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Artificial Intelligence in Gastrointestinal Motility Diagnostics: A Systematic Review

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ABSTRACT

Background: The assessment of gastrointestinal (GI) motility disorders is limited by the invasive, resource-intensive, and subjective nature of current testing. Artificial Intelligence (AI) is being applied to address these challenges. This review aimed to comprehensively identify, appraise, and synthesize the spectrum of AI applications in GI motility diagnostics.

Methods: A systematic search of PubMed, Embase, Scopus, Web of Science, and Medline for original studies was conducted in March 2025. Results were narratively synthesized and grouped by anatomic region.

Key Results: Of 1383 articles, 90 primary studies met the inclusion criteria. In the esophagus ($n = 31$), the primary focus was automation of High-Resolution Esophageal Manometry (HREM), pH impedance, and Functional Luminal Imaging Probe (FLIP) panometry analysis. In the gastroduodenum ($n = 21$), studies looked to improve diagnostic accuracy and interpretability of legacy electrogastrography (EGG). In the small and large intestine ($n = 19$), AI was used to determine transit time and predict post-operative ileus. In the anorectum ($n = 9$), tools focused on standardizing manometry interpretation. Review of pan-GI applications ($n = 10$) highlighted AI's application to wireless capsule endoscopy and bowel sounds analysis. While promising, all areas need more rigorous research and external validation before widespread deployment.

Conclusions and Inferences: AI will play an essential role in improving and automating the interpretation of GI motility diagnostics. However, even the most promising models require large-scale prospective validation before clinical implementation.

Trial Registration: PROSPERO (ID: 1128662)

1 | Introduction

Gastrointestinal (GI) motility disorders often require complex, resource-intensive diagnostic investigations, rely on subjective interpretation, and involve a complex underlying GI physiology. Artificial Intelligence (AI) approaches are emerging to address some challenges, offering promising avenues to expand to motility diagnostics.

GI motility encompasses the coordinated muscular contractions of the alimentary tract and is essential for digestion, nutrient absorption, and waste excretion. Disorders of this system, such as achalasia, gastroparesis, and dyssynergic defecation, are traditionally challenging to diagnose and depend on physiological assessments, such as manometry, electrophysiology, and transit analysis, which can be challenging to interpret and are often only available in highly specialized centers [1–3]. AI approaches to ingesting and interpreting high-dimensional material are rapidly maturing and could be particularly useful in GI diagnostics [4, 5]. Potential high-value uses include improved access to complex diagnostic test interpretations, reduced resource consumption, improved clinical efficiency, standardized test interpretations, and ultimately, improved patient outcomes.

Plain Language Summary

Gastrointestinal motility disorders are diverse and can be challenging to diagnose, often requiring specialized testing and analysis. Artificial Intelligence (AI) is increasingly being explored as a tool to improve the efficiency, accessibility, and accuracy of diagnostics in this field. In this systematic review, we identified 90 primary studies investigating AI applications to a range of different diagnostic tests including those examining esophageal pressure, gastric electrical activity, intestinal transit time, and anorectal pressure. Many models showed promising performance regarding accuracy and efficiency. However, most studies were based on small datasets and had limited internal validation. Further large, prospective studies with external validation are needed before AI tools can be widely implemented into routine clinical care.

Key Points

- Artificial intelligence is being increasingly applied to gastrointestinal motility testing.
- This systematic review identified and narratively synthesized 90 primary studies across all major gastrointestinal motility domains.
- Diagnostic models for esophageal manometry showcased impressive accuracy and potential.
- Most studies lacked external validation and were performed on small, single-center datasets.
- Further work including robust validation is required before the translation of AI tools into routine clinical practice is possible.

Several subspecialty domain-specific summaries of applications of AI in GI motility disorders exist [6–11]; however, this work extends previous work, presenting a comprehensive systematic review synthesis of the full spectrum of AI applications in all aspects of GI motility diagnostics.

2 | Methodology

This systematic review was conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for systematic reviews and meta-analyses of observational studies [12]. The PRISMA diagram is presented as Figure S1. The study protocol was prospectively registered on PROSPERO.

2.1 | Search Strategy

A literature search was conducted on Embase, Scopus, PubMed, Web of Science, and Medline without limits. The search terms were broad, including a range of terms for AI and various GI motility conditions, concepts, and tests, aiming to be nonrestrictive in order to capture all potentially relevant studies (Appendix S1).

2.2 | Eligibility Criteria

This review includes original research articles reporting primary data from human subjects of any age undergoing gastrointestinal motility assessment, where artificial intelligence methods were also applied. Preprints and conference proceedings were included if they met the eligibility criteria. Excluded were studies focused on oro-pharyngeal motility, animal studies, articles without full-text availability in English, and those limited to traditional statistical or mathematical modeling without a machine learning component. Review articles, abstracts, editorials, letters, and case reports without original data analysis were also excluded.

The primary outcomes of interest were the development, validation, or clinical application of AI tools related to gastrointestinal motility. Eligible applications included diagnostic classification, patient risk stratification, automated processing or classification of motility metrics, and prediction of patient outcomes.

2.3 | Study Selection and Data Extraction

Automated de-duplication of all studies found in the literature search was performed using EndNote. Titles and abstracts were then screened by one author, with a second reviewer independently verifying the selections. Articles meeting the inclusion criteria were retrieved in full text for detailed review.

Data extraction was performed manually by one author using a standardized table (Appendix S2) and independently checked by a second reviewer. The table captured study identifiers, objectives, population demographics, methodology, findings, limitations, and proposed next steps. The second reviewer verified all extracted outcomes, and any disagreements were resolved through discussion.

The primary outcomes of interest were measures of AI tool performance in diagnostic classification, risk stratification, automated analysis, and outcome prediction, compared to a recognized reference standard where possible. In-depth discussion of various AI and machine learning methods is beyond the scope of this review, but they are mentioned for reference. Further analysis of the methods is reviewed elsewhere, for example, in more focused reviews such as [7].

2.4 | Analysis

Given the heterogeneity of the included studies, formal risk of bias assessment and meta-analysis were deemed inappropriate. Instead, the data was structured into anatomical categories and narratively synthesized. A full list of used abbreviations (Appendix S3) is attached for the readers' convenience.

3 | Results

After removing duplicates, 1383 unique articles remained for screening by title and abstract. Two reviewers agreed on 146 articles for full-text review and data extraction. The full-text review excluded an additional 56 articles, leaving 90 primary studies for this review (Figure S1). A table (Table S1) summarizing the various AI methods mentioned throughout this paper has been included as a Supporting Information table for easy reference.

3.1 | Esophageal Motility

AI for esophageal motility has aimed to improve the efficiency and standardization of interpreting High-Resolution Esophageal Manometry (HREM), pH-impedance studies, and Functional Luminal Imaging Probe (FLIP) Panometry [8, 10]. A total of 31 appropriate studies were identified, of which the majority ($n = 16$) came from the United States of America (USA) or Romania (Table 1).

3.1.1 | Data Pre-Processing and Optimization

AI models have been developed to reduce noise and artifacts in physiological data, enhancing clinician and autonomous interpretation accuracy. For example, a decision tree-based model was able to extract artifact-free impedance values from 24-h pH-impedance monitoring with an Area Under the Curve (AUC) of 0.77 [37], and an Ensemble Empirical Mode Decomposition tool (a signal processing method) improved automated HREM diagnostic accuracy using neural networks in cases of achalasia by 0.07 [25]. Additionally, AI has proven helpful for processing large datasets by significantly reducing analysis time [39–41].

3.1.2 | Diagnostic Applications

3.1.2.1 | HREM. While there are some pre-Chicago Classification (CC) AI tools that achieved promising results [27, 29, 30], the majority of the work in this field aims to automate the CC. A group from Northwestern University has explored various machine learning models [13, 14], with their Long Short-Term Memory (LSTM) model achieving the highest study-level classification accuracy of 0.88 compared to specialist evaluation using version 3.0 of the CC (CCv3.0) [15]. A group from Iuliu University in Romania also developed several AI tools (mostly using convolutional neural networks (CNNs)) to aid in the automation of the CCv3.0 [1, 17, 18]. Their most recent work utilized Gemini as a coding assistant to develop an explainable CNN (through incorporation of LIME heatmaps) that classifies raw manometry data into seven motility patterns (0.88 accuracy) [16]. There are several other noteworthy contributions to the field [23, 24, 26, 28], with lightweight models such as PortableNet (0.94 accuracy) [21] and Mixed Attention Ensemble (0.98) [22] attaining particularly impressive classification accuracy into distinct esophageal motility disorders.

3.1.2.2 | Impedance Testing and Flip Panometry. Multiple AI models have also been applied to impedance testing with reflux detection (AUC 0.87) on 24-h pH-impedance monitoring [36, 38] and diagnosis of functional esophageal dysphagia on High-Resolution Impedance Manometry (AUC 0.95) [19, 20], being particular areas of interest due to their potential to reduce the time burden of analysis.

The researchers from Northwestern University are frontrunners in the automation of FLIP panometry, developing models to identify achalasia (0.89 accuracy for identification, 0.78 for spastic differentiation, 0.55 for subtype differentiation) [33, 34], and esophagogastric junction outflow obstruction (EGJOO) (0.89 accuracy) [35]. The group has also worked on a mechanics-informed model that combines physical parameters with FLIP data to build a "virtual disease landscape" [32], and has developed MechView, an AI-based software aiming to standardize FLIP analysis [43], which can be challenging to interpret clinically [44].

3.1.3 | Outcome and Risk Prediction

AI models for predicting treatment outcomes are emerging [32]. Machine learning has been used to indicate the likelihood of developing persistent symptoms (AUC 0.7), reflux esophagitis (AUC 0.61), and gastroesophageal reflux disease (GERD) (AUC 0.50–0.53) post-peroral endoscopic myotomy (POEM) [31]. While the predictive performance was limited, this study paves the way for future research. Additionally, Shapley Additive Explanations (SHAP) analysis, an explainable AI method that explains the degree to which each factor contributes to a given output, was used to identify the key predictive factors for specific complications, yielding valuable data.

3.1.4 | Summary and Commentary

While promising for improving efficiency, inter-observer objectivity, and diagnostic accuracy [8, 10], the field has limited generalizability due to research predominantly on small, single-center datasets. Furthermore, most HREM models are validated against the CCv3.0, meaning they may require updating to the latest version (v4.0). In efforts to improve standardization, FLIP studies now have a consensus framework (the Dallas Consensus) recently published in June of 2025 [44], while pH-impedance studies have the Lyon consensus [45]. With ongoing implementation and uptake, these criteria are expected to offer structured frameworks for the introduction, benchmarking, and validation of new AI tools.

Another issue is the invasiveness of current testing, which, while not an AI issue, could be improved with an AI solution. Thus, although still conceptual, unproven, and highly experimental, additional research into novel AI-enhanced alternatives, such as swallow sound analysis, whereby the acoustic data recorded by a digital stethoscope during swallowing is analyzed by a neural network, is of interest [42]. Finally, although some studies have incorporated explainable AI (XAI) techniques such as SHAP analysis [31] and LIME heatmaps [16], the application of XAI in GI motility research remains limited. XAI provides transparency by revealing the factors behind an AI's decisions, which allows clinicians to evaluate its reasoning and helps regulatory bodies inspect the system for fairness, bias, and legal compliance. As novel

TABLE 1 | Studies related to esophageal motility, sorted by test modality.

First author, year	Test modality	AI method(s)	Primary outcome (quantitative)
Kou et al. (2021) [13]	HREM	VAE	Swallow-level classification accuracy: 0.64
Kou et al. (2021) [14]	HREM	Multi-stage (CNN, XGBoost)	Study-level Dx accuracy: 0.81
Kou et al. (2022) [15]	HREM	LSTM	Study-level peristalsis classification accuracy: 0.88
Popa et al. (2024) [16]	HREM	CNN (Gemini-assisted)	Swallow classification accuracy: 0.88
Popa et al. (2022) [17]	HREM	CNN (InceptionV3)	Swallow classification F1-score: 0.92
Czako et al. (2021) [18]	HREM	CNN	Probe positioning failure detection accuracy: 0.90 IRP classification accuracy: 0.96
Surdea-Blaga et al. (2022) [1]	HREM	CNN and Decision Trees	CCv3.0 Dx accuracy: 0.86
Zifan et al. (2023) [19]	HREM	Logistic Regression and Random Forest	Functional dysphagia Dx accuracy (proximal): 0.97, (distal): 0.91
Zifan et al. (2024) [20]	HREM	SVM	Functional dysphagia Dx AUC: 0.95
Lin et al. (2023) [21]	HREM	PortableNet (Lightweight CNN)	EMD recognition accuracy: 0.94
Wu et al. (2025) [22]	HREM	Mixed Attention Ensemble (MAE)	Classified 6 EMDs with accuracy: 0.98
Wang et al. (2021) [23]	HREM	3D-CNN and Bi-ConvLSTM	EMD severity classification accuracy: 0.91
Wang et al. (2021) [24]	HREM	CVP-Graph Attention Network	Contraction pattern recognition accuracy: 0.96
Alaodolehei et al. (2019) [25]	HREM	EEMD and MLP	Achalasia detection accuracy: 0.97
Rafieivand et al. (2023) [26]	HREM	Expert per Class Fuzzy Classifier (EPC-FC)	Subject-level Dx accuracy: 0.92
Santos et al. (2006) [27]	HREM	ANN	Swallow classification accuracy > 0.80
Storonova et al. (2024) [28]	HREM	Random Forest	Achalasia subtype F1-score: 0.91
Abou-Chadi et al. (2002) [29]	HREM	Feed-forward neural network	Accurate two-stage classification: tubular esophagus: 0.97, LES: 1.00
El-Zehiry et al. (2001) [30]	HREM	Feed-forward neural network	Peristalsis classification accuracy: 1.00
Takahashi et al. (2024) [31]	HREM, Esophagography, GERD	Multiple ML models	Post-POEM symptoms prediction AUC: 0.70
Halder et al. (2022) [32]	FLIP	VAE and Random Forest	—
Carlson et al. (2021) [33]	FLIP	Decision Trees	Achalasia spasticity identification accuracy: 0.78 Achalasia subtype accuracy: 0.55
Kou et al. (2023) [34]	FLIP	CNN	Achalasia identification accuracy: 0.89
Schauer et al. (2022) [35]	FLIP	Bayesian Additive Regression Tree	EGJ obstruction prediction accuracy: 0.90
Wong et al. (2023) [36]	24-Hour Impedance pH monitoring	CNN (ResNet18)	Reflux episode identification accuracy: 0.87

(Continues)

TABLE 1 | (Continued)

First author, year	Test modality	AI method(s)	Primary outcome (quantitative)
Rogers et al. (2020) [37]	24-Hour Impedance pH monitoring	Decision Trees	Established artifact-free baseline impedance and identified esophageal events with high sensitivity: 0.90
Zhou et al. (2023) [38]	24-Hour Impedance pH monitoring	Structured State Space Model (S4)	Reflux event identification AUC: 0.87
Jell et al. (2019) [39]	24-Hour HREM	Weighted Empirical Risk Minimisation	40% reduction in evaluation time vs. manual
Jell et al. (2020) [40]	24-Hour HREM	Weighted Empirical Risk Minimisation	Swallow detection accuracy: 0.98
Kruse-Anderson et al. (1995) [41]	Longterm HREM	ANN	Contraction identification accuracy: 0.89–0.98 (location dependent)
Lankarani et al. (2024) [42]	Swallow sound analysis	Neural Network	IRP prediction accuracy: 0.97

AI architectures continue to emerge, limited transparency remains a major barrier, constraining clinician and regulatory body trust and therefore impeding wider adoption [46]. Therefore, future work should prioritize the development of more robust and domain-adapted XAI approaches to enhance model interpretability and clinical acceptance.

3.2 | Gastroduodenal Motility

Research in this area is limited and has historically focused on transit studies and the electrogastrogram (EGG); however, newer technologies such as body surface gastric mapping (BGSM) are emerging. A total of 21 appropriate studies were identified, of which the majority ($n = 13$) were from the USA (Table 2).

3.2.1 | Transit Studies

AI models have demonstrated utility in assessing gastric transit and identifying and predicting delayed gastric emptying. Machine learning has been utilized to optimize the clinical feasibility and applicability of Gastric Emptying Scintigraphy (GES) by reducing study duration by 1.5 h whilst retaining an AUC of 0.92 [59]. AI models have also been used to identify delayed gastric emptying from legacy EGG data, with different models achieving accuracies ranging from 0.83 to 0.90 [48, 50, 51, 56].

Additionally, machine learning models have been used in postoperative settings, including an XGBoost model to predict delayed gastric emptying after pancreatoduodenectomy (AUC 0.59) [65] and other forms of post-surgical gastroparesis [64, 66]. Machine learning has also displayed the ability to predict comorbid gastroparesis in chronic pancreatitis patients (AUC 0.74) [60]. Related to this, AI has been utilized to predict responsiveness to gastroparesis interventions, with one study investigating the use of AI-derived gastric myoelectric thresholds to predict positive pyloric balloon dilation outcomes [57] and another predicting pharmacological response to prokinetics and neuromodulators using ridge regression [60]. These models performed well internally but require external validation on diverse datasets before clinical integration.

3.2.2 | From EGG to Novel Modalities

EGG recordings are notoriously susceptible to data artifacts, significantly complicating their interpretation [68]. Researchers have developed neural network solutions to identify and eliminate artifacts [49, 55] and differentiate between different spectral profiles, such as those seen pre- and post-prandially [53, 54]. These studies lay the groundwork for automated analysis. Diagnostically, Multi-Layer Perceptron (MLP) neural networks have been utilized in conjunction with other AI techniques to identify gastric dysrhythmia [52], achieving a differentiation accuracy of 0.97 between bradygastria, tachygastria, arrhythmia, and normal rhythm [47]. Unfortunately, legacy EGG has not found clinical utility due to poor sensitivity, standardization limitations, and susceptibility to confounders [68], resulting in investment into the development of alternative modalities.

Some novel modalities are potentially advantageous as they optimize clinical feasibility and applicability with AI enhancement. The Gastric Electrical Impedance Tomography (gEIT) suit is an innovative approach that uses a shirt-like garment with EIT sensors. It is conceptually similar to the EGG but measures conductivity instead of electrical signals. It has been demonstrated that gEIT data analysis with a dual-step fuzzy clustering algorithm estimates gastric function and volume with good agreement compared to ultrasound (Pearson correlation $r = 0.88$) [58]. Another potential method is using the recognition ability of machine learning models to detect and measure gastric contraction waves on video acquired by magnetically controlled capsule endoscopy (AUC 0.94) [61, 62].

One group has reported using finger photoplethysmography (PPG) to non-invasively measure gastric function, proposing that gastric slow waves can be reconstructed to match the patients' EGG, with correlation values of 0.95 fasting and 0.97

TABLE 2 | Studies related to gastroduodenal motility, sorted by test modality.

First author, year	Test modality	Primary AI method(s)	Primary outcome (quantitative)
Wang et al. (1999) [47]	EGG	MLP and ANN	Automatically assessed the regularity of gastric myoelectrical activity with accuracy: 0.97
Liang et al. (2000) [48]	EGG	GCCA	Diagnosed gastric emptying with accuracy: 0.83
Liang et al. (1997) [49]	EGG	BPNN	Developed optimal feature combinations to detect motion artifacts with accuracy: 1.00
Chen et al. (2000) [50]	EGG	ANN	Correctly classified delayed gastric emptying with accuracy: 0.85
Liang et al. (2001) [51]	EGG	SVM	Gastric emptying detected with accuracy: 0.90
Kara et al. (2005) [52]	EGG	MLP with DWT analysis	Detected gastric dysrhythmia with accuracy: 0.97
Giacomini et al. (2000) [53]	EGG	Kohonen Neural Network	Successful clustering of EGG data into three distinct categories
Chen et al. (1995) [54]	EGG	BPNN	Recognized gastric contractions with accuracy: 0.92
Wang et al. (1999) [55]	EGG	Neural Networks	Effectively separates different signals and artifacts
Lin et al. (1997) [56]	EGG	MFNN	Diagnosed delayed gastric emptying with accuracy: 0.85
Noar et al. (2022) [57]	EGG	Undisclosed	AN AI-derived threshold was used to predict balloon dilation outcomes with accuracy: 0.93
Sakai et al. (2023) [58]	gEIT	Dual-step fuzzy clustering	Gastric volume estimation was comparable to ultrasound (Pearson Correlation coefficient: 0.88)
Georgiou et al. (2024) [59]	GES	ML	A 2.5 h study strongly predicted the 4 h study outcome, AUC: 0.92
Takakura et al. (2024) [60]	GES and WCE	Ridge regression and MissForest	Predicted medication response with AUC: 0.72
Li et al. (2023) [61]	MCCE	CNN and LSTM	Predicts wave or no wave with accuracy: 0.87
Li et al. (2023) [62]	MCCE	CNN and LSTM	Detected and measured gastric contraction waves with accuracy: 0.89
Yacin et al. (2011) [63]	PPG	RBFNN	Reconstructed similar gastric slow waves to EGG (Correlation coefficient consistently > 0.90)
Wang et al. (2024) [64]		XGBoost	Gastroparesis prediction AUC: 0.91
Ingwersen et al. (2023) [65]		XGBoost	Identified delayed gastric emptying with AUC: 0.59
Liu et al. (2025) [66]		XGBoost	Gastroparesis prediction AUC: 0.88
Ramai et al. (2025) [67]		Multimodal (LASSO, multivariate logistic model, MissForest)	Comorbid chronic pancreatitis with gastroparesis predicted with AUC: 0.74

postprandial [63]. However, these results should be interpreted with caution and independent confirmation and validation of this novel strategy is necessary, given the conceptual uncertainty and physiological plausibility of how EGG could be reliably reflected in a peripheral pulse signal.

Body surface gastric mapping (BSGM) is a new technique (approved for clinical use in the USA, UK, New Zealand, and Australia) that employs dense arrays of electrodes to record gastric electrophysiology at the body surface, providing marked gains in specificity, accuracy, and symptom correlation for gastric disorders compared to traditional EGG [68–70]. As body surface data suffers from a poor signal-to-noise ratio, sophisticated signal processing algorithms are necessary to extract valid clinical data [71]. Neural networks have therefore been applied, with FDA clearance, resulting in significant gains in test quality and potentially enabling wearable applications [72]. Expanded BSGM clinical datasets with simultaneous digital symptom and mental health data also provide additional AI applications in multidimensional phenotyping and patient classification [73–75], with further validation pending.

3.2.3 | Summary and Commentary

AI applications in gastroduodenal motility are relatively embryonic but demonstrate AI's capacity to automate complex analyses, extract subtle patterns, and improve both diagnostic accuracy and patient management. With the exception of BSGM, there remains a clear need for translational progress, as none of the other modalities evaluated are currently clinical-grade or have achieved FDA clearance for clinical use.

3.3 | Small and Large Intestinal Motility

AI is being applied to streamline the analysis of intestinal motility studies and predict the risk of post-operative ileus (POI), reducing clinician workload and enabling continuous patient monitoring. A total of 19 appropriate studies were identified, with the majority ($n=12$) coming from Spain, China, or the USA (Table 3).

3.3.1 | Automated Analysis

3.3.1.1 | Wireless Capsule Endoscopy (WCE). Early efforts focused on the automatic detection of intestinal contractions and distinguishment of normal from abnormal [76–78], while a more recent publication used a CNN-based approach to correctly classify WCE videos into six distinct motility categories (0.96 accuracy compared to clinician interpretation) [79].

3.3.1.2 | Colonic Transit. Neural networks have automated the counting of radiopaque markers in X-ray colonic transit studies with high accuracy (0.97–0.99) [80, 81]. Additionally, AI-enhanced phonoenterography systems have demonstrated the ability to accurately recognize bowel sounds [85] and analyze acoustic features to estimate colonic transit time with a reasonably strong correlation ($r=0.89$) to radiologic diagnosis [83].

3.3.1.3 | Intestinal Manometry. A recent publication developed a rule-based expert system to automatically analyze small intestinal manometry tracings in healthy fasted participants [82]. The system could identify propagated contractile events with an accuracy of 0.86 compared to manual analysis.

3.3.1.4 | Cine MRI. Researchers have used deep learning models to extract small bowel diameter autonomously, with the best performing model achieving a mean squared error of 3.27 mm [87, 88], while other research has focused on CNN extraction of the intestinal centerline [89, 90]. These applications are steps toward an automated 3D intestinal motility assessment.

3.3.2 | Post-Operative Ileus (POI) Prediction

Machine learning has also shown promise in POI risk modeling, with models achieving AUCs of 0.64–0.92 depending on the cohort and model used [84, 91–94]. The XGBoost model tuned with grid search was particularly encouraging, achieving an AUC of 0.92 for post-colorectal surgery patients [94]. Tools for POI diagnosis are, however, in their infancy. Of relevance, an encoder-based AI has been developed that automatically segments the intestine, hoping to assist with visualization and thus improve physicians' diagnostic accuracy of ileus [86].

3.3.3 | Summary and Commentary

AI can improve the practicality of data analysis in tests such as WCE, while also enabling 24-h bowel sound monitoring, which is manually implausible. Once further feasibility has been established, external validation and multi-center prospective testing must be prioritized to confirm these approaches' utility and clinical suitability. Developing deep learning models that effectively utilize 4D data obtained in imaging studies is an important step to improve imaging interpretation. POI prediction models have shown promise, so establishing an accompanying early warning protocol is crucial to transition these models into functional hospital systems.

3.4 | Anorectal Motility

The application of AI in anorectal motility is an emerging field [7] with the potential to standardize complex data analysis, improve accessibility, lessen resource constraints, and reduce interpretation subjectivity. A total of 9 appropriate studies were identified, of which the majority ($n=7$) were from China, Portugal, or the USA (Table 4).

3.4.1 | Diagnostic Applications

Several AI models have been applied to anorectal manometry, demonstrating the feasibility of the potential applications in single-center studies. Machine learning has exhibited the ability to differentiate between normal and abnormal motility patterns (0.85 accuracy) [95], distinguish obstructed defecation from fecal incontinence (AUC 0.94) [97], diagnose dyssynergic defecation (DD) (AUC 0.91–0.96) [98], and discriminate between four distinct manometric phenotypes (0.87 accuracy) [96]. AI has also been used to combine data from multiple modalities, integrating abdominal X-ray results with the information obtained from a symptomatic questionnaire to diagnose DD more effectively (0.82 accuracy) [103].

3.4.2 | Other Applications

Outside of diagnostics, AI enables non-invasive monitoring solutions and aids clinical decision-making. In initial studies, AI analysis of bowel sound features was proposed to predict defecation with accuracy up to 0.91 [100, 101], indicating emergent potential to provide incontinent patients with advanced warning.

TABLE 3 | Studies related to small and large intestinal motility, sorted by test modality.

First author, year	Test modality	Primary AI method(s)	Primary outcome (quantitative)
Vilarino et al. (2006) [76]	WCE	SOMs and SVM	Identifies intestinal contractions with sensitivity: 0.73
Malagelda et al. (2008) [77]	WCE	SOMs and SVM	Identified diagnosed patients with accuracy: 0.95 and normals with accuracy: 1.0
Vilarino et al. (2010) [78]	WCE	SVM	Removed 92% of frames while keeping 96% of findings
Segui et al. (2016) [79]	WCE	Deep CNN	Classified into six motility events with accuracy: 0.96
Tsai (2022) [80]	Radiopaque Marker Study	CNN	Detected slow colonic transit time with accuracy: 0.97
Kelly et al. (2023) [81]	Radiopaque Marker Study	SNN	Identified beads with accuracy: 0.99 and colonic transit time with MAE: 0.9 days
Samaddar et al. (2025) [82]	Intestinal Manometry	Rule-based expert system	Identified propagated contractile events with accuracy: 0.86
Kim et al. (2011) [83]	Phonoenterography	BPNN	Estimated colonic transit time with correlation coefficient: 0.89, compared to radiographic measurement
Shi et al. (2024) [84]	Phonoenterography	Naive Bayesian Model	Predicted prolonged POI with accuracy: 0.69
Dimoulas et al. (2008) [85]	Phonoenterography	Neural Networks	Recognized bowel sounds with accuracy: 0.95
An et al. (2024) [86]	CT	M U-Net	Segmentation achieved with Dice coefficient: 0.73
Wu et al. (2019) [87]	Cine-MRI	Attentive Encoder-Decoder	Captures segmental motion patterns with low MSE: 3.27
Pei et al. (2017) [88]	Cine-MRI	FCN and LSTM	Predicted intestine diameter with MSE: 4.47
van Harten et al. (2022) [89]	3D Cine-MRI	CNN	Patient centre-line extraction F1: 0.80
van Harten et al. (2021) [90]	3D Cine-MRI	CNN	Subject-level center-line extraction achieved 0.69 overlap with the ground truth
Ruan et al. (2024) [91]	Electronic Records	GRU-D	Predicts POI consistently across datasets, reducing variance by up to 0.86 compared to existing models
Traeger et al. (2024) [92]		MLP	Predicted POI with AUC: 0.80
Zhou et al. (2024) [93]		XGBoost and Decision Trees	Predicted POI with accuracy: 0.81
Brydges et al. (2024) [94]		XGBoost	Predicted POI with AUC: 0.92

AI has also been used to compare EndoFLIP and high-definition manometry in the assessment of fecal incontinence [99] and to analyze Obstructed Defecation Syndrome (ODS) patient data to determine which factors are predictive for surgical intervention [102]. These applications highlight the potential scope of the field and illustrate how AI may influence clinician decision-making.

3.4.3 | Summary and Commentary

While potential exists, applications in this subfield of motility are only just emerging. Although alternative modalities should be explored, developing AI tools to automate the London Classification for anorectal manometry assessment is one logical next step, considering researchers' success in pursuing analogous goals of automating the CC for HREM [1, 13–17]. However, it should be noted that anorectal manometry automation has some additional challenges when compared to HREM automation. The London Classification places more importance on non-manometric measures than the CC; it is more difficult to simulate defecation than it is to swallow, there are several different types of anorectal manometry (3D, high-resolution, solid state, water-perfused), and the framework is more focused on physiological abnormalities that contribute to symptoms, as opposed to a distinct diagnosis [104]. The test is also conducted at a lower frequency and the classification is newer. Nevertheless, whilst potentially more challenging,

TABLE 4 | Studies related to anorectal motility, sorted by test modality.

First author, year	Test modality	Primary AI method(s)	Primary outcome (quantitative)
Zan et al. (2021) [95]	HRAM	EEMD and DBN	Determined optimal network and diagnosed abnormal function with accuracy: 0.85
Mascarenhas et al. (2025) [96]	HRAM	LGBM Classifier	Classified four motility patterns with accuracy: 0.87
Savaria et al. (2022) [97]	HRAM	XGBoost	Differentiated FI from OD with AUC: 0.94
Levy et al. (2022) [98]	HDAM	ML, DL, and Hybrid Approach	All identified DD with accuracy > 0.90. DL was the best model for reporting ambiguity
Zifan et al. (2018) [99]	EndoFLIP and HDAM	Unsupervised ML	No significant difference, concurrence achieved sensitivity: 0.69 and specificity: 0.97
Zhang et al. (2024) [100]	Phonoenterography	1D-IResNet	Predicted defecation with accuracy: 0.91
Zhang et al. (2022) [101]	Phonoenterography	BPNN	Predicted defecation with accuracy: 0.89
Marra et al. (2024) [102]	Complete diagnostic workup	Classification Trees	Correctly identified surgical candidates with accuracy: 0.79
Sangnark et al. (2024) [103]	Abdominal X-Ray and Questionnaire	CBAM, Grad-CAM, and DeepSHAP	Diagnosed DD with accuracy: 0.82

elements of anorectal manometry can absolutely be automated using AI and the continued development of these technologies together with establishment of large clinical databases has the potential to significantly improve the field.

3.5 | Pan-Gastrointestinal Motility

Some studies took a holistic approach, analyzing phonoenterography and WCE data across anatomical boundaries of the GI tract. A total of 10 appropriate studies were identified coming from 7 different countries (Table 5).

3.5.1 | Phonoenterography

Neural networks have proven efficacy for differentiating bowel sounds from noise, with reported accuracies of 0.93 [106] to 0.99 [112]. A few more sophisticated models exist, providing more accurate sound localization, distinguishing "no bowel sounds" from "single bowel sounds" and "multiple bowel sounds" [108], and demonstrating robustness to the alteration of several factors, including data availability [111]. One study demonstrated some potential to differentiate different levels of digestive activity with AI-enhanced phonoenterography; however, the accuracy is limited, and testing was only conducted on three volunteers [107].

An additional clinical advancement that may be possible with AI-enhanced phonoenterography is the improved clinical feasibility of long-term, continuous bowel sound monitoring. An autonomous system that detects post-operative bowel recovery (0.94 accuracy) could make early initiation of feeding possible, improving post-surgical outcomes [105]. Continuous monitoring is also valuable for neonatal populations, enabling early detection of bowel dysfunction. Studies have used AI to successfully quantify data into five acoustic parameters [110] and detect bowel sounds with reasonable efficacy (AUC 0.84) [109].

3.5.2 | Wireless Capsule Endoscopy (WCE)

Machine learning models can autonomously assess intestinal location and estimate transit times, significantly reducing the time needed for annotation and analysis [113]. Combined models have achieved a peak organ classification accuracy of 0.97 and reported gastric and intestinal transit times with mean time differences of 4.3 and 24.7 min, respectively [114].

3.5.3 | Summary and Commentary

The vision of an AI-supported device that screens the entire gut is compelling but distant. Both AI-enhanced phonoenterography and WCE have potential due to their enablement of continuous monitoring, analytic automation, analytical standardization, improved feature extraction, and reduced invasiveness. This sparse and nascent field requires significant growth, proof-of-concept studies, and validation before any clinical applications can be put forward.

TABLE 5 | Studies related to Pan-GI motility, sorted by test modality.

First author, year	Test modality	Primary AI method(s)	Primary outcome (quantitative)
Ulusar (2014) [105]	Phonoenterography	Naive Bayesian Model	Bowel sound recognition accuracy: 0.94
Ficek et al. (2021) [106]	Phonoenterography	CRNN	Identified bowel sounds with accuracy: 0.98
Yin et al. (2015) [107]	Phonoenterography	ANN	Classified three digestion states with accuracy > 0.70 in 3 volunteers
Zhang et al. (2024) [108]	Phonoenterography	Novel DL	Segmentation F1: 0.69
Sitaula et al. (2022) [109]	Phonoenterography	CNN and Laplace HSMM	Recognized neonatal bowel sounds with accuracy: 0.90
Zhou et al. (2022) [110]	Phonoenterography	CNN and CRNN	Identified and quantified five acoustic parameters
Yu et al. (2024) [111]	Phonoenterography	Brachformer Architecture	Achieved accuracy: 0.66–0.85, depending on functions and strategy/model
Bilionis et al. (2021) [112]	Phonoenterography	Autoencoder	Bowel sound detection accuracy: 0.99
Cunha et al. (2008) [113]	WCE	SVM	Transit time errors were < 0.06 for gastric and < 0.08 for intestinal
Nam et al. (2024) [114]	WCE	CNN and LSTM	Organ classification accuracy: 0.97, mean time difference of 4.3 (±9.7) and 24.7 (±33.8) min for gastric and intestinal transit

4 | Discussion

This review expands upon prior work [6–8, 10, 11, 115], offering insights across the full spectrum of AI-enhanced GI motility diagnostics, identifying promise in a wide range (Table S1) of emergent technologies. While a vast breadth of applications was explored, a key recurring theme is the drive toward autonomous analysis, reflecting a clear need to improve efficiency in a field highly dependent on technically sophisticated physiological tools and significantly subjective interpretation. This review also identified a growing trend toward AI-enabled diagnostic modalities, such as capsule endoscopy and 24-h acoustic monitoring, where the test results are data-heavy and thus difficult to manually assess [36–38, 76–79]. In these long-term monitoring tests, it would be challenging, and in some cases impossible, to obtain valuable insights manually, highlighting AI's potential to augment clinician expertise. Furthermore, emerging methodologies have been shown to improve analytical insights and pattern recognition [32, 43, 103, 105, 109, 110], predict clinical outcome probabilities with consideration of pathology and treatment strategy [31, 57, 60, 64–67, 84, 91–94], and in some cases offer a less invasive alternative compared to current diagnostic approaches [83].

The direction of research evident in the findings shows that GI motility clinicians can expect substantial augmentation of their expertise and practice in the AI era, especially in the following areas:

- *Imminent efficiency gains*. Automation tools will largely replace manual analysis in tasks such as radiopaque marker detection and counting, HREM analysis, report generation, and WCE landmarking. Functioning as powerful "physician-assistants," AI will not immediately replace doctors but rather reduce workload and mundanity, increasing opportunities for critical thought and meaningful patient interaction.
- *Emergence of AI-enabled minimally invasive devices*. Tools such as BSGM and capsule endoscopy technologies will likely gain further popularity with AI augmentation in key areas such as noise reduction and improved test accuracy, replacing some of the need for transit evaluations or radiologic imaging. Some studies suggest that phonenterography has potential as a continuous monitoring tool; however, the reliability of this device is yet to be proven, and the literature is yet to include any clinical implementation.
- *Personalization of patient management with improved risk stratification*. Predictive models for POI, while requiring expert validation, can already help stratify risk in postoperative patients, potentially guiding monitoring protocols and prophylactic measures to improve resource efficiency and patient outcomes. Predictive models for treatment guidance are more nascent but will become increasingly prominent in clinical practice, allowing the clinician to make more personalized treatment decisions.

With these exciting developments, clinicians must remain cautious of commercial AI tools. There are several methodological aspects that warrant careful scrutiny. In particular, one should question the size and representativeness of the training data, the evidence base supporting the study and whether it was independently and externally validated, and the ground truth against which the model's outputs have been evaluated. Readers should look out for models trained on small, single center, or highly selected datasets as they may demonstrate inflated performance that generalizes poorly when trialed on local populations. Additional questions around the transparency of model architecture, reproducibility of results, handling of borderline cases, and the clinical interpretability of the outputs should also be considered when evaluating new AI models. These factors are especially relevant for commercialized tools, where there may be constraints on independent evaluation and thus on the quality of the clinical appraisal, although regulatory approval through bodies such as the FDA is typically a marker of robust training and validation.

The strength of the existing literature lies in its innovation and consistent demonstration of feasibility, successfully showing that AI models can match or exceed expert performance in specific, well-defined tasks [18, 33, 77, 98, 103]. Three AI models were particularly prominent across the literature for their effectiveness in performing specific tasks. *Convolutional Neural Networks (CNNs)* are deep learning models that excel at processing grid-like data such as images. They are ideal for analyzing visual outputs from motility tests, such as HREM color plots, by automatically detecting spatial patterns. *Long Short-Term Memory (LSTM)* is a type of neural network designed to recognize patterns in sequential data over time. It is therefore highly effective for interpreting time-series data, such as a sequence of swallows in a manometry study or continuous 24-h recordings. *Extreme Gradient Boosting (XGBoost)* is a powerful algorithm that builds a predictive model from many simple decision trees. It performs exceptionally well on structured, tabular data (e.g., patient clinical records) for risk stratification tasks like predicting POI.

Despite increasing academic interest in the field, none of the referenced methods have yet broadly impacted clinical practice, with the emerging exception of neural networks applied to noise cancellation in BSGM, which has received FDA clearance and is now routinely implemented in testing. There are several factors that contribute to this gap. Firstly, most of the proposed systems have only undergone feasibility analyses performed in single centers, with retrospective data and limited patient diversity, raising generalizability concerns. Therefore, there is limited confidence in the system's abilities to perform across a range of populations, equipment platforms, and clinical workflows. Secondly, the majority of the referenced studies focus on retrospective performance metrics rather than real-world diagnostic utility or patient outcomes. Finally, while these barriers can be overcome with additional research, clinician trust and acceptance often demand a higher evidence bar. Additionally, gaining regulatory approval can be difficult if experts cannot visualize the "thought process" behind an AI's decision. Therefore, the implementation of explainable AI tools will also likely become important for widespread clinical application, especially when applied in direct diagnostic roles. Thus, despite existing frameworks demonstrating technical feasibility, widespread clinical adoption will only be achieved when robustness is established, system interpretability is improved, adaptability and safety are consistently showcased, and clear clinical value is shown.

Furthermore, the use of varied and sometimes outdated "ground truths" for validation and result reporting makes it difficult to ascertain a model's true efficacy and compare it to alternatives. Consensus in each respective field and regarding each respective modality is crucial to test and analyze the utility of AI systems. Generating standardized protocols and forming large, well-annotated, public datasets would streamline this process and improve confidence in reported accuracy statistics. Taking things a step further, as AI models continue to evolve, it is vital that the evaluation of their efficacy shifts toward clinical outcomes rather than exclusively technical metrics (such as accuracy and AUC). Validation against outcomes such as patient-reported outcomes, length of hospitalization, need for follow-up treatment, and treatment response makes the data more valuable by relating it to tangible clinical improvement.

Across the board there were several common methodological shortcomings such as susceptibility to overfitting, poor generalizability, exclusively internal validation, substantial ground truth variation, and performance metrics that were frequently reported for narrowly defined tasks or highly selected cohorts. Taken together, these limitations suggest that while AI may demonstrate impressive performance in controlled research environments, caution is needed until they can be externally and reproduced in clinical workplaces.

This review has several notable limitations. First, it was restricted to full-text articles available in English, which could result in language bias and omission of relevant studies. Second, a formal risk-of-bias assessment of the included studies was not included due to the profound heterogeneity in study designs. Consequently, while the field has been critically appraised, the quality of individual studies has not been formally scored, limiting the definitive conclusions about the evidence base. This heterogeneity also necessitated a narrative synthesis instead of a quantitative meta-analysis. Third, like all systematic reviews, this work is susceptible to publication bias, wherein studies with positive results are more likely to be discussed. Finally, given the rapid pace of innovation in AI, this review represents a snapshot in time, so new, relevant studies will inevitably have emerged between our search date and final publication. Further, some AI applications or improvements in development for existing diagnostic tools may not be published for intellectual property concerns, meaning that these developments cannot be included in this review.

The application of AI in GI motility is a rapidly evolving field with the potential to automate analyses, improve efficiency, enable non-invasive and long-term testing, and provide powerful prognostic insights. Ultimately, the pathway from research to clinical deployment is contingent upon three fundamental requirements: established technical validity, clear demonstration of clinical benefit, and attainment of regulatory approval. This discussion has mostly focused on how technical validity can be proven (external validation, larger more diverse cohorts, prospective evaluation), but it is essential that clinical utility is demonstrated for each system, for example by clearly showcasing reduced interpretation time, improved diagnostic consistency, enhanced decision-making, or improved patient outcomes. It is also important that ethical and equity considerations are met so that regulatory bodies can be confident in the safety of the proposed technology. Focusing on these key areas will help translate these tools from code to the clinic, transforming the diagnosis and management of GI motility disorders.

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Literature review, manuscript preparation: D.M., C.V., and G.O.; supervision, manuscript review, funding: G.O. and C.A.

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Conflicts of Interest

Dr. Greg O'Grady is a co-founder and the current director of Alimetry Ltd. and has various grants and patents in the field of AI for gastrointestinal motility. Dr. Christopher Andrews is affiliated with Alimetry Ltd. Dr. Chris Varghese is affiliated with Alimetry Ltd.

Data Availability Statement

The authors have nothing to report.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Data S1:** Supporting Information. **Figure S1:**: PRISMA 2020 flow diagram for new systematic reviews which included searches of databases and registers only. **Table S1:** nmo70310-sup-0003-TableS1.docx.