renal cell carcinoma (ccRCC) and identify appropriate models for clinical decision-making	Retrospective study	Oncology, Radiology, Surgery	1532	Clear cell renal cell carcinoma patients with bone metastasis
71	Zhang H et al., 2023 [93]	Construction and evaluation of an artificial intelligence-based risk prediction model for death in patients with nasopharyngeal cancer.	Screen risk factors for death in nasopharyngeal carcinoma (NPC) patients and establish a risk prediction model using AI technology	Retrospective study	Oncology, Legal Studies	2116	NPC patients in SEER database and Bengbu Medical College
72	Etter JF et al., 2023 [94]	Predicting smoking cessation, reduction and relapse six months after using the Stop-Tabac app for smartphones: a machine learning analysis.	Identify predictors of smoking cessation, reduction, and relapse among users of the Stop-Tabac smoking cessation app	Secondary analysis	Public Health, Addiction Medicine, Behavioral Science	5293	Daily smokers from Switzerland and France using Stop-Tabac app
73	Lyu Z et al., 2023 [95]	Establishment and evaluation of a predictive model for early neurological deterioration after intravenous thrombolysis in acute ischemic stroke based on machine learning	Establish a model to predict the risk of early neurological deterioration (END) in patients with acute ischemic stroke (AIS) after intravenous thrombolysis	Retrospective analysis	Neurology, Emergency Medicine, Cardiology	704	AIS patients receiving intravenous thrombolytic at Qinhuangdao City Hospital
74	Huang J et al., 2023 [96]	Twenty-eight-day in-hospital mortality prediction for elderly patients with ischemic stroke in the intensive care unit: Interpretable machine learning models	Establish and validate ML models for 28-day in-hospital mortality prediction in elderly patients with ischemic stroke (IS) in the ICU	Retrospective analysis	Neurology, Geriatrics, Critical Care Medicine	1236	Elderly patients with IS in the ICU from eICU Collaborative Research Database

Table 5: Intervention, Outcomes, Findings, Limitations, and Conclusions of 74 Studies

SN	Study	Intervention/Exposure	Outcome Measures	AI or Machine Learning Model Used	Key Findings	Limitations	Conclusion
1	Wang et al., 2021 [23]	Analysis of electronic medical record data	Onset of sepsis	Random forest machine-learning model	AUC: 0.91, Sensitivity: 87%, Specificity: 89%. Good	Limited to the specific hospital's ICU patients; may not generalise	Newly established machine learning-based model shows good predictive ability in Chinese sepsis

					predictive ability in Chinese sepsis patients.	to other populations.	patients. External validation needed to confirm universality.
2	Ma et al., 2022 [24]	Clinical characteristics and imaging features	Breast cancer molecular subtypes	Decision tree (DT) and others	DT model: AUC: 0.971; accuracy: 0.947. Improved radiologist performance in predicting subtypes with model assistance.	Limited to invasive breast carcinoma; findings may not apply to other types of breast cancer or early stages.	Machine learning model assists in differentiating breast cancer molecular subtypes, significantly improving radiologist performance.
3	Huang et al., 2022 [25]	CT-based radiomic and clinical-radiological signatures	Pathology invasiveness	LASSO algorithm and logistic regression	AUCs: 0.93, 0.91, 0.90. Accurately predicts interstitial invasion in solitary pulmonary nodules.	Limited to early-stage non-small-cell lung cancer; generalizability to other lung conditions or stages unclear.	Nomogram combining clinical-radiological and radiomic signatures accurately predicts pathology invasiveness in solitary pulmonary nodules, aiding in clinical decision-making.
4	Fremond et al., 2023 [26]	Haematoxylin and eosin-stained whole-slide images	Molecular classification of endometrial cancer	Deep learning pipeline (im4MEC)	Macro-average AUROCs: 0.874 on cross-validation, 0.876 on test set. Identified morpho-molecular correlates and prognostic refinement.	Specific to intermediate-to-high-risk endometrial cancer.	The deep learning model im4MEC enables haematoxylin and eosin-based prediction and prognostic refinement of molecular endometrial cancer classification.
5	Xu et al., 2021 [27]	CT radiomics	6-month outcome based on the modified Rankin Scale	Multiple machine learning algorithms	RF and XGBoost models had best accuracy: >92%. Provided accurate prognostic prediction models for HICH.	Retrospective design may limit the applicability of findings; further prospective studies needed for validation.	Radiomics and machine learning models, especially RF and XGBoost, offer accurate prognostic predictions for hypertensive intracerebral hemorrhage.
6	Qin et al., 2021 [28]	Contrast-enhanced CT and curative resection	Early recurrence of perihilar cholangiocarcinoma	Machine learning analysis of radiomic features	AUC: 0.883. Higher accuracy than conventional staging systems. Identified 7 independent factors for the multilevel model.	Limited to patients with perihilar cholangiocarcinoma after curative resection.	Radiomics-based multilevel model outperforms rival models and staging systems, assisting in post-operative management of perihilar cholangiocarcinoma.
7	Salah et al., 2021 [29]	Application of different cosmetic products	Treatment effect perception in cosmetics	Random Forest (RF) classifier	Good accuracy in predicting treatment effect perception. Simplifies interpretability in clinical trials.	Small sample size; specific to cosmetic products.	Random Forest classifier effectively predicts treatment effect perception, aiding consumer-centered claim substantiation in clinical trials.
8	Shu et al., 2022 [30]	Coronary computed tomography angiography (CCTA)	Chronic myocardial ischemia (MIS)	Machine learning combined with clinically related factors	Accuracy of nomogram: Training set - 0.839, Test set - 0.832, Validation set - 0.816. Improved	Limited to patients with CAD undergoing CCTA.	Radiomics nomogram based on CCTA images is a non-invasive tool for predicting MIS in CAD patients, aiding in identifying high-risk patients.

					diagnosis accuracy over vascular stenosis alone.		
9	Yue et al., 2022 [31]	Radiotherapy planning CT and clinical plans	Dose prediction in radiotherapy	Deep learning method based on boundary distance	Superior performance in dose prediction compared to mask-based methods. Enhanced accuracy for inverse planning of GTVnx and OARs.	Limited to nasopharyngeal carcinoma cases; further validation needed for other cancer sites.	The proposed distance-guided method for dose prediction offers enhanced performance in nasopharyngeal carcinoma radiotherapy cases, suggesting further studies for broader validation.
10	Zhang et al., 2021 [32]	High-resolution T2-weighted magnetic resonance images	Microsatellite instability (MSI) status	Modified MobileNetV2 architecture	Combined model correctly classified 85.4% of MSI status, outperforming the clinical model. No significant difference with or without clinical factors.	Limited to single-center data; applicability to broader populations needs further study.	Deep learning models based on high-resolution MRI images demonstrate good predictive performance for MSI status in rectal cancer, aiding in individualised therapeutic strategies.
11	Groos et al., 2022 [33]	Video recording of spontaneous movements	Prediction of CP	Deep learning-based method	Sensitivity of 71.4%, specificity of 94.1% in predicting CP. Higher accuracy than conventional methods but similar to GMA tool.	Data on race and ethnicity not consistently collected across studies.	Deep learning-based method demonstrates predictive accuracy for early detection of CP in clinical settings.
12	Howell et al., 2021 [34]	Clinical, electrocardiographic, echocardiographic, and biomarker characteristics	Short-term CRT response	Machine learning models	Adaptive lasso model most accurate with 19 predictors. Predicted CRT response with 70% accuracy, sensitivity, and specificity.	Further validation in prospective studies needed.	Machine learning predicts short-term CRT response, aiding in CRT procedure and early post-CRT care planning.
13	Wen-Zhi et al., 2022 [35]	Preoperative clinical variables	Tumor pathological staging and grading	Deep learning algorithms (BiLSTM, CNN-BiLSTM, CNN-BiGRU)	High AUC values (0.933 to 0.948) for tumor staging prediction using various models.	Limited to a single hospital's data.	Accurate projection of staging and grading of renal clear cell carcinoma, aiding clinicians in treatment planning.
14	Cui et al., 2022 [36]	CT image radiomics signatures	PFS and OS in ESCC	LASSO Cox model, machine learning models	Combined radiomics and clinical models showed higher performance than either alone.	Limited to a specific patient population and cancer type.	Combined radiomics and clinical machine learning models accurately predict PFS and OS in non-surgical ESCC patients, aiding in clinical decision-making.
15	Li et al., 2022 [37]	Analysis of epidemiological information	Prognostic factors related to death	Machine learning methods	Identified main predictors of death prognosis: serum creatinine level, age, length of stay, ICU stay, serum	Limited to a single-center retrospective study.	Identified key prognostic factors in patients with invasive candidiasis infection, contributing to improved clinical management.

					albumin level, CRP, leukocyte count, PCT, total bilirubin.		
16	Zhong et al., 2024 [38]	Baseline and restage enhanced CT images and clinical characteristics	Response of LAGC to NACT	Deep learning radiomics nomogram	DL delta radiomics nomogram (DLDRN) predicted therapeutic response in metastatic lymph nodes with high accuracy.	Specific to LAGC patients undergoing NACT.	DLDRN effectively predicts therapeutic response in metastatic lymph nodes in LAGC, aiding in individualised treatment planning.
17	Liu et al., 2022 [39]	Analysis of health and nutrition survey data	Risk of knee pain	Logistic regression, random forest, Extreme Gradient Boosting	Logistic regression showed highest accuracy (AUC = 0.71). Nomogram model based on logistic regression showed good discrimination ability.	Only considered self-reported knee pain, not validated by clinical examination.	Developed a nomogram tool for evaluating the risk of knee pain in the US middle-aged and elderly population in primary care.
18	Feng et al., 2021 [40]	Analysis of clinical and laboratory data	Fibrosis severity in NAFLD	Machine learning algorithm (MLA)	MLA showed higher diagnostic accuracy (AUROC: 0.902) than conventional fibrosis biomarkers for identifying significant fibrosis.	Specific to patients with biopsy-confirmed NAFLD.	Newly developed MLA algorithm demonstrates excellent diagnostic performance for predicting significant fibrosis in NAFLD.
19	Yagi et al., 2022 [41]	Health-related quality of life data	Postoperative outcomes of decompression surgery	Machine learning algorithms	Developed a machine learning model with excellent prediction accuracy for postoperative outcomes in LSS surgery.	Limited to a specific patient population and surgery type.	Successful development of a machine learning model to predict outcomes of decompression surgery for LSS, aiding in patient management and surgical decision-making.
20	Min et al., 2021 [42]	Pre- and post-stenting IVUS images	Occurrence of stent underexpansion	Deep learning algorithms	Accurately predicted incomplete stent expansion using deep-learning algorithms.	Limited to patients undergoing percutaneous coronary intervention.	Deep-learning algorithms can predict incomplete stent expansion, aiding in treatment decisions to avoid stent underexpansion.
21	El-Sappagh et al., 2021 [43]	11 modalities including biological and clinical measures	Early diagnosis of AD and MCI-to-AD progression	Random forest (RF) with SHAP framework	Cross-validation accuracy of 93.95% and 87.08% in first and second layers, respectively.	Limited to data from ADNI; may not generalise to broader populations.	Developed an accurate, interpretable model for AD diagnosis and progression, enhancing clinical understanding.
22	Arabyarmohammadi et al., 2022 [44]	Computer-extracted morphology and texture features of myeloblasts	Relapse and RFS after HCT	LASSO with Cox regression model	Risk score associated with RFS and predictive of AML relapse.	Limited to specific patient population and conditions.	Texture features from chromatin patterns of myeloblasts predict post-HCT relapse and prognosticate RFS in AML/MDS.
23	Liu et al., 2022 [45]	EORTC QLQ-C30 questionnaire	Decreased QoL 3 months post-thyroidectomy	Random forest model	AUCs of 0.834 and 0.897 in training and validation cohorts, respectively.	Study design and patient sample may limit generalizability.	Developed a random forest model with high accuracy for predicting decreased QoL in thyroid cancer

							patients post-thyroidectomy.
24	Salari et al., 2023 [46]	Computational analysis of VMAT plans	GPR in VMAT plans	Random forest regression and support vector regression	Comparable prediction values and errors for both models. Similar performance in predicting GPR.	Focused on a specific radiation therapy technique; may not generalize.	Effective algorithm developed for predicting GPR in VMAT plans, aiding in planning and radiation delivery.
25	Wen et al., 2023 [47]	Preoperative optical coherence tomography (OCT) images	6-month postoperative best-corrected visual acuity (BCVA)	Deep learning and multimodal deep fusion network (MDFN) models	MAE of 0.070 logMAR and RMSE of 0.11 logMAR in testing dataset. Superior performance with R2 = 0.80 compared to regression model.	Retrospective design and specific patient population.	DL model based on OCT images accurately predicts postoperative BCVA in iERM patients, aiding in surgical planning.
26	Liu et al., 2021 [48]	Full-field digital mammography and clinical variables	Malignancy of BI-RADS 4 microcalcifications	Combined DL model	AUC of 0.910, better than clinical model, DL image model, and BI-RADS. Non-inferior performance as senior radiologists.	Limited to BI-RADS 4 microcalcifications and specific patient population.	Combined deep learning model improves malignancy prediction of BI-RADS 4 microcalcifications and assists junior radiologists.
27	Liu et al., 2023 [49]	Analysis of clinical data	Risk of sepsis in AP patients	Six machine learning models including SVM, KNN, MLP, LR, GBDT, AdaBoost	GBDT model outperformed LR and scoring systems with AUC of 0.985.	Retrospective design and reliance on specific databases.	Machine learning model-GBDT model has better performance in predicting sepsis in AP patients, aiding early identification and intervention.
28	Li et al., 2023 [50]	Patient demographic information, tumor characteristics, treatment details	Survival in early-stage HCC	Neural network, DeepSurv, random survival forest (RSF), CoxPH	ML models showed better discrimination than standard CoxPH model. Recommended treatments associated with higher survival rates.	Limited to early-stage HCC and retrospective database analysis.	ML model predicts survival and aids in treatment decisions for early-stage HCC, providing individualised recommendations.
29	Xia et al., 2023 [51]	Analysis of SEER database data	Long-term cancer-specific survival in LPADC	Ensemble models (GBS, RSF, EST) and CoxPH model	Good discriminative ability and calibration; RSF and GBS models most effective. Web application developed for clinical use.	Specific to LPADC and based on SEER database data.	Effective prediction models for long-term cancer-specific survival in LPADC, aiding in personalised treatment and prognosis.
30	Vodencarevic et al., 2021 [52]	Clinical data collection	Flares after tapering bDMARDs	Four basic machine learning models and ensemble learning method	AUROC of 0.81. Percent dose change of bDMARDs, DAS-28 ESR, disease duration, and inflammatory markers most important predictors of a flare.	Limited to a specific patient population and condition.	Machine learning methods predict flares after tapering bDMARDs in RA patients in sustained remission.
31	Li et al., 2022 [53]	DWI omics characteristics	Prognosis after thrombectomy	Support vector machine classifier	AUC 0.945 and 0.920 in training and test sets, respectively	Based on retrospective data	Effective prediction of post-thrombectomy prognosis in stroke patients

32	Verma et al., 2022 [54]	Patient-reported outcome measurements (PROMs)	Patient outcomes	Various ML models	Potential of ML to predict and classify PROMs	Limited to specific patient conditions	ML methods can support clinical decision making using PROMs
33	Hae et al., 2023 [55]	Clinical, laboratory findings, ABPM data, medication details	Individual BP response	CatBoost and other ML models	Accurate prediction of post-treatment BP levels, aiding personalised treatment	Focus on hypertension patients	ML models assist clinicians in personalising anti-hypertensive treatment
34	Lee et al., 2022 [56]	Clinical findings, laboratory values, CT findings	Early death after traumatic brain injury	ML models including random forest, SVM, logistic regression	Comparable performance to CRASH model, developed with smaller sample size	Retrospective design	ML models effectively predict early death after traumatic brain injury
35	Kong et al., 2023 [57]	MRI radiomics features	Differentiation and histological stratification of ISFT	ML models based on radiomics features	AUC values of 0.917, 0.923, 0.950 in test group for differentiating ISFT from AM	Retrospective and specific patient population	ML models aid in preoperative prediction and stratification of ISFT
36	Sundar et al., 2022 [58]	Customised gene panel	Survival benefit from paclitaxel	Random forest machine-learning model	Identification of first predictive biomarker for paclitaxel benefit in GC	Based on specific trial data	Machine-learning techniques identify gene signature for paclitaxel benefit in GC
37	Sun et al., 2022 [59]	CT image analysis	Prediction of colorectal liver metastases	AI algorithms including logistic regression classifier	LR classifier showed the highest prediction accuracy for CRLM	Focused on colorectal cancer patients	CT image texture features predict CRLM effectively using AI algorithms
38	Zhang et al., 2022 [60]	Clinical and non-clinical characteristics	Early death of mCRC patients	ML algorithms and nomograms	Random forest model provided more clinical benefits than other models	Based on SEER database data	ML algorithms combined with nomograms effectively predict early death in mCRC patients
39	Fan et al., 2022 [61]	PET/CT and enhanced CT radiomics features	Lymphovascular invasion status	ML models including AdaBoost, LDA, LR	Combined model (AUC up to 0.944) outperformed other models	Retrospective, limited to gastric cancer	ML models using radiomics features predict LVI in gastric cancer effectively
40	Ou et al., 2022 [62]	Clinical factors, blood tests	Pathologic risk factors post RH	Gradient Boosting Machine and other ML classifiers	Accurate prediction of deep stromal infiltration and lymphatic metastasis	Limited to early-stage CC patients	Machine learning methods predict PRF in CC patients post RH effectively
41	Luo Y et al., 2023 [63]	DWI-based radiomics and clinical data	Futile recanalization despite successful recanalization (mRS 4-6)	LASSO regression, SVM	High AUC in training (0.897) and test (0.935) cohorts; better than clinical model	Limited sample size and retrospective nature	The model effectively predicts futile recanalization in ABAO patients
42	Huang J et al., 2022 [64]	Deep learning CEUS and clinical factors	Aggressiveness of pancreatic neuroendocrine neoplasms (PNENs)	SE-ResNeXt-50 network	Combined model showed strong discrimination (AUC 0.85 in test set); better than clinical model alone	Limited to retrospective data; needs further validation in diverse populations	Effective for preoperative prediction of PNEN aggressiveness
43	Yin P et al., 2023 [65]	Clinical and CT perfusion imaging data	Delayed cerebral ischemia (DCI) and poor 3-month functional outcome	KNN, LR, SVM, RF, CatBoost	CatBoost optimal for predicting DCI and poor outcome; outperformed traditional clinical models	Not specified	ML models using clinical and CTP data are superior in predicting aSAH outcomes

44	Zhang Z et al., 2023 [66]	Clinical and laboratory data within 24 hours of ICU admission	28-day mortality	Artificial neural network (NNET)	NNET model had the highest AUC (0.837) for predicting mortality; outperformed existing scores like MELD and MELD-Na	Based on retrospective data; requires external validation	NNET model is superior in predicting 28-day mortality in HE patients
45	Cheng M et al., 2023 [67]	CT-based radiological factors and clinical factors	Risk of immune checkpoint inhibitor-related pneumonitis (ICI-P)	CNN	Nomogram combining CT-based radiological and clinical factors showed better prediction accuracy	Limited sample size and retrospective nature	Nomogram is a non-invasive tool for early prediction of ICI-P in lung cancer patients
46	Kao YT et al., 2023 [68]	Diagnostic codes, medications, and laboratory data from EMRs	1-year new-onset atrial fibrillation (AF) risk	Decision tree, SVM, LR, Random Forest	Random Forest model achieved an AUC of 0.74 with high specificity; effective in differentiating AF risk in the next year	Relies on retrospective EMR data; may not capture all relevant clinical details	Targeted screening using EMRs can effectively predict incident AF risk in older patients
47	Saux P et al., 2023 [69]	Clinical and surgery-related data	BMI at 5 years post-surgery	Least absolute shrinkage and selection operator, Classification and regression trees	Model provided accurate predictions of 5-year weight loss trajectories post-surgery; incorporated in an interpretable web-based tool	Retrospective analysis; variations in follow-up schedules among cohorts	The model is internationally validated and effective for predicting individual 5-year weight loss trajectories after bariatric surgery
48	Li J et al., 2023 [70]	Clinical and laboratory data, tumor characteristics	Acute liver function deterioration (ALFD) after DEB-TACE	LASSO regression	Nomogram demonstrated good discrimination (AUC 0.762 in training and 0.878 in validation); identified FIB-4 as an independent factor	Single-center study; requires external validation	The nomogram may improve clinical decision-making and surveillance protocols for HCC patients at high risk of ALFD after DEB-TACE
49	Faraone SV et al., 2022 [71]	Viloxazine extended-release (viloxazine ER) treatment	Response to treatment (≥50% reduction in ADHD symptoms)	Lasso model	Early improvements predicted treatment response at week 6 with high sensitivity and specificity	Post-hoc analysis; limited to trial participants	Consistency of viloxazine ER treatment effects across age groups confirmed
50	Zhang K et al., 2023 [72]	Clinical data and HE-stained pathological images	5-year overall survival (OS) in cervical cancer patients	Lasso-Cox model	Clinical-pathomic model (C-index 0.83) predicted 5-year OS; outperformed pathomic and clinical models alone	Retrospective data; limited to specific patient population and treatment modality	The model may aid in the precision of personalised therapy for non-surgical cervical cancer patients
51	Cai ZH et al., 2023 [73]	Pelvic MRI	Use of ≥3 linear stapler cartridges in DST anastomosis	Mask R-CNN, 3D Convolutional Networks	Integrated model showed higher accuracy and	Limited to retrospective analysis and specific patient population	MRI-based deep learning model can predict the need for multiple linear stapler cartridges in DST

					AUC compared to clinical and image models alone		anastomosis effectively
52	Wang Y et al., 2023 [74]	NHANES data (2007-2018)	Risk of heart failure	Random Forest (RF)	RF model demonstrated the best prediction performance with high AUC	Based on survey data; may lack detailed clinical data	ML models, especially RF, can accurately predict heart failure risk in patients with prediabetes or diabetes
53	Bao Z et al., 2021 [75]	Genotyping data	Response to ketamine treatment (based on HAMD score change)	Random Forests, SVM, other ML models	SVM algorithm showed the best performance with high accuracy, precision, and sensitivity	Limited sample size; focused on genetic predictors only	GWAS-based machine learning approach can predict the treatment outcomes of ketamine in MDD patients effectively
54	Li P et al., 2023 [76]	Clinical data	Postoperative infections in elderly patients	Deep Learning Model	Deep learning model demonstrated improved predictive accuracy for postoperative infections	Observational data; further validation needed	Deep learning models can assist in predicting postoperative infections in elderly patients effectively
55	Liu Y et al., 2023 [77]	MRI and clinical data	Ordinal 90-day modified Rankin Scale (mRS) score	Deep Learning Model	Fused models outperformed clinical and imaging models alone in predicting ordinal mRS score and unfavorable outcome	Limited to retrospective analysis and specific imaging data	Fused imaging and clinical deep learning models enhance prediction of 90-day stroke outcome
56	Xie N et al., 2023 [78]	Multiparameter MRI	Prediction of extrapancreatic extension (EPE) in pancreatic cancer	XGBoost, other ML classifiers	XGBoost achieved high AUC values in both internal and external test sets	Retrospective design; validation in larger datasets required	Radiomics models can accurately predict EPE in pancreatic cancer patients, aiding in treatment decision-making
57	Chen X et al., 2023 [79]	Clinical data	Likelihood of postoperative blood transfusion	Logistic, MLP, XGBoost, RF, SVM	All models performed well in predicting blood transfusion likelihood, with high AUC values in training and testing groups	Single-center study; further validation required	ML models have great potential in predicting the likelihood of blood transfusion after hip fracture surgery
58	Forrest LN et al., 2023 [80]	Behavioral and stepped-care treatments	Binge-eating reduction, abstinence, eating-disorder psychopathology, weight loss	Elastic Net, Random Forests, other ML models	Machine-learning models provided minimal advantage over traditional models in predictive accuracy	Limited to trial participants; low predictive accuracy in both model types	Different analytic approaches, including ML, reveal some predictors of BED treatment outcomes, but with limited accuracy
59	Tan TH et al., 2021 [81]	Clinical data from electronic health records	Hospitalization, pneumonia, sepsis or septic shock, ICU admission, in-hospital mortality	Random Forest, XGBoost, Logistic Regression	Models showed high AUCs for predicting various outcomes, integrated into hospital information systems for real-time assistance	Limited to retrospective data; focused on influenza in older patients	ML can assist in real-time prediction of outcomes in older ED patients with influenza, aiding in decision-making

60	Chandra RS et al., 2023 [82]	Clinical and image data from CATT trial	Number of PRN injections of anti-VEGF in two years	SVM, Random Forest, XGBoost	SVM model demonstrated high AUCs and MAE in predicting the number of injections, highlighting important predictive features	Limited to participants in a specific clinical trial; further validation needed	ML models using initial treatment data can predict long-term anti-VEGF demand for nAMD, aiding in treatment optimization
61	Jin Y et al., 2023 [83]	Clinical data, survival data	First tumor relapse, secondary malignant tumor diagnosis, or death	Random Forest, Logistic Regression	RF model showed better specificity, sensitivity, and AUC compared to logistic regression	Limited to retrospective data and specific patient population	RF model is effective in predicting events among breast cancer patients with poor response to neoadjuvant chemotherapy
62	Su Z et al., 2023 [84]	Clinical indicators	Pulmonary metastasis risk	Multiple ML algorithms	Developed a nomogram to predict risk of pulmonary metastasis in osteosarcoma patients	Based on retrospective data, requires further validation	Helps clinicians predict lung metastases risk in osteosarcoma and provide personalised treatment guidance
63	Liu Y et al., 2023 [85]	Clinical parameters	Amputation-free survival (AFS)	Random Survival Forest and others	RSF algorithm developed the optimal model with high AUCs for predicting AFS	Retrospective data and focused on a specific patient group	RSF model effectively predicts AFS after first revascularization in PAD patients
64	Wu Y et al., 2023 [86]	Clinical data, stone analysis	Identification of infection stones in vivo	SVM, MLP, DT, RFC, AdaBoost	AdaBoost model showed strong discrimination in identifying infection stones (AUC: 0.772)	Retrospective design, limited to specific patient data	Machine learning model can quickly identify infection stones in vivo with good predictive performance
65	Zhang K et al., 2022 [87]	Clinical data, CT features	Malignancy prediction of solid nodules in multiple pulmonary nodules	Extreme Gradient Boosting (XGBoost)	PKU-ML model (AUC=0.838) outperformed models designed for single pulmonary nodules	Limited to specific patient data, retrospective analysis	PKU-ML model effectively predicts malignancy of solid nodules in multiple pulmonary nodules and single solid nodules
66	Tran QNN et al., 2023 [88]	Clinical data	In-hospital mortality of lung cancer patients	Logistic regression and others	Developed a static nomogram and web app for stratifying lung cancer patients into high- and low-risk of in-hospital mortality	Limited to data from SEER database	Model can assist in clinical planning for new lung cancer patients
67	Zhang H et al., 2023 [89]	Clinical and laboratory data	N2 lymph node metastasis prediction	ResNet18, LASSO, and others	Deep learning model (AUC: 0.83) outperformed radiomics model in predictive accuracy	Limited to specific patient population, retrospective design	Nomogram based on multiview radiomics, deep learning, and clinical features effectively predicts presurgical N2 diseases in stage I-II NSCLC patients
68	Ma X et al., 2023 [90]	CT images, clinical characteristics	Lymph node metastasis prediction	Swin Transformer	DL signature (AUC: 0.948-0.961) significantly outperformed clinical-semantic model and radiomics	Retrospective data, limited to lung adenocarcinoma	DL signature based on Swin Transformer offers important information in noninvasive mediastinal LN staging and individualised therapeutic options

					signature in predicting lymph node metastasis		
69	Li D et al., 2023 [91]	Clinical data	90-day mortality risk prediction	Lasso, RSF, and others	Developed a nomogram with good predictive power for 90-day risk of death in the target patient population	Based on retrospective data from DRYAD database	The nomogram provides an effective tool for predicting 90-day mortality risk in the target patient population
70	Le Y et al., 2023 [92]	Clinical data	Overall survival prediction	XGB, LR, RF, NB	ML algorithms performed well in predicting 1-year and 3-year overall survival of patients with ccRCC-BM	Limited to retrospective data from SEER database and a single center. limited external validation.	ML models can positively impact clinical applications in predicting survival of patients with ccRCC-BM
71	Zhang H et al., 2023 [93]	Clinical data from SEER and hospital database	Death risk in NPC patients	XGBoost, DT, LASSO, RF	Identified risk factors such as age, race, gender, TNM stage; model accurately predicted risk of death in NPC patients	Limited to retrospective analysis from specific databases	AI-based model can accurately predict risk of death in NPC patients, aiding in treatment planning and patient counseling
72	Etter JF et al., 2023 [94]	Stop-Tabac smartphone app	Smoking cessation, reduction, and relapse after 6 months	Machine learning algorithms	Identified predictors such as tobacco dependence, app use frequency, and nicotine medication use; machine learning algorithms effectively predicted smoking behavior changes	Limited to app users; may not generalise to broader population	Machine learning can identify independent predictors of smoking behavior changes among app users, useful for app development and experimental studies
73	Lyu Z et al., 2023 [95]	Clinical and laboratory data	Risk of early neurological deterioration (END) after intravenous thrombolysis	LR, KNN, SVM, RF	SVM model showed the highest accuracy, specificity, and overall prediction ability in identifying risk of END after intravenous thrombolysis	Limited to single-center data; needs larger, multi-center validation	Machine learning models can effectively predict the risk of END in AIS patients, aiding clinical decision-making for thrombolysis
74	Huang J et al., 2023 [96]	Electronic health records	28-day in-hospital mortality	NB, xgboost, LR	The xgboost model showed the best predictive performance; ML models can stratify patients into risk groups for medical disputes	Based on data from a specific database; may not reflect general ICU population	xgboost model effectively predicts mortality in elderly IS patients in the ICU, aiding in patient management and resource allocation