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Artificial intelligence in gastroenterology: Enhancing clinical practice, managing challenges and exploring future directions

Applications of AI in Gastroenterology and Hepatology

Abstract
Artificial Intelligence (AI) is transforming gastroenterology by enhancing diagnostic accuracy, enabling personalized treatment, and improving disease management efficiency. This review explores the evolution and application of core AI technologies—including Machine Learning (ML), Deep Learning (DL), and neural networks—that underpin modern computational advancements in the field. These tools have demonstrated significant success in detecting premalignant and malignant lesions, and in managing gastrointestinal bleeding, colorectal cancer, and *Helicobacter pylori* infection. AI also supports the diagnosis and treatment of liver and pancreatic diseases. Its use is expanding in functional gastrointestinal disorders such as irritable bowel syndrome (IBS), with emerging applications in pediatric gastroenterology. In addition, AI enables advanced risk stratification and addresses persistent challenges in conventional diagnostic and therapeutic approaches, including interobserver variability and inefficiencies in care delivery. However, integration into routine clinical practice faces several barriers, including data privacy concerns, algorithmic bias, limited model interpretability, regulatory gaps, and interoperability issues with existing healthcare infrastructure. Future directions include real-time procedural guidance, multi-omic prediction models, minimally invasive surgical automation, and drug discovery. Achieving the full potential of AI will require ethical governance, regulatory clarity, and sustained interdisciplinary collaboration.

Key Words: Artificial intelligence; Gastroenterology; Machine learning; Neural networks; Algorithms; Diagnosis; Management.

Core Tip: Artificial Intelligence (AI) is being applied across a range of gastrointestinal conditions—from cancer and liver disease to functional disorders—and is driving the development of new tools in digital health. It has demonstrated equal or superior efficiency compared to humans in diagnostic accuracy, treatment planning, and healthcare delivery. However, several important challenges remain, including data privacy concerns, limited transparency of algorithms, inherent biases, and difficulties integrating AI into traditional clinical workflows. Addressing these issues is essential for clinicians to fully benefit from AI and for its continued development in the field.

INTRODUCTION

Artificial Intelligence (AI) refers to the capability of machines or computer systems to perform tasks that typically require human intelligence. These tasks range from simple activities, such as driving a car, to complex processes like formulating medical solutions by analyzing clinical data[1].

The foundational idea of machine intelligence was first proposed by Alan Turing, who introduced the Turing Test, a benchmark to determine whether a machine can exhibit human-like intelligent behavior. The term "Artificial Intelligence" was officially termed during the Dartmouth Workshop in the 1950s, marking the formal recognition of AI as an academic discipline[2].

Over time, AI has undergone significant evolution in the medical field. Early developments focused on rule-based expert systems, primarily used to diagnose infectious diseases and recommend antibiotic therapies[3]. These systems evolved into Clinical Decision Support Systems (CDSS), which were integrated with Electronic Medical Records (EMRs) to provide clinicians with alerts, reminders, and guideline-based recommendations to support clinical decision-making[2,4].

Substantial progress occurred in the early 2000s with the introduction of Machine Learning (ML), enabling AI to interpret complex imaging modalities such as X-rays, MRIs, and CT scans to assist in diagnostic processes[5]. The development of deep learning, particularly Convolutional Neural Networks (CNNs), further revolutionized AI's role in healthcare by allowing it to perform complex diagnostic tasks, formulate personalized treatment plans, and support follow-up care across multiple specialties. Currently, AI is advancing towards multimodal integration, a system which combines text, images, and structured clinical data to deliver real-time clinical support[1,6].

In gastroenterology, the need for AI arises from several clinical demands. These include continuous patient monitoring, execution of repetitive procedures, delivery of personalized treatment, early detection of disease, and accurate prediction of disease flares. Chronic conditions such as IBD often generate vast volumes of data requiring efficient analysis, while the high stakes of misdiagnosis emphasize the need to reduce human error. AI meets these demands by enhancing diagnostic accuracy and improving clinical outcomes by providing automated support.

This review aims to provide an overview of the key AI technologies used in medicine, with a particular focus on their application in gastroenterology. It examines how AI contributes to both diagnosis and treatment, explores the challenges associated with its implementation and outlines future directions.

AI TECHNOLOGY

AI systems fundamentally rely on data, which they process using various models to generate clinically meaningful outputs. Two key approaches in this domain are Machine Learning (ML) and its specialized subset, Deep Learning (DL).

ML involves developing algorithms that learn from data and make independent predictions or decisions. These models improve over time as they are exposed to more data[6]. They are broadly categorized into three main types: Supervised Learning (SL), Unsupervised Learning (UL), and Reinforcement Learning(RL), as illustrated in Figure 1.

In supervised learning (SL), models are trained on labeled datasets containing both inputs and corresponding outputs. Once trained, these models can predict or classify new, unseen data[7]. For example, a model trained on endoscopic videos labeled with the presence or absence of polyps can subsequently diagnose similar lesions in new patients[8]. SL can be applied through two main approaches: Classification and regression. Classification models predict discrete outcomes, such as determining whether a patient has a particular pathology. Regression models, on the other hand, estimate continuous output values, such as predicting liver stiffness based on variables like age, BMI, and blood test results[9].

Unsupervised learning (UL), in contrast, uses unlabeled data to detect hidden patterns or groupings within it. A common technique is clustering, where the model groups similar data together. This can lead to the identification of new tumor subtypes with distinct prognoses and therapeutic responses[10]. Another technique, association rule learning, identifies frequent new relationships within data, such as the common co-occurrence of hypertension with chronic kidney disease[11].

In Reinforcement Learning (RL), a system learns to make decisions by interacting with the environment and receiving feedback in the form of rewards or penalties based on its actions. RL focuses on learning optimal responses through trial and error to maximize cumulative rewards over time. It has been applied to develop personalized treatment strategies. For example, RL models have been used to optimize dosing strategies in sepsis management by continuously adjusting drug levels based on a patient's changing physiological state[12].

Several classical machine learning algorithms are routinely used in clinical settings, as illustrated in Figure 2. The k-Nearest Neighbors (kNN) algorithm classifies data based on their similarity to previously labeled examples and is useful in tasks like skin lesion classification and distinguishing between benign and malignant breast tumors[13] . Linear regression is used to explore the relationship between dependent and independent variables and is often applied to predict outcomes such as blood pressure based on demographic and clinical factors[14]. Logistic regression, designed for binary outcomes, is widely used to estimate the probability of events such as sepsis or hospital readmission[15].

In addition, other advanced algorithms, such as Naive Bayes, Support Vector Machines (SVM), AdaBoost, and XGBoost are becoming increasingly prominent. These models have proven effective in tasks like disease prediction, tumor classification, and patient outcome forecasting, particularly when dealing with large, complex datasets[16-18].

Deep learning (DL), a specialized subset of machine learning, primarily relies on artificial neural networks (ANNs). ANNs are computational models inspired by the structure of the human brain, consisting of interconnected layers of artificial neurons, as illustrated in Figure 3. The most basic form is the feedforward network, where data passes in one direction through multiple layers. These networks are used in tasks such as pattern recognition and classification[19]. Another important type is the Recurrent Neural Network (RNN), which is specifically designed to process sequential data. Unlike traditional feedforward networks, RNNs incorporate loops in their architecture, allowing them to maintain a form of memory. This capability enables them to use information from previous inputs to influence current predictions, making them effective in analyzing time-series medical data such as heart rate variability in ECG signals, respiratory patterns, and fluctuations in blood glucose levels, thereby predicting flare ups in chronic conditions[20-22]. Similarly, RNNs are widely used in natural language processing (NLP) tasks such as analyzing clinical notes, patient histories, and symptom timelines. However, their limitations in capturing long-range temporal dependencies led to the development of Transformer neural networks (TNNs). Transformers utilize self-attention mechanisms to identify and prioritize the most relevant features within input data. These models are applied across clinical document analysis, speech recognition, and even image-based diagnosis. The attention mechanisms can also highlight critical regions in medical images, aiding clinicians in making more accurate diagnostic decisions[23]. Transformers form the foundation of large language models (LLMs) like GPT and BERT, which excel at understanding and generating human-like medical text[24]. These models support advanced clinical decision-making by enabling rapid retrieval of medical knowledge, summarizing vast medical literature, and providing context-aware recommendations. This also significantly improves clinician-patient communication.

Deep Neural Networks (DNNs), which consist of multiple hidden layers, represent a more advanced form of ANNs which are more accurate. Within this category, Convolutional Neural Networks (CNNs) are a specialized type tailored for image analysis. They extract features directly from raw pixels and use them in tasks such as detecting pulmonary nodules and coronary artery calcifications on CT scans[25]. CNNs are extensively used for semantic segmentation, where each pixel in an image is classified into predefined categories, such as normal tissue, malignant lesion, or inflamed area, allowing precise identification of pathological regions. This pixel-level classification enables accurate mapping of lesion boundaries aiding targeted interventions[26]. CNNs also perform instance segmentation, which not only labels each pixel but also differentiates between distinct instances of the same class (*e.g.*, multiple polyps within a single colonoscopy image). This capability is critical in clinical scenarios where distinguishing individual lesions impacts treatment decisions. Algorithms such as U-Net and Mask R-CNN have been widely used for these segmentation tasks, facilitating enhanced visualization, quantification, and monitoring of disease progression[27].

Other notable types of DNNs include autoencoders, which are unsupervised models used to reconstruct normal anatomy, such as in brain MRI, and detect anomalies[28]. Generative Adversarial Networks (GANs), composed of a generator and a discriminator, are capable of producing synthetic medical data such as realistic ECG signals or medical images, which can be used to train data models[29]. In addition advanced DL strategies such as transfer learning and few-shot learning further enhance these models. Transfer learning allows models to apply knowledge gained from one task to another, which is particularly beneficial when labeled data are limited[30]. Few-shot learning enables generalization from very few examples, making it especially valuable for diagnosing rare diseases[31]. Deep Reinforcement Learning (DRL), which integrates neural networks with reward-based learning frameworks, extends the capabilities of traditional DL by enabling dynamic decision-making in complex environments, with promising applications in robotic surgery, clinical decision support, and the optimization of clinical trial design[32,33].

Certain ML algorithms are inherently scalable to DL architectures and serve as effective bridges between traditional ML and DL approaches. Notably, semi-supervised learning and self-supervised learning exemplify such strategies. Semi-supervised learning leverages a small amount of labeled data alongside a large volume of unlabeled data to enhance model performance, making it particularly valuable in domains where annotated data is often limited[34]. In contrast, self-supervised learning generates supervisory signals directly from the input data by formulating pretext tasks, allowing models to learn from vast unlabeled datasets. For example, in medical imaging, models can be trained to reconstruct randomly masked regions of chest X-rays. Through this process, the algorithm learns general anatomical features and pathological patterns by predicting missing portions of the image based on the surrounding visible context[35].

AI IN DIAGNOSIS AND MANAGEMENT

AI has significantly enhanced the diagnosis and management of a wide range of gastroenterological conditions, from acute presentations such as Gastrointestinal Bleeding (GIB) to chronic disorders like irritable bowel syndrome (IBS). A summary of AI applications across these conditions is provided in Table 1

AI in detection of malignant and premalignant lesion

Substantial advancements have been made in the assessment of precancerous and cancerous esophageal lesions, particularly in the early and accurate detection of adenocarcinoma and Squamous Cell Carcinoma (SCC). These developments are especially critical given the increasing incidence and poor prognosis associated with esophageal adenocarcinoma[36].

In Barrett's esophagus (BE), a well-known precursor to Adenocarcinoma , AI-driven Computer-Assisted Diagnosis (CAD) systems have improved endoscopic surveillance and enabled more accurate diagnosis. These systems have demonstrated sensitivities as high as 84% and specificities up to 90.7%, outperforming conventional, non-AI-guided methods, which report sensitivities and specificities of 77% and 86%, respectively[37].

Beyond BE, AI integration has improved various endoscopic modalities. Techniques such as White-Light Endoscopy (WLE), Narrow-Band Imaging (NBI), and Wide-Area Transepithelial Sampling (WATS), when combined with DL algorithms, have shown increased detection rates[38,39]. Similarly, Volumetric Laser Endomicroscopy (VLE) and I-Scan imaging, augmented by AI, improve diagnostic accuracy by analyzing complex imaging data and assisting in targeted biopsies[40]. These AI-enhanced tools not only outperform traditional methods in efficiency but also serve as effective alternatives to labor-intensive approaches[41].

AI also contributes to real-time quality control during endoscopic procedures by providing immediate feedback on technique and helping to standardize practices across operators. This reduces inter operator variability and supports consistent diagnostic performance[41].

Furthermore, AI significantly improves polyp detection during colonoscopy, a key factor in identifying premalignant lesions for colorectal cancer prevention. AI facilitates the accurate identification of polyps, particularly small or flat lesions that are often missed using conventional techniques[42]. Studies have shown that AI-assisted colonoscopy increases the Adenoma Detection Rate (ADR) from 20.3% to 29.1%, and the Polyp Detection Rate (PDR) from 29.8% to 45.0%[43,44]. These systems, especially those employing DL algorithms, analyze real-time endoscopic video to highlight suspicious lesions, thereby assisting endoscopists in timely and accurate detection.

AI in colorectal carcinoma

The integration of AI has revolutionized the diagnosis, early detection of metastasis, and treatment of colorectal carcinoma.

In diagnostic applications, automated histopathological image analysis provides more objective and rapid tumor grading, biomarker assessment, and evaluation of tumor growth patterns[45]. Additionally, AI algorithms aid in radiological interpretation, facilitating earlier detection of tumors and metastases through imaging modalities such as MRI, CT, and ultrasonography .

Liver metastasis is a common complication of colorectal cancer. Radiomics combined with CNNs, which integrate imaging data with clinical information, have been used to predict the development of Colorectal Liver Metastases (CRLM)[46,47]. AI has shown ability comparable to radiologists in detecting liver metastases *via* imaging, and even through non-invasive methods like breath analysis[48].

In treatment planning, AI supports clinical decision-making by predicting responses to therapies such as ablation and chemotherapy and by identifying optimal treatment regimens. For example, ML models have been developed to predict chemotherapy outcomes and potential complications, enabling oncologists to tailor treatment strategies effectively[49]. Moreover, AI tools analyze radiomic and clinical data to forecast disease progression, recurrence risk, and patient survival, thereby guiding personalized follow-up and management strategies[50,51].

Significant progress has also been made in assessing bowel preparation quality for colonoscopy—an essential factor in both the diagnosis and surveillance of colorectal carcinoma. Traditional scoring systems, like the Boston Bowel Preparation Scale (BBPS), are often inaccurate due to interobserver variability. To address this, a study developed two CNN models trained on large colonoscopy video datasets. These AI systems demonstrated an accuracy of 85.3% in detecting inadequate bowel cleanliness and achieved 100% sensitivity in certain testing scenarios[52]. These findings suggest that AI can offer real-time, objective assessments of bowel preparation quality, potentially enhancing colonoscopy effectiveness and standardizing evaluation practices across operators.

AI in Helicobacter pylori infection

The management of *Helicobacter pylori* (H. pylori) infections is undergoing significant advancement, particularly in the areas of diagnosis, personalized treatment, and eradication strategies.

AI aided diagnostic tools, especially those utilizing CNNs, have demonstrated high accuracy in detecting *H. pylori* infection through endoscopic images. Some models have achieved sensitivities of up to 100% and specificities of approximately 81%, facilitating early and accurate diagnosis[53].

Moreover, AI is contributing to personalized treatment planning. Systems such as "H. pylori AI-Clinician" utilize patient-specific data to customize therapeutic regimens, predicting the most effective treatment combinations[54]. These AI-driven platforms employ advanced ML models to generate individualized recommendations. This personalized approach has been shown to enhance treatment success, increase eradication rates, and potentially reduce the long-term risk of H. pylori-associated gastric cancer[54,55].

Additionally, AI is being applied to the discovery of novel eradication strategies. It assists in screening herbal compounds and alternative therapies with potential anti-H. pylori properties, thereby accelerating the identification and development of new treatment options[55].

AI in gastrointestinal bleeding(GIB)

The application of AI addresses several challenges in the management of GIB, including the prediction of bleeding episodes, risk assessment, and outcome forecasting

For the prediction of bleeding episodes, ML algorithms have been integrated into EMRs. These models, trained on retrospective datasets, are applied to real-time clinical data to identify patients with acute GIB. This approach has demonstrated superiority over traditional systems such as SNOMED, enabling timely risk stratification by automatically activating ML models when predefined clinical criteria are met[56].

In outcome prediction, ML models have outperformed conventional scoring systems. Traditional tools such as the Glasgow-Blatchford Score (GBS), admission Rockall score, and AIMS65 are limited in their ability to predict key outcomes including rebleeding, the need for intervention, and mortality[57]. In contrast, ML models—particularly those utilizing algorithms like XGBoost—have demonstrated improved predictive accuracy[58,59]. For instance, one study showed that an ML model surpassed traditional scores in predicting the composite endpoint of intervention or death within

30 days, enhancing the identification of low-risk patients who may be managed as outpatients[60]. In another study involving 5,691 Intensive Care Unit (ICU) patients with acute GIB, an ML model predicted mortality more accurately than the widely used APACHE IVa score[61]. AI has also been employed to forecast antithrombotic-associated GIB and to predict transfusion requirements, providing timely insights to support clinical decision-making[62].

Furthermore, AI has enhanced diagnostic precision during endoscopic procedures by analyzing video footage to detect bleeding sources such as ulcers or varices. These tools can also assess bleeding severity and guide therapeutic decisions, ultimately contributing to improved patient outcomes[63].

AI in irritable bowel syndrome (IBS)

AI is increasingly being used in the management of IBS, particularly in improving diagnosis, personalizing treatment, and enhancing symptom monitoring.

An important area of research involves the analysis of bowel sounds, which offers a non-invasive and cost-effective diagnostic modality. One study demonstrated significant differences in bowel sound intervals between IBS patients and healthy individuals, achieving a sensitivity of 89% and a specificity of 100%[64] . Subsequently, various ML algorithms have been applied to refine this approach. The development of the IBS Acoustic Index, which achieved 87% sensitivity and specificity, has provided an objective and practical tool for diagnosis[65].

Similarly, in a 2023 study, ML models were applied to clinical datasets to accurately differentiate between IBS subtypes, thereby improving diagnostic precision and enabling better-targeted therapeutic strategies[66].

Another emerging application is the AI-assisted colonoscopic imaging. While IBS has traditionally been considered a functional disorder without endoscopic abnormalities, researchers utilized Google Cloud AutoML Vision to analyze colonoscopy images from IBS patients and healthy controls. The model demonstrated high specificity (97.6%) in distinguishing IBS patients from controls, suggesting that AI can detect subtle mucosal changes not visible to the human eye[67].

In terms of treatment, ENBIOSIS, an AI-driven dietary recommendation platform, has emerged as a personalized intervention tool. This system employs microbiota profiling in conjunction with XGBoost algorithms to tailor dietary interventions. In a comparative study, IBS patients who received AI-personalized diets showed significantly greater improvements in symptom severity and gut microbiota composition compared to those on a standard low-FODMAP diet[68].

Second-generation AI systems further enhance treatment efficacy through the use of closed-loop, adaptive feedback mechanisms. These systems integrate real-time data, including clinical symptoms, genomic and microbiome profiles, heart rate variability (HRV), and gastrointestinal motility, to continuously deliver personalized care[69].

Another emerging approach is the AI-enabled digital pill system, which adjusts medication regimens based on clinician input and patient-reported outcomes. This system extends from basic symptom tracking to biologically informed dosing protocols, utilizing metrics such as cytokine levels and HRV to individualize therapy[70].

In symptom monitoring, AI also demonstrates significant potential. The Dieta mobile application uses AI to classify stool images according to the Bristol Stool Scale. In a pilot study, the application outperformed patient self-reporting, achieving an accuracy of 95%, thereby highlighting its utility in real-time symptom tracking and treatment monitoring[71].

AI in liver conditions

AI has brought significant advancements to the non-invasive diagnosis, risk stratification, and treatment planning of liver diseases through prognosis-based predictions.

In liver fibrosis and steatosis, AI-powered tools utilizing ultrasound, CT, MRI, and elastography combined with DL and CNNs have demonstrated high sensitivity and specificity in detecting and staging disease severity[72,73]. CNNs applied to imaging data enable non-invasive assessment of liver stiffness and fat content, thereby reducing reliance on liver biopsies[72]. For example, in patients with chronic hepatitis C, ANNs trained on biopsy data accurately predicted significant fibrosis[74,75]. ML models incorporating parameters such as age, AST, albumin, and platelet count have also been effective in identifying advanced fibrosis . Similarly, in chronic hepatitis B, ANN-based models have outperformed traditional scoring systems such as Fib-4[76] .

In the diagnosis of focal liver lesions, ML models have shown high accuracy in classifying hepatic nodules, such as cysts, hemangiomas, and Hepatocellular Carcinoma (HCC), especially when integrated with clinical data[77].

In Non-Alcoholic Fatty Liver Disease (NAFLD) and Non-Alcoholic Steatohepatitis (NASH), ML models have aided in predicting disease progression and clinical outcomes by analyzing a combination of laboratory data, demographic variables, and imaging biomarkers. These models have also been effective in forecasting complications such as portal hypertension and HCC[78-80].

In HCC specifically, AI contributes to early diagnosis, risk stratification, treatment selection, and post-treatment monitoring. ML-based diagnostic models have outperformed traditional tumor markers like AFP, while DL algorithms have enhanced the accuracy of risk stratification in patients with compensated cirrhosis[81-82]. Multi-modal AI models using RNA, mRNA, and methylation data have successfully identified molecular features associated with tumor aggressiveness and prognosis[83-84] .

AI is also being employed to predict prognosis in chronic liver disease. Radiomics extracted from CT images can identify high-risk varices, and DL models have demonstrated utility in predicting post-transplant survival[85,86]. Furthermore, AI algorithms trained on histopathological slides can predict survival outcomes in patients with HCC undergoing surgical resection[87].

AI in pancreatic conditions

AI has demonstrated significant progress in differentiating various pancreatic pathologies and in facilitating personalized treatment planning through risk prediction

In both acute and chronic pancreatitis, ML algorithms and ANNs have outperformed traditional scoring systems such as APACHE-II in predicting disease severity, complications, and mortality, with some models achieving accuracies up to 97.5%[88,89].

AI applications have also demonstrated high specificity in distinguishing chronic from autoimmune pancreatitis and identifying functional abdominal pain, particularly when using imaging techniques such as Endoscopic Ultrasound (EUS) and radiomics[90].

In the assesement of Pancreatic Cystic Neoplasms (PCNs), DL and radiomics-based models have surpassed radiologists and conventional clinical guidelines in accurately classifying cyst types and estimating malignancy risk[91,92]. Tools like CompCyst, which integrate clinical, imaging, and biochemical data, have significantly reduced the rate of unnecessary surgical interventions[93].

For Pancreatic Ductal Adenocarcinoma (PDAC), DL models applied to CT and PET-CT imaging have demonstrated superior tumor detection rate compared to conventional methods[94] . AI has also proven effective in distinguishing PDAC from benign pancreatic conditions and in improving survival prediction through the analysis of complex, multidimensional datasets. These capabilities support earlier diagnosis and enable more personalized therapeutic strategies[95-97].

AI in pediatric gastroenterology

AI techniques have been applied to enhance early diagnosis and management of pediatric gastrointestinal and hepatobiliary diseases.

In neonatal liver disease, particularly biliary atresia, ML algorithms have significantly improved diagnostic accuracy. A study employing XGBoost algorithm integrated clinical data, laboratory indices, and imaging findings from ultrasound and hepatobiliary scintigraphy to distinguish biliary atresia in neonates with cholestasis.

This model outperformed traditional diagnostic methods and enabled earlier intervention, leading to better clinical outcomes[98].

In Eosinophilic Esophagitis (EoE), an AI platform using semantic segmentation of biopsy slides achieved a histological classification accuracy of 86.7%[99]. The model effectively identified, quantified, and graded key histopathologic features across the EoE spectrum, with performance comparable to that of gastrointestinal pathologists, highlighting its potential in both diagnosis and treatment planning.

Similarly, AI has facilitated the non-invasive diagnosis of pediatric intussusception. A DL algorithm applied to abdominal ultrasound images demonstrated potential in improving diagnostic speed and accuracy. Continued advancements of AI systems for real-time detection of hallmark sonographic signs—such as the "concentric circle" sign—may further enhance clinical decision-making in children presenting with suspected intussusception[100].

BENEFITS

The integration of AI in gastroenterology has led to transformative advancements, significantly improving diagnostic accuracy, detection rates, and clinical decision-making. DL and ML algorithms have demonstrated superior sensitivity and specificity compared to conventional clinician-based assessments across a wide spectrum of gastrointestinal diseases[37,41,42,53] .

Unlike traditional risk prediction models, which typically rely on a limited set of variables, AI-based models can integrate large volumes of clinical, imaging, and histopathological data to forecast disease progression and personalize treatment strategies. Key advantages of AI include its ability to recognize complex patterns, function without fatigue, continuously learn and adapt, and remain unaffected by human error. These capabilities enable accurate risk prediction, early identification of complications or treatment failure, and the development of personalized therapies, ultimately contributing to improved patient outcomes[50,60,78,79] .

AI also addresses long-standing limitations in conventional diagnostic and therapeutic approaches, such as the invasive nature of certain procedures, inter-operator variability, and the challenges of integrating patient-specific data and preferences into treatment plans. Moreover, it accelerates research efforts by identifying novel hypotheses, streamlining data analysis, and opening new avenues for exploration[41,69].

Beyond diagnostics, AI enhances overall healthcare delivery by improving cost-effectiveness—reducing unnecessary procedures, automating administrative tasks, and optimizing resource allocation [101.102] . It also contributes to lower hospital readmission rates through predictive analytics that facilitate timely interventions[103]. Additionally, AI supports remote monitoring and telemedicine, expanding access to care in underserved areas while alleviating the burden on healthcare systems[104].

CHALLENGES

Despite the transformative potential of AI, its integration into clinical practice is accompanied by several significant challenges

A primary concern involves data privacy and cybersecurity. As AI systems routinely handle sensitive patient information, they are inherently vulnerable to data breaches and cyber-attacks. Addressing these risks necessitates the enforcement of stringent data protection regulations, such as the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA). Additionally, the adoption of privacy-preserving techniques in machine learning—such as federated learning, differential privacy, and encrypted computation—is essential to ensure secure data storage and transmission, thereby enabling responsible and ethical data sharing for AI applications[105].

Ethical considerations also represent a major obstacle, particularly regarding algorithmic bias, transparency, and accountability. AI tools trained on non-diverse or unrepresentative datasets may yield biased outputs, which can lead to underdiagnosis or misdiagnosis in specific demographic groups, perpetuating health disparities[106].

Compounding this issue is the lack of interpretability in many AI models, especially DL architectures. This "black box" nature renders it difficult for clinicians to comprehend or validate the rationale behind AI-generated recommendations, thereby eroding trust and impeding clinical adoption. Moreover, when such opaque systems make erroneous decisions, attributing responsibility or determining legal liability becomes problematic[107]. Another emerging concern is the phenomenon of AI hallucinations, particularly observed in large language models (LLMs). These models can generate outputs that are syntactically plausible yet factually incorrect or misleading. In a clinical context, such hallucinations pose a serious risk to patient safety if not rigorously vetted by medical professionals[108].

These issues highlight the urgent need for well-defined ethical guidelines and regulatory frameworks. However, formulating such frameworks is particularly challenging due to the rapid pace of AI development and the heterogeneous and fragmented nature of global regulatory standards

Additionally, most existing AI systems represent "narrow AI," designed for specific tasks without general reasoning abilities. Consequently, they cannot replicate the nuanced clinical judgment or contextual understanding that human physicians possess. This limitation undermines their generalizability and adaptability: While an AI model may perform well in the environment in which it was trained, its performance often deteriorates when applied to new clinical settings or slightly varied data inputs. Furthermore, narrow AI models typically lack the capacity for transfer learning, necessitating retraining for each new application. They also remain fragile, with small perturbations in input data potentially resulting in significant output errors—raising concerns about their robustness in dynamic, real-world clinical environments[109].

Finally, the technical and practical integration of AI into existing healthcare systems presents logistical hurdles. AI systems must be interoperable with EHRs, which often differ between institutions and were not originally designed for AI compatibility. Successful implementation also demands clinician training, workflow restructuring, and institutional support, which may disrupt established practices and encounter resistance from healthcare personnel[110]. Overcoming these multifaceted challenges is crucial to ensure the safe, ethical, and effective adoption of AI in gastroenterology and broader clinical practice.

FUTURE DIRECTIONS

There remains substantial scope for further innovation and application of AI in gastroenterology. One key area of advancement lies in the use of AI models for predicting disease progression through the analysis of longitudinal data and early detection of clinical deterioration[111]. Such predictive tools are particularly valuable in managing chronic gastrointestinal conditions prone to exacerbations, including Inflammatory Bowel Disease (IBD), liver cirrhosis, and pancreatic insufficiency

Another promising frontier is the development of real-time AI assistance embedded within EHRs and deployed *via* edge-computing-enabled wearable devices. These systems can locally process physiological signals, laboratory results, and vital signs to generate immediate clinical alerts, thereby supporting clinicians in real-time at the point of care[112].

Advanced risk stratification algorithms offer the potential to refine patient classification by integrating multi-modal data—including genomic, biochemical, and lifestyle information—to predict complications or therapeutic responsiveness. This would enable truly personalized management strategies, particularly for diseases where reliable risk models are currently lacking[113].

In the surgical domain, AI is poised to support automated or semi-automated minimally invasive procedures, enhancing precision, safety, and efficiency while reducing patient recovery times[114]. AI models can also forecast postoperative complications such as surgical site infections, facilitating early interventions and improved postoperative care[115] . Furthermore, intraoperative AI guidance can assist surgeons by providing real-time decision support and optimizing outcomes.

Beyond clinical care, AI holds transformative potential in drug discovery and development. By accelerating target identification, optimizing compound screening, and predicting therapeutic responses, AI can drastically shorten drug development timelines. It can also refine clinical trial design and forecast adverse events, thereby enhancing safety and efficacy in pharmacological interventions[116]. While there are emerging efforts to develop unified guidelines for the use of AI in gastroenterology , these frameworks still require substantial refinement to ensure comprehensive, standardized, and ethically sound implementation across clinical and research settings[117,118].

CONCLUSION

AI has already begun to revolutionize the field of gastroenterology by significantly improving diagnostic accuracy, therapeutic planning, and long-term patient monitoring. Its ability to process and learn from vast and complex datasets enables earlier disease detection, personalized care, and improved clinical outcomes.

Nevertheless, several challenges must be addressed to ensure the responsible and effective integration of AI into clinical practice. Concerns surrounding data privacy, regulatory compliance, ethical use, and the seamless incorporation of AI tools into existing clinical workflows remain pressing issues. Overcoming these barriers will require coordinated efforts involving technologists, clinicians, ethicists, and policymakers.

Looking ahead, the future of AI in gastroenterology is promising. Continued research and development are likely to enhance real-time procedural support, improve prediction of disease flares, enable safer and more effective surgical interventions, and accelerate the development of novel therapeutics. As these technologies mature, they have the potential to redefine standards of care, improve access, and ultimately transform the landscape of gastrointestinal healthcare.

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