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Review Article

Artificial Intelligence In Esophageal Motility Diagnostics: Automated Interpretation Of High-Resolution Manometry And Flip Panometry.

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Running Title: AI in Esophageal Motility Testing

Abstract

Esophageal motility disorders are important causes of dysphagia, regurgitation, non-cardiac chest pain, and refractory reflux-like symptoms. High-resolution manometry (HRM) remains the reference standard for esophageal motility assessment, while functional lumen imaging probe (FLIP) panometry provides complementary information on esophagogastric junction opening, distensibility, and distension-induced contractile responses during endoscopy. However, both techniques require technical expertise, standardized acquisition, and careful interpretation within the clinical context. Artificial intelligence (AI) may help address these challenges by supporting study quality control, artefact detection, swallow selection, automated pattern recognition, FLIP contractile-response classification, and structured reporting. Early studies suggest that AI can assist with HRM and FLIP interpretation and may reduce interobserver variability, improve workflow efficiency, and expand access to standardized motility assessment. Nevertheless, current evidence remains limited by retrospective designs, selected datasets, single-centre development, device-specific models, and insufficient prospective validation. AI should therefore be viewed as a clinician-supervised decision-support tool rather than an autonomous diagnostic authority. Future research should focus on multicentre validation, explainable outputs, standardized data acquisition, integration with endoscopy and radiology, and evaluation of real-world clinical impact.

Keywords: Artificial intelligence; Esophageal motility; High-resolution manometry; FLIP panometry.

INTRODUCTION

Esophageal motility disorders are a major cause of dysphagia, regurgitation, non-cardiac chest pain, and refractory reflux-like symptoms. Because symptoms, endoscopy, barium imaging, and cross-sectional imaging may be normal or non-specific, diagnosis often requires physiological testing. At present, high-resolution manometry (HRM) is the reference standard for assessing esophageal motor function and classifying conditions such as achalasia, esophagogastric junction outflow obstruction, distal esophageal spasm, hypercontractile esophagus, absent contractility, and ineffective esophageal motility [1,2]. The Chicago Classification has provided a better level of standardization, yet interpretation still relies on technical quality, adherence to protocol, pressure-pattern identification, and clinical judgment [1,2].

Although HRM is a central element, it is not always easy to interpret. The Chicago Classification version 4.0 strengthened the standardized protocol by incorporating upright swallows, provocative testing, and greater emphasis on supportive evidence before defining clinically relevant diagnoses, including esophagogastric junction outflow obstruction [1,2]. Although diagnostic precision has improved, the interpretative process has become more challenging. The reporting process can be hindered by borderline integrated relaxation pressure readings, catheter malposition, artefacts, inconsistent swallows, opioid-induced dysmotility, post-surgical anatomy, and discordance between symptom presentation and manometric features. Interpretation may differ even among experienced readers, particularly in borderline and mixed

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motility patterns [3].
Functional lumen imaging probe (FLIP) panometry has been developed as an adjunct method for evaluating esophagogastric junction opening and esophageal body contractile responses during sedated endoscopy. While HRM evaluates pressure patterns during awake transnasal testing, FLIP provides rapid data on luminal geometry, distensibility, and secondary contractile activity. It is especially relevant when HRM results are ambiguous, incomplete, poorly tolerated, or inconsistent with the clinical picture [4,5]. Nonetheless, FLIP interpretation also demands expertise and standardized acquisition, together with judicious integration with endoscopy, HRM, symptoms, and imaging findings. The recent development of consensus-based FLIP panometry interpretation demonstrates its increasing clinical value and the need for more reproducible reporting frameworks [5].
Several limitations of esophageal motility testing may be addressed through the application of artificial intelligence (AI) techniques. Machine-learning and deep-learning models could help with automated swallow identification, artefact recognition, catheter-position quality control, integrated relaxation pressure classification, pressure-topography pattern recognition, and diagnostic classification in HRM. In FLIP panometry, AI may support automated evaluation of esophagogastric junction distensibility and contractile findings during endoscopy. These applications are particularly appealing because motility testing produces organized, high-density physiological data suitable for computational methods. Recent articles and systematic reviews suggest that AI-based methods are being explored for HRM analysis, with potential improvements in standardization, efficiency, and reproducibility [6–8].
Nonetheless, AI in esophageal motility diagnostics is still developing and is not a mature replacement for expert evaluation. Most available data come from retrospective model-building studies or preliminary validation studies. Many are limited by single-centre datasets, narrow diagnostic definitions, inconsistent acquisition protocols, and lack of external validation. Physiological diagnoses are not merely pattern-recognition tasks; they require clinical context, symptom correlation, exclusion of mechanical obstruction, medication review, endoscopic evaluation, and consideration of treatment implications. The realistic near-term role of AI is therefore decision support, not autonomous diagnosis: improving study quality, reducing reader variability, demonstrating abnormal patterns, promoting standardized reporting, and aiding clinicians in the integration of HRM and FLIP results in patient-centred management.
This review highlights the advancement of AI in esophageal motility diagnostics, with specific focus on automated interpretation of HRM and FLIP panometry. It addresses the current limitations of conventional interpretation, emerging AI applications in HRM, early opportunities for AI-assisted FLIP analysis, and the clinical, technical, and governance considerations that must be addressed before these technologies can be safely utilized in real-world practice.

CURRENT LIMITATIONS OF HIGH-RESOLUTION MANOMETRY AND FLIP PANOMETRY

High-resolution manometry (HRM) has become the gold standard for the evaluation of esophageal motor function, but it remains difficult to interpret. The Chicago Classification version 4.0 has increased diagnostic precision by requiring a standardized protocol, assessment in different positions, provocative maneuvers, and supportive evidence for certain diagnoses, in particular esophagogastric junction outflow obstruction (EGJOO) [1,2]. However, these advances have also made interpretation more difficult. A technically adequate study requires correct catheter placement, reliable pressure recording, appropriate swallow selection, identification of artefacts, and knowledge of factors such as body position, opioid exposure, prior surgery, large hiatal hernia, and mechanical obstruction. When these factors are overlooked, HRM can lead to overdiagnosis, underdiagnosis, or clinically problematic classifications.
One of the main weaknesses of HRM is that borderline or mixed patterns are hard to interpret. Achalasia is typically easier to identify when the manometric pattern is typical, but conditions such as EGJOO, distal esophageal spasm, hypercontractile esophagus, and ineffective esophageal motility may be harder to classify clinically. This is especially important in patients with borderline integrated relaxation pressure, weak peristaltic reserve, fragmented contractions, or discordance between symptoms and manometric findings. Previous studies demonstrated greater interobserver agreement in esophageal manometry for normal studies and achalasia than for less distinct motility disorders [9,10]. This variability underscores the challenge of improving standardization without supplanting expert interpretation.
The diagnosis of EGJOO demonstrates these challenges effectively. EGJOO should not be diagnosed through manometry alone according to the Chicago Classification version 4.0. It requires compatible symptoms, increased integrated relaxation pressure in relevant positions, preserved peristalsis, and supportive evidence from other tests such as timed barium esophagram or functional lumen imaging probe (FLIP) [1,2]. This stricter approach minimizes the chance of overcalling clinically insignificant obstruction, but it also forces the clinician to synthesize multiple sources of evidence. AI may ultimately assist in this setting through the integration of manometric metrics, symptom profiles, endoscopic findings, FLIP measurements, and radiological evidence into a more cohesive diagnostic matrix.

FLIP panometry has extended the physiological characterization of esophageal motility by assessing esophagogastric junction distensibility and distension-mediated contractility during sedated endoscopy [4,5]. Its main benefit is that it can offer complementary information when HRM is unavailable, poorly tolerated, or inconsistent with the clinical presentation. However, FLIP also has certain limitations. Results may be affected by balloon location, fill volume, sedation, esophageal geometry, operator technique, and interpreter familiarity. FLIP also produces dynamic data requiring classification of absent contractile response, repetitive antegrade contractions, repetitive retrograde contractions, impaired esophagogastric junction opening, and decreased distensibility [5]. These features make FLIP appealing for AI-assisted data analysis, but also support the need for further validation.

A further limitation, shared by HRM and FLIP, is that physiological variations may not necessarily represent clinically meaningful disease. Motility testing needs to be interpreted in the context of symptoms, endoscopic exclusion of structural disease, medication history, previous foregut surgery, barium findings, reflux assessment, and therapy implications. A system that diagnoses a pressure or distensibility pattern without clinical context may reach incorrect conclusions. Therefore, the future role of AI should be to support study quality, pattern recognition, and structured interpretation, while final diagnosis and management decisions remain in the hands of clinicians. These limitations and the corresponding potential roles of AI in HRM and FLIP panometry are illustrated in **Table 1**.

Table 1. Potential applications of AI in esophageal motility testing.

Area	Current limitation	Potential AI role
HRM acquisition	Catheter malposition, pressure artefacts, poor swallow quality	Automated quality control and detection of technically inadequate studies
Swallow selection	Manual review is time-consuming and reader-dependent	Automated identification and exclusion of artefactual swallows
HRM interpretation	Complex pressure topography and borderline metrics	Pattern recognition and diagnostic decision support
Achalasia classification	Subtype classification may be difficult in atypical cases	Support classification into achalasia types I, II, and III
EGJOO assessment	Risk of overdiagnosis if manometry is interpreted alone	Integration of HRM, symptoms, FLIP, barium, and endoscopic findings
FLIP panometry	Dynamic distensibility and contractility patterns require expertise	Automated assessment of EGJ opening and contractile response patterns
Training	Variable exposure to motility studies among trainees	Feedback, benchmarking, and case-based learning support
Reporting workflow	Delays in expert interpretation	Preliminary structured reports for expert review

In summary, the major limitation of current approaches to esophageal motility testing is not simply the availability of HRM or FLIP, but the complex task of translating physiological data into clinically meaningful decisions. HRM and FLIP provide rich datasets, but interpretation is influenced by technical quality, reader expertise, borderline findings, and clinical context. These limitations provide a strong rationale for AI-assisted methodologies, especially in quality control, automated pattern recognition, and integrated decision support.

AI in High-Resolution Manometry: Pattern Recognition, Classification, and Quality Control

High-resolution manometry (HRM) is one of the most suitable tools for artificial intelligence (AI) because it generates structured physiological data that can be presented as pressure topography plots, numeric measurements, and swallow-level sequences. Unlike traditional narrative clinical data, HRM contains repeated standardized events such as wet swallows, upright and supine positions, and provocative maneuvers. This structure allows models to learn associations between pressure patterns, esophagogastric junction relaxation, peristaltic integrity, pressurization, and final diagnostic categories. As a result, contemporary AI-based work in HRM has mainly concentrated on three aspects: automated measurement, quality control, and diagnostic classification [6,11].

One early and clinically relevant use is automated quality control. HRM interpretation can be affected by catheter malposition, poor swallow quality, artefacts, incomplete capture of the esophagogastric junction, or technically inadequate recordings. Czako et al. developed machine-learning models to classify integrated relaxation pressure and detect probe-positioning failure using HRM images, showing that AI can assist with both measurement interpretation and technical adequacy assessment [6]. This is important because even a highly accurate diagnostic algorithm may be misleading if the input study is technically incorrect. In routine practice, an AI system that first checks catheter position, swallow validity, and recording quality may be more valuable than a system that simply generates a final diagnosis.

A second significant application is automated swallow-level interpretation. HRM diagnosis requires review of multiple individual swallows, which is time-consuming and reader-dependent. AI models could detect swallow onset, identify swallow type, recognize failed or premature contractions, assess panesophageal pressurization, and estimate whether integrated relaxation pressure is normal or abnormal. Kou et al. presented a multi-stage machine-learning approach using swallow-level models and study-level classification to approximate the Chicago Classification [11]. This is appealing because it parallels clinical reasoning: specific swallow features are assessed first, then aggregated into an overall motility diagnosis.

AI may also facilitate classification of major esophageal motility disorders. Achalasia, especially typical type I or type II achalasia, is frequently more distinguishable than borderline or mixed patterns. Yet automated systems may be useful for standardizing subtype classification and reducing reporting variability. More difficult categories include esophagogastric junction outflow obstruction, distal esophageal spasm, hypercontractile esophagus, absent contractility, and ineffective esophageal motility. Recent systematic reviews suggest that AI studies in HRM have moved from traditional machine-learning methods toward deep-learning models, with increasing focus on automated Chicago Classification interpretation and motility-pattern recognition [7]. However, performance still depends on dataset size, diagnostic mix, reference standards, and whether the model has been externally validated.

In recent years, there has been progress toward broader automated diagnosis across multiple motility types. Popa et al. reported that AI could support automatic diagnosis of HRM studies and may help standardize interpretation across centres [12]. This is significant because many previous studies focused on single centres, a single device platform, or narrow diagnostic classifications. Multidevice and multicentre validation is critical because HRM systems, acquisition practices, patient populations, and reporting protocols vary across institutions. Without this type of validation, models may work well on development datasets but fail when transferred to everyday clinical settings.

AI-assisted interpretation of long-term HRM represents another promising area. Standard HRM tests have shorter testing periods, which may overlook variable symptoms or intermittent motility patterns. While long-term HRM produces more representative physiological data, it also produces large recordings that are difficult to review manually. Geiger et al. described a deep-learning approach to enhance the accuracy and scalability of long-term HRM analysis, supporting the extraction of clinically relevant events from large physiological datasets [13]. This remains an emerging application, but it shows how AI could extend motility assessment beyond routine short-duration protocols.

Although these advancements are promising, several limitations remain. First, most AI models trained on expert-labelled HRM diagnoses may inherit the same limitations and biases of the reference interpretation. Second, diagnostic labels may evolve with changes in classification systems; for example, Chicago Classification version 4.0 has strengthened diagnostic criteria for some diagnoses [1,2]. Third, model performance should not be mistaken for clinical utility. An HRM system may identify patterns accurately and yet fail to improve patient outcomes, reporting time, or treatment decisions. Lastly, AI output should be interpretable enough for clinicians to understand why a study is classified as achalasia, EGJOO, spasm, ineffective motility, or normal.

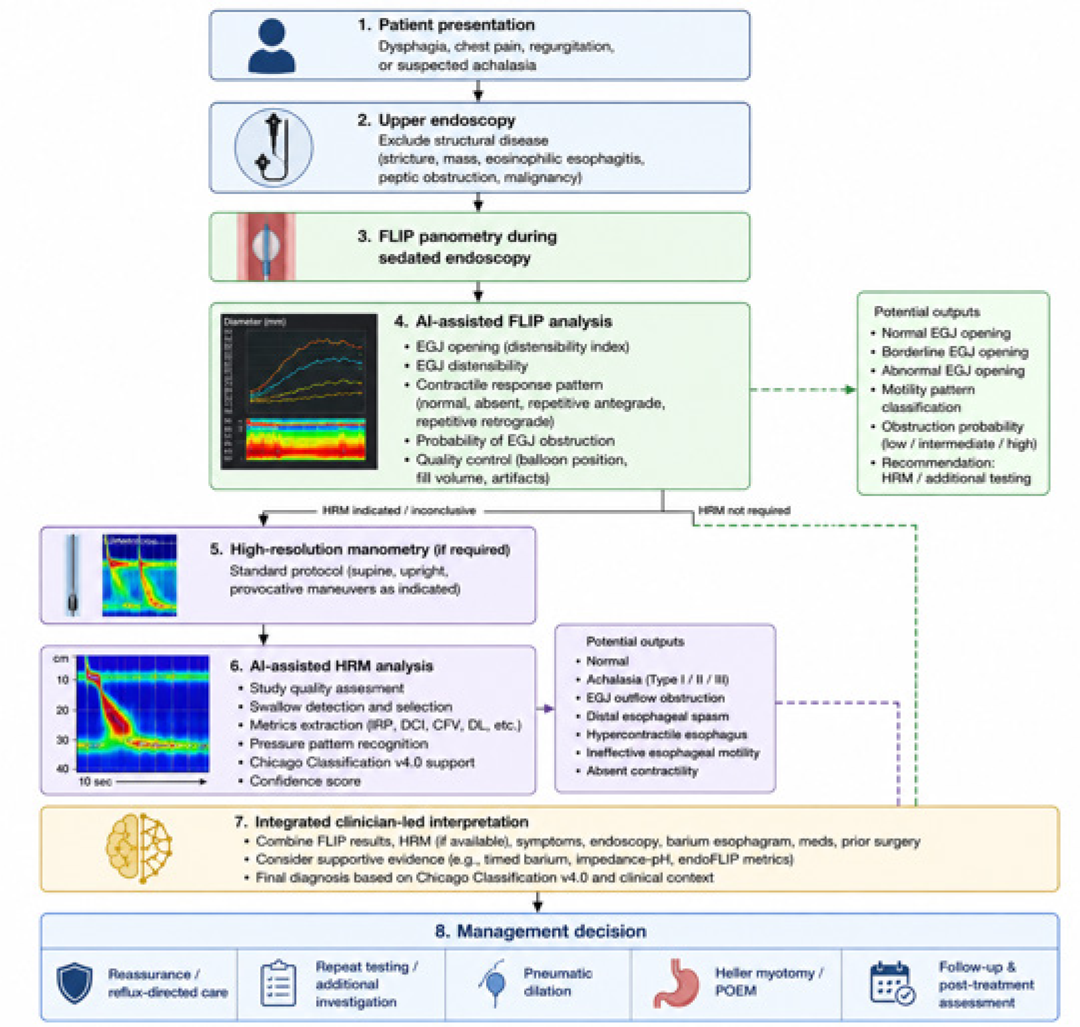
The most practical role of AI in HRM is therefore as a supportive layer rather than a stand-alone diagnostic expert. In practice, this could include quality checking, swallow selection, measurement extraction, abnormal-pattern highlighting, preliminary classification, and structured reporting. Final clinician-endorsed interpretation should continue and should incorporate symptoms, endoscopic findings, medication history, barium imaging, FLIP results, and treatment implications. Used in this manner, AI may allow HRM interpretation to become faster, more reproducible, and more accessible, while retaining the clinical reasoning required for safe motility diagnosis.

AI in FLIP Panometry: Automated Interpretation During Endoscopy

Functional lumen imaging probe (FLIP) panometry is another approach for evaluating esophageal motility during sedated endoscopy. It assesses esophagogastric junction (EGJ) opening, luminal diameter, distensibility, and distension-induced contractile responses. This contrasts with high-resolution manometry (HRM), which measures pressure responses during awake swallow-based testing. FLIP is therefore attractive in patients who cannot tolerate HRM, have inconclusive HRM findings, or require additional physiological assessment during the same endoscopic examination [4,5,14]. The clinical utility of FLIP is based on its capacity to detect patterns of EGJ opening and esophageal body contractile activity. Carlson et al. proposed a FLIP panometry classification system in a large cohort of subjects who also underwent HRM, demonstrating that FLIP can classify motility patterns and complement Chicago Classification-based interpretation. This classification includes evaluation of both EGJ opening and contractile response patterns, including normal contractile

response, absent contractile response, repetitive antegrade contractions, and repetitive retrograde contractions [14].
FLIP panometry is particularly useful in suspected achalasia, EGJ outflow obstruction, and equivocal motility disorders. Artificial intelligence (AI) may assist in this area by automatically identifying abnormal EGJ opening, estimating obstruction probability, and identifying contractile response patterns. Schauer et al. created a machine-learning decision-support tool using FLIP panometry data to estimate the probability of EGJ obstruction according to Chicago Classification version 4.0 and HRM [1,2,15]. A more direct AI application is automated FLIP panometry interpretation. Kou et al. developed and tested an AI platform for automated interpretation of FLIP panometry data, suggesting that automated analysis could classify esophageal motility patterns with good agreement compared with expert interpretation. This is important because FLIP is frequently performed during endoscopy, and real-time or near-real-time interpretation may influence the decision to perform further assessment, refer for HRM, consider achalasia-directed therapy, or reassure the patient. **Figure 1** demonstrates the AI-assisted process of combining FLIP and HRM parameters in esophageal motility diagnostics [16].

Figure 1. Proposed AI-assisted workflow for esophageal motility diagnostics.



AI = artificial intelligence; EGJ = esophagogastric junction; FLIP = functional lumen imaging probe; HRM = high-resolution manometry; IRP = integrated relaxation pressure; DCI = distsal contractile integral; CFV = contarctile front velocity; DL = distal latency; POEM = peroral endoscopic myotomy.

One of the primary benefits of AI-assisted FLIP interpretation is that it could simplify panometry interpretation in non-expert motility centres. Once validated, AI could offer immediate feedback during endoscopy, flag technically poor balloon positioning, classify EGJ opening, identify abnormal contractile responses, and form an initial structured interpretation. This may reduce delays in diagnosis and guide the need for formal HRM, timed barium esophagram, or specialist referral. In institutions where motility expertise is limited, AI may decrease reliance on specialized interpretation and encourage standardized reporting [15,16].

Nonetheless, AI-assisted FLIP is still in the preliminary phase. Existing models are limited by sample size, single-centre or selected datasets, device-specific acquisition, and reliance on expert-labelled reference standards. FLIP results may also be affected by sedation, balloon position, fill volume, catheter movement, and patient anatomy. These factors introduce possible sources of error if an AI model is trained on high-quality studies and then applied to routine clinical practice [5,15,16].

Furthermore, FLIP should not be interpreted in isolation. A low distensibility index or abnormal contractile response may support a diagnosis; however, final interpretation requires symptoms, endoscopic findings, HRM when available, barium imaging, medication review, and exclusion of mechanical obstruction. Thus, AI in FLIP panometry should complement, not substitute, clinician-led interpretation [1,2,5].

Future AI systems for FLIP panometry should move beyond simple pattern classification. An ideal model would combine real-time quality control, automated EGJ opening assessment, contractile response classification, obstruction probability estimation, and integration with HRM and clinical data. Multicentre prospective validation will be required across different endoscopy environments, patient populations, clinicians, sedation protocols, and software platforms. Until enough evidence is available, AI in FLIP panometry should be viewed as a promising decision-support tool rather than a stand-alone diagnostic system [15,16].

Clinical Implementation, Validation, and Future Directions

The realistic near-term application of artificial intelligence (AI) in esophageal motility diagnostics is as a clinical decision-support tool rather than an independent diagnostic system. This translates into the use of automated quality control, preliminary pattern recognition, structured output, and faster reporting to support high-resolution manometry (HRM) and functional lumen imaging probe (FLIP) panometry, while leaving final interpretation to the clinician. This clinician-in-the-loop approach is particularly important for motility disorders, where physiological findings need to be interpreted alongside symptoms, endoscopy, barium studies, medication history, and treatment implications [17,18].

Robust validation is necessary before AI can be incorporated into routine motility practice. However, most current studies of HRM and FLIP are retrospective, single-centre, and limited to selected datasets, raising concerns about overfitting and generalizability. Further validation of existing models across various centres, device platforms, acquisition protocols, and patient populations, with special focus on borderline diagnoses such as esophagogastric junction outflow obstruction and ineffective esophageal motility, is needed. Prospective validation is also required to determine whether AI improves reporting consistency, diagnostic confidence, interpretation efficiency, and patient outcomes, rather than classification accuracy alone [19].

Standardization of data acquisition and annotation is also required. AI results depend largely on the quality of input data and the reliability of the diagnostic labels used for training. For motility testing, this involves correct catheter or balloon positioning, standardized swallow protocols, consistent FLIP acquisition methods, and expert-verified reference diagnoses. Variation in how studies are performed or labelled may lead to model underperformance and reduced reproducibility. This is especially relevant in esophageal motility, where diagnostic criteria continue to evolve, as shown by the stricter standards introduced in Chicago Classification version 4.0 and the growing standardization of FLIP panometry interpretation [1,2,5].

Such systems also depend on explainability and clinician trust. Endoscopists and motility specialists are unlikely to use a “black-box” algorithm if it yields a final diagnosis without demonstrating how it reached that conclusion. More helpful systems would identify which swallows were included, which pressure or distensibility features were abnormal, the model’s level of confidence, and where technical quality may have compromised interpretation. Responsible use will also require safeguards against bias, hidden failure mechanisms, and over-reliance on automation, particularly in complex or ambiguous studies [20].

Integration into workflow is another real-world issue. For AI to be useful, it needs to be integrated with current motility software and reporting systems, rather than functioning as a separate research tool. Ideally, AI output should be available during or shortly after HRM or FLIP acquisition, offering real-time quality alerts, preliminary pattern classification, and structured recommendations for expert review. Besides its diagnostic role, AI could supplement training by benchmarking performance, identifying complex motility patterns, and reducing reader-related variability among less experienced readers [17,18].

As AI tools move closer to clinical use, regulatory and reporting standards will become increasingly important. Future research should move beyond retrospective model-building and adhere to reporting guidance for AI-based interventions, with detailed description of datasets, intended end-users, clinical settings, and human-AI interaction. Early clinical evaluation of the tool’s safety, acceptability, and feasibility in real-world settings should also be performed before full implementation [21,22].

In the long term, the future may lie in multimodal AI rather than HRM-only or FLIP-only approaches. Future systems could incorporate motility data with endoscopy, timed barium esophagram, symptom profiles, medication exposure, and post-treatment outcomes to support a more clinically meaningful diagnostic and management plan. Nonetheless, this next phase will require multicentre collaboration, shared data standards, and outcome-oriented assessment. Until then, AI in esophageal motility assessment should be considered a potential adjunct that may improve quality, consistency, and efficiency, rather than a replacement for expert clinical judgment [23].

CONCLUSION

AI has promising potential to enhance the interpretation and management of esophageal motility assessment. HRM and FLIP panometry produce complex physiological data that are amenable to computational analysis. AI can help with study quality assessment, swallow selection, artefact recognition, pressure-pattern interpretation, FLIP contractile-response classification, and structured reporting. These applications could reduce interobserver variability, improve reporting efficiency, and extend advanced motility interpretation beyond specialist centres.

Despite this promise, AI remains at an early stage in esophageal motility diagnostics. Existing literature is characterized by retrospective designs, selected datasets, single-centre development, limited external validation, and reliance on expert-labelled reference standards. Moreover, motility diagnoses are not strictly a statistical correlation of physiological patterns. They require consideration of symptoms, endoscopic findings, barium imaging, medication exposure, prior surgery, and treatment implications. Hence, AI should not replace expert interpretation, but should serve as a clinician-supervised decision-support tool.

Future studies should aim for prospective multicentre validation, standardized data acquisition, transparent reporting, explainable outputs, and outcome-based evaluation. Future systems are most likely to be multimodal platforms that combine HRM, FLIP, endoscopy, radiology, symptoms, and treatment-response data into one diagnostic pathway. In the meantime, AI may enhance quality, consistency, and efficiency in esophageal motility testing; however, final diagnosis and management should remain clinician-led.

Declarations

Conflicts of Interest

The author declares no conflicts of interest related to this manuscript.

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Informed Consent

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Data Availability

Data sharing is not applicable to this article, as no new datasets were generated or analysed.

Author Contributions

Ahmed Salman contributed to the conception, literature review, manuscript drafting, critical revision, and approval of the final manuscript.

Use of Artificial Intelligence

Artificial intelligence tools were used in a limited manner to assist with language refinement and organization of the manuscript. All content was reviewed, edited, and approved by the author, who takes full responsibility for the final manuscript.

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