

A Review on Artificial Intelligence and Digital Health In Viral Hepatitis Care: Current Landscape And Future Horizons

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Abstract

Viral hepatitis remains one of the most significant global public health challenges, affecting more than 300 million individuals worldwide and causing approximately 1.3 million deaths annually due to cirrhosis, liver failure, and hepatocellular carcinoma (HCC). Despite remarkable advances in vaccination strategies, highly effective direct-acting antivirals (DAAs), and nucleos(t)ide analogues, substantial gaps persist in disease screening, early diagnosis, treatment initiation, long-term monitoring, and healthcare accessibility, particularly in low- and middle-income countries. Artificial intelligence (AI) and digital health technologies are transforming hepatology by providing innovative approaches for disease prediction, automated diagnosis, precision medicine, remote monitoring, and clinical decision support. Machine learning, deep learning, natural language processing, computer vision, wearable sensors, mobile health applications, electronic health records, and telemedicine platforms enable rapid analysis of multimodal clinical data and facilitate individualized patient management. AI-assisted imaging significantly improves non-invasive liver fibrosis staging and hepatocellular carcinoma detection, while predictive algorithms optimize antiviral treatment selection, estimate sustained virological response, and identify patients at risk of disease progression. Emerging technologies such as digital liver twins, multi-omics integration, explainable AI, federated learning, and generative AI are expected to revolutionize precision hepatology and accelerate progress toward the World Health Organization's goal of eliminating viral hepatitis as a public health threat by 2030. However, successful implementation requires overcoming challenges related to data privacy, algorithmic bias, regulatory approval, interoperability, clinical validation, and equitable healthcare access. This review comprehensively summarizes the current landscape of artificial intelligence and digital health in viral hepatitis care, highlights recent technological advances, discusses ethical and regulatory considerations, and explores future opportunities for integrating intelligent digital ecosystems into routine hepatology practice.

Key words: Artificial intelligence; Viral hepatitis; Hepatitis B; Hepatitis C; Machine learning; Digital health; Telemedicine; Precision medicine; Hepatocellular carcinoma; Digital liver twin.

1. Introduction

Viral hepatitis remains one of the leading infectious causes of morbidity and mortality worldwide and continues to represent a major obstacle to achieving global health equity. Hepatitis viruses—including hepatitis A virus

(HAV), hepatitis B virus (HBV), hepatitis C virus (HCV), hepatitis D virus (HDV), and hepatitis E virus (HEV)—infect hundreds of millions of individuals and are responsible for progressive liver disease ranging from acute hepatitis to chronic hepatitis, liver fibrosis, cirrhosis, hepatic decompensation, and hepatocellular carcinoma (HCC). Among these viruses, chronic HBV and HCV infections account for more than 95% of hepatitis-related deaths globally and remain major contributors to disability-adjusted life years (DALYs), healthcare expenditures, and socioeconomic burden, particularly in low- and middle-income countries (LMICs).^{1–4}

According to the World Health Organization (WHO), approximately 254 million individuals were living with chronic hepatitis B infection and nearly 50–58 million individuals with chronic hepatitis C infection worldwide in 2024. Together, these infections resulted in nearly 1.3 million deaths annually, primarily due to complications such as liver cirrhosis and hepatocellular carcinoma. Alarming, despite the availability of highly effective preventive vaccines against HBV and curative direct-acting antiviral (DAA) therapies for HCV, a substantial proportion of infected individuals remain undiagnosed or untreated. Current estimates suggest that less than one-third of HBV-infected individuals are aware of their infection status, while treatment coverage remains below the targets established by the WHO Global Health Sector Strategy on Viral Hepatitis.^{1–4}

The World Health Organization has established ambitious targets for eliminating viral hepatitis as a public health threat by 2030, including a 90% reduction in new infections and a 65% reduction in hepatitis-related mortality. Achieving these objectives requires substantial improvements in early diagnosis, population screening, linkage to care, treatment adherence, long-term surveillance, and equitable healthcare delivery. Conventional healthcare systems, however, continue to face numerous limitations, including delayed diagnosis, fragmented healthcare records, inadequate specialist availability, limited access to advanced diagnostic facilities, and increasing healthcare costs. These challenges are particularly pronounced in resource-limited settings where the burden of viral hepatitis is highest.^{1, 5–7}

Recent advances in artificial intelligence (AI), machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision, and digital health technologies have created unprecedented opportunities to transform viral hepatitis management. AI systems are capable of processing enormous quantities of heterogeneous healthcare data—including laboratory investigations, radiological imaging, histopathology slides, genomic information, proteomic signatures, wearable sensor data, and electronic health records—to generate clinically meaningful insights with remarkable speed and accuracy. Unlike traditional statistical approaches, machine learning algorithms continuously improve their predictive performance through iterative training and can identify complex nonlinear relationships among clinical variables that may not be readily apparent to human observers.^{8–11}

One of the most promising applications of AI in hepatology is the development of automated diagnostic systems capable of identifying viral hepatitis at earlier stages. Machine learning algorithms have demonstrated superior performance in predicting HBV and HCV infection using routine laboratory parameters, demographic characteristics, and electronic health record data. Similarly, convolutional neural networks (CNNs) have significantly enhanced the interpretation of ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and transient elastography by accurately identifying liver fibrosis, cirrhosis, steatosis, and hepatocellular carcinoma without requiring invasive liver biopsy. These advances contribute to earlier intervention, improved treatment outcomes, and reduced healthcare costs.^{9–13}

Beyond diagnosis, AI has emerged as a powerful tool for precision medicine in viral hepatitis. By integrating host genetic factors, viral genotypes, pharmacogenomic information, liver disease severity, and treatment history, predictive algorithms can estimate sustained virological response (SVR), identify patients at risk of antiviral resistance, personalize therapeutic regimens, and optimize treatment duration. AI-assisted clinical decision support systems further assist healthcare professionals by integrating evidence-based guidelines with real-time patient information to generate individualized recommendations for diagnosis, treatment selection, and longitudinal disease monitoring.^{12–16}

Digital health technologies have further expanded the capabilities of AI by enabling continuous patient engagement outside traditional healthcare settings. Telemedicine, mobile health (mHealth) applications, wearable biosensors, remote patient monitoring platforms, and cloud-based electronic medical records have substantially improved healthcare accessibility, particularly for populations residing in geographically isolated or underserved regions. These technologies facilitate medication adherence, symptom monitoring, laboratory result tracking, and virtual specialist consultations while reducing travel costs and improving healthcare efficiency. During the COVID-19 pandemic, telemedicine demonstrated its value by maintaining continuity of hepatitis care despite widespread disruptions to conventional healthcare delivery, further accelerating the adoption of digital hepatology worldwide.^{17–20}

The convergence of AI, digital health, big data analytics, multi-omics technologies, and precision medicine is now driving a paradigm shift from reactive disease management toward proactive, predictive, preventive, and personalized hepatology. Emerging innovations such as digital liver twins, federated learning, explainable artificial intelligence (XAI), blockchain-enabled health data security, generative AI, and large language models (LLMs) have the potential to further revolutionize viral hepatitis care by enabling individualized disease simulation, automated clinical documentation, advanced biomarker discovery, and intelligent healthcare ecosystems. Nevertheless, widespread implementation requires careful consideration of ethical, legal, regulatory, and socioeconomic challenges, including data privacy, algorithmic transparency, clinical validation, healthcare disparities, and interoperability among digital health platforms.^{21–25}

This review aims to comprehensively summarize the current landscape of artificial intelligence and digital health technologies in viral hepatitis care. We discuss recent advances in machine learning–based diagnosis, imaging, precision medicine, telemedicine, clinical decision support systems, and multi-omics integration while critically examining existing challenges and future directions. Understanding these developments is essential for researchers, clinicians, policymakers, and healthcare organizations seeking to integrate intelligent digital technologies into routine hepatology practice and accelerate progress toward the global elimination of viral hepatitis.

2. Global Burden of Viral Hepatitis

Viral hepatitis remains one of the most significant infectious diseases worldwide and continues to pose a major challenge to global public health despite substantial advances in vaccination, antiviral therapies, and healthcare infrastructure. Hepatitis viruses infect hundreds of millions of individuals annually and are responsible for progressive liver injury leading to fibrosis, cirrhosis, hepatic failure, and hepatocellular carcinoma (HCC). Among the five primary hepatitis viruses (HAV, HBV, HCV, HDV, and HEV), chronic hepatitis B virus (HBV) and hepatitis C virus (HCV) infections account for the overwhelming majority of hepatitis-related deaths and disability-adjusted life years (DALYs). Viral hepatitis has now surpassed tuberculosis, HIV/AIDS, and malaria

as one of the leading causes of infectious disease mortality globally, emphasizing the urgent need for innovative healthcare strategies, including artificial intelligence (AI) and digital health technologies, to improve disease surveillance, diagnosis, treatment, and prevention. ^{1–4}

According to the World Health Organization (WHO), approximately **304 million people** were living with chronic viral hepatitis in 2022, including nearly **254 million individuals with chronic HBV infection** and approximately **50 million individuals with chronic HCV infection**. Together, these infections resulted in approximately **1.3 million deaths annually**, primarily from cirrhosis and hepatocellular carcinoma, with nearly 3,500 people dying every day from hepatitis-related complications. Alarming, despite the availability of highly effective antiviral therapies, approximately **83% of HBV infections and 64% of HCV infections remain undiagnosed**, creating a substantial hidden disease burden that contributes to continued viral transmission and delayed treatment initiation. ^{1–4}

The burden of viral hepatitis is unevenly distributed across different geographical regions, socioeconomic groups, and healthcare systems. Low- and middle-income countries (LMICs) bear nearly 80% of the global hepatitis burden because of inadequate healthcare infrastructure, limited access to vaccination, insufficient screening programs, poor public awareness, and restricted availability of antiviral medications. Countries in Sub-Saharan Africa, Southeast Asia, and the Western Pacific Region continue to experience the highest prevalence of chronic HBV infection, whereas HCV prevalence remains particularly high in parts of Eastern Europe, Central Asia, North Africa, and South Asia. The WHO African Region alone accounts for nearly two-thirds of all newly acquired HBV infections, highlighting persistent inequalities in vaccine coverage and maternal-child transmission prevention programs. ^{1–6}

HBV infection remains the dominant contributor to hepatitis-related mortality worldwide. Approximately **820,000 deaths annually** are attributed to HBV-related cirrhosis and hepatocellular carcinoma. Chronic HBV infection is particularly concerning because of its ability to establish covalently closed circular DNA (cccDNA) within hepatocyte nuclei, allowing viral persistence even after prolonged antiviral therapy. Although universal infant vaccination has significantly reduced HBV incidence in many countries, millions of adults remain chronically infected and require lifelong clinical monitoring. Moreover, vertical transmission from infected mothers continues to contribute substantially to new HBV infections in regions with inadequate antenatal screening and limited access to birth-dose vaccination. ^{5–8}

HCV infection represents another major public health challenge despite the remarkable success of direct-acting antiviral (DAA) therapy. Approximately **50–58 million individuals** currently live with chronic HCV infection, resulting in nearly **290,000 deaths annually**. Unlike HBV, HCV lacks an effective preventive vaccine because of its high genetic variability and rapid mutation rate. Nevertheless, modern pan-genotypic DAAs achieve sustained virological response (SVR) rates exceeding 95%, making HCV one of the few chronic viral infections that can be cured. Unfortunately, limited screening programs, delayed diagnosis, treatment costs, and inadequate healthcare infrastructure continue to prevent universal access to these highly effective therapies. ^{6–10}

2.1 Global Epidemiological Trends

Recent epidemiological studies indicate encouraging progress in some aspects of viral hepatitis control while simultaneously revealing substantial gaps that threaten achievement of the WHO elimination targets by 2030. Since 2015, global HBV incidence has declined by approximately 30% due to improvements in childhood immunization programs, increased birth-dose vaccination, blood safety measures, and infection control

practices. Similarly, HCV-related mortality has decreased modestly following widespread adoption of DAAs in high-income countries. Nevertheless, these gains have been partially offset by persistent underdiagnosis, delayed linkage to care, reinfection among high-risk populations, and unequal healthcare access across different regions.^{1–4}

Mathematical modeling studies conducted by the Polaris Observatory have demonstrated that although global HBV prevalence is gradually declining among younger populations, aging cohorts of chronically infected individuals continue to contribute substantially to the burden of cirrhosis and hepatocellular carcinoma. Consequently, liver-related mortality is expected to remain high for several decades unless diagnosis and treatment rates increase dramatically. Similar trends have been observed for HCV, where reductions in new infections are being counterbalanced by inadequate treatment uptake among marginalized populations such as people who inject drugs, incarcerated individuals, migrants, and homeless populations.^{9–12}

2.2 Regional Distribution of Viral Hepatitis

Western Pacific Region

The WHO Western Pacific Region remains the global epicenter of chronic HBV infection, accounting for approximately 40–45% of all HBV cases worldwide. China alone contributes nearly one-third of the global HBV burden despite substantial improvements in universal vaccination. The prevalence of HBV remains particularly high among adults born before implementation of nationwide childhood immunization programs. Although antiviral treatment coverage has expanded considerably in recent years, millions of infected individuals remain undiagnosed.^{1, 2, 5}

African Region

Sub-Saharan Africa experiences the highest incidence of newly acquired HBV infections worldwide. Limited access to maternal screening, inadequate birth-dose vaccination, shortages of antiviral medications, and fragile healthcare infrastructure continue to hinder elimination efforts. Coinfection with HIV further complicates disease management because both viruses share common transmission pathways and require integrated treatment strategies.^{3, 5, 13}

South-East Asia

South-East Asia, particularly India, Bangladesh, Indonesia, Myanmar, Thailand, and Vietnam, represents another major hotspot for chronic viral hepatitis. Rapid population growth, socioeconomic disparities, and variations in healthcare accessibility contribute to ongoing viral transmission. Expanded vaccination programs and national hepatitis control initiatives have improved disease awareness; however, diagnosis and treatment coverage remain below WHO targets.^{2, 6, 14}

European Region

Eastern Europe continues to report relatively high HCV prevalence, largely associated with injection drug use and healthcare-associated transmission. Western European countries have successfully expanded DAA access and implemented micro-elimination strategies targeting specific high-risk populations.^{7, 15}

Americas

North America has experienced increasing HCV incidence associated with the opioid epidemic and injection drug use. In Latin America, HBV remains endemic in Amazonian regions, while HCV prevalence varies substantially among countries depending on healthcare infrastructure and public health interventions.^{6, 16}

2.3 Viral Hepatitis in India

India bears one of the largest burdens of viral hepatitis globally because of its enormous population and heterogeneous healthcare system. It is estimated that approximately **40 million Indians live with chronic HBV infection**, while **6–12 million individuals are chronically infected with HCV**. Chronic viral hepatitis accounts for a substantial proportion of liver cirrhosis and hepatocellular carcinoma cases across the country.^{14,17}

Several factors contribute to the high prevalence of viral hepatitis in India, including:

- Unsafe medical injections
- Inadequately screened blood transfusions
- Mother-to-child HBV transmission
- Poor sanitation in certain regions
- Limited awareness regarding hepatitis screening
- Delayed diagnosis
- Unequal access to antiviral therapy

To address this burden, the Government of India launched the **National Viral Hepatitis Control Programme (NVHCP)** in 2018, aiming to provide free screening, diagnosis, and treatment services while aligning with the WHO goal of hepatitis elimination by 2030.^{17,18}

2.4 Diagnostic and Treatment Gap

One of the greatest barriers to hepatitis elimination is the large diagnostic and treatment gap. Because chronic HBV and HCV infections often remain asymptomatic for years, many patients are diagnosed only after developing advanced fibrosis, cirrhosis, or hepatocellular carcinoma. According to WHO estimates, only **13–18% of HBV-infected individuals receive antiviral therapy**, whereas fewer than **25% of HCV patients worldwide** have received curative treatment.^{1–4}

The principal barriers include:

- Lack of routine population screening
- Poor healthcare accessibility
- High diagnostic costs
- Limited specialist availability
- Social stigma
- Poor patient awareness
- Fragmented healthcare systems

Artificial intelligence and digital health technologies offer promising solutions to overcome these barriers by enabling automated risk prediction, electronic health record (EHR)-based screening alerts, telemedicine, and decentralized care pathways.^{19–22}

2.5 Economic Burden

Beyond clinical morbidity and mortality, viral hepatitis imposes a substantial economic burden on healthcare systems. The direct costs include laboratory testing, antiviral medications, hospitalization, liver transplantation, and long-term management of cirrhosis and hepatocellular carcinoma. Indirect costs arise from reduced

productivity, disability, premature mortality, and caregiver burden. Economic modeling studies suggest that early diagnosis and treatment using AI-assisted screening programs could significantly reduce long-term healthcare expenditures by preventing advanced liver disease and liver cancer. ^{23–25}

2.6 Need for Artificial Intelligence in Viral Hepatitis

The growing global burden of viral hepatitis, combined with shortages of hepatologists and increasing healthcare demands, underscores the need for intelligent healthcare systems capable of improving efficiency and accuracy. AI can support population-level screening, automate fibrosis staging, identify patients requiring antiviral therapy, predict disease progression, optimize treatment selection, and facilitate remote patient monitoring. Integration of AI with digital health technologies has the potential to accelerate progress toward achieving WHO elimination targets by enabling earlier intervention, personalized medicine, and equitable healthcare delivery across diverse populations. ^{19–25}

3. Fundamentals of Artificial Intelligence in Healthcare

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in modern medicine, fundamentally changing how diseases are diagnosed, monitored, and treated. AI refers to the capability of computer systems to perform tasks that traditionally require human intelligence, including learning from experience, recognizing patterns, understanding language, making predictions, and supporting clinical decision-making. Unlike conventional software that follows predefined rules, AI systems continuously improve their performance by learning from large and complex datasets. This ability is particularly valuable in healthcare, where enormous volumes of heterogeneous data—including electronic health records (EHRs), medical imaging, laboratory results, genomic information, wearable sensor data, and clinical notes—are generated daily. By integrating these diverse data sources, AI enables clinicians to deliver more accurate diagnoses, personalized treatments, and proactive disease management while improving healthcare efficiency and reducing costs. ^{1–4}

The rapid growth of digital health has accelerated AI adoption across nearly every medical specialty, including oncology, cardiology, neurology, ophthalmology, radiology, pathology, and hepatology. In liver diseases, AI has shown exceptional potential for improving viral hepatitis screening, predicting liver fibrosis progression, detecting hepatocellular carcinoma (HCC), optimizing antiviral therapy, and enhancing long-term patient monitoring. As healthcare systems transition toward precision medicine, AI is increasingly recognized as an indispensable component of future hepatology practice. ^{5–8}

3.1 Evolution of Artificial Intelligence in Medicine

The concept of artificial intelligence originated during the Dartmouth Conference in 1956, where John McCarthy introduced the term "Artificial Intelligence." Early AI systems relied primarily on rule-based expert systems that utilized predefined logical rules to solve specific clinical problems. Although these systems demonstrated promising diagnostic capabilities, they were limited by their inability to learn from new information and adapt to changing clinical scenarios. ^{9–11}

The emergence of machine learning (ML) during the late twentieth century represented a major breakthrough by enabling computers to learn directly from data without explicit programming. Advances in computational power, cloud computing, graphics processing units (GPUs), and big data analytics subsequently facilitated the development of deep learning (DL), a subset of ML capable of analyzing highly complex datasets using multilayer artificial neural networks. Today, AI systems achieve diagnostic accuracies comparable to or

exceeding experienced clinicians in several medical disciplines, including radiology, dermatology, ophthalmology, and pathology.^{12–15}

The COVID-19 pandemic further accelerated AI adoption by highlighting the need for digital healthcare infrastructure, telemedicine, remote patient monitoring, and automated clinical decision support systems. These technological advances have laid the foundation for integrating AI into routine viral hepatitis management, particularly in resource-limited settings where specialist availability remains limited.^{16–18}

3.2 Components of Artificial Intelligence

Artificial intelligence encompasses several complementary computational technologies that collectively enable intelligent healthcare systems.

Machine Learning (ML)

Machine learning is the most widely used branch of AI in healthcare. ML algorithms identify hidden relationships within datasets and use these patterns to make predictions or classifications without explicit programming. In viral hepatitis, ML models analyze demographic characteristics, laboratory biomarkers, liver function tests, viral loads, imaging findings, and treatment history to predict disease progression, fibrosis stage, treatment response, and mortality risk. Common ML algorithms include logistic regression, decision trees, random forests, support vector machines (SVM), gradient boosting machines, and artificial neural networks (ANNs). ML has demonstrated superior predictive performance compared with conventional statistical models, particularly when analyzing high-dimensional clinical datasets.^{19–22}

Deep Learning (DL)

Deep learning represents an advanced subset of machine learning that utilizes multilayer artificial neural networks to automatically extract hierarchical features from raw data. Unlike traditional ML algorithms that require manual feature engineering, deep learning algorithms learn relevant features directly from input data, making them particularly effective for image analysis, speech recognition, and natural language processing. In hepatology, convolutional neural networks (CNNs) analyze ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and histopathological images to detect liver fibrosis, steatosis, cirrhosis, and hepatocellular carcinoma with remarkable accuracy. Recurrent neural networks (RNNs) and transformer-based architectures further support longitudinal analysis of clinical records and time-series physiological data.^{23–26}

Natural Language Processing (NLP)

Natural Language Processing enables computers to understand, interpret, and generate human language. Healthcare institutions generate large volumes of unstructured clinical information through physician notes, pathology reports, discharge summaries, radiology interpretations, and medical literature. NLP algorithms automatically extract clinically relevant information from these textual sources, facilitating automated disease coding, literature mining, pharmacovigilance, and clinical decision support. In viral hepatitis management, NLP can identify patients requiring HBV or HCV screening, recognize missed follow-up appointments, extract fibrosis scores from clinical notes, and support automated reporting within electronic health records.^{27–29}

Computer Vision

Computer vision focuses on enabling machines to interpret visual information from medical images. Modern computer vision algorithms powered by convolutional neural networks accurately detect abnormalities within radiological and histopathological images. In hepatology, computer vision supports automated quantification of

liver fibrosis, steatosis, portal hypertension, cirrhosis, and hepatocellular carcinoma while reducing interobserver variability and minimizing dependence on invasive liver biopsy. ^{30–32}

3.3 Categories of Machine Learning

Machine learning algorithms are generally classified into supervised, unsupervised, semi-supervised, and reinforcement learning approaches.

Supervised Learning

Supervised learning utilizes labeled datasets in which both input variables and corresponding outcomes are known. The algorithm learns relationships between predictors and outcomes to classify future observations or predict continuous variables. Applications in hepatology include predicting antiviral treatment response, diagnosing HBV infection, estimating fibrosis stage, and forecasting hepatocellular carcinoma risk. ³³

Unsupervised Learning

Unsupervised learning analyzes unlabeled datasets to identify hidden structures or clusters without predefined outcomes. This approach is widely used for patient phenotyping, biomarker discovery, disease subtyping, and multi-omics integration. Clustering algorithms can identify novel viral hepatitis subgroups that exhibit distinct clinical outcomes and therapeutic responses. ³⁴

Semi-supervised Learning

Semi-supervised learning combines small labeled datasets with larger unlabeled datasets, improving model performance when manually annotated clinical data are limited. This strategy is particularly valuable in medical imaging, where expert annotation is expensive and time-consuming. ³⁵

Reinforcement Learning

Reinforcement learning trains algorithms through continuous interaction with an environment using reward-based feedback mechanisms. Although currently less common in hepatology, reinforcement learning shows promise for optimizing individualized antiviral treatment strategies, drug dosing, and adaptive clinical decision support systems. ³⁶

3.4 Artificial Neural Networks

Artificial Neural Networks (ANNs) mimic the structure and function of biological neurons. An ANN consists of interconnected input, hidden, and output layers that process information through weighted mathematical transformations. During training, the network adjusts these weights to minimize prediction errors. Deep neural networks containing multiple hidden layers achieve exceptional performance in recognizing complex nonlinear relationships within medical datasets. ³⁷

Convolutional Neural Networks (CNNs) specialize in image recognition and are extensively used for liver imaging analysis. Recurrent Neural Networks (RNNs) analyze sequential clinical data, whereas transformer-based architectures have become the foundation of modern large language models capable of understanding complex clinical narratives. ³⁸

3.5 Explainable Artificial Intelligence (XAI)

Despite remarkable predictive accuracy, many deep learning models function as "black boxes," producing predictions without transparent explanations. This lack of interpretability limits clinician trust and complicates regulatory approval for clinical deployment. Explainable Artificial Intelligence (XAI) addresses this challenge by providing interpretable reasoning behind algorithmic decisions.

Several techniques—including SHAP (Shapley Additive Explanations), LIME (Local Interpretable Model-Agnostic Explanations), attention maps, and Grad-CAM visualizations—help clinicians understand which variables contributed most strongly to AI predictions. Explainability is particularly important in hepatology, where treatment decisions may have lifelong consequences for patients with chronic HBV or HCV infection. ^{39–}

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3.6 Advantages of AI in Healthcare

Artificial intelligence offers numerous advantages that extend beyond diagnostic accuracy.

Enhanced Diagnostic Accuracy: AI algorithms detect subtle abnormalities within laboratory data and medical images that may be overlooked during routine clinical interpretation. Deep learning systems achieve high sensitivity and specificity for liver fibrosis staging and hepatocellular carcinoma detection. ⁴²

Personalized Medicine: AI integrates genomic information, viral genotype, liver disease severity, comorbidities, and pharmacogenomic data to recommend individualized treatment strategies that maximize therapeutic efficacy while minimizing adverse effects. ⁴³

Predictive Analytics: Machine learning identifies patients at increased risk of disease progression, hepatic decompensation, treatment failure, or hepatocellular carcinoma, enabling earlier intervention. ⁴⁴

Workflow Automation: AI automates repetitive administrative tasks such as documentation, appointment scheduling, billing, medical coding, and report generation, allowing healthcare professionals to devote more time to direct patient care. ⁴⁵

Drug Discovery: AI accelerates identification of antiviral compounds through virtual screening, molecular docking, protein structure prediction, and optimization of candidate molecules, substantially reducing drug development time and costs. ⁴⁶

3.7 Limitations of AI in Healthcare

Despite its enormous potential, AI implementation faces several important limitations.

Data Privacy: AI requires access to large volumes of sensitive patient information, necessitating strict compliance with healthcare privacy regulations and cybersecurity standards. ⁴⁷

Algorithmic Bias: AI models trained on non-representative datasets may produce inaccurate predictions for underrepresented populations, potentially exacerbating healthcare disparities. ⁴⁸

Generalizability: Algorithms developed within single institutions may perform poorly when applied to different healthcare settings because of demographic and clinical differences. ⁴⁹

Clinical Validation: Many AI models demonstrate excellent retrospective performance but require prospective multicenter validation before routine clinical adoption. ⁵⁰

Integration Challenges: Successful implementation requires interoperability with electronic health records, regulatory approval, clinician acceptance, and adequate digital infrastructure. ⁵¹

3.8 Relevance of AI to Viral Hepatitis

The complex natural history of chronic viral hepatitis makes it particularly suitable for AI-assisted healthcare. Disease progression depends upon multiple interacting factors, including viral genotype, viral load, host genetics, immune responses, liver fibrosis stage, metabolic syndrome, alcohol consumption, and treatment adherence. AI can integrate these multidimensional datasets to support precision hepatology by predicting disease progression, identifying candidates for antiviral therapy, estimating treatment response, monitoring medication adherence, and detecting hepatocellular carcinoma at earlier stages. Consequently, AI has become a cornerstone technology supporting the transition from reactive disease management toward predictive, preventive, personalized, and participatory healthcare. ^{52–55}

4. Digital Health Technologies in Viral Hepatitis Care

Digital health technologies, including telemedicine, mobile health (mHealth) applications, electronic health records (EHRs), wearable devices, and cloud-based monitoring systems, are transforming hepatitis care by improving access to screening, diagnosis, treatment, and long-term follow-up. These tools enable decentralized care delivery, particularly in rural and underserved regions, and support medication adherence, symptom monitoring, and data sharing between healthcare providers. AI-enabled EHR alerts can automatically identify patients eligible for HBV or HCV screening, while telemedicine platforms facilitate specialist consultations without requiring travel. Such technologies have demonstrated high treatment completion and sustained virological response (SVR) rates comparable to conventional in-person care. ^{76–80}

5. AI for Early Diagnosis of Viral Hepatitis

Early diagnosis is essential because chronic HBV and HCV infections are often asymptomatic for many years. Machine learning algorithms can analyze routine laboratory parameters, demographic data, and clinical histories to identify individuals at high risk of infection before significant liver damage occurs. AI-based screening systems integrated into EHRs can automatically flag patients requiring hepatitis testing, thereby reducing missed opportunities for diagnosis. These approaches are particularly valuable in large healthcare systems and resource-limited settings where universal screening may not be feasible. ^{81–85}

6. AI in Liver Fibrosis Assessment

Assessment of liver fibrosis traditionally relies on liver biopsy, which is invasive and subject to sampling error. AI-assisted imaging using ultrasound, CT, MRI, and transient elastography has emerged as a reliable non-invasive alternative. Deep learning models can accurately classify fibrosis stages, detect cirrhosis, and quantify liver stiffness with performance comparable to expert radiologists. Automated fibrosis assessment reduces interobserver variability, improves diagnostic efficiency, and enables large-scale population screening for chronic liver disease. ^{86–90}

7. AI for Hepatocellular Carcinoma Prediction

Hepatocellular carcinoma is the most serious complication of chronic viral hepatitis. AI models integrate clinical, laboratory, imaging, and genomic data to predict HCC risk and identify patients who require intensive surveillance. Deep learning algorithms can detect small liver lesions on imaging studies earlier than conventional methods, potentially improving curative treatment rates and overall survival. Predictive models also assist in estimating recurrence risk after surgical resection or liver transplantation. ^{91–95}

8. Treatment Optimization Using AI

AI supports precision treatment by predicting antiviral response, identifying patients at risk of treatment failure, and optimizing drug selection and treatment duration. For HBV, machine learning models analyze viral load, HBeAg status, liver fibrosis stage, and host factors to guide long-term antiviral therapy. For HCV, AI can predict sustained virological response and help select the most appropriate direct-acting antiviral regimen. These tools may reduce unnecessary treatment exposure and improve cost-effectiveness. ^{96–100}

9. Precision Medicine in Viral Hepatitis

Precision medicine aims to tailor therapy according to an individual's viral genotype, host genetics, liver disease severity, and comorbidities. Integration of AI with genomic and clinical data enables personalized treatment strategies that maximize efficacy while minimizing adverse effects. In HBV infection, genetic variants such as PNPLA3 and TM6SF2 may influence fibrosis progression and HCC risk, whereas HCV genotype and resistance-associated substitutions remain important determinants of therapeutic response. ^{101–104}

10. Telemedicine and Remote Patient Monitoring

Telemedicine has become an important component of hepatitis care, especially for patients living in remote areas. Virtual consultations, electronic prescription systems, and remote laboratory review allow continuous management of chronic HBV and HCV infections. Mobile applications provide medication reminders, symptom reporting, and educational resources, while wearable devices can monitor physiological parameters relevant to advanced liver disease. Studies have shown that telemedicine achieves SVR rates exceeding 90% and significantly improves healthcare accessibility. ^{105–108}

11. AI-Based Clinical Decision Support Systems

Clinical Decision Support Systems (CDSS) integrate AI algorithms with EHRs to provide real-time recommendations for diagnosis, fibrosis staging, antiviral therapy, and monitoring. These systems can automatically identify patients with abnormal liver tests, suggest appropriate hepatitis investigations, and alert clinicians to potential drug interactions or treatment contraindications. AI-powered CDSS enhances adherence to evidence-based guidelines and supports non-specialist physicians in managing complex hepatitis cases. ^{109–112}

12. Multi-Omics and Precision Hepatology

Multi-omics approaches combine genomics, transcriptomics, proteomics, metabolomics, and microbiomics to provide a comprehensive understanding of liver disease biology. AI algorithms are essential for integrating these high-dimensional datasets and identifying biomarkers associated with fibrosis progression, treatment response, and hepatocellular carcinoma development. This approach is expected to enable highly individualized risk stratification and targeted therapeutic interventions in the future. ^{113–116}

13. Ethical, Legal, and Regulatory Challenges

Despite its potential, AI implementation raises important ethical and legal concerns. Patient data privacy, cybersecurity, informed consent, algorithmic bias, and transparency remain major challenges. AI models trained on non-representative datasets may produce inaccurate predictions for marginalized populations, potentially worsening healthcare disparities. Regulatory frameworks must ensure clinical validation, accountability, and explainability before widespread deployment of AI systems in routine hepatology practice. ^{117–119}

14. Future Horizons in Hepatology

Future developments include digital liver twins, federated learning, explainable AI, generative AI, and AI-assisted drug discovery. Digital twins may simulate disease progression and treatment response for individual

patients, while federated learning allows collaborative model training without sharing sensitive patient data. Integration of AI with regenerative medicine, stem-cell therapy, and bioartificial liver technologies could further transform the management of advanced liver disease.¹²⁰

15. Conclusion

Artificial intelligence and digital health technologies are reshaping viral hepatitis care by enabling early diagnosis, non-invasive fibrosis assessment, personalized treatment, remote monitoring, and intelligent clinical decision support. These innovations have the potential to improve patient outcomes, reduce healthcare costs, and expand access to specialist care. Although challenges related to privacy, bias, regulation, and infrastructure remain, continued technological advancement and equitable implementation could significantly accelerate progress toward the WHO goal of eliminating viral hepatitis as a public health threat by 2030.

References

1. World Health Organization. *Global Hepatitis Report 2024*. World Health Organization; 2024.
2. World Health Organization. *Global Health Sector Strategies on HIV, Viral Hepatitis and Sexually Transmitted Infections 2022–2030*. World Health Organization; 2022.
3. Polaris Observatory Collaborators. Global prevalence, treatment, and prevention of hepatitis B virus infection in 2022. *Lancet Gastroenterol Hepatol*. 2023.
4. Polaris Observatory HCV Collaborators. Global epidemiology of hepatitis C virus infection. *Lancet Gastroenterol Hepatol*. 2023.
5. Schweitzer A, Horn J, Mikolajczyk RT, Krause G, Ott JJ. Estimations of worldwide prevalence of chronic hepatitis B virus infection: a systematic review of data published between 1965 and 2013. *Lancet*. 2015;386(10003):1546-1555. doi:10.1016/S0140-6736(15)61412-X
6. Stanaway JD, Flaxman AD, Naghavi M, et al. The global burden of viral hepatitis from 1990 to 2013: findings from the Global Burden of Disease Study 2013. *Lancet*. 2016;388(10049):1081-1088. doi:10.1016/S0140-6736(16)30579-7
7. European Association for the Study of the Liver. EASL Clinical Practice Guidelines on the management of hepatitis B virus infection. *J Hepatol*. 2024.
8. European Association for the Study of the Liver. EASL recommendations on treatment of hepatitis C. *J Hepatol*. 2024.
9. Terrault NA, Lok ASF, McMahon BJ, et al. Update on prevention, diagnosis, and treatment of chronic hepatitis B. *Hepatology*. 2024.
10. Ghany MG, Morgan TR; AASLD-IDS A HCV Guidance Panel. Hepatitis C guidance: recommendations for testing, managing, and treating hepatitis C. *Hepatology*. 2024.
11. Blach S, Zeuzem S, Manns M, et al. Global prevalence and genotype distribution of hepatitis C virus infection. *Lancet Gastroenterol Hepatol*. 2022.
12. Spearman CW, Dusheiko GM, Hellard M, Sonderup M. Hepatitis C. *Lancet*. 2019;394(10207):1451-1466. doi:10.1016/S0140-6736(19)32320-7
13. Razavi H, Robbins S, Zeuzem S, et al. Strategies toward hepatitis B and C elimination. *J Hepatol*. 2024.

14. Cooke GS, Andrieux-Meyer I, Applegate TL, et al. Accelerating the elimination of viral hepatitis: a Lancet Gastroenterology & Hepatology Commission. *Lancet Gastroenterol Hepatol*. 2019;4(2):135-184.
15. Ministry of Health and Family Welfare, Government of India. *National Viral Hepatitis Control Programme: Operational Guidelines*. Government of India; 2018.
16. World Health Organization South-East Asia Regional Office. *Hepatitis in South-East Asia*. WHO SEARO; 2023.
17. Global Burden of Disease Liver Cancer Collaboration. The burden of liver cancer attributable to viral hepatitis. *Lancet Oncol*. 2022.
18. Coffin CS, Fung SK, Ma MM. Management of chronic hepatitis B. *CMAJ*. 2023.
19. Thomas DL. Global elimination of chronic hepatitis. *N Engl J Med*. 2019;380(21):2041-2050. doi:10.1056/NEJMr1810477
20. Yuen MF, Chen DS, Dusheiko GM, et al. Hepatitis B virus infection. *Nat Rev Dis Primers*. 2018;4(1):18035. doi:10.1038/nrdp.2018.35
21. Hajarizadeh B, Grebely J, Dore GJ. Epidemiology and natural history of hepatitis C virus infection. *Nat Rev Gastroenterol Hepatol*. 2013;10(9):553-562. doi:10.1038/nrgastro.2013.107
22. World Health Organization. *Global Progress Report on HIV, Viral Hepatitis and Sexually Transmitted Infections 2025*. World Health Organization; 2025.
23. Polaris Observatory Collaborators. Progress toward global hepatitis elimination targets. *Lancet Gastroenterol Hepatol*. 2024.
24. Stanaway JD, et al. Global burden of liver diseases attributable to viral hepatitis. *Hepatology*. 2023.
25. Razavi H, Robbins S, Zeuzem S. Achieving WHO hepatitis elimination goals: current progress and future priorities. *J Hepatol*. 2024.
26. Russell SJ, Norvig P. *Artificial Intelligence: A Modern Approach*. 4th ed. Pearson; 2021.
27. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44-56. doi:10.1038/s41591-018-0300-7
28. Rajkomar A, Dean J, Kohane IS. Machine learning in medicine. *N Engl J Med*. 2019;380(14):1347-1358. doi:10.1056/NEJMr1814259
29. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24-29. doi:10.1038/s41591-018-0316-z
30. Beam AL, Kohane IS. Big data and machine learning in health care. *JAMA*. 2018;319(13):1317-1318. doi:10.1001/jama.2017.18391
31. Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. *Nat Biomed Eng*. 2018;2(10):719-731. doi:10.1038/s41551-018-0305-z
32. Yip TCF, Wong GLH. Artificial intelligence in hepatology. *J Hepatol*. 2023.
33. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med*. 2019;17(1):195. doi:10.1186/s12916-019-1426-2
34. Holzinger A, Biemann C, Pattichis CS, Kell DB. What do we need to build explainable AI systems for the medical domain? *arXiv*. Published online 2017.

35. Lundberg SM, Lee SI. A unified approach to interpreting model predictions. In: *Advances in Neural Information Processing Systems*. 2017.
36. Ribeiro MT, Singh S, Guestrin C. "Why Should I Trust You?": Explaining the predictions of any classifier. In: *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. 2016:1135-1144.
37. LeCun Y, Bengio Y, Hinton G. Deep learning. *Nature*. 2015;521(7553):436-444. doi:10.1038/nature14539
38. Goodfellow I, Bengio Y, Courville A. *Deep Learning*. MIT Press; 2016.
39. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. *Med Image Anal*. 2017;42:60-88. doi:10.1016/j.media.2017.07.005
40. Erickson BJ, Korfiatis P, Akkus Z, Kline TL. Machine learning for medical imaging. *Radiographics*. 2017;37(2):505-515. doi:10.1148/rg.2017160130
41. Yasaka K, Abe O. Deep learning and artificial intelligence in radiology: Current applications and future directions. *Jpn J Radiol*. 2018;36(4):257-273. doi:10.1007/s11604-018-0723-1
42. Deo RC. Machine learning in medicine. *Circulation*. 2015;132(20):1920-1930. doi:10.1161/CIRCULATIONAHA.115.001593
43. Rieke N, Hancox J, Li W, et al. The future of digital health with federated learning. *NPJ Digit Med*. 2020;3:119. doi:10.1038/s41746-020-00323-1
44. Bibault JE, Giraud P, Burgun A. Big data and machine learning in radiation oncology. *Nat Rev Clin Oncol*. 2016;13(6):354-365. doi:10.1038/nrclinonc.2016.18
45. Collins FS, Varmus H. A new initiative on precision medicine. *N Engl J Med*. 2015;372(9):793-795. doi:10.1056/NEJMp1500523
46. Obermeyer Z, Emanuel EJ. Predicting the future—Big data, machine learning, and clinical medicine. *N Engl J Med*. 2016;375(13):1216-1219. doi:10.1056/NEJMp1606181
47. Shortliffe EH, Sepúlveda MJ. Clinical decision support in the era of artificial intelligence. *JAMA*. 2018;320(21):2199-2200. doi:10.1001/jama.2018.17163
48. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: Past, present and future. *Stroke Vasc Neurol*. 2017;2(4):230-243. doi:10.1136/svn-2017-000101
49. Topol EJ. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. Basic Books; 2019.
50. Yu KH, Kohane IS. Framing the challenges of artificial intelligence in medicine. *BMJ*. 2019;366:l4570. doi:10.1136/bmj.l4570
51. Keesara S, Jonas A, Schulman K. Covid-19 and health care's digital revolution. *N Engl J Med*. 2020;382(23):e82. doi:10.1056/NEJMp2005835
52. Hollander JE, Carr BG. Virtually perfect? Telemedicine for Covid-19. *N Engl J Med*. 2020;382(18):1679-1681. doi:10.1056/NEJMp2003539
53. Bashshur RL, Shannon GW, Bashshur N, Yellowlees PM. The empirical foundations of telemedicine interventions in primary care. *Telemed J E Health*. 2016;22(5):342-375. doi:10.1089/tmj.2016.0045
54. Omboni S, Padwal RS, Alessa T, et al. The worldwide impact of telemedicine during COVID-19: Current evidence and recommendations. *J Med Internet Res*. 2022;24:e31726. doi:10.2196/31726

55. World Health Organization. *WHO Guideline: Recommendations on Digital Interventions for Health System Strengthening*. World Health Organization; 2019.
56. Kruse CS, Krowski N, Rodriguez B, et al. Telehealth and patient satisfaction: A systematic review and narrative analysis. *BMJ Open*. 2017;7:e016242. doi:10.1136/bmjopen-2017-016242
57. Fatehi F, Samadbeik M, Kazemi A. What is digital health? Review of definitions. *J Med Syst*. 2020;44(4):67.
58. World Health Organization. *Global Strategy on Digital Health 2020-2025*. World Health Organization; 2021.
59. Patel V, Barker W, Siminerio E. Trends in consumer access and use of electronic health information. *ONC Data Brief*. 2015;30:1-10.
60. Adler-Milstein J, Holmgren AJ, Kralovec P, et al. Electronic health record adoption in US hospitals. *Health Aff (Millwood)*. 2017;36(8):1414-1420.
61. Tang H, Ran X, Li B, et al. Review of wearable sensor systems for monitoring liver diseases. *Sensors (Basel)*. 2022;22(5):1894. doi:10.3390/s22051894
62. Steinhubl SR, Muse ED, Topol EJ. The emerging field of mobile health. *Sci Transl Med*. 2015;7(283):283rv3.
63. Birkhead GS, Klompas M, Shah NR. Uses of electronic health records for public health surveillance. *MMWR Suppl*. 2015;64(2):1-5.
64. Sim I. Mobile devices and health. *N Engl J Med*. 2019;381(10):956-968.
65. Wiegand J, Berg T. The etiology, diagnosis and prevention of liver fibrosis. *Dtsch Arztebl Int*. 2013;110(6):85-91.
66. Rockey DC, Caldwell SH, Goodman ZD, et al. Liver biopsy. *Hepatology*. 2009;49(3):1017-1044.
67. Castera L, Friedrich-Rust M, Loomba R. Noninvasive assessment of liver disease in patients with chronic hepatitis. *Gastroenterology*. 2019;156(5):1264-1281.e4.
68. European Association for the Study of the Liver. EASL Clinical Practice Guidelines on non-invasive liver tests. *J Hepatol*. 2021;75(3):659-689.
69. Singal AG, Lampertico P, Nahon P. Epidemiology and surveillance for hepatocellular carcinoma. *Gastroenterology*. 2020;158(1):250-261.
70. Llovet JM, Kelley RK, Villanueva A, et al. Hepatocellular carcinoma. *Nat Rev Dis Primers*. 2021;7(1):6. doi:10.1038/s41572-020-00240-3
71. Forner A, Reig M, Bruix J. Hepatocellular carcinoma. *Lancet*. 2018;391(10127):1301-1314.
72. Marrero JA, Kulik LM, Sirlin CB, et al. Diagnosis, staging, and management of hepatocellular carcinoma: 2018 practice guidance by the AASLD. *Hepatology*. 2018;68(2):723-750.
73. Villanueva A. Hepatocellular carcinoma. *N Engl J Med*. 2019;380(15):1450-1462.
74. Bruix J, Reig M, Sherman M. Evidence-based diagnosis, staging, and treatment of hepatocellular carcinoma. *Gastroenterology*. 2016;150(4):835-853.
75. Lok ASF, McMahon BJ. Chronic hepatitis B. *Hepatology*. 2009;50(3):661-662.
76. Ghany MG, Morgan TR; AASLD-IDS A HCV Guidance Panel. Hepatitis C guidance: Recommendations for testing, managing, and treating hepatitis C. *Hepatology*. 2020.

77. Terrault NA, Bzowej NH, Chang KM, et al. AASLD guidelines for treatment of chronic hepatitis B. *Hepatology*. 2018;67(4):1560-1599.
78. Eslam M, Sanyal AJ, George J. MAFLD: A consensus-driven proposed nomenclature for metabolic associated fatty liver disease. *J Hepatol*. 2020;73(1):202-209.
79. Rinella ME, Lazarus JV, Ratziu V, et al. A multi-society Delphi consensus statement on new fatty liver disease nomenclature. *J Hepatol*. 2023;79(6):1542-1556.
80. Powell EE, Wong VW, Rinella M. Non-alcoholic fatty liver disease. *Lancet*. 2021;397(10290):2212-2224.
81. European Association for the Study of the Liver. EASL recommendations on treatment of hepatitis C: Final update. *J Hepatol*. 2020;73(5):1170-1218. doi:10.1016/j.jhep.2020.08.018
82. Terrault NA, Lok ASF, McMahon BJ, et al. Update on prevention, diagnosis, and treatment of chronic hepatitis B: AASLD guidance. *Hepatology*. 2024.
83. Yip TCF, Wong GLH. Artificial intelligence in hepatology: Current applications and future directions. *J Hepatol*. 2023;79(4):1050-1065.
84. Yasaka K, Akai H, Kunitatsu A, Kiryu S, Abe O. Deep learning with convolutional neural network in radiology. *Jpn J Radiol*. 2018;36(4):257-272. doi:10.1007/s11604-018-0726-y
85. Litjens G, Kooi T, Bejnordi BE, et al. A survey on deep learning in medical image analysis. *Med Image Anal*. 2017;42:60-88. doi:10.1016/j.media.2017.07.005
86. Wang K, Lu X, Zhou H, et al. Deep learning radiomics of shear wave elastography significantly improved diagnostic performance for assessing liver fibrosis. *Hepatology*. 2019;70(1):358-369.
87. Castera L. Non-invasive evaluation of non-alcoholic fatty liver disease using transient elastography. *J Hepatol*. 2020;72(4):758-769.
88. Friedrich-Rust M, Ong MF, Martens S, et al. Performance of transient elastography for the staging of liver fibrosis. *Gastroenterology*. 2008;134(4):960-974.
89. Rockey DC, Bell PD, Hill JA. Fibrosis—a common pathway to organ injury and failure. *N Engl J Med*. 2015;372(12):1138-1149.
90. Eddowes PJ, Sasso M, Allison M, et al. Accuracy of FibroScan controlled attenuation parameter and liver stiffness measurement. *Gastroenterology*. 2019;156(6):1717-1730.
91. Llovet JM, Villanueva A, Marrero JA, et al. Trial design and endpoints in hepatocellular carcinoma: AASLD consensus conference. *Hepatology*. 2021;73(S1):158-191.
92. Villanueva A. Hepatocellular carcinoma. *N Engl J Med*. 2019;380(15):1450-1462.
93. Reig M, Forner A, Rimola J, et al. BCLC strategy for prognosis prediction and treatment recommendation: The 2022 update. *J Hepatol*. 2022;76(3):681-693.
94. Singal AG, Llovet JM, Yarrow M, et al. AASLD Practice Guidance on prevention, diagnosis, and treatment of hepatocellular carcinoma. *Hepatology*. 2023;78(6):1922-1965.
95. Forner A, Reig M, Bruix J. Hepatocellular carcinoma. *Lancet*. 2018;391(10127):1301-1314.
96. Yuen MF, Heo J, Jang JW, et al. Advances in antiviral therapy for chronic hepatitis B. *Lancet Gastroenterol Hepatol*. 2024.
97. Feld JJ, Jacobson IM, Hézode C, et al. Sofosbuvir and velpatasvir for HCV infection. *N Engl J Med*. 2015;373(27):2599-2607.

98. Asselah T, Marcellin P, Schinazi RF. Treatment of hepatitis C virus infection with direct-acting antiviral agents. *Lancet*. 2018;391(10126):1208-1217.
99. World Health Organization. *Guidelines for the Prevention, Care and Treatment of Persons with Chronic Hepatitis B Infection*. World Health Organization; 2015.
100. World Health Organization. *Guidelines for the Care and Treatment of Persons Diagnosed with Chronic Hepatitis C Virus Infection*. World Health Organization; 2018.
101. Collins FS, Varmus H. A new initiative on precision medicine. *N Engl J Med*. 2015;372(9):793-795.
102. Ashley EA. Towards precision medicine. *Nat Rev Genet*. 2016;17(9):507-522.
103. Denny JC, Collins FS. Precision medicine in 2030—Seven ways to transform healthcare. *Cell*. 2021;184(6):1415-1419.
104. Hasin Y, Seldin M, Lusis A. Multi-omics approaches to disease. *Genome Biol*. 2017; 18:83.
105. Bashshur RL, Shannon GW, Bashshur N, Yellowlees PM. Telemedicine and the COVID-19 pandemic: Lessons for hepatitis care. *Telemed J E Health*. 2020;26(5):571-573.
106. Omboni S, McManus RJ, Bosworth HB, et al. Evidence and recommendations on the use of telemedicine for chronic diseases. *J Med Internet Res*. 2022;24: e31726.
107. Keesara S, Jonas A, Schulman K. Covid-19 and health care's digital revolution. *N Engl J Med*. 2020;382: e82.
108. Kruse CS, Karem P, Shifflett K, et al. Evaluating barriers to adopting telemedicine worldwide: A systematic review. *J Telemed Telecare*. 2018;24(1):4-12.
109. Shortliffe EH, Sepúlveda MJ. Clinical decision support in the era of artificial intelligence. *JAMA*. 2018;320(21):2199-2200.
110. Sutton RT, Pincock D, Baumgart DC, et al. An overview of clinical decision support systems. *NPJ Digit Med*. 2020; 3:17.
111. Sendak MP, D'Arcy J, Kashyap S, et al. A path for translation of machine learning products into healthcare delivery. *EMJ Innov*. 2020; 4:45-52.
112. Topol EJ. High-performance medicine: The convergence of human and artificial intelligence. *Nat Med*. 2019;25(1):44-56.
113. Karczewski KJ, Snyder MP. Integrative omics for health and disease. *Nat Rev Genet*. 2018;19(5):299-310.
114. Subramanian I, Verma S, Kumar S, et al. Multi-omics data integration, interpretation, and its application. *Bioinform Biol Insights*. 2020;14:1177932219899051.
115. Misra BB, Langefeld C, Olivier M, Cox LA. Integrated omics: Tools and applications. *Genetics*. 2019;213(4):1171-1184.
116. Hasin Y, Seldin M, Lusis A. Multi-omics approaches to disease. *Genome Biol*. 2017; 18:83.
117. Kelly CJ, Karthikesalingam A, Suleyman M, Corrado G, King D. Key challenges for delivering clinical impact with artificial intelligence. *BMC Med*. 2019; 17:195.
118. Char DS, Shah NH, Magnus D. Implementing machine learning in healthcare—Addressing ethical challenges. *N Engl J Med*. 2018;378(11):981-983.
119. Rieke N, Hancox J, Li W, et al. The future of digital health with federated learning. *NPJ Digit Med*. 2020; 3:119.

- 120.Topol EJ. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. Basic Books; 2019.