COMPUTATIONAL METHODS AND INTELLIGENT TECHNIQUES USED ACROSS AI-BASED HEALTHCARE SYSTEMS

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Abstract
Artificial intelligence (AI) is increasingly used in healthcare to support diagnosis, prediction, clinical decision-making, patient monitoring, medical imaging, electronic health record analysis, and healthcare administration. This theoretical review examines the major computational methods and intelligent techniques used across AI-based healthcare systems. A narrative literature review approach was adopted by synthesising peer-reviewed articles, review papers, reporting guidelines, and policy documents related to healthcare AI. The review shows that supervised machine learning remains common in structured clinical data, while deep learning dominates image-based and high-dimensional healthcare tasks. Natural language processing is increasingly important because a large amount of healthcare information exists in free-text clinical notes. Knowledge-based and hybrid decision support systems remain relevant because clinical decisions require both data-driven prediction and guideline-based reasoning. However, the literature also highlights several limitations, including poor external validation, dataset bias, lack of interpretability, weak workflow integration, privacy risks, and limited prospective clinical evaluation. The paper concludes that AI-based healthcare systems should not be judged only by algorithmic accuracy. Their value depends on safety, explainability, fairness, clinical usefulness, interoperability, governance, and continuous monitoring.

Keywords: *artificial intelligence, healthcare systems, machine learning, deep learning, natural language processing, clinical decision support, explainable AI, federated learning, medical informatics*

1. Introduction

Artificial intelligence is arguably one of the most important technological developments in healthcare. In other words, AI refers to computer systems that perform tasks that normally require human intelligence. These tasks include recognizing, learning, predicting, classifying, interpreting, recommending and making decisions. It is possible to assess EHRs, medical images, laboratory tests, genomics, clinical notes, wearable sensor data, and administrative datasets with the help of AI. In general, such systems can be used for diagnosis, prognosis, triage, personalized treatment, public health monitoring, hospital resource planning, and clinical workflow improvement.[1]

There is a strong linkage between the digitalisation of healthcare moving at a much faster pace. As a consequence, hospitals, clinics, laboratories, imaging centres, pharmacies and public health system are all generating huge volumes of data now. Information contained in an EHR includes diagnosis codes, medication history, lab values, clinical observation, nursing notes etc. Imagining platforms produces images like radiographs, CT-scans, MRI-scans, ultrasound images, retinal images and pathology slides. Wearable devices and remote monitoring technologies constantly feed us with real-time physiological information. According to Beam, these multi-modal data represents opportunity for computational models to pick out hidden patterns which expert human investigators cannot do so.[1]

Artificial intelligence (AI) in the healthcare industry used systems on the premise of expert rules but is now slowly shifting towards more complex systems powered on big data. Early clinical decision support systems operated according to explicit rules of clinical medicine, expert knowledge and pre-determined logic. A system may alert when a prescription drug interacts with another drug, for example. Nonetheless, numerous new-age AI implementations are equipped with machine learning and deep learning patterns that learn from data for predictions. As a result, the development of the AI approach shows a significant shift from explicit rules towards learning models. Further, the predictive power of AI systems has greatly improved but so too are increasing concerns regarding transparency, bias, generalisability and accountability of AI systems.[2,3]

Although AI in clinical care holds great promise, successful implementation is not guaranteed. A model may work well for a research dataset (this is its validation) but fail when trying to deploy into clinical practice. This can happen for several reasons: the data is different, the clinical workflow is not appropriate, clinicians do not trust the system, or the model provides unsafe recommendations. Healthcare AI needs to be designed as a socio-technical intervention and not just an algorithm. To put it another way, the construction, confirmation, management and oversight of AI systems are critical, just as the model.[4,5]

1.1 Objective

To examines the major computational methods and intelligent techniques used across AI-based healthcare systems.

2. Literature Review

2.1 Artificial Intelligence in Healthcare

Artificial intelligence in healthcare incorporates a wide range of techniques including machine learning (ML), deep learning (DL), natural language processing (NLP), expert systems, computer vision, reinforcement learning (RL), explainable AI, and federated learning. Clinical, administrative, operational and research settings use these methods. However, Artificial intelligence is found useful in diagnosis, treatment planning, drug discovery and patient monitoring. In the same fashion, believes that a merger of human intelligence and artificial intelligence, if used correctly, would enable more accurate and efficient medicine.[6,3] (Yu et al., 2018; Topol, 2019).

Healthcare AI and AI in other industries differ markedly because clinical decisions impact patient safety directly. Patients could be harmed if the inaccurate prediction or unsafe recommendation is used for a patient. As a result, AI systems in medicine need to be assessed on clinical, ethical, technical and organisational standards. However, machine learning development in medicine requires careful attention to the problem definition, reliability of data, appropriate validation, and clinical context.[1]

2.2 Classical Machine Learning

The traditional machine learning had been the most used technique in health care AI. There are many such algorithms. The most popular are logistic regression, decision trees, random forests, support vector machines, k-nearest neighbours, naïve Bayes classifiers, gradient boosting machines, etc. You can often get structured data for techniques such as electronic health record fields, laboratory results, diagnosis codes, procedure codes, medication records, insurance claims, and administrative data.[7]
The classical machine learning technique is widely employed in carrying out risk prediction, disease classification, readmission prediction, mortality prediction, adverse event detection and length-of-stay prediction. The healthcare system can use machine learning to better utilize the datasets. Nonetheless, the performance of models are mostly dependent on quality of data, missing data, coding practices and so on, and correct definition of outcomes.[7]

Tree-based methods and ensemble methods have a wide applicability because they can model non-linear relationships and interactions. Random forests and gradient boosting models are common choices for structured clinical data because they are able to capture complex patterns without the use of statistical assumptions. Nonetheless, some ensemble models may be less interpretable than logistic regression and other similar models. The interpretable models can perform satisfactorily on prediction tasks in healthcare, and may at times be more suited for clinical use than complex black-box models.[8]

2.3 Deep Learning and Medical Data

Deep learning is a significant advancement in healthcare AI as it can learn complex representations directly from raw or semi-structured data. Deep learning models traditionally use multiple layers of artificial neural networks to help machines recognize patterns in images, signals, and text. Further, it has opened up doors in disease prediction, diagnosis, medical imaging and personalization. [9]

Convolutional neural networks find many medical imaging uses. Radiology, dermatology, ophthalmology pathology and cardiology images are applied. It performs particularly well in image-related healthcare tasks where visual features would be difficult to define manually. Just because high image classification accuracy is achieved does not mean that it is clinically useful. It is crucial to validate artificial intelligence (AI) systems in real-world clinical settings. [10]

Deep learning has applications for electronic health records. Temporal patient data can be analysed via recurrent neural networks, long short-term memory networks, gated recurrent units, attention-based models. Sequential clinical events and health changes make these models practical for patient-use over time. It demonstrated how deep learning aimed at diagnosis prediction, phenotype discovery, patient representation learning, and clinical event forecasting. Nonetheless, deep learning models require larger datasets and may be less interpretable.[11]

2.4 Natural Language Processing and Large Language Models

NLP is a key artificial intelligence application in health care because much of the clinical information is kept as text. Clinical notes, discharge summaries, referral letters, pathology reports, and radiology reports are written by doctors, nurses, radiologists and more. These documents are likely to contain more useful information that won't be in the structured fields.

Techniques from Natural Language Processing are able to extract symptoms, diagnoses, medications, side effects, test results, determinants of health, and time. Prior NLP systems utilized dictionaries, rules and statistical classifiers. Later models are based on transformer and large language models. The utilization of NLP is on the rise in clinical decision support systems, particularly in the extraction of relevant information from electronic health records.[12]

The emergence of large language models created new opportunities for healthcare applications such as clinical note summarisation, documentation drafting, patient question answering, medical education support, and clinical knowledge retrieval. Nonetheless, they pose dangers too. These consist of hallucinated facts, privacy issues, concealed bias, inadequate reproducibility, and unclear accountability. Thus, these language-based AI systems in healthcare must have strong human oversight with rigorous validation.[13]

2.5 Knowledge-Based and Hybrid Clinical Decision Support

AI systems that operate based on knowledge are still important in the health field. Medical guidelines, ontologies, drug-interaction databases, expert knowledge-set are used through explicit rules. Medication alerts, guideline reminders, diagnosis prompts, laboratory follow-up, and preventive care recommendations are commonly used. [13]

Although machine learning has been on the rise, rule-based systems still have value because of their transparency, easy alignment with clinical guidelines. The comprehensive clinical decision support for the era of artificial intelligence should bring together computational intelligence with the human factor, process, and clinical knowledge management.[2]

In reality, lots of health systems do use hybrid AI. A patient's risk is predicted by a machine learning model and a rule-based engine decides which action to recommend. As an illustration, you might have a model that has deemed a patient high risk for sepsis, while a clinical guidelines system recommends monitoring/escalation steps. Essentially, the world of hybrid systems is useful; since the healthcare process requires data-driven prediction as well as explicit clinical reasoning.[2]

2.6 Explainable Artificial Intelligence

It is essential for clinicians, patients, managers, and regulators to know what has led to a system's recommendation. This makes explainable AI a major concern in health care. Explainability is critical to ensure trust, safety, accountability, and detecting errors. Methods that often help explain model predictions are feature importance, SHAP values, LIME, saliency maps, counterfactual explanations, attention visualisation, rules lists, and interpretable scoring systems.[3]

The explainability in healthcare is more than a technical issue. It also features dimensions that are ethical, legal, clinical and social. An explanation that is useful must make clinicians safer not just provide a complex mathematical output. However, it studies shows that some post-hoc explanation methods can create false confidence if they do not reflect the actual model behaviour. Thus, explicability should be tailored to the clinical task, user requirements, and risk level.[14,15]

2.7 Federated Learning and Privacy-Preserving AI

AI that is used in healthcare generally needs large and diverse datasets. Yet, the sharing of data is inhibited patient privacy, legal requirements, institutional governance, and ethics. Federated learning is a privacy-preserving model training technique that prevents moving patient data to one place across several institutions. Each institution locally trains the model, and combines center model updates.

Federated learning is a highly promising approach for digital health, since healthcare data mostly reside within separate institutional systems. However, hospitals may not share raw patient information due to being unwilling or unable to. As such, federated and secure machine learning methods are used in medical imaging. [16,17]

Despite its effectiveness, federated learning does not solve all your privacy problems. Model updates can still leak information in some instances. Furthermore, multi-site collaboration needs strong governance, data harmonisation, cybersecurity, and monitoring. There are other approaches which protect the privacy of individuals such as Differential privacy, Secure multiparty computation, Homomorphic encryption, and Synthetic data generation. [16,17]

2.8 AI Governance and Reporting Standards

Robust reporting, regulation, governance are keys to the safe use of AI in healthcare. The CONSORT-AI and the SPIRIT-AI extensions offer guidance for the reporting of clinical trials and trial protocols respectively of clinical trials using AI interventions (Cruz Rivera et al, 2020; Liu et al, 2020). DECIDE-AI offers guidance on reporting for the early-phase clinical evaluation of AI-based decision support systems (Vasey et al., 2022). The need to report input data, used model version, human-AI interaction, error handling, workflow integration, clinical evaluation is highlighted.

The World Health Organization (2021) identifies ethical issues and stakeholder responsibilities relevant for AI in health The World Health Organization (2021) identifies ethical principles for AI in health. Respect for human autonomy Safety and effectiveness Transparency Responsibility Inclusiveness Equity Sustainability. The WHO (2023) also highlights the regulatory aspects regarding documentation, transparency, risk management, validation, data quality, privacy, and post-market monitoring. According to these frameworks, healthcare AI must be regulated throughout its life cycle i.e. design, deployment and monitoring.[21]

3. Methods

This paper uses a theoretical narrative review method. A theoretical review is suitable because the aim is not to test a hypothesis using primary data but to examine, organise, and critically discuss existing knowledge about computational methods used in AI-based healthcare systems.

The review focused on peer-reviewed journal articles, review papers, methodological papers, clinical AI reporting guidelines, and policy documents related to artificial intelligence in healthcare. Priority was given to literature published between 2018 and 2026 because this period reflects the rapid expansion of deep learning, clinical NLP, explainable AI, federated learning, and large language models in healthcare. Earlier foundational sources were included where they helped explain the development of clinical decision support and interpretable models.

The literature was synthesised around major AI method families: classical machine learning, deep learning, natural language processing, knowledge-based systems, explainable AI, federated learning, reinforcement learning, and multimodal AI. The synthesis considered four main issues: common healthcare data types, typical applications, methodological strengths, and implementation limitations.

Because this is a theoretical review, no patient data were collected, and no statistical meta-analysis was conducted. The "results" section therefore presents a conceptual synthesis of the literature rather than numerical findings from a primary empirical study.

4. Results and Discussion

4.1 Main Computational Methods Used in AI-Based Healthcare Systems

The existing literature shows that many major computational approaches have been adopted by the AI-based healthcare systems. Classical machine learning, deep learning, natural language processing, knowledge-based clinical decision support, explainable AI, federated learning, reinforcement learning, and multimodal AI were the most cited approaches. The methods being described have applications in a variety of healthcare settings, such as diagnosis, prognosis, patient monitoring, medical imaging, clinical documentation, hospital administration, risk prediction, treatment planning and population health.[7,1,6]

The traditional approach of machine learning is often applied to structured healthcare data, including electronic health records, claims data, lab results, diagnosis codes, and medication records. Deep learning is usually applied on complex high-dimensional data, especially on medical images, physiological signals, genomic data, and longitudinal electronic health records.[10,9,11] As a result of the presence of substantial healthcare information in unstructured clinical text such as discharge summaries, radiology reports, pathology reports, referral letters and clinical notes, the importance of natural language processing is increasing.[12]

Knowledge-based decision support systems remain critical since many clinical decisions require explicit rules, guidelines, medication safety alerts and workflow-based recommendations. Notwithstanding the emergence of AI, clinical decision support remains relevant as effective AI in health care requires both computational methods and clinical knowhow and workflow design. Also, emerging approaches like explainable AI, federated learning, and multimodal AI are gaining importance as healthcare systems require clinically relevant AI applications that are transparent and privacy-preserving.[15,16,3,2]

Table 1. Major computational methods in AI-based healthcare systems

Method family	Common techniques	Main healthcare data	Common uses	Key limitations
Classical machine learning	Logistic regression, random forest, support vector machine, gradient boosting	Structured EHR, claims data, laboratory data	Risk prediction, triage, classification	Feature engineering, bias, limited transferability
Deep learning	CNN, RNN, LSTM, GRU, transformers	Images, signals, EHR sequences	Imaging, diagnosis, prognosis, temporal prediction	High data demand, opacity, overfitting
NLP and LLMs	Named entity recognition, BERT, GPT-style models	Clinical notes, reports, guidelines	Information extraction, summarisation, decision support	Hallucination, privacy, evaluation difficulty
Knowledge-based AI	Rules, ontologies, guideline engines	Clinical rules, medication databases	Alerts, reminders, guideline support	Maintenance burden, alert fatigue
Explainable AI	SHAP, LIME, saliency maps, counterfactual explanations	Model outputs and features	Trust, transparency, error detection	Explanations may be misleading
Federated learning	Distributed model training, secure aggregation	Multi-site EHR,	Collaborative modelling without centralising data	Governance, technical heterogeneity

		imaging, genomics		
Reinforcement learning	Policy learning, Markov decision processes	ICU data, treatment sequences	Treatment optimisation, resource allocation	Safety, causal uncertainty
Multimodal AI	Data fusion, ensemble learning	Images, text, EHR, genomics	Holistic prediction, personalised care	Missing data, complexity, interpretability

4.2 Classical Machine Learning Remains Highly Relevant

The structured and tabular format of many health datasets validates the relevance of classical methods. However, hospital information systems generally include coded variables like age, sex, diagnosis codes, medication orders, admission history, laboratory values, vital signs, and treatment records. The suitability of these data evaluated for the logistic regression model, decision trees model, random forests model, support vector machine model, and gradient boosting model.[7,1]

It is common to use classical machine learning approaches for predicting hospital readmission, estimating mortality risk, identifying high risk patients, adverse drug event detection, length of stay forecasting, clinical triage. Further, machine learning facilitates medical decision-making by solving complex patterns in medical data and the clinical problem, target population, and outcome must be clearly specified. It further revealed that AI and machine learning are important as they can analyse large-scale clinical dataset. Further, this can help support diagnosis, prognosis and treatment planning.[1,6]

Traditional patterns tend to have better interpretability. Furthermore, they are not black boxes like neural networks; they give an insight into feature weight and influence. Certain classical models are also easier to understand. For example, logistic regression and decision trees can illustrate how a single variable influences predictions. Hence, healthcare can benefit significantly from interpretable models because clinical users must understand and trust the model's output.[8]

Nonetheless, conventional ML method is not without limitations. The current models typically utilize feature engineering, whereby the researcher or developer decides which variables to include. If key clinical features are missing or coded incorrectly, or if they are biased, the model may not be valid. The machine learning systems in healthcare must be developed carefully and purposefully to prevent doing harm when there is bias or omission affecting historical data.[5]

4.3 Deep Learning Dominates Image-Based and Complex Data Tasks

Deep learning is particularly essential in healthcare AI systems that deal with complex, high-dimensional, or unstructured data. Deep learning models utilize artificial neural networks with several levels that learn the pattern directly from data. These techniques are mostly used in the fields of medical imaging, pathology, ophthalmology, dermatology, and genomics.[9,10]

Medical imaging is one of the most promising areas of deep learning applications. Medical and healthcare images are analysed using convolution neural networks which include X-ray, CT, MRI, retinal images, dermatology photos, and histopathology slides. Deep learning shows strong performance on image-based healthcare as the models can learn from images directly. AI could help realize the potential of high-performance medicine and interpret complex clinical data.[9,10]

Electronic health records and time series prediction also benefit from deep learning. Recurrent neural networks, long short-term memory networks, gated recurrent units, and transformer-based architectures are models that can analyse patient data over time. However, deep learning has been used for prediction of diagnosis, discovering phenotypes, predicting failures, and forecasting clinical events. Sequential clinical events and the temporal evolution of patient condition make these models useful.[11]

The application of deep learning has numerous challenges. Many training samples and high computing resource usage are necessary for these models along with validation. Machine learning models are often called "black-box" models since one cannot understand how they produce their output. While many AI models perform well in research environments, they fail to show clinical impact due to weak external validation, poor integration into the workflow, and limited prospective evaluation.[4]

4.4 Natural Language Processing Is Essential Because Healthcare Is Text-Heavy

Natural language processing happens to be one of the most relevant techniques in artificial intelligence in health because clinical practice relies heavily on written documentation. Most of the patient information is stored in unstructured text like doctor's notes, nurse's notes, discharge summaries, radiology reports, pathology reports, referral letters, and patient messages. Due to incompleteness in the structured fields in electronic health records, useful information instead arises from some unstructured narratives. Thus, NLP is needed to extract needed information.[12]

NLP aids in identifying symptoms, the diagnosis, and medicines. It also assists in clinical coding, summarising, information retrieval and detecting adverse event. Natural Language Processing is increasingly being used for clinical decision support because it can transform unstructured clinical text into structured information by harnessing the power of AI. NLP is likely to play an important role as a link between clinical documentation, predictive analytics, and healthcare information systems.[12]

The introduction of transformer-based models and large language models has further advanced the application of NLP in healthcare. These systems can summarize clinical documents, respond to medical questions, assist in the literature search, help in documentation, and enhance patient interaction. However, large language models have the potential to encode various clinical knowledge which could be viably used in answering medical questions and supporting decisions. But at the same time these systems also pose risks by producing inaccurate, biased or hallucinated information.[13]

Clinical language is complex because of contract ions, spelling errors, uncertainity, negation and specific meaning. The statement "no evidence of pneumonia" does not imply a diagnosis of pneumonia for example. Hence, you must properly train, validate and monitor NLP systems. NLP and large language models in healthcare also raise concerns about privacy, transparency, accountability, and patient safety.[12,13]

4.5 Hybrid Systems May Be More Practical Than Purely Data-Driven Models

Making decisions in health care often requires prediction and reasoning. A patient may be classified by a model as having a high risk of deterioration, but clinicians still need guidance on what to do next. Hybrid systems may be more viable than purely data-driven ones for this reason. The hybrid "Clinical Decision Support Systems" comprise machine learning models integrated with rule-based knowledge, clinical guidelines, medication safety rules, and workflow logic. For instance, a machine learning model may predict sepsis risk, while a rules-based clinical pathway may recommend blood cultures, lactate, antibiotics, or escalation to senior clinicians. Combining the two can make AI systems more clinically useful by linking prediction to action.[12,13]

Further, clinical decision support in the age of AI must integrate computational intelligence with clinical workflow, knowledge management, and human judgement (Shortliffe and Sepulveda, 2018). Rule-based systems are still of great value because they often have transparent links to clinical guidelines. But, if these systems generate too many alerts, they may cause alert fatigue. Even if an AI tool is accurate, it will fail in practice if it does not fit into clinical workflow and does not produce outputs clinicians can act on.[4]

Further, a balanced approach may be offered by hybrid systems. Utilizing explicit clinical guidelines helps them use machine learning complex prediction for safe and interpretable actions. That makes hybrid AIs especially relevant for real-world health information systems.[4]

4.6 Explainability Is Necessary but Not Sufficient

Explainability matters as clinicians need to understand AI outputs prior to their use in patient care. In the health care sector AI predictions may influence diagnosis, treatment, triage, and monitoring. As such, clinical professionals, patients, health system managers, and regulators require some level of explanation about how AI systems make recommendations. Feature importance, SHAP values, LIME, saliency maps, counterfactual explanations, attention visualisation, rule lists, and interpretable scoring systems are popular XAI methods. The aim of these methods is to make the output of models more interpretable. However, one of the important challenges is explainability which is more not just a technical challenge but also an ethical, legal, clinical, and organizational challenge.[15]

Different users may have different explanation requirements. For instance, a clinician may require reasoning that is clinically meaningful, while a patient may require an explanation of how the AI system affects their care. Nevertheless, safety is not ensured by explainability itself. Some post-hoc explanation methods may generate false confidence as they may not capture the model's actual reasoning. Consequently, explainability of AI tools must be supplemented through external validation, clinical trials, fairness tests, usability evaluations, and post-deployment monitoring.[14]

In general, explainability is necessary but not sufficient. An AI system can have a degree of explainability while remaining biased, inaccurate or dis-integrated. Thus, the responsibleness of healthcare AI define explainability as one part and not the whole solution

4.7 Privacy-Preserving AI Is Increasingly Important

Privacy-preserving artificial intelligence is becoming more critical due to the sensitive nature of medical data. Patient files contain personal, medical, genetic, behavioural, and social data. Artificial intelligence models often require large and diverse datasets at the same time to improve performance and generalhasion. There is tension between data access and patient privacy.[16]

Federated learning is a privacy-preserving technique playing an important role in healthcare AI. Data in federated learning do not leave local institutions, but model updates do, which are aggregated. Several hospitals or research centres can work together without centralising raw patient data. The federated learning is a promising approach for digital health since healthcare data is often distributed across organisations. Further, federated and secure machine learning are particularly useful in medical imaging, as it is often challenging to share raw patient images due to privacy and legal issues.[16,17]

Various other techniques are Differential privacy, secure multiparty computing, homomorphic encryption, synthetic data generation, and secure aggregation. Patient re-identification and unauthorized access are sought to be reduced through these techniques. All by itself, a privacy-preserving AI is not a cure-all. Governance, technical standards, cybersecurity controls, continuous monitoring, and data harmonisation are still required for federated learning. In cases where security measures are inadequate, model upgrades might also expose information.[16,17]

Thus, privacy-preserving AI should be seen as part of a larger governance framework. While it may mitigate privacy risks, it should be accompanied by ethical review, legal compliance, cybersecurity, transparency and institutional accountability.

4.8 Clinical Implementation and Evaluation Remain Major Weaknesses

One significant finding from the review of the literature is that many healthcare AI systems are stronger on the technical development side than on implementation in real clinical condition. Both clinical and statistical significance should be evaluated during clinical model development. High accuracy of the model does not mean automatically mean the AI system improves patient outcomes, reduce workload and improves healthcare efficiency. However, it identifies several barriers to clinical impact: limited external validation; poor integration from the workflow; elusive clinical responsibility; data quality; weak proof of patient benefit. It also stresses that "do no harm" is vital for machine learning in healthcare. Models which are unsafe or biased can-do real patient harm. Healthcare AI must be assessed as a clinical intervention and not simply as a technical model, these concerns suggest.[4,5]

Reporting guidelines are available to enhance the transparency and quality of evaluation. The guide of CONSORT-AI is for reporting clinical trials of AI interventions, while that of SPIRIT-AI is for the protocols of AI clinical trials.[18,19] DECIDE-AI helps with early phases of clinical evaluation of artificial intelligence decision support systems.[21] The report should include information about the input data, version of the AI model, interaction with the AI, error analysis, integration into the clinical workflow, and clinical evaluation.

Thus, the literature suggests that beyond more advanced algorithms, the future of healthcare AI depends on better validation, implementation, governance, monitoring and clinical accountability. Criteria for evaluating AI-based healthcare (AIBH) systems include safety, effectiveness, fairness, usability, interoperability, privacy, and benefit to patients.

4.9 Overall Synthesis of Results

The literature review shows that AI-based healthcare systems result from a combination of computational methods and intelligent techniques. The classical machine learning still has a lot of use for structured electronic health records and administrative data. The relative importance of deep learning for medical imaging, temporal prediction, and high-dimensional biomedicine. The need for natural language processing is primarily due to the reliance of healthcare on clinical text. Knowledge based and hybrid systems will continue to matter as health care decisions require both prediction and guideline-based reasoning.[14,15]

The scope of AI field is being enlarged by upcoming techniques like explainable AI, federated learning, large language models etc. Nonetheless, the literature itself shows that technical performance does not suffice alone. AI models need external validation to be clinically useful and explainable, fair and privacy-preserving, and workflow-integrated. The review of the literature covered in the paper provides strong evidence that AI should be considered a socio-technical healthcare intervention rather than only a computational tool. The success of AI in healthcare depends on many things like the quality of data, design of the algorithm, and more.[4,11,12,13]

4.8 Research Gaps

The paper identifies several important gaps in AI-based health care research. A large number of studies often focus exclusively on accuracy metrics like area under the ROCR. Nevertheless, high accuracy does not necessarily improve outcomes. The second limitation is the external validation. A model can function effectively in one dataset, but may not work in another.

Most importantly, assessment does not always authorization bias and fairness. When AI models are trained on historic healthcare data, they could perpetuate existing inequities in diagnosis, treatment access, and health outcomes. Integration into workflows is often overlooked. An AI tool that interrupts the clinician at the wrong moment or makes too many alerts can be ignored. Post-deployment monitoring is typically weak, on average. Healthcare data evolves due to the development of new treatments, changing coding conventions, population shifts, and system upgrades. Thus, drift and safety monitoring of AI models is essential.

5. Conclusion

The review analysed the computational techniques and intelligent methods employed in the AI based healthcare systems. The review found that, the most common method families are supervised machine learning, deep learning, natural language processing and knowledge-based clinical decision support. Classical ML methods are still valuable for structured EHR and administrative datasets. Deep learning is of great significance in medical imaging, temporal prediction, and other fields. The use of NLP is important due to the presence of rich healthcare-related information contained in clinical texts. For clinical decisions in the future, it is important to use knowledge-based and hybrid systems because they require both guideline-based reasoning and data-driven prediction.

The field continues to grow through the introduction of a range of new ideas, such as explainable AI, federated learning, large language models, RL, and multimodal AI.

Nevertheless, there are still significant issues that AI-based health systems suffer from. These issues include inadequate external validation, poor interpretability, dataset shift and algorithmic bias. It is concluded that mere computational performance is not sufficient. Healthcare AI should be secure, intelligible, just, useful, preserve privacy, notify interoperability, and monitor constantly.

6. Implications

6.1 Implications for Clinical Practice

Instead of replacing clinicians, healthcare organisations should let AI act as a decision-support tool. Clinicians are ultimately responsible for making final clinical decisions in high-risk situations. AI tools must deliver clear results that allow for action. Their goal should be to make life easier, not documentation or alert fatigue.

6.2 Implications for System Developers

When designing the AI systems, developers should consider the clinical workflow from the start. In development, clinicians should be patients, informatics specialists, and more governance teams. Validation of models must be performed on independent datasets and tested for fairness, safety, calibration, and usability.

6.3 Implications for Researchers

Future research studies should focus on non-retrospective accuracy. There is a need for additional research on many topics such as prospective validation, clinical trials, implementation science, cost-effectiveness, bias mitigation, human-AI interaction and post-deployment monitoring. Researches should adopt reporting standards like CONSORT-AI

6.4 Implications for Policy and Governance

Regulators and healthcare stakeholders must establish governance frameworks to manage AI-based healthcare systems. The frameworks we adopt for the deployment of artificial intelligence must have a data quality standard, privacy protection, transparency, clinical safety accountability, algorithmic accountability, cybersecurity, and monitoring on a consistent basis. There must be appropriate audits to make certain the AI system stays safe and secure after deployment.

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