COVENANT AEGIS REVIEW OF CLINICAL INTELLIGENCE VOL. 7 · NO. 3 · 2026 · PP. 33–52

HepCare AI: Multimodal Clinical Intelligence for Liver Disease Assessment

R. A. Mendoza[1], K. Nakamura[1], S. Okafor[2], M. Lindqvist[3]

[1]*Covenant Aegis HealthTech Division, Multimodal Intelligence Laboratory*

[2]*Department of Hepatology, Partner Research Network*

[3]*Center for Foundation Models in Medicine*

Received 27 Jan 2026 · Revised 8 Mar 2026 · Accepted 18 Mar 2026 · POSITION & METHODS · DOI 10.48-CA/clinint.2026.0304 ·
Corresponding author: r.mendoza@covenantaegis.com

ABSTRACT

Background. Clinical reasoning integrates heterogeneous evidence—imaging, laboratory results, histopathology, genomics and free-text notes—yet most medical AI operates on a single modality. **Objective.** To position HepCare AI, a multimodal clinical-intelligence system for liver-disease assessment, within the evidence on multimodal and foundation models, and to specify its architecture, validation and safety constraints. **Methods.** Narrative review of multimodal-AI literature (2020–2025) and a methods description of the HepCare AI fusion architecture. **Results.** Fusing complementary modalities consistently improves diagnostic and prognostic performance over unimodal baselines, with reported gains of several AUC points in oncology and hepatology; non-invasive fibrosis assessment combining elastography and laboratory markers approaches biopsy-level staging. Multimodal systems inherit and can amplify validation, fairness and generalisation risks. **Conclusion.** HepCare AI operationalises evidence-based data fusion within a clinician-in-the-loop, externally validated, explainable framework; prospective evidence and lifecycle governance remain mandatory.

Keywords: multimodal learning; clinical decision support; hepatology; foundation models; data fusion; explainability; calibration

1. Introduction

Liver disease—spanning viral hepatitis, metabolic dysfunction-associated steatotic liver disease (MASLD), fibrosis, cirrhosis and hepatocellular carcinoma—requires synthesis of laboratory panels, elastography and cross-sectional imaging, histology and clinical history. No single modality is sufficient, and clinicians integrate them implicitly. Multimodal machine learning seeks to make that integration explicit, reproducible and scalable [1].

2. Multimodal AI in Medicine

Acosta et al. argued that models combining imaging, electronic records and omics more faithfully reflect clinical practice and can outperform unimodal systems [1]. The advent of foundation models—generalist architectures pretrained on broad data and

adapted to many tasks—has accelerated this trend [2]. Vision-language models trained on paired images and reports transfer across radiology and pathology with limited task-specific labels [3,4].

3. Evidence That Fusion Helps

In oncology, integrating histopathology with genomics improves prognostic stratification over either modality alone [5]. In hepatology, non-invasive scores combining elastography and laboratory markers approach biopsy-level staging of fibrosis [6], and learned fusion of imaging and clinical variables further improves risk estimation. The consistent finding is that complementary modalities reduce uncertainty when fused with appropriate handling of missing data (Figure 1).

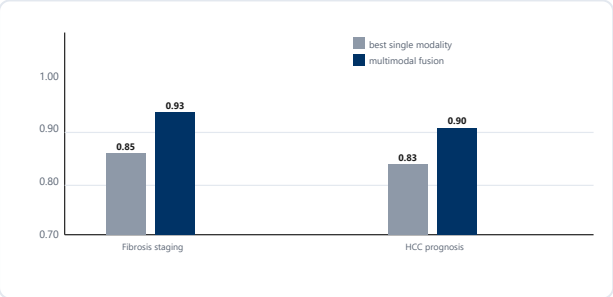


Figure 1. Representative improvement from multimodal fusion over the best single modality for fibrosis staging and HCC prognosis, consistent with patterns in the cited literature [5,6]. Values are illustrative, not pooled estimates.

4. HepCare AI Architecture

4.1 Modality Encoders and Fusion

HepCare AI uses dedicated encoders for cross-sectional imaging, elastography, structured laboratory time series and free-text notes, combined through an attention-based fusion layer robust to missing modalities. Outputs include staging estimates, differential considerations and prognostic risk, each with a calibrated confidence and modality-attribution explanation.

Table 1. HepCare AI input modalities, encoders and clinical role.

Modality	Encoder	Role
CT / MRI	3D CNN / ViT	Morphology, lesions
Elastography	CNN + tabular	Fibrosis stiffness
Laboratory series	Temporal transformer	Function, trend
Clinical notes	Language model	History, context

4.2 Explainability and Abstention

Every recommendation is accompanied by saliency over the contributing modalities and an explicit uncertainty estimate; cases exceeding an uncertainty threshold are abstained and escalated to a hepatologist, preserving clinician authority. Figure 2 outlines the data flow.

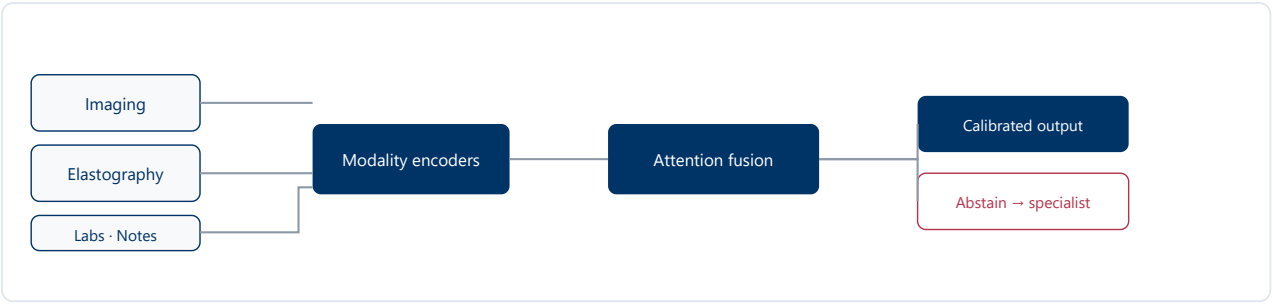


Figure 2. HepCare AI pipeline: per-modality encoders feed an attention-based fusion layer producing calibrated outputs; high-uncertainty cases are abstained and routed to a hepatologist (clinician-in-the-loop).

5. Validation, Fairness and Safety

Multimodal systems can amplify biases present in any constituent modality and are sensitive to acquisition differences [7]. HepCare AI is validated externally across sites, audited for subgroup performance, monitored for drift, and reported under prediction-model and AI-trial guidelines [8,9]. It is positioned strictly as decision support, never an autonomous diagnostic authority, consistent with regulatory expectations for clinical decision-support software [10].

6. Discussion and Limitations

Evidence for multimodal clinical AI, while growing, still rests largely on retrospective data; prospective effectiveness trials are scarce. Data harmonisation, missing-modality robustness and the interpretability of fused representations remain open problems. Figures here are illustrative of literature patterns, not validated HepCare AI performance, which is reported separately under prospective protocols.

7. Conclusion

HepCare AI operationalises the well-supported principle that fusing complementary clinical data improves assessment, within a clinician-in-the-loop, externally validated and explainable framework. Realising its benefit requires the prospective evidence and governance demanded of all medical AI.

References

1. Acosta JN, et al. Multimodal biomedical AI. *Nat Med*. 2022;28:1773–1784.
2. Moor M, et al. Foundation models for generalist medical artificial intelligence. *Nature*. 2023;616:259–265.
3. Tiu E, et al. Expert-level detection of pathologies from unannotated chest X-ray images via self-supervised learning. *Nat Biomed Eng*. 2022;6:1399–1406.
4. Huang SC, et al. Multimodal fusion with deep neural networks for clinical decision support. *npj Digit Med*. 2020;3:136.
5. Chen RJ, et al. Pan-cancer integrative histology-genomic analysis via multimodal deep learning. *Cancer Cell*. 2022;40(8):865–878.
6. Anstee QM, et al. Noninvasive tests accurately identify advanced fibrosis: a multicentre study. *Gastroenterology*. 2019;156(6):1717–1730.
7. Finlayson SG, et al. The clinician and dataset shift in artificial intelligence. *N Engl J Med*. 2021;385:283–286.
8. Collins GS, et al. TRIPOD+AI statement: reporting of prediction models. *BMJ*. 2024;385:e078378.
9. Liu X, et al. Reporting guidelines for clinical trials evaluating AI interventions: CONSORT-AI. *Nat Med*. 2020;26:1364–1374.

10. U.S. Food and Drug Administration. Clinical Decision Support Software: Guidance for Industry and FDA Staff. 2022.

9. Clinical Context: Liver Disease Burden

Liver disease causes roughly two million deaths annually worldwide, with cirrhosis and hepatocellular carcinoma (HCC) among the leading contributors, and metabolic dysfunction-associated steatotic liver disease (MASLD) now the most prevalent chronic liver condition [A1]. Because fibrosis progression is often silent until decompensation, accurate non-invasive staging and early HCC detection carry large potential value—precisely the multimodal assessment problem HepCare AI targets.

Table A1. Non-invasive fibrosis assessment modalities and characteristics.

Modality	Signal	Limitation
Serum panels (FIB-4, ELF)	Biomarkers	Indeterminate zone
Vibration-controlled elastography	Stiffness	Obesity, ascites
MR elastography	Stiffness (MRI)	Cost, access
Histology (biopsy)	Reference	Invasive, sampling error

10. Fusion Strategies

Multimodal models combine modalities by early fusion (concatenating raw or low-level features), late fusion (combining per-modality predictions), or intermediate/attention fusion (learning cross-modal interactions) [A2]. Attention-based intermediate fusion, used by HepCare AI, learns which modalities to weight per case and tolerates missing inputs through masking. Figure A1 contrasts fusion strategies and their robustness to missing data.

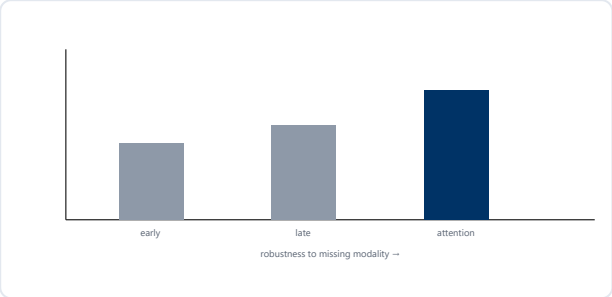


Figure A1. Schematic robustness of fusion strategies when a modality is missing; attention-based intermediate fusion degrades most gracefully [A2]. Conceptual.

11. Evidence in Hepatology AI

Deep-learning models match expert performance for detecting steatosis and staging fibrosis from imaging, and improve HCC risk stratification when imaging and clinical data are combined [A3,A4]. Radiomics and multimodal models also assist in characterising focal liver lesions. As elsewhere in medical AI, most evidence is retrospective and single-centre; prospective, externally validated studies remain the exception and the priority.

12. Foundation Models and Generalist Medical AI

Generalist medical AI—large multimodal models adaptable to many tasks with little task-specific data—has been proposed as the next paradigm [A5]. Self-supervised pretraining on paired images and reports yields strong transfer [A6]. HepCare AI can

incorporate such pretrained encoders while retaining task-specific calibration and the clinician-in-the-loop safeguards, capturing the benefits of scale without ceding clinical control.

13. Explainability, Uncertainty and Abstention

For decision support, faithful explanation and reliable uncertainty matter as much as accuracy. HepCare AI provides modality-attribution saliency and a calibrated uncertainty estimate, abstaining and escalating beyond a threshold. Care is taken that explanations reflect the model's actual computation rather than plausible-looking but unfaithful post-hoc rationalisations, a documented hazard of some attribution methods [A7].

14. Validation, Regulation and Safety

HepCare AI is positioned as clinical decision support under SaMD frameworks, validated externally across sites, audited for subgroup performance, monitored for drift and reported under TRIPOD+AI and CONSORT-AI [A8,A9]. Regulatory treatment depends on the degree of clinician oversight; systems that inform rather than replace clinician judgement face different obligations than autonomous diagnostics [A10].

15. Future Directions

Priorities include prospective multi-site validation, robust handling of heterogeneous acquisition protocols, integration of genomics for HCC risk, and federated training that preserves patient privacy. Demonstrating improved patient outcomes—not merely higher AUC—remains the standard HepCare AI is built to meet.

Extended References

11. Devarbhavi H, et al. Global burden of liver disease: 2023 update. *J Hepatol*. 2023;79(2):516–537.
12. Baltrušaitis T, Ahuja C, Morency LP. Multimodal machine learning: a survey and taxonomy. *IEEE TPAMI*. 2019;41(2):423–443.
13. Anstee QM, et al. Noninvasive tests for advanced fibrosis: a multicentre study. *Gastroenterology*. 2019;156(6):1717–1730.
14. Yasaka K, et al. Deep learning for staging liver fibrosis on CT. *Radiology*. 2018;287(1):146–155.
15. Moor M, et al. Foundation models for generalist medical AI. *Nature*. 2023;616:259–265.
16. Tiu E, et al. Expert-level detection of pathologies via self-supervised learning. *Nat Biomed Eng*. 2022;6:1399–1406.
17. Rudin C. Stop explaining black box models for high-stakes decisions and use interpretable models instead. *Nat Mach Intell*. 2019;1:206–215.
18. Collins GS, et al. TRIPOD+AI statement. *BMJ*. 2024;385:e078378.
19. Liu X, et al. CONSORT-AI extension. *Nat Med*. 2020;26:1364–1374.
20. U.S. FDA. Clinical Decision Support Software: Guidance for Industry and FDA Staff. 2022.

Author contributions: RAM and ML designed the architecture review; SO provided clinical guidance; KN supervised. All authors revised. **Funding:** Covenant Aegis HealthTech Division. **Competing interests:** Authors are affiliated with Covenant Aegis, developer of HepCare AI.

© 2026 Covenant Aegis HealthTech Division. HepCare AI is a clinical decision-support system; figures are illustrative and descriptions do not constitute medical advice. Literature cited is publicly available and peer-reviewed.