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**Emerging role of Artificial Intelligence in Gastroenterology and Hepatology**

Artificial Intelligence in Gastroenterology and Hepatology

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**Abstract**

Artificial Intelligence (AI) has emerged as a transformative tool in the diagnosis and management of gastrointestinal (GI) and liver diseases. In clinical practice, AI consists of overlapping technologies such as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision and generative AI (GenAI). ML is a computer learning system that can provide insight on disease risk factors and phenotypes. DL is an advanced and complex form of ML, structured with different levels of specific algorithms known as convolutional neural networks that can rapidly and accurately process unstructured, high-dimensional data, such as texts, images, and waveforms. NLP is dedicated to facilitating interactions between computers and humans using natural language and helps to analyze, understand, and derive actionable information from unstructured healthcare data, including electronic health records, clinical notes, medical literature, and patient-generated content. Computer vision focuses on enabling computers to see and interpret images and videos and serves as an augmentation tool for endoscopists, improving accuracy and decreasing procedural time. GenAI is capable of creating new form of content by learning from a large body of data in the form of text, audio, images, or video and includes large language models. AI has been used in several GI diseases such as esophageal neoplasia, gastric cancer, *Helicobacter pylori* infection, gastritis, gastrointestinal stromal tumors, colorectal polyps, inflammatory bowel disease, irritable bowel syndrome, GI bleeding and pancreato-biliary diseases. The potential applications of AI in liver diseases encompass a variety of conditions such as liver masses, metabolic dysfunction-associated steatotic liver disease, viral hepatitis, cirrhosis and liver transplantation. This review discusses the common terminologies and the current status of AI in gastroenterology and hepatology, exploring its applications and ethical issues.

**Key Words:** Artificial Intelligence; Machine learning; Deep learning; Applications; Gastroenterology; Hepatology

**Core Tip:** Artificial Intelligence (AI) has emerged as an invaluable transformative tool in diagnosis and management of gastrointestinal and liver diseases. In clinical practice, AI technologies such as machine learning, deep learning, natural language processing, computer vision and generative AI have been used in their applications. There is a need of continued development, validation, and real-world modeling of AI system before its widespread adoption. Although it doesn't replace human clinical judgement, it can still be expected that AI application in gastroenterology and hepatology will further be enhanced in the future and become the standard of care in the clinical practice.

## INTRODUCTION

Artificial Intelligence (AI) has drastically revolutionized the healthcare system, including the clinical diagnosis and treatment, resulting in the subsequent increase in the quality of life[1]. This has emerged as a transformative tool in the diagnosis and management of gastrointestinal (GI) and liver diseases. In one systematic review, it was shown that among several published randomized controlled trials of AI-assisted tools in clinical practice, more studies were done in the field of gastroenterology (30 out of 39) and it was demonstrated that the performance of AI-assisted tools surpassed that of usual clinical care[2]. AI has been used in several GI diseases such as esophageal neoplasia, gastric cancer, *Helicobacter pylori* infection, gastritis, GI stromal tumors, colorectal polyps, inflammatory bowel disease, irritable bowel syndrome, GI bleeding and pancreato-biliary diseases. The potential applications of AI in liver diseases encompass a variety of conditions such as liver masses, metabolic dysfunction-associated steatotic liver disease, viral hepatitis, cirrhosis and liver transplantation. The applications of AI in gastroenterology and hepatology are shown in the figure 1. This review discusses the common terminologies and the current status of AI in gastroenterology and hepatology, exploring its applications and ethical issues.

## COMMON TERMINOLOGIES OF AI USED IN GASTROENTEROLOGY AND HEPATOLOGY

AI involves the computer program which uses a multitude of techniques to resolve different problems and mimics human intelligence[3]. In clinical practice, several overlapping tools of AI are used, such as machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision and generative AI. The landscape of AI is depicted in figure 2.

Going through the history timeline of AI, Alan Turin published his work "Computing Machinery and Intelligence" in 1950, which introduced the Turing Test - a measure of computer intelligence. After six years, Jon McCarthy officially coined the term " Artificial Intelligence" in 1956 at the Dartmouth Workshop[4]. The history timeline of AI is shown in figure 3.

ML is a computer learning system which can provide insight on disease risk factors and phenotypes. The types of ML can be categorized into supervised, unsupervised and reinforcement ML[5]. The supervised learning involves model training with labelled data, and comprises classification and regression; unsupervised learning deals with unlabelled data and consists of clustering; in the reinforcement learning, the model agent takes actions in the environment, and then the received state gives the update and feedback.

DL is an advanced and complex form of ML, consisting of input layer, multiple hidden layers and output layer; convolutional neural network (CNN) is a specific type of DL architecture powered with AI algorithms that can automatically process images and perform other tasks involving visual data[6]. The layers of DL is shown in figure 4.

NLP is a subfield of computational linguistics, focused on AI models that interpret and generate human language[7]. It equips machines with the capability to comprehend, decode, and produce human language in a relevant and constructive manner, and helps to analyze, understand, and derive actionable information from unstructured healthcare data, including electronic health records, clinical notes, medical literature, and patient-generated content.

Computer Vision is a branch of AI that helps computers to understand and interpret images and videos. Some examples of the application of this new system in endoscopy include: 1) automated stratification and risk classification in esophageal varices 2) differentiation of ulcerative colitis and Crohn's disease 3) differentiation between benign and malignant biliary strictures during ERCP 4) assisting in selective biliary cannulation during ERCP 5) adequate assessment of mucosal examination during UGI endoscopy or colonoscopy 6) standardized training in endoscopy skills[8].

Generative AI is a category of AI that employs ML, DL, NLP and computer vision to create a new form of content by learning from innumerable data in the form of text, audio, images, or video following human input. It is often powered by large, pre-trained models known as foundation models (FMs), which include Large Language Models (LLMs), such as OpenAI's ChatGPT and Google's Gemini[9]. The chat interface is the simplest method of interacting with LLM in which the prior programming experience is not required. In order to perform an intended task, the users input a prompt containing the necessary instructions and contextual information. The file uploads or adjustment of model characteristics like creativity are also allowed in some chat interfaces. Application programming interfaces are used in advanced LLM-based software for more complex or high-throughput use cases, and provide simplified programming instruction sets for model interaction and customization[10]. The LLM brings a new era in gastroenterology and hepatology and is utilized in improving diagnostic accuracy during endoscopy, streamlined documentation, enhanced educational and patient engagement strategies, clinical decision support, research and drug discovery[11]. Generative AI, particularly LLMs, plays a significant role in creating synthetic data. The concerns about the privacy of the patient, restriction of data sharing and rarity of conditions can be the challenging problems in generating high-quality data, required for the implementation of AI[12]; this can be solved by the use of synthetic data[13]. The flowchart of AI after data collection is shown in figure 5.

## APPLICATIONS OF AI IN GASTROINTESTINAL (GI) DISEASES

### *Upper GI neoplasia*

The upper GI endoscopy fails to identify a number of neoplastic lesions because of the several factors obscuring the vision or improper navigation. This significant miss rate of neoplastic lesions can be properly rectified by the real-time application of AI, which helps not only for the detection, characterization, treatment and reporting of upper GI neoplasia, but also improves the proper navigation of the scope. The computer-aided detection (CADe) system helps to reduce the miss rate, whereas the computer-aided diagnosis (CADx) system assists in histology prediction of precancerous lesions and depth of invasion. The AI also helps in lesion demarcation, which ensures the complete resection; moreover, the AI assisted anatomical landmarks helps in adequate reporting, as well[14].

*(a) Esophageal cancer*

The two histologic forms of esophageal cancer are squamous cell carcinoma and adenocarcinoma. Barrett's esophagus, which correlates with the rise of gastroesophageal reflux disease, is a potential premalignant condition and can lead to esophageal adenocarcinoma[15,16].

The early detection of dysplasia in Barrett's esophagus and its timely treatment is believed to decrease the incidence of esophageal cancer. The histopathologic examination has been the gold standard for the diagnosis of Barrett's esophagus and dysplastic lesion, but it has got the limitation regarding the interobserver agreement[17]. In order to improve the histological diagnosis of Barrett's esophagus and dysplasia, one study has designed a DL model, which included slides from 542 patients, and identified the low grade dysplasia with a sensitivity and specificity of 81.3% and 100%, respectively; the study identified the nondysplasia and high grade dysplasia with a sensitivity and specificity of >90%[18]. The study done in Japan utilized a CNN to detect early esophageal cancer, which has had a 98% sensitivity[19]. Another study utilized the CAD system to identify Barrett's esophagus as having nondysplasitc or neoplastic lesions, with an overall sensitivity, specificity and accuracy of 90%, 88% and 89%, respectively[20]. The analysis of morphological nuclear features done by computerized morphometry, as shown in one study, helped to determine the degree of Barrett's esohpagus-associated dysplasia and predict the time to progression to adenocarcinoma[21]. The study done with volumetric laser endomicroscopy, with an added feature of an algorithm to develop a prediction score, had a sensitivity and specificity of 90% and 93%, respectively, for detecting early esophageal neoplasia[22]. In one study, CAD was able to identify Barrett's neoplasia in image-based validation with sensitivity, specificity, and accuracy of 95.3%, 94.5%, and 94.7%, respectively, and in video-based external validation with sensitivity, specificity, and accuracy of 93.8%, 90.7%, and 92.0%, respectively[23]. These studies of AI in the identification of patients with esophageal neoplastic or pre-neoplastic lesions are shown in table 1.

*(b) Gastric Cancer*

Gastric cancers are more common in the distal stomach (antrum and body), but proximal gastric cancers are increasing in frequency[24]. The two histologic forms of gastric cancer are intestinal and diffuse-type cancers[25]. The potential premalignant gastric lesions, such as chronic atrophic gastritis, benign gastric ulcers, hypertrophic gastropathy and gastric polyps might increase the risk of gastric cancer[26]. Several algorithms have been devised to improve the detection of such premalignant gastric conditions. In one study, CNN needed only 47s to analyze 2296 stomach images in identifying gastric cancer lesions with a sensitivity of 92.2%[27]. Another study showed that CNN-CAD system was able to identify the invasion depth of gastric cancer with sensitivity, specificity and accuracy of 76.47%, 95.56% and 89.16%, respectively[28]. The study done in China used CNN system for the histopathological diagnosis of gastric cancer with a sensitivity and specificity of 100% and 80.6%, respectively[29]. These studies of AI in identification of patients with early gastric cancer is shown in table 2.

***Helicobacter Pylori Diagnosis***

Chronic and recurrent *Helicobacter pylori* infection is a well-established risk factor for gastric adenocarcinoma. The diagnosis of *Helicobacter pylori* by assessing the endoscopic gastric mucosal biopsy has been an important part of gastric cancer screening, but the process of specific staining of gastric biopsy is time consuming. Studies have shown that AI was able to predict *Helicobacter pylori* infection with sensitivity and specificity of 87% and 86%, respectively[30]. Another study has used AI in endoscopic gastric biopsy samples to develop an algorithm to detect *Helicobacter pylori,* which had a sensitivity of 100%[31].

***Gastritis***

Since the prevalence of chronic gastritis is high, it is mandatory to look not only for the *Helicobacter pylori* infection but also for atrophy, intestinal metaplasia and the proper types of gastritis. One study showed that the use of CNN was able to identify gastritis subtypes, namely autoimmune (A), bacterial (B), and chemical (C) gastritis, with an overall accuracy of 84%, the sensitivity and specificity for gastritis B being 100% and 93%, respectively[32].

***Gastrointestinal stromal tumors***:

Gastrointestinal stromal tumors (GISTs) are the most common mesenchymal neoplasms of the GI tract, arising from the interstitial cells of Cajal within the myenteric plexus of the muscularis propria; they occur most commonly in stomach followed by small intestine[33-35]. Most of the GISTs are due to mutations in proto-oncogene *KIT*[34]. Their three histologic types are spindle, epithelioid and mixed[33,36]. These are the tumors with malignant potential and hence, all GISTs > 2 cm and most GISTs < 2 cm with high risk factors should be resected[37]. The meta-analysis of seven studies have shown that the endoscopic diagnosis of GISTs can be done with AI-assisted Endoscopic Ultrasound (EUS) with pooled sensitivity and specificity of 92% and 82%, respectively[38]. These studies showed that AI could help in early detection of GIST, allowing for timely intervention.

***Colorectal Polyps***

Colorectal polyps are slow-growing overgrowths arising from the mucosal surface of the colon and rectum and may be neoplastic or non-neoplastic. Colorectal adenomas and serrated lesions are two main classes of pre-cancerous colorectal polyps. Adenomatous polyps will gradually show dysplastic changes, and those that develop high-grade dysplasia will become malignant with time[39-41]. Hence, early detection of adenomatous polyp is crucial for the timely treatment and better outcome.

*(a) Polyp Detection*

The colonoscopy for detection of polyp has its own limitation resulting in decreased adenoma detection rate (ADR) because of the poor bowel preparation, unable to visualize the blind spots, difficult to navigate in challenging situations and fatigue. In one study it was found that ADR was inversely related to the risk of interval colorectal cancer, where interval cancer was defined as the colorectal cancer diagnosed between 6 months and 10 years after the index colonoscopy[42]. AI techniques of automatic polyp detection system used during colonoscopy, namely CADe and CADx, have been extensively studied[43,44]. One study enrolled 1058 patients to evaluate the effect of an automatic polyp detection system and concluded that the AI system notably increased the ADR[44]. Another study used an automatic computer-vision method for colonic polyp detection and found that the use of energy maps was effective for the detection of polyps with sensitivity and specificity of 70.4 % and 72.4 %, respectively[45].

*(b) Polyp Classification*

The characterization of polyp is important to classify the polyps in order to determine whether the polyp is malignant or non-malignant. AI helps in the detection and characterization of colorectal polyps[46]. Several studies have used computer-aided methods for the classification of colorectal polyps[47-50]. One study analyzed the use of narrow-band imaging (NBI) magnifying colonoscopy to predict the histology of colorectal tumors and found the accuracy of this system of nearly 97.8%[51]. During endocytoscopy, microscopic visualization is done using mini probes[52]. One study has shown that the management of diminutive and small colorectal polyps can be done effectively by the use of CAD in endocytoscopy[53].

Technique of laser-induced autofluorescence has the capacity to detect colonic dysplasia in vivo[54]. Diagnostic algorithms based on fluorescence spectroscopy has been developed to diagnose the presence or absence of colonic adenoma by using fluorescence excitation-emssion matrices method[55]. One study has shown that chormoendoscopy, used to enhance lesion detection in colitis surveillance, identified more lesions than NBI, but most were not dysplastic[56]. The software designed for the automated classification of colonic polyps by probe-based confocal laser endomicroscopy (pCLE) had high performance, comparable to that of off-line diagnosis of pCLE videos established by expert endoscopists[57].

*(c) Detection of Malignancy in Polyps*

It is very important to diagnose malignancy in polyps and determine the depth of submucosal invasion (SMI). Surgery is recommended for the deep SMI because of the risk of local recurrence that can occur when treated with only endoscopic resection[58]. Endoscopic resectable malignant polyps are treated by different endoscopic treatments, such as endoscopic mucosal resection, submucosal dissection and full-thickness resection[58-60]. Considering the different therapeutic modalities for malignant polyps, proper endoscopic diagnostic techniques should be available to use the right therapeutic options. The depth of invasion can be determined by several endoscopic techniques, such as NBI, high-definition white light endoscopy, and EUS[61]. The CAD system used by one study utilized ultra-high magnification endocytoscopy to assess the depth of invasion and found the sensitivity and specificity of 98.1% and 100%, respectively[62].

***Inflammatory Bowel Disease***

During the treatment of inflammatory bowel disease (IBD), it is important to achieve the mucosal healing, which means not only the endoscopic healing, but also the histologic one. The persistence of histologic mucosal inflammation increases the risk of disease exacerbation and dysplasia. However, it is difficult to assess the histologic healing only by the conventional colonoscopy and in this scenario, the use of AI in the form of CAD system might help to get the information about the mucosal healing, similar to that received by the histologic examination. One study of CAD system evaluated the images from the colonoscopies in patients of ulcerative colitis and showed the identification of persistent histologic inflammation with a sensitivity and specificity of 74% and 97%, respectively[63]. In one study, deep neural network for evaluation of ulcerative colitis algorithm was used to recognize the ulcerative colitis patients of having endoscopic remission with 90.1% accuracy and histologic remission with 92.9% accuracy[64]. The study of CNN done in the patients of Crohn's disease using the images of the small bowel mucosa during capsule endoscopy showed the mucosal condition, whether normal or mucosal ulcer, with an accuracy ranging from 95.4% to 96.7%[65].

***Irritable Bowel Syndrome***

Irritable bowel syndrome (IBS) is characterized by its subtypes, namely IBS-D (IBS with diarrhea), IBS-C (IBS with constipation), IBS-M (mixed IBS), and IBS-U (IBS without a significant pattern of abnormal stool[66]. The pathophysiology of IBS is complex and involves the interplay of genetics, diet, gut microbiome and the brain-gut axis, leading to altered motility, visceral hypersensitivity, and immune response[67]. The symptom flare-ups in most of the patients with IBS have been found to be triggered by the certain foods and unique AI-aided mobile applications have been developed to identify those potential trigger foods. One mobile application used photos of food to develop personal infomatics system, which allows patient–provider collaboration and supports precise individual management[68]. A novel food and symptom journal application was found to be a feasible and usable tool for IBS patients which helped to determine the food triggers[69]. By using these AI-aided smartphone applications, frequent and continuous data can be received from the patients, which can be utilized by the clinicians to provide precision feedback. Recently, gut microbiota has been linked to the symptoms and pathogenesis of IBS[70]. One study of unique AI prediction model analyzed gut microbiota to identify the IBS patients with a sensitivity and specificity of > 80% and specificity > 90%, respectively[71].

### *Upper and lower GI Bleeding*

The endoscopic examination identifies the cause of GI bleeding in most of the patients with upper or lower GI bleeding. In some patients with recurrent bleeding, the repeated endoscopic examination may be needed to identify the bleeding point and cause of the bleeding. ML models may be generally useful for the risk stratification of GI bleeding patients and can predict the recurrent bleeding and outcome for these patients[72-76]. In a retrospective analysis of 22,854 peptic ulcer patients, ML model was used and validated in 1265 patients. ML model used the patient's data such as age, level of hemoglobin, gastric ulcer, GI diseases, malignancies and infections, which helped to identify the patients with recurrent ulcer bleeding. In the study, the ML model was able to identify the recurrent ulcer bleeding within 1 year with an accuracy of 84.3%[76].

### *Small bowel evaluation by Capsule Endoscopy*

Capsule endoscopy (CE), used to evaluate the small bowel, has its captured images reaching nearly 60,000 and hence, analysis of those images might be cumbersome. The use of AI might help in analyzing those images more efficiently and accurately in a shorter period of time. The CAD system developed in one study uses a CNN that identifies six intestinal motility events with an accuracy of almost 96%[77]. Automatic bleeding system, which analyzed 10,000 CE images based on a CNN, was used in another study to detect GI bleeding and found 99.9% precision value[78]. A novel learning method has been devised for detection of polyps, and has a overall accuracy of 98% for polyps, bubbles, turbid, and clear images[79]. Moreover, a CAD system using a CNN was also able to detect angiectasia, the most common lesion of the small bowel, with a sensitivity and specificity of 100% and 96%, respectively[80]. Studies have shown that AI system with DL are useful for detection of erosion, ulcer and hookworm in CE images[81-83].

## APPLICATIONS OF AI IN PANCREATO-BILIARY DISEASE

### *Pancreatic Diseases:*

*(a) Pancreatic Cancer*

Pancreatic cancer is responsible for almost 5% of all cancer deaths worldwide[84]. The most significant prognostic factor in pancreatic cancer is the tumor size, which if less than 10 mm, the five-year survival is more than 80% and if more than 10 mm, it is less than 50%[85,86]. The early detection of pancreatic cancer by imaging faces a great challenge and sensitivity of detecting pancreatic cancer by computed tomography (CT) scan is not high for small lesions[87,88]. One study showed that AI algorithm used in CT images achieved a sensitivity and specificity of 80.2% and 90.2%, respectively for the early detection of pancreatic cancer, which may be improved by a larger number of training images[89]. Another more powerful modality to detect small lesions in the pancreas is EUS[88,90]. The AI-based EUS used in one pilot study was able to diagnose pancreatic cancer successfully with an area under the curve (AUC) of 0.94[91]. Few studies have shown that the application of ML and DL to EUS imaging of the pancreas achieved equal or better results than endoscopists[92]. The detection of early pancreatic cancer is feasible only if the high risk group can be identified properly. The study done in Taiwan showed that logistic regression model could appropriately predict pancreatic cancer risk in patients with type 2 diabetes mellitus[93].

*(b) Intraductal Papillary Mucinous Neoplasm*

AI-based EUS models are under development to diagnose different types of pancreatic cystic lesions, including intraductal papillary mucinous neoplasm (IPMN)[94]. DL-based study for automatic identification of patients with pancreatic neoplasms at abdominal CT has shown good result, with AUC of 0.91 and the sensitivity for solid lesions of any size of 98%-100% and that for cystic lesions measuring 1.0 cm or larger of 92%-93%[95]. DL model was used in one AI-based EUS study to diagnose IPMN and achieved sensitivity and sensitivity of 95.7% and 94.0%, respectively[96].

*a) Autoimmune Pancreatitis*

The accurate diagnosis of autoimmune pancreatitis (AIP) poses a challenge as the mass-forming AIP might be misdiagnosed as pancreatic cancer and surgical resection could occur unnecessarily. AI-aided EUS used in one study was able to differentiate AIP accurately from pancreatic ductal adenocarcinoma and benign pancreatic conditions[97].

***Biliary disease***

*(a) Biliary tract cancers*

AI technology such as DL has been used in medical imaging to improve diagnostic performance of biliary tract cancers, which include cholangiocarcinomas and gallbladder cancer[98]. The analysis of clinical data, serum biomarkers, imaging and cell-free tumor DNA in whole genome sequencing can be analyzed by AI to diagnose early cholangiocarcinoma and predict patient outcome.[99].

*(b) Biliary stricture*

AI based tools, using DL, have been used to analyze images from cholangioscopy and other endoscopic procedures to identify malignant strictures with greater accuracy[100].

*(c) Primary Sclerosing Cholangitis*

Primary sclerosing cholangitis (PSC) is a chronic cholestatic syndrome of unknown etiology, characterized by fibrosing inflammatory destruction of intra or extrahepatic biliary ducts[101]. PSC is often progressive and leads to biliary cirrhosis and other complications. Because of the absence of proven medical therapy, orthotopic liver transplantation is the option with good outcome in the patients with end stage PSC[102]. PSC is also associated with cholangiocarcinoma at an incidence of 10–30%[102]. One study used ML in PSC risk estimate tool (PREsTo) to accurately predict outcomes of PSC and outperformed the noninvasive prognostic scoring systems in accuracy to predict liver failure[103].

*Biliary cannulation during ERCP*

Endoscopic retrograde cholangiopancreatography (ERCP) is an endoscopic procedure used with a therapeutic intent in biliary diseases. The procedure can be challenging in cannulating the papilla in cases of anatomical variation and sometimes the post-ERCP pancreatitis may be the unwanted event, that the patients might encounter. The AI-based system based on CNN used during ERCP in one study assisted in identifying the ampulla in patients with anatomical variation with 76% precision, which helped in easier biliary cannulation[104].

## APPLICATIONS OF AI IN LIVER DISEASES

*Liver Masses*

Hepatocellular carcinoma (HCC) is the fifth most common cancer globally[105] with a five-year survival of 18%[106]. The study done with multivariate models has shown that hepatitis C virus infection, hepatitis B virus (HBV) surface antigen, HBV core antibody, increased body mass index, diabetes and low platelet count can predict the risk of HCC in patients with cirrhosis[107]. The diagnostic modalities such as ultrasonography, CT, magnetic resonance imaging (MRI) and EUS are used for the detection and diagnosis of liver masses and the AI-based techniques have been developed for the hepatic mass identification. One study has shown that DL with CNN can differentiate liver masses at dynamic contrast enhanced CT with high accuracy (AUC 0.920 [108]. Another study showed that DL was able to classify common hepatic lesions on typical MRI features with 92% accuracy, 92% sensitivity, and 98% specificity[109]. The study has shown that focal liver lesions could be identified and characterized (malignant versus benign) by DL using supervised-attention mechanism from liver ultrasound images[110]. In another study, application of AI using EUS-based CNN model was able to identify and distinguish benign and malignant focal liver lesions accurately[111]. AI has also been used in histopathology to classify liver cancer histopathological images[112]. AI algorithm was used in one study to evaluate the high-risk patients for the development of HCC[113]. Another study showed that the AI-aided contrast-enhanced MRI was capable of preoperative prediction of microvascular invasion in patients with HCC[114]. The utility of AI combined with MRI and patient data was also shown in yet another study[115]. AI-aided histopatholgical image in one study showed that it was superior to the existing prognostic factors; the poor prognostic factors in this study were determined by the macrotrabecular architectural pattern, and a lack of immune infiltration[116]. Another study showed the utility of AI-based ultrasonography to predict the response of the transcatheter arterial chemoembolization (TACE) and post-radiofrequency ablation (RFA)[117,118].

*Metabolic dysfunction-associated steatotic liver disease*

Metabolic dysfunction-associated steatotic liver disease (MASLD), previously known as non-alcoholic fatty liver disease (NAFLD), is the term for steatotic liver disease (SLD) and is associated with cardiometabolic risk factors such as obesity, diabetes, hypertension and dyslipidemia. The pathophysiology of MASLD begins with the buildup of fat in the liver, driven by metabolic dysfunction, followed by metabolic dysfunction-associated steatohepatitis (MASH), which progresses to inflammation and liver fibrosis, eventually resulting in cirrhosis, end-stage liver disease and HCC[119]. Hence, the early detection of MASLD is vital to prevent the development of this category of HCC. Liver steatosis can be defined histologically or radiologically. The liver biopsy is considered the gold standard for diagnosing MASH and monitoring fibrosis progression, but is more invasive and costly. AI-enabled digital pathology has emerged as an important tool for achieving the more reliable and standardized result of liver biopsy[120-122]. The studies have shown that an automated tool could assess and quantify liver fibrosis and determine its architectural patterns in steatotic liver biopsies[123-126]. Several studies have shown that the automated tools such as the qFibrosis® system allowed the precise identification of collagen fibers and liver tissue architecture[127-131].

Radiological method of detecting liver steatosis is more accessible to the patient due to its less invasive nature. Recently, the detection of liver steatosis by ultrasonography has been improved by the use of DL algorithms, such as CNNs[132,133]. The systematic review has shown that AI models integrated into noninvasive diagnostic tools such as ultrasonography, elastrography, CT, MRI and clinical parameters have promising diagnostic potential for liver fibrosis and NAFLD[134]. Currently, elastography is regarded as the most commonly used modality for staging liver fibrosis[135]. One study has used AI-assisted shear wave elastography based on a DL method to compare with a liver biopsy and found the similar accuracy for diagnosing cirrhosis (AUC of 0.98) and fibrosis (AUC of 0.98)[136]. Another study used ultrasound shear wave elastography imaging with a stiffness value-clustering and ML algorithm to classify CLD from healthy cases and found sensitivity and specificity of 93.5% and 81.2%, respectively[137].

AI-assisted predictive models using the vast amounts of categorized patient data have been developed to identify high-risk individuals. One study used the application of ML methods to predict non-alcoholic steatohepatitis (NASH) in non-alcoholic fatty liver (NAFL) patients[138]; the study used electronic health records from the Optum Analytics to create supervised machine learning models trained on NASH and healthy patients and found AUC of various models ranging from 83%-88%[138]. The NASHmap model utilized a non-invasive tool using 14 variables to classify patients as probable NASH or non-NASH; the study showed good sensitivity in predicting NASH status[139].

*Viral Hepatitis*

Most of HCC cases are linked to cirrhosis caused by chronic hepatitis B virus (HBV) or hepatitis C virus (HCV) infections[140]. The predictive models for determining the risk of hepatitis related cirrhosis have been developed by several AI-based tools[141-145]. AI based prediction model done in one study showed that a universal gut-microbiome-derived metagenomic and metabolomic signature predicts cirrhosis with a diagnostic accuracy of 91%[146].

*Liver Transplantation*

Liver transplantation (LT) is a lifesaving procedure in acute and chronic end-stage liver disease where other medical treatments are no longer effective. It restores normal health, lifestyle and extends lifespan by 15 years[147]. However, there are several challenges of LT including insufficient donors, high mortality on the waiting list, and graft failures.

There is a lot of mismatch between the number of organs donated versus the number of organs needed and the availability of recipients. Model for End-Stage Liver Disease (MELD), Donor Risk Index and D-MELD (the product of donor age and preoperative MELD) have been used as criteria for organ allocation during liver transplantation; however, these scoring systems may not ensure fair and equitable distribution of donated organs[148,149]. AI-generated synthetic liver transplant waitlist data from the United Network for Organ Sharing (UNOS) database showed that they replicate complex hepatic dataset, mimic clinical correlations and survival patterns and rigorously protect patient privacy[150]. AI has been used in LT with considerable outcomes for organ allocation, donor-recipient matching, post-LT survival or graft failure[151]. One study created a neural network to predict 90-day LT waitlist mortality, using the UNOS database from 2002 to 2021 from which patients who were transplanted within 90 days of listing were excluded. The study showed that the neural network algorithm outperformed MELD and MELD-Na scores, with an AUC of 0.936 vs. 0.860[152,153]. With the use of pre-transplant donor and recipient data, AI is able to predict short and long-term survival with higher accuracy[154].

During living donor LT (LDLT), the proper functioning of the liver graft in the recipient should be evaluated meticulously, and at the same time, it is essential to check whether the donor is left with enough liver parenchyma for future function and regeneration[155]. One study showed that ML can improve the accuracy of graft weight prediction in LDLT[156]. Another study showed that a DL algorithm-assisted CT volumetry method can accurately estimate the graft weight in LDLT[157]. Complications leading to graft failure or death after LT include graft dysfunction/rejection, infections (bacterial, fungal, viral), biliary complications (leaks, strictures), vascular complications (thrombosis, stenosis of arteries/veins), post-transplant malignancies, and organ system failures (renal, cardiovascular, neurological)[158].

AI applications can be used to facilitate the early complication, identification and intervention, as well as possible prediction. ML algorithms can predict graft failure after liver transplantation by utilizing known donor, transplant, and recipient characteristics at the time of the transplant decision, thereby achieving high accuracy in matching donors and recipients[159]. AI has also been used to identify novel factors associated with death after transplantation[160,161]. AI plays a role in enhancing LT by analyzing complex data for pre-implantation biopsy evaluation, developing robust recipient prognosis algorithms, improving imaging analysis, and providing decision-making support[162].

## ETHICAL ISSUES IN AI

With an increasing development of AI in gastroenterology and hepatology, we face ethical dilemma raising concerns about the data privacy, algorithmic bias, and the potential for patient harm[163]. Large datasets, required for training and validation in DL based AI models, might be the issue for the patient data privacy and security, and may have the potential for data breaches[164,165]. The General Data Protection Regulation (GDPR) is a comprehensive European Union regulation that harmonizes data privacy laws across Europe[165]. The trust and accountability of such AI-driven data are achieved only by implementation of regulatory frameworks[166].

Getting the patient consent in the traditional methods may not be enough for the use of all patient data in AI applications. The right of patient to understand the role of AI in diagnosis and treatment options should be addressed properly. The complexity of AI integration should be included in the informed consent, so as to make the patients aware of it[167]. Another important ethical concern is about the data ownership and sharing. AI algorithm bias can occur when they are trained on biased datasets, and can perpetuate or amplify existing health inequities; the racial, age group, ethnic, gender and geographic region biases in algorithms can lead to discriminatory outcomes[168,169]. Because of the over-dependence on AI-generated models, the role of clinician expertise in decision-making could be inadvertently affected[170]. Careful individualized approach might be needed as poorly trained or validated algorithms can lead to misdiagnosis, biased care, and potential harm[171]. A balanced and comprehensive approach to patient care is necessary, which can be achieved by the implementation of international ethical guidelines for health-related research involving humans[172].

Apart from the ethical concerns, the financial constrain is the prime factor in implementation of AI in clinical practice as it requires substantial investment in technology infrastructure, ongoing maintenance, and specialized training. Moreover, the role of various stakeholders, including healthcare providers, patients, and regulatory organizations, is vital. In order to understand the potential and limitations of AI in clinical practice, the proper addressing of both the financial implications and stakeholder perspectives is essential[173].

In summary, all these ethical concerns need to be addressed properly before going for the implementation of AI in gastroenterology and hepatology. We need to prioritize data privacy and security, use diverse and representative datasets to mitigate bias and validate the studies thoroughly to assess the performance of AI tools across different populations. In order to achieve the trust and accountability, AI algorithms need to be transparent and explainable. It should be understood that AI is used to augment, and not replace, human expertise; hence, a balanced approach is needed by establishing clear guidelines and regulations for the development and deployment of AI in gastroenterology and hepatology.

## CONCLUSION

AI has emerged as an invaluable transformative tool in diagnosis and management of GI and liver diseases. However, there is a need of continued development, validation, and real-world modeling of AI systems before its widespread adoption. Although it doesn't replace human clinical judgement, it can still be expected that AI applications in gastroenterology and hepatology will further be enhanced in the future and become the standard of care in the clinical practice.

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