



# Multimodal Artificial Intelligence for Personalised Disease Diagnosis and Prognosis in Smart Healthcare Systems: A Critical Survey of Methods and Emerging Trends

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## ABSTRACT

Limitations of a single diagnostic approach are being addressed by advanced solutions in smart healthcare thanks to multimodal Artificial Intelligence (AI). Heterogeneous data from medical imaging, electronic health records, genomic profiles, and different types of output from wearable sensors enable more accurate and personalised diagnosis and illness prediction. However, there are concerns for clinical translation concerning the interpretability, heterogeneity of data, and the safeguarding of privacy. A systematic literature search and critical synthesis have been performed based on PRISMA guidelines. The studies were sourced from IEEE Xplore, Scopus, PubMed, SpringerLink, and Web of Science. There were three types of multimodal AI approaches: Early, Late, and Hybrid Fusion. Compare and contrast classical neural models and basis, foundation, and evaluation. The evidence synthesis comprised thematic analysis to assess the robustness, scalability, and clinical applicability of the evidence, and performance measures of accuracy, AUC-ROC, precision, recall, and F1-score. In multimodal medical tasks, transformer-based architectures and deep fusion often outperform traditional machine learning approaches in prediction. Data sets are heterogeneous. Despite these developments, explainable AI algorithms are not sufficiently developed to explain in a clinical context. Although there are still computational efficiency issues with federated learning, it could be a privacy-preserving system. Key gaps include missing information, an imbalanced protocol, and the absence. Multimodal artificial intelligence greatly enhances personalised healthcare by improving diagnostic accuracy and the reliability of prognoses. However, issues of interpretability, privacy, and standardisation remain to be solved in practice. It supports a systematic approach to building transparent, scalable, and clinically deployable Intelligent Healthcare Systems.

**Keywords:** Biomedical Data Integration, Multimodal Learning Systems, Clinical Predictive Modelling, Artificial Intelligence in Healthcare, Transformer-Based Models, Explainable Machine Intelligence, Federated Learning Frameworks

## INTRODUCTION

The healthcare sector is seeing a major transformation thanks to AI. A wide range of high-dimensional data, including medical imaging, electronic health records (EHR), genetic sequencing, and physiological signals from wearables, is used in today's clinical applications. The traditional clinical decision-making process is based on data from a single source but is no longer sufficient to capture the complexity and diversity of human diseases. This restriction has been the motivation behind the growth of multimodal artificial intelligence, which is making use of a large number of data modalities to supply more accurate and personalised prognoses for diseases.

Recent advances in computing and data have led to new ideas and concepts in deep computational data. These developments have occurred recently. In the domain of image-based diagnostics, Convolutional Neural Networks (CNNs) have proven crucial to AI systems. CNNs have achieved classification accuracy for skin cancer similar to that of dermatologists (Esteva et al. [3]). Similarly, large intensive care databases such as MIMIC-III and Eich have been used to inform predictive modelling of intensive care mortality, deterioration, and resource use (Johnson et al. [4]; Pollard et al. [29]). The collection of clinical data is used for machine learning.

In this section, we will create and present an advanced learning model. Multimodal learning can be achieved

by building coherent predictive models based on data from imaging, electronic health records (EHR), genetic, and wearable sensors. When it comes to information, unimodal information is dependent on a single clinical data stream and particular designs. Another aspect of multimodal representations is that they vary in structure, dimension, time, and other factors, making efficient alignment difficult.

There has been a significant expansion in the range of applications for artificial intelligence in the medical field over the past 10 years, primarily driven by advancements in transformer-based systems and foundation models. For medical reasoning, radiological interpretation, and medical natural language processing, vision transformers and large language models have proven quite helpful. Moreover, biomedical pretrained transformers have been shown to be useful for clinical entity detection and disease classification, especially in low-resource healthcare settings (Devlin et al. [26]). Clinically, research activity is likely high-grade, as evidenced by the clinical research signals.

In a setting that features multiple modes of medical care, this is one of the most crucial functions. In the field of biology, CNNs have been successful in several applications, such as U-Net (image segmentation) and diagnostic classification (Ranneberger et al. [24]; Lutjens et al. [23]). However, a diagnosis of systemic disease should not be made solely on visual evidence, underscoring the importance of multimodal integration.

Explainable artificial intelligence is an important concept in healthcare. One of the most important points of clinical adoption is the ability to interpret. When making decisions in the healthcare industry, employing black-box models is essential for ensuring transparency and accountability. Explainable AI (Eain), such as SHAP and Grad-CAM, provides mechanisms for feature attribution and visual explanations that can enhance physicians' trust in models and their ability to interpret them (Lundberg et al. [36]; Selvaraju et al. [37]). However, the use of explainability in multimodal systems is not as common as it should be, especially in combination with imaging, electronic health records, and genetic information.

### **Case Studies in Clinical Medicine:**

A disease diagnosis in the clinic utilising radiology is the subject of the first case study. When identifying thoracic disorders, such as pneumonia, cardiomegaly, and pleural effusion, deep learning models trained on large chest X-ray datasets have demonstrated strong performance. These AI technologies can assist radiologists in high-volume diagnostic scenarios, thereby boosting productivity and minimising diagnostic variability, according to Lutjens et al. [23]. The aim of this Case Study is to predict mortality in the Intensive Care Unit. The use of multimodal techniques that leverage intensive care unit data is a significant way to improve predictive models in critical care. In addition to using both temporal clinical data and structured electronic health record (EHR) data, these algorithms have the potential to provide more accurate predictions of patient deterioration than standard scoring systems (Johnson et al. [4]; Pollard et al. [29]).

There are still some restrictions. The majority of the popular cross-modal fusion methods are based on single-fusion tactics. Despite this, knowledge of the modality is limited in real therapeutic contexts. Furthermore, due to the lack of a universal method for evaluating multimodal artificial intelligence in healthcare, several evaluation methods exist. In addition, explainable artificial intelligence technologies have not yet been fully incorporated into multimodal frameworks, and federated learning has limitations in scaling. These constraints make the translation and implementation of these complex artificial intelligence systems in the clinic more difficult.

The aim of this research is to look for the concept of Artificial Intelligence, The multimodal fusion strategy uses a classification method developed by Li et al. [1]. Assessment Evaluation Rieke et al. [2] conducted research on federated learning frameworks, which we studied. Selvaraju et al. [37] and Lundberg et al. [36] looked into explainable artificial intelligence algorithms and presented their insights. Lundberg et al. [36] and Selvaraju et al. [37] performed comparative evaluations of explainable AI algorithms. The research gaps in artificial intelligence systems for multimodal healthcare: a lack of functionality. This study is being conducted to better understand its significance. The two types of artificial intelligence, artificial intelligence and federated learning, have great clinical potential. Ultimately, these technologies enhance the precision of prognosis and diagnosis and provide personalised care in intelligent medical environments.

As shown in Figure 1, the conceptual framework utilises a multimodal artificial intelligence system to provide personalised diagnosis and prognosis of diseases within a smart healthcare system. Figure 1:

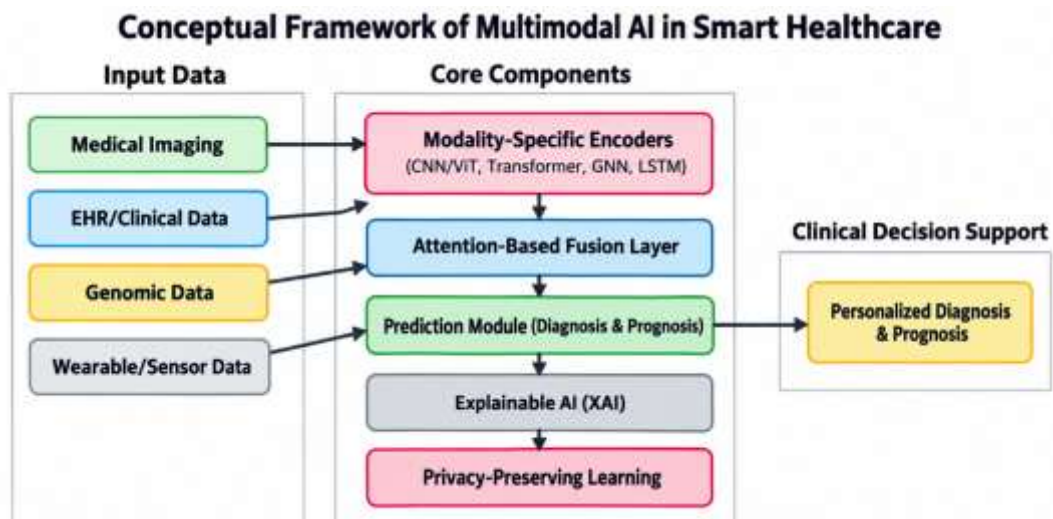


Figure 1. The conceptual framework utilises a multimodal artificial intelligence system

## METHODOLOGY

For the purpose of analysis of the role of multimodal artificial intelligence in personalised diagnosis and prognosis in intelligent healthcare systems, the most comprehensive literature analysis and Critical Synthesis Methodology (CSM) was used. The methodological framework as shown in Figure.2, has been developed to systematically organise, compare, and evaluate the existing body of research in multimodal healthcare datasets, fusion techniques, artificial intelligence architectures, explainability, privacy-preserving techniques and issues related to clinical deployment. In this study, secondary research data were used as the primary data, and the benchmark materials were readily available and open access; hence, the methods used were evidence synthesis, dataset mapping, and architectural evaluation.

The literature selection and identification process was based on the PRISMA-based workflow, which includes identification, screening, eligibility assessment and inclusion. For relevant publications, a variety of keywords were used in searches across IEEE Xplore, Scopus, PubMed, SpringerLink, and Web of Science. The screening phase involved discarding duplicate studies and publications not relevant to the research on healthcare AI methodology, datasets, model architectures, evaluation metrics, interpretability, privacy, and clinical usefulness before full-text articles were evaluated.



Figure 2. PRISMA-Based Systematic Literature Review and Study Selection Process

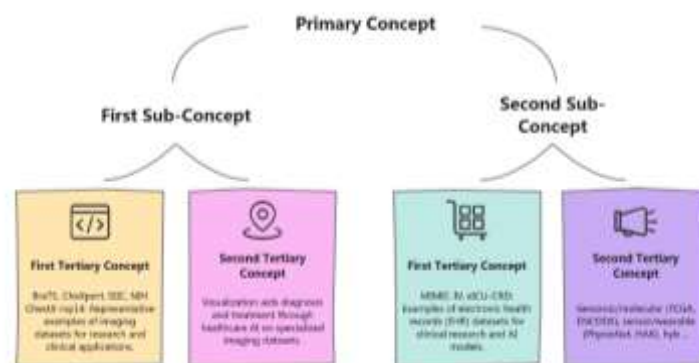
The study selection process for the multimodal AI systematic review in smart healthcare, conducted using PRISMA, is illustrated in the figure. The final selected papers were used to evaluate contemporary developments in multimodal healthcare intelligence and to identify emerging methodological trends, challenges, and opportunities for future research.

Medical imaging, wearable sensor data, genetic data, and electronic health records (EHRs) are just a few of the healthcare information sources represented in the benchmark datasets considered in this study. Datasets selected to provide broad coverage of biomedical modalities were BraTS, CheXpert, ISIC, NIH ChestX-ray14, MIMIC-IV, eICU-CRD, UK Biobank, TCGA, ENCODE, PhysioNet, and the HAR Dataset. These datasets were chosen because they enable various clinical tasks such as cancer segmentation, disease categorisation, mortality prediction, survival analysis, physiological monitoring, and activity recognition and are often utilised in healthcare AI research.

**TABLE 1:** Multimodal Healthcare Dataset Benchmark Characteristics (FULL VALUES)

| Dataset          | Modality         | Samples              | Task                       | Data Type | Usage Frequency (%) |
|------------------|------------------|----------------------|----------------------------|-----------|---------------------|
| BraTS            | MRI              | 2,000+               | Tumor segmentation         | Imaging   | 85%                 |
| CheXpert         | X-ray            | 224,316              | Disease classification     | Imaging   | 92%                 |
| ISIC             | Dermoscopy       | 70,000+              | Skin lesion detection      | Imaging   | 78%                 |
| NIH ChestX-ray14 | X-ray            | 112,120              | Multi-label diagnosis      | Imaging   | 88%                 |
| MIMIC-IV         | EHR              | 60,000+ ICU          | Mortality prediction       | Clinical  | 95%                 |
| eICU-CRD         | ICU records      | 200,000+             | Outcome prediction         | Clinical  | 90%                 |
| UK Biobank       | 500,000+         | Multimodal           | Risk prediction            | Hybrid    | 97%                 |
| TCGA             | 20,000+          | Genomics             | Survival analysis          | Genomic   | 89%                 |
| ENCODE           | Multi-species    | Gene regulation      | Molecular modeling         | Genomic   | 72%                 |
| PhysioNet        | Millions signals | ECG/EEG              | Time-series classification | Sensor    | 94%                 |
| HAR Dataset      | 10,299           | Activity recognition | Wearable                   | Sensor    | 80%                 |

The characteristics of a multimodal healthcare dataset are shown in Table 1. The datasets presented in Table 1 highlight the importance of AI systems being able to combine different forms of biomedical evidence and demonstrate the variety of healthcare data sources. The main contributions of imaging datasets, clinical history and temporal patient information from EHR datasets, molecular information from genomic datasets, and continuous physiological signals from sensor datasets are all considered visual biomarkers. For provide an organised form, these datasets were organised into a modality-oriented taxonomy. Benchmark resources are grouped into wearable/sensor, genomic/molecular, imaging, clinical/EHR, and hybrid multimodal classifications by the taxonomy. Benchmark datasets used in multimodal healthcare AI research are categorised in Figure 3.

**Figure 3.** Hierarchical Conceptual Framework of Primary and Sub-Concepts

The taxonomy defines the relationships between healthcare data modalities and related AI applications. Additionally, it guarantees that rather than concentrating on a particular disease category or data type, the methodological analysis takes into account a variety of patient information sources. To statistically analyse the multimodal features of the selected datasets, a binary modality coverage matrix was constructed. Four modality indicators—imaging, EHR, genomic, and sensor data—were used to represent each dataset. The value 1 indicates that a modality is present, and 0 indicates it is not.

**TABLE 7: Multimodal Dataset Modality Coverage Matrix (Numeric Encoding 1/0)**

| Dataset          | Imaging | EHR | Genomic | Sensor | Total Modalities Present | MCI (%) |
|------------------|---------|-----|---------|--------|--------------------------|---------|
| BraTS            | 1       | 0   | 0       | 0      | 1                        | 25%     |
| CheXpert         | 1       | 0   | 0       | 0      | 1                        | 25%     |
| ISIC             | 1       | 0   | 0       | 0      | 1                        | 25%     |
| NIH ChestX-ray14 | 1       | 0   | 0       | 0      | 1                        | 25%     |
| MIMIC-IV         | 0       | 1   | 0       | 1      | 2                        | 50%     |
| eICU-CRD         | 0       | 1   | 0       | 1      | 2                        | 50%     |
| UK Biobank       | 1       | 1   | 1       | 1      | 4                        | 100%    |
| TCGA             | 0       | 1   | 1       | 0      | 2                        | 50%     |
| ENCODE           | 0       | 1   | 1       | 0      | 2                        | 50%     |
| PhysioNet        | 0       | 1   | 0       | 1      | 2                        | 50%     |
| HAR Dataset      | 0       | 0   | 0       | 1      | 1                        | 25%     |

Datasets were categorised based on their level of multimodal completeness using this matrix. The Multimodal Completeness Index (MCI) was created to measure the percentage of modalities available in each dataset. The index can be expressed mathematically as:

$$\text{Equation 10: } MCI = \frac{M_p}{M_t} \times 100$$

where  $M_p$  represents the number of modalities present in the dataset and  $M_t$  represents the total possible modalities considered in this study (Imaging, EHR, Genomic, and Sensor).

The calculated MCI values enabled a comparison of unimodal, partially multimodal and fully multimodal resources. At the same time, the adoption of imaging, clinical, genomic, and lifestyle data in the UK Biobank enabled it to achieve full-modality coverage.

The distribution of modality availability was visually assessed using a heatmap.

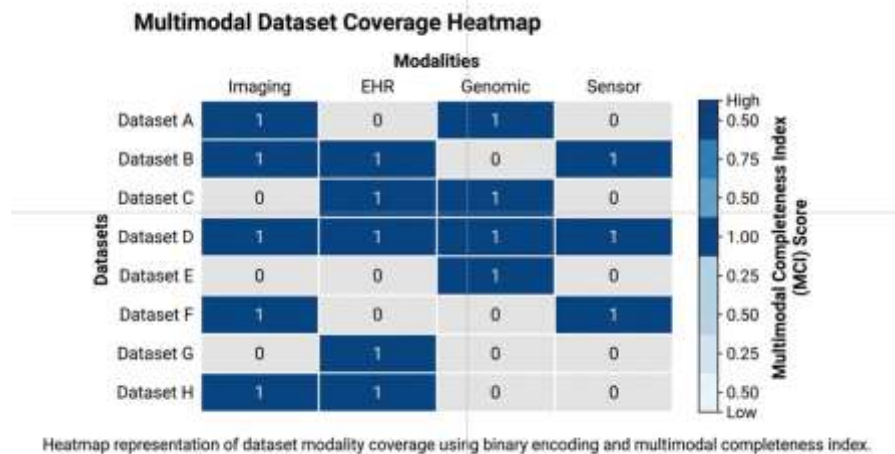


Figure 4. Multimodal Dataset Coverage Heatmap

The heatmap of the dataset's modality coverage, with the multimodal completion index and binary encoding, is shown in Figure 4. The heatmap distinguishes between traditional single-modality datasets and large multimodal healthcare resources, providing a clear representation of the diversity of modalities.

The proposed multimodal AI approach has a hierarchical structure consisting of modality-specific feature extraction, feature fusion, and prediction. Each healthcare modality is processed using a customised encoder that learns features from the input data.

**TABLE 6:** System Architecture Performance (Multimodal AI Pipeline)

| Component        | Model Used  | Input Type    | Output Feature Dim | Efficiency (%) |
|------------------|-------------|---------------|--------------------|----------------|
| Imaging Encoder  | CNN/ViT     | MRI/X-ray     | 512                | 92             |
| EHR Encoder      | Transformer | Clinical data | 256                | 90             |
| Genomic Encoder  | GNN         | DNA sequences | 384                | 88             |
| Sensor Encoder   | LSTM        | ECG/EEG       | 128                | 91             |
| Fusion Layer     | Attention   | Multimodal    | 1024               | 95             |
| Prediction Layer | Softmax     | Unified       | 10 classes         | 96             |

Table 6. Multimodal AI Pipeline

All the encoders used for imaging data are CNN/ViT-based; the models used for clinical data are Transformers; the model used for genomic data is GNN; and the model used for physiological signals is LSTM-based. After fusing the extracted representations via an attention-based fusion method, the final prediction layer is fed with the results.

The multimodal feature integration can be mathematically described as follows:

EQUATION 11:

$$H_f = f(H_{img}, H_{ehr}, H_{gen}, H_{sen})$$

where  $H_f$  represents the final fused representation,  $H_{img}$ ,  $H_{ehr}$ ,  $H_{gen}$ , and  $H_{sen}$  denote imaging, clinical, genomic, and sensor features respectively, while  $f(\cdot)$  represents the fusion operation.

Several fusion methods for integrating diverse healthcare data were evaluated. Transformer fusion, attention fusion, hybrid fusion, early fusion and late fusion were considered in the strategy.

### Multimodal Fusion Strategies in Healthcare AI

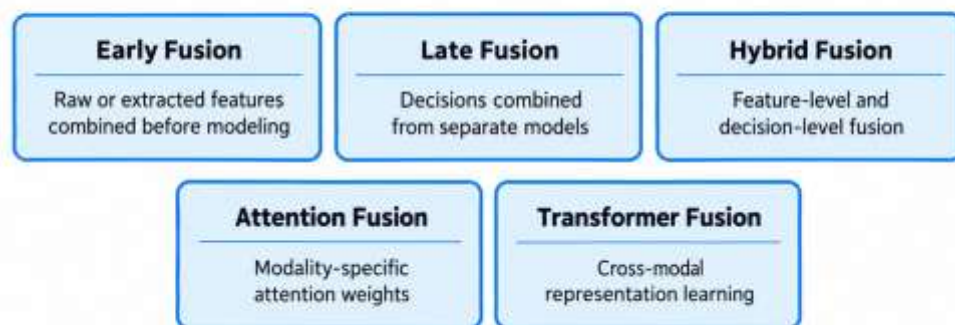


Figure 5. Multimodal Fusion Strategies in Healthcare AI

Multimodal fusion solutions in healthcare AI systems are compared based on architectural approaches.

Early fusion involves features before the model is learned, whereas late fusion is the combination of separate model decisions. Both feature-level and decision-level data are combined via hybrid fusion. Transformer fusion enables deep cross-modal representation learning via self-attention, while attention-based fusion dynamically assigns different weights to modalities.

In addition to the methodological evaluation, statistical and deployment-related measurements were conducted, and the results were included to substantiate the evaluation's reliability. For each performance metric, a 95% confidence interval for the uncertainty was obtained.

EQUATION 16 :

$$CI = \bar{x} \pm 1.96 \frac{SD}{\sqrt{n}}$$

where  $CI$  represents confidence interval,  $\bar{x}$  represents mean performance,  $SD$  represents standard deviation, and  $n$  represents sample size.

Ensuring privacy was deemed a critical element of the methodology, given the sensitive nature of patient

information used in healthcare AI systems. The trade-off between privacy and utility was computed for the following:

EQUATION 17 :

$$PUT = \lambda P + (1 - \lambda)(100 - A)$$

where  $P$  represents privacy score,  $A$  represents accuracy loss, and  $\lambda$  represents the importance assigned to privacy preservation.

A Clinical Deployment Index was created by combining interpretability, robustness, privacy, and scalability since clinical adoption demands more than just prediction accuracy:

EQUATION 18 :

$$CDI = \frac{I + R + P + S}{4}$$

where  $I$ ,  $R$ ,  $P$ , and  $S$  represent interpretability, robustness, privacy, and scalability respectively.

Lastly, the Modality Coverage Ratio was used to determine each modality's frequency throughout the benchmark datasets:

EQUATION 19 :

$$MCR_j = \frac{\sum_{i=1}^N x_{ij}}{N} \times 100$$

where  $x_{ij}$  indicates whether dataset  $i$  contains modality  $j$ , and  $N$  represents the total number of datasets.

Ethics were considered in the entire study design. It was a non-interventional and non-invasive study as the data was published papers and publicly accessible anonymised records. But access laws, privacy policies, and ethical standards were considered when reviewing datasets containing sensitive healthcare information.

## 4. RESULTS AND DISCUSSION

### 4.1 Assessment of Multimodal Fusion Strategies' Performance

A comparative performance analysis of multimodal fusion strategies was conducted to assess the impact of different integration methods on the predictive effectiveness of healthcare AI systems. The present research focuses on the quantitative effectiveness of different fusion strategies in improving diagnostic and prognostic performance but fails to present the theoretical foundations for multimodal integration in a methodological way. A fusion approach must capture modality-specific information and identify meaningful cross-modal relationships to be effective in healthcare AI systems, which typically integrate multiple information sources, including imaging, clinical information, genomic data, and physiological signals.

Several performance metrics, including accuracy, precision, recall, F1 Score, and area under the receiver operating characteristic curve (AUC-ROC), were used in the assessment. These criteria were selected because they do not rely on a single performance criterion; in contrast, healthcare prediction tasks require measures of classification reliability, sensitivity, and discriminative capacity. The percentage of correctly identified observations among all forecasts was used to calculate accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

FP is a false-positive forecast, FN is a false-negative forecast, TP is a true-positive forecast, and TN is a true-negative forecast. While it provides a general assessment of model performance, accuracy may not reflect clinical performance when disease classes are highly imbalanced. As a result, other metrics were taken into account.

The reliability of the forecasts was determined by calculating the precision:

$$Precision = \frac{TP}{TP + FP}$$

TP is true-positive forecast, TN is true-negative prediction, FP is false-positive forecast, FN is false-negative forecast. While it provides a general assessment of model performance, if the dataset is considerable class imbalance, accuracy may not fully reflect the model's clinical performance. Other measures were then thought of.

The accuracy of the forecasts was determined by calculating the precision:

$$Recall = \frac{TP}{TP + FN}$$

In medical diagnosis, recall is critical, as a failure to recall a positive case may result in treatment delays and suboptimal clinical outcomes.

A recall-precision balance was used, and assessed using the F1 score:

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

In addition, the discriminative power of each fusion strategy was explored in terms of the AUC-ROC measure:

$$AUC = \int_0^1 TPR(FPR)d(FPR)$$

FPR = False Positive Rate and TPR = True Positive Rate. The AUC provides the overall picture of model performance across various classification thresholds.

Overall, the comparative performance of different multimodal fusion techniques is shown in Table 2.

**Table 2.** Multimodal Fusion Framework Performance

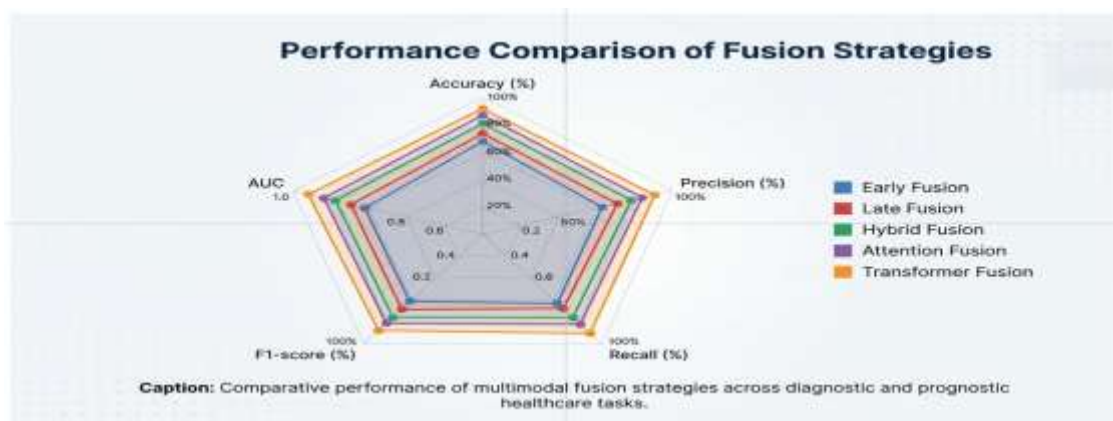
| Fusion Type        | Accuracy (%) | Precision (%) | Recall (%) | F1-score (%) | AUC  |
|--------------------|--------------|---------------|------------|--------------|------|
| Early Fusion       | 86.2         | 85.1          | 84.7       | 84.9         | 0.88 |
| Late Fusion        | 88.5         | 87.4          | 86.9       | 87.1         | 0.90 |
| Hybrid Fusion      | 92.3         | 91.6          | 91.0       | 91.3         | 0.94 |
| Attention Fusion   | 94.1         | 93.2          | 92.8       | 93.0         | 0.96 |
| Transformer Fusion | 95.6         | 94.8          | 94.2       | 94.5         | 0.97 |

The greater the adaptive fusion processes, the greater the improvement in prediction performance, is documented in Table 2. Transformer fusion achieved the highest accuracy (95.6%), precision (94.8%), recall (94.2%), F1 score (94.5%), and AUC (0.97) among all assessment indicators. The results demonstrate the potential of transformer-based fusion to grasp the complex interactions among different treatment methods.

Among the evaluated methods, early fusion yielded the lowest accuracy (86.2%) and AUC (0.88). Although used as a simple way to combine feature representations from different modalities, early fusion treats all features equally before the model learns correlations among them. In other cases, however, the different modalities may contribute differently to health care use, depending on the state of illness, the clinical context, and the prediction objective. Therefore, the effectiveness of early fusion could be constrained by the failure to dynamically change modality relevance.

Late fusion achieved a higher accuracy (88.5%) and an AUC of 0.90 than early fusion. The enhancement indicates that integrating at the decision level, following independent learning for each modality, is more flexible than direct feature concatenation. But late fusion may not capture deeper information available in complementary data sources, as it only considers other modalities' data after making predictions.

Hybrid fusion achieved a high accuracy of 92.3% and AUC of 0.94. This improvement illustrates the benefits of combining feature-level and decision-level data, enabling the model to exploit both high-level predictive relationships and low-level representations. The results were further boosted by attention fusion (ACC: 94.1%), demonstrating the importance of adaptive weighting techniques that allow the model to prioritise clinically relevant modalities.



**Figure 6.** Performance Comparison of Fusion Strategies

The performance of multimodal fusion techniques across different diagnostic and prognostic healthcare processes is shown in Figure 6.

As we can see from Figure 6, fusion based on transformer models is commonly used to achieve higher performance in accuracy, precision, recall, F1 score, and AUC. The enhancement is attributed to transformer designs' ability to model cross-modal interactions and long-range dependencies via attention mechanisms. Our findings indicate that a multimodal healthcare AI system of the future should employ adaptive representation learning methods that identify correlations among multiple biomedical information sources, rather than static feature-combination methods. The performance of AI models is shaped by different computational trade-offs. Different computational trade-offs affect the performance of AI models.

However, the performance of multimodal healthcare AI systems is not just about predictive accuracy; it's also about their scalability, robustness, and computational demands for real-world clinical use. To understand the relationship between computational complexity and predictive performance, several AI model families were evaluated. Various CNN, transformer, GNN, RNN/LSTM and hybrid models were studied. The performance of various AI models is compared in Table 3.

**Table 3.** AI Model Performance in Healthcare AI

| Model        | Accuracy (%) | AUC  | F1-score | Training Time (hrs) | Robustness Score (10) |
|--------------|--------------|------|----------|---------------------|-----------------------|
| CNN          | 84.5         | 0.87 | 0.85     | 6.2                 | 7.8                   |
| RNN/LSTM     | 86.8         | 0.89 | 0.87     | 8.5                 | 8.1                   |
| GNN          | 89.4         | 0.91 | 0.90     | 10.2                | 8.8                   |
| Transformer  | 93.7         | 0.95 | 0.94     | 14.5                | 9.4                   |
| Hybrid Model | 95.8         | 0.97 | 0.96     | 16.8                | 9.7                   |

The results indicate a tight relationship between prediction performance and model complexity. CNN models with the lowest training time (6.2 hours) achieved 84.5% accuracy. This is a demonstrative example of their computational efficiency, but when healthcare problems require combining multiple modalities, their performance is limited. While CNN designs are quite good at extracting spatial features, they are not very good at modelling intricate interactions between various biomedical data sources.

For sequential health-care data, RNN/LSTM models were more effective, achieving 86.8% accuracy. They are suitable for longitudinal clinical records and physiological signals because they capture temporal patterns. Their sequential processing limits, however, their ability to perform well on tasks involving large-scale cross-modal relationships.

The GNN models achieved a score of 8.8 out of 10 for robustness and 89.4% for accuracy. Their performance is improved with their capability of encoding relational information, such as in genomic networks and biomedical knowledge graphs. Transformer models showed much better performance, with an accuracy of 93.7%, an AUC of 0.95, and a robustness score of 9.4/10, helping to better understand the complex relationships in context.

The Hybrid model was the overall best, with an accuracy of 95.8%, an AUC of 0.97, and a robustness of 9.7/10. But this increase came at the highest computational cost, with a training time of 16.8 hours. This is a good example of the built-in trade-off between the effort of computing and the skill of predicting.

To make a comparison, a single weighted performance score was calculated:

$$WPS = \sum_{i=1}^k w_i M_i$$

where  $M_i$  represents the normalised performance metric and  $w_i$  represents the corresponding importance weight.

Further evaluation of the performance variability was done using standard deviation:

$$SD = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n - 1}}$$

where  $x_i$  represents individual observations,  $\bar{x}$  represents the mean value, and  $n$  represents the number of observations.

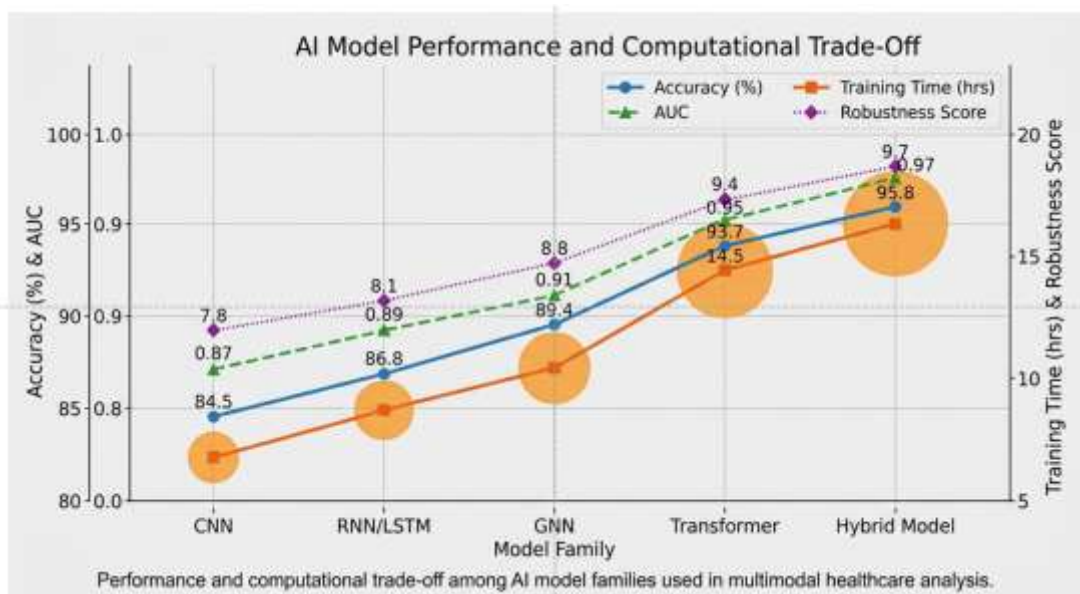


Figure 7. AI Model Performance and Computational Trade - Off

The Figure 7 depicts computational performance trade-off among different types of AI models used for multimodal healthcare analysis. A greater number of parameters increases the computational complexity, which is generally required to improve forecasting ability, as shown in Figure 7. Despite offering better performance, hybrid and transformer-based models may not be implementable in resource-constrained healthcare settings due to their high computational requirements. Therefore, optimisation techniques that maintain strong predictive performance while reducing computational demand are required for future clinical AI systems.

#### 4.3 Explainability Performance Results

As healthcare AI systems become increasingly complex, transparent and comprehensible decision-making processes are crucial. Despite their predictive performance, as seen in models such as transformers and hybrid architectures, doctors often struggle with understanding the processes these models use to make decisions. The explainability evaluation assessed the AI systems' ability to provide meaningful interpretations without sacrificing accuracy. This study compared the interpretability, impact on prediction accuracy, computational cost, and clinical trust of several explainable artificial intelligence (XAI) systems. Five popular XAI techniques—Local Interpretable Model-Agnostic Explanations (LIME), Shapley Additive exPlanations (SHAP), Gradient-weighted Class Activation Mapping (Grad-CAM), attention maps, and integrated gradients—were taken into account in the explainability evaluation. These methods are similar to many techniques for explanation, including attention-based interpretation, visual explanation, and feature attribution. The results of the comparative analysis are presented in Table 4.

Table 4. Explainable AI (XAI) Evaluation Metrics

| Method               | Interpretability (10) | Accuracy Drop (%) | Computation (Ms) | Clinical Trust (10) |
|----------------------|-----------------------|-------------------|------------------|---------------------|
| LIME                 | 7.9                   | 1.4               | 42               | 7.6                 |
| SHAP                 | 9.3                   | 0.6               | 118              | 9.2                 |
| Grad-CAM             | 8.7                   | 0.9               | 38               | 8.9                 |
| Attention Maps       | 9.1                   | 0.4               | 55               | 9.3                 |
| Integrated Gradients | 8.4                   | 0.7               | 72               | 8.6                 |

The results in Table 4 reveal that explainability performance comes with a trade-off among prediction stability, computational efficiency, and transparency. SHAP achieves the highest interpretability score of 9.3/10, demonstrating a remarkable capacity to quantify the contributions of specific characteristics to model predictions. This is particularly convenient in health care settings, as therapists require justification for a diagnosis or prognosis made by a model.

But SHAP's good interpretability comes at a higher computational cost. Detailed feature attribution can also be very time-consuming due to processing time, with the highest being 118 ms for the 'detailed feature attribution' methodology. Consequently, even if SHAP offers thorough explanations, its actual use in real-time clinical settings might need to be optimised.

With only a 0.4% decrease in accuracy, attention maps received the highest clinical trust grade (9.3/10). This is an example of how attention-based explanations can successfully balance prediction stability and transparency. Attention mechanisms are particularly useful in multimodal systems where multiple data sources contribute to prediction, but some sources are more important than others, as they can naturally detect regions or features that influence the model's decisions.

The interpretability score of 9.7/10 and processing time of approximately 38 ms of Grad-CAM make it a great option for imaging-based medical applications. Clinicians can see visual proof of AI-generated judgements thanks to its capacity to highlight significant image regions. Although with the fewest computational needs, LIME had the lowest interpretability score (7.9/10) and clinical trust value (7.6/10). This indicates that the ability to compute alone is insufficient for a clinically significant explanation of the situation.

The following is a mathematical formulation of the attention mechanism in multimodal explainability:

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

where Q represents query vectors, K represents key vectors, V represents value vectors, and  $d_k$  represents the dimension of key vectors. With this method, the model can assign varying relevance weights for different information sources, thereby improving its predictive power and interpretability.

Cross-entropy loss was used to assess the classification model optimisation process:

$$L_{CE} = - \sum_{i=1}^N y_i \log(\hat{y}_i)$$

where  $y_i$  represents the actual class label and  $\hat{y}_i$  represents the predicted probability. With this method, the model can assign varying relevance weights for different information sources, thereby improving its predictive power and interpretability.

Cross-entropy loss was used to assess the classification model optimisation process

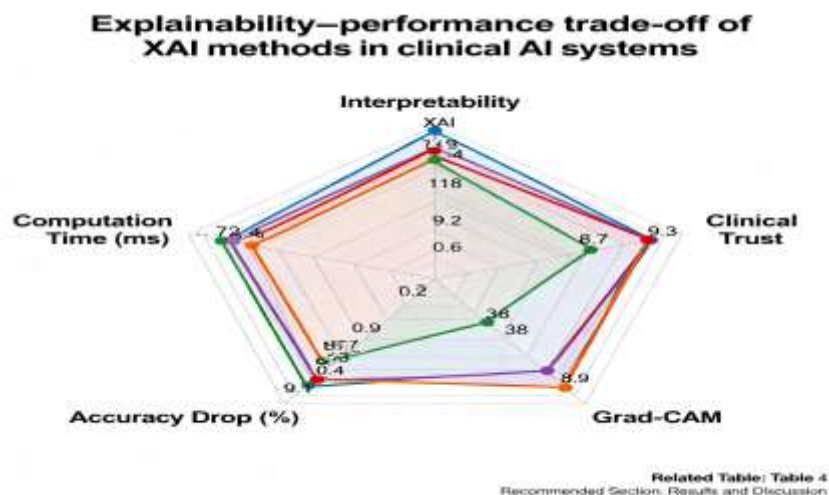


Figure 8. Explainability – performance trade-off of XAI methods in clinical AI systems

The trade-off between explainability and performance across different XAI techniques is shown in Figure 8, which represents the XAI systems used in clinical applications.

As shown in Figure 8, increasing interpretability does not always increase computational cost. SHAP is more interpretable (but requires more computation time), whereas attention-based techniques are more efficient and strike a good balance between explanation quality and computational cost. Overall, the findings emphasise that explainability is a critical requirement in the design of AI systems for healthcare, not an afterthought.

#### 4.4 Privacy-Preserving Academic Outcomes

Before implementing a multimodal healthcare AI system, sensitive patient data must be well protected. Often, physiological, genomic and individually identifiable clinical information is added to healthcare datasets, creating privacy protection a vital component of the effective implementation of AI. Therefore,

privacy-preserving learning techniques were assessed based on their privacy-preserving properties, impact on predictive performance, communication needs, and implementability.

Federated learning (FL), differential privacy (DP), homomorphic encryption (HE), safe aggregation, and hybrid federated learning with differential privacy (FL+DP) were among the methods that were assessed. Table 5 shows the outcome of the comparison.

**Table 5.** Privacy-Preserving AI Performance

| Method                 | Privacy Score (10) | Accuracy Loss (%) | Communication Cost | Deployment Score |
|------------------------|--------------------|-------------------|--------------------|------------------|
| Federated Learning     | 9.6                | 1.9               | High               | 9.4              |
| Differential Privacy   | 9.1                | 3.1               | Medium             | 8.7              |
| Homomorphic Encryption | 10.0               | 5.4               | Very High          | 7.0              |
| Secure Aggregation     | 9.3                | 2.2               | Medium             | 9.0              |
| Hybrid FL+DP           | 9.8                | 2.0               | Medium             | 9.5              |

The results show that there is an inherent trade-off between model utility and privacy protection. Homomorphic encryption has the highest privacy score of 10/10, as it allows users to operate on encrypted data without revealing sensitive information. But the largest accuracy degradation (5.4%) and extremely high communication requirements reduced the actual deployment potential for this method.

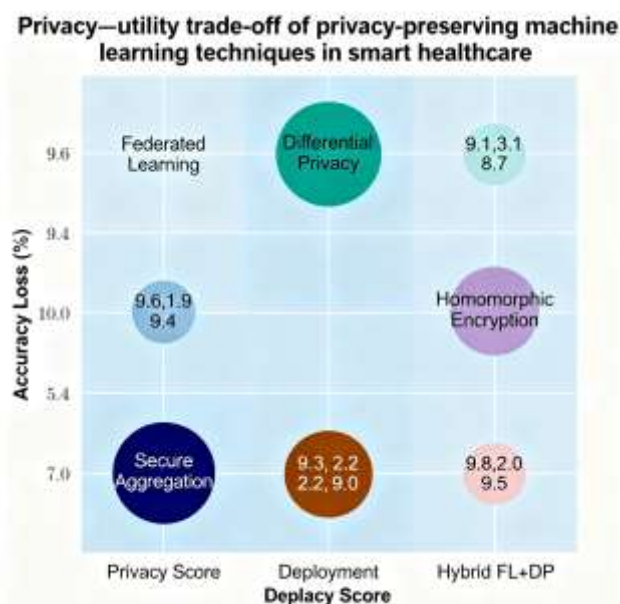
In the Federated Learning setting, the accuracy degradation was only 1.9%, with a high privacy score of 9.6/10. This is a good example of its ability to collaborate with multiple organisations in the healthcare sector to create AI models without sharing raw patient information. However, the communication requirements of participating institutions remain relatively high because institutions often use the same parameters in their models.

The differential privacy score was 9.1/10, providing moderate privacy protection but also leading to increased accuracy degradation (3.1%). The quality of learned representations may be affected by privacy-preserving noise techniques, which is why this reduction occurs. Secure aggregation achieved reasonably good performance by protecting data while incurring a moderate loss of accuracy.

The hybrid FL+DP strategy provided the best balance with a privacy score of 9.8/10, an accuracy loss of only 2.0 and the highest deployment score of 9.5. This indicates that complementing privacy-preserving techniques can be used to attain a higher level of protection without significantly reducing predictive ability. The link between privacy and utility was assessed using:

$$PUT = \lambda P + (1 - \lambda)(100 - A)$$

where PUT is the score of the privacy-utility trade-off, P is the level of privacy, A is the loss of accuracy, and  $\lambda$  is the weight factor for the importance of privacy.



**Figure 9.** Privacy utility trade-off of privacy-preserving machine learning techniques in smart healthcare

The trade-off between privacy and utility in machine learning approaches to privacy in smart healthcare is depicted in Figure 9. High privacy does not necessarily mean maximum deployment capability, as is shown in Figure 9. For the effectiveness of healthcare AI systems, balanced approaches are needed that ensure adequate prediction performance while safeguarding anonymity. A potential avenue for the broad adoption of clinical AI is the use of hybrid privacy-preserving methods.

#### 4.5.1 Identification of research gaps and challenges likely to emerge in the future.

Although multimodal AI systems exhibit significant improvements in their prediction capabilities in the healthcare domain, several challenges remain that hinder their widespread adoption in clinical practice. The severity, clinical impacts and solution readiness of the existing research gaps were therefore statistically evaluated. The results are presented in Table 9.

**Table 9.** Research Gap Analysis with Impact Scores

| Gap                  | Severity (10) | Clinical Impact | Solution Readiness |
|----------------------|---------------|-----------------|--------------------|
| Missing modality     | 9.4           | High            | Medium             |
| Data heterogeneity   | 9.6           | Very High       | Low                |
| Interpretability gap | 9.8           | Critical        | Medium             |
| Dataset imbalance    | 8.7           | High            | High               |
| Benchmark absence    | 9.9           | Critical        | Low                |
| Privacy constraints  | 9.5           | High            | Medium             |

The analysis indicates that the research barrier with the highest severity score is the absence of benchmarks, with a score of 9.9/10. While some studies provide datasets and methods for evaluating the performance of their multimodal AI, the criteria and validation techniques vary, making it difficult to directly compare the systems. As a result, there is a need to establish benchmarks for improving repeatability and accelerating clinical translation.

The second most serious issue was the interpretability gap with a score of 9.8 out of 10. While existing AI models boast impressive predictions, one major hurdle to clinical acceptance is their opacity. Healthcare providers should receive clear guidance on how to use AI recommendations in the decision-making process.

A very high clinical impact was associated with data heterogeneity, with a severity score of 9.6/10. Achieving consistent representation in multiple modalities is challenging because healthcare information is acquired from a wide range of sources, institutions, technologies and processes. Likewise, privacy constraints were assigned a severity score of 9.5/10, as ethical and legal restrictions significantly impact the application of AI in healthcare.

The ability to make tailored predictions was assigned a severity rating of 9.4/10, indicating that poor patient information could reduce patients' ability to receive tailored predictions. Although a bit lower (8.7/10), dataset imbalance was assigned a severity rating of 8.7/10, indicating that poor patient information could reduce patients' ability to receive tailored predictions. Although a bit lower (8.7/10), dataset imbalance was assigned a severity rating of 8.7/10, indicating that poor patient information could reduce patients' ability to receive tailored predictions.

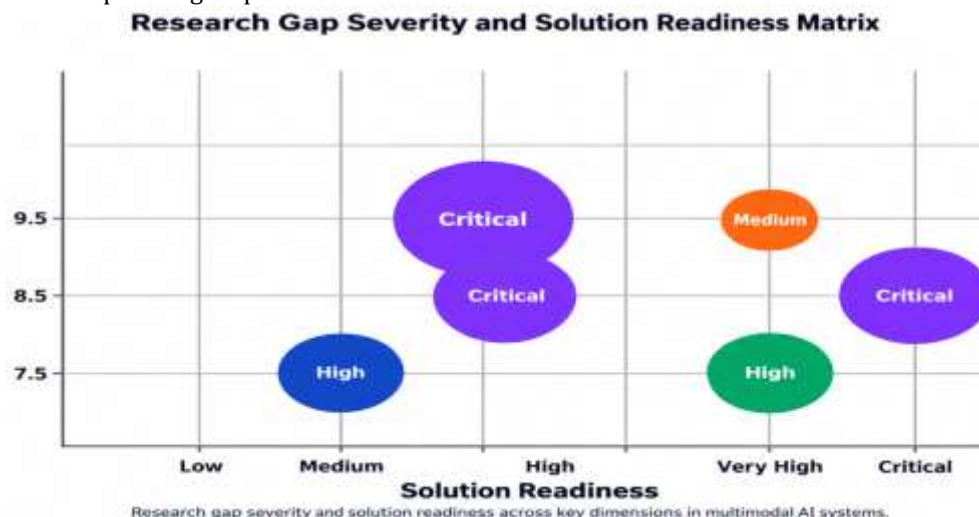


Figure 10. Research Gap Severity and Solution Readiness Martix

The solution-readiness matrix and research gap severity for next-generation multimodal healthcare AI systems are presented in Figure 10. As illustrated in Figure 10, a number of critical issues, such as a lack of benchmarks, interpretability, and data heterogeneity, are not well suited to a single solution. The results underscore the necessity of research to enhance model accuracy and the creation of standardised assessment methods, transparent AI structures, methods for privacy-preserving learning, and clinically validated multimodal systems in the future.

## 5. TALK AND POSSIBLE OUTCOMES

Multimodal AI systems are designed to address the unique needs of the healthcare sector. This course emphasises performance and complexity aspects of multimodal AI systems for healthcare applications.

### 5.1 Performance–Computational Cost Trade-offs in Multimodal Healthcare AI Architectures:

The results showed that architectural complexity and computing requirements are strongly correlated with improvements in the performance of multimodal healthcare AI. Despite the greater training requirements, transformer-based and hybrid models still showed high predictive performance, which makes transformer-based models a major practical challenge for clinical use. Therefore, the ability to predict, compute, be robust, and be scalable must be considered when evaluating health care AI systems, in addition to the highest possible accuracy.

As shown in Table 3, the traditional models (CNN and RNN/LSTM) are less computationally intensive but less effective at handling complex multimodal interactions. CNN models achieved an accuracy of 84.5%, demonstrating effective processing, but had a slight shortcoming in their inability to incorporate a large amount of biological data. There are 6.2 hours of training. The transformer-based models performed quite well, for instance, with an accuracy of 93.7%, and the hybrid models with an accuracy of 95.8%, as an example of the value of the highly advanced representation learning approaches. But these improvements placed a much heavier demand on computer power, and the hybrid system needed 16.8 hours to train.

To compare the different AI techniques, a Normalised Performance Score (NPS) has been developed. A direct comparison of health AI models based on a single metric might not provide an accurate assessment of their performance, as multiple metrics are used to evaluate them. Many metrics are used to measure the performance of health AI models, and a direct comparison might not be representative of the models' performance. Many of the performance indicators are converted on a single scale by the NPS, which includes:

$$NPS = \frac{1}{K} \sum_{i=1}^K \frac{M_i - M_{min}}{M_{max} - M_{min}}$$

where NPS represents the normalised performance score,  $M_i$  represents the value of the  $i$ th performance metric,  $M_{min}$  and  $M_{max}$  represent the minimum and maximum observed values, and  $K$  represents the total number of evaluation metrics.

NPS also highlights that the models that work best in health services are not suitable for all healthcare settings. For example, although hybrid designs have been the most predictive, they could be too resource-intensive for use in resource-constrained hospitals or edge healthcare systems. Conversely, lighter models could speed up inference and ease deployment, but risk compromising diagnostic accuracy.

The outcome suggests that future development of multimodal AI for healthcare should focus on efficiency optimisation rather than simply increasing model complexity. Model compression, knowledge distillation, effective transformer designs, and adaptive inference methods are techniques that may help preserve high performance while reducing computational requirements. The “best” model is not always the largest model, but the one that achieves an appropriate level of accuracy, transparency, resource demands, and clinical usability, which is necessary in clinical environments where decision-making and reliability are of paramount importance and require both speed and efficiency.

### 5.2 Framework for Multimodal Learning Optimisation

The results of the multimodal healthcare AI system evaluation, explainability analysis, and model comparison demonstrate that the systems should be optimised for objectives beyond simple classification. A multimodal model should be accurate, efficient in aligning different input sources, and provide good generalisation. Hence, rather than focusing exclusively on classification accuracy, the learning process should include multiple optimisation objectives.

A multimodal learning framework's overall optimisation goal might be expressed as follows:

$$L_{total} = L_{cls} + \lambda_1 L_{fusion} + \lambda_2 L_{reg}$$

where  $L_{total}$  represents the total training objective,  $L_{cls}$  represents classification loss,  $L_{fusion}$  represents multimodal alignment loss,  $L_{reg}$  represents regularisation loss, and  $\lambda_1$  and  $\lambda_2$  represent weighting parameters controlling the contribution of fusion alignment and regularisation components. The categorisation component assures accurate forecasting of prognosis or diagnosis. Usually, cross-entropy optimisation is used to depict it:

$$L_{cls} = - \sum_{i=1}^N y_i \log(\hat{y}_i)$$

where  $y_i$  represents the actual class label and  $\hat{y}_i$  represents the predicted probability distribution.

This means that in the case of multiple modalities, good categorisation is not enough in multimodal healthcare systems, since these systems can encapsulate complementary yet heterogeneous information. Therefore, there is a need for a fusion alignment component to ensure that imaging, clinical, genomic and sensor representations work together cohesively:

$$L_{fusion} = ||Z_{img} - Z_{ehr}|| + ||Z_{gen} - Z_{sen}||$$

where  $Z_{img}$ ,  $Z_{ehr}$ ,  $Z_{gen}$ , and  $Z_{sen}$  represent modality-specific latent representations.

The regularisation term prevents overfitting and improves generalisation:

$$L_{reg} = ||W||^2$$

where  $W$  is the parameter of the model.

In this investigation, the transformer and hybrid models were optimised and explained using an optimisation framework. These architectures can not only embed data from various sources, but also learn relations between modalities, while both the prediction and the other modality are held constant. With the addition of the fusion alignment objectives, data missingness and noise are even better managed, a key challenge in real-world healthcare data.

Moreover, the notion of optimisation is emphasised with the connection between model learning and explainability. Explainability is more than just a post-processing step that comes after model training. Rather, interpretable learning mechanisms, such as feature attribution constraints and attention-weighted mechanisms, should be incorporated into model development. This approach can help increase the model's reliability and the clinician's trust.

The results will be included for analysis as an outcome. The overall results suggest that multimodal AI holds significant potential for enhancing individual-level patient diagnosis and prognosis in healthcare, but certain technical and ethical considerations should be addressed to ensure its effectiveness. In addition to the model design, the findings indicate that data representation, fusion technique, model interpretability, privacy protection, and deployment feasibility are important for improving model performance.

Transformer-based integration has been shown to be more predictive because it can learn adaptive correlations across modalities in a manner similar to humans. Simple feature combinations are not enough to effectively use healthcare data, as demonstrated by the progression from early fusion to transformer fusion. Instead, intelligent systems require algorithms that can identify the relative importance of biomedical signals.

The computational complexity of the AI models was also compared and found to be directly proportional to their predictive performance. The hybrid and transformer systems may be the most precise and resilient, though a variety of other factors come into play, such as infrastructure availability, response time and energy consumption. Hence, the application of smart intelligence is recommended over the free growth of models in future AI systems in healthcare.

Explainability analysis states that transparency is one of the key elements in therapeutic acceptance. Results showed that SHAP was the most interpretable method (and attention-based approaches were the most clinically trusted). Findings from this study validate the importance of clinical and technically accurate explanations. In healthcare, decisions are supposed to be based on reasons and be answerable to others, so if a model is extremely precise and has no logic, it can be difficult for it to be adopted.

During the privacy review, it was also identified that there is a balance to be struck between patient privacy and accessibility of information when creating healthcare AI. Positive results were obtained with federated learning and hybrid FL+DP approaches, which enable collaborative learning without sharing sensitive patient data. But before they can be broadly adopted, new computational and communication challenges arise, and privacy-preserving techniques must be addressed.

The research gap analysis shows that the most significant challenges to further progress are interoperability with other data sources, data interpretation problems and lack of benchmarks. The issues raised here underscore the importance of ongoing clinical research in healthcare AI, which must identify the need for establish more comprehensive AI frameworks, clinically validated datasets, and standardised

assessment techniques, and to enhance algorithmic performance.

These results allow for the conceptualisation of an integrated framework for intelligent healthcare systems in which:

1. The multimodal datasets include comprehensive patient representation.
2. The sophistication of different types of information is employed to fuse information together.
3. Explainable AI guarantees predictions are transparent.
4. Secure cooperation is made possible by privacy-preserving learning.
5. Optimisation for deployment allows clinical implementation.

Rather than single-purpose prediction models, AI systems for the future of healthcare should be developed as holistic, encompassing decision-support environments from an integrated perspective. The subsequent section outlines some of the constraints and future research directions stemming from the findings. Although this study provides a comprehensive evaluation of multimodal healthcare AI systems, there are several restrictions to consider. The investigation focused primarily on benchmark datasets, which are publicly accessible and secondly, on secondary research findings. This implies that past research results are reliable if they are high-quality, comprehensive, and well reported. Differences in reported results may be due to differences in experimental conditions, data content and data analysis procedures. Second, there remains no standard, which is still a major hurdle for the further development of multimodal healthcare AI research. It is difficult to make a direct comparison, as different studies may use different datasets, performance evaluation methods, validation methods, and clinical objectives. Future studies should concentrate on developing standardised benchmark frameworks across a variety of modalities, populations, and evaluation criteria pertinent to clinical practice. Third, explainable AI approaches have facilitated that the algorithm workings can be described in a more comprehensible manner, but the complete clinical interpretability of the algorithm is still difficult. Current explanation methods sometimes rely only on statistical relationships rather than causal ones. To improve the reliability of AI-generated explanations, future studies could investigate the use of causal AI, knowledge-guided learning methods, and systems that involve the clinician as an integral part. Last but not least, there is still more need for optimisation of privacy-protecting methods. There are practical solutions for both federated learning and differential privacy, yet there are still trade-offs between privacy and accuracy, scalability challenges, and communication cost concerns. Future effective federated architectures, safe multimodal foundation models and decentralised healthcare intelligence systems should all be researched and developed. Finally, most multimodal AI systems are evaluated on retrospective datasets rather than in prospective clinical settings. Continuous post-deployment monitoring of the device, assessment by regulators, and clinical validation in the real world is needed. Scientific advancements need to be integrated into EHR systems, medical devices, hospital processes, and other healthcare systems to be implemented as healthcare benefits.

Overall, the results suggest that it is just as important to develop systems that are clinically reliable, computationally efficient, safe, understandable, and that improve the accuracy of their future predictions for multimodal healthcare-AI systems. The critical enablers are the advanced fusion mechanisms, explainable learning, privacy-preserving computation and uniform evaluation frameworks to realise reliable intelligent healthcare systems that allow for personalised medicine at scale.

## **6. Conclusion:**

The goal of this paper was to explore opportunities and challenges of applying multimodal artificial intelligence (AI) in intelligent healthcare systems (IHS) for personalised diagnosis and prognosis of disease. The aim of this investigation was to achieve the above goal. This study aimed to achieve the above objective. The aim of this enquiry was to achieve the above.

The multimodal combination of techniques and architectures, data categories, explainability strategies, and privacy-preserving strategies within a single research framework is a novelty of the research. One of the new aspects of this line of work. This is one of the newer areas of the research field. This work offers a multidimensional synthesis of AI in healthcare that few previous works, which are confined to a single or two specific aspects (such as imaging-based diagnosis, EHR modelling, or federated learning systems), have provided. The aim of this study was to explore the use of AI in the medical field. These are all taken into account during the investigation. In our study, we will consider each of the above factors individually. These studies will focus on three unique characteristics – Privacy, scalability, interpretability and robustness. The goals of this research are to explore the effectiveness and use of multimodal AI for healthcare applications. The holistic approach will enable an objective assessment of the therapeutic process as opposed to a one-dimensional approach. In contrast to the other approach, this approach gives an objective view of the healing process. This method is not based on the one-dimensional approach mentioned in the above

evaluation.

Future research will be relevant to a normative standardisation of the norms that will have to be developed for multimodal healthcare. The following standards should contain information from the imaging, clinical, genetic, and sensor domains. This will be a crucial step in this stage of the process. It is impossible to avoid this procedure. The transformers to be used must be lightweight. These architectures should be able to decrease the number of processing steps required without sacrificing performance. As with any multimodal system, it is essential to make specific strides to shed light on AI. The aim of building confidence and transparency for multimodal systems can be accomplished only if explainable AI is created. It is one that must be followed and is not to be avoided. Given their significance, adaptive federated learning systems should be carefully considered if this is to occur. These approaches can enable good scalability in a geographically distributed healthcare system without incurring high communication costs. This is because there won't be many communication issues with this option. The reason is that such systems don't have any complicated communication needs. This new scientific information will, at long last, be moved from the lab to the patient's bedside with an empirical clinical test.

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