Review

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Artificial intelligence applied to achalasia: an emerging frontier in precision motility care? State of the art and future prospects

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Abstract

Introduction: Esophageal achalasia is a rare motility disorder characterized by impaired lower esophageal sphincter relaxation and absent peristalsis. Diagnostic tools such as high-resolution manometry (HRM) and functional lumen imaging probe (FLIP) have improved disease recognition; however, interpretation remains complex and highly operator dependent. Artificial intelligence (AI) has emerged as a promising approach to automate data analysis and enhance diagnostic accuracy, but its specific role in achalasia is not yet clearly defined.

Content: A narrative review was conducted using PubMed, Scopus, and Web of Science, searching for studies published up to June 2025 that investigated AI applications in esophageal motility disorders, with particular attention to achalasia. Search terms included “artificial intelligence,” “machine learning,” “achalasia,” “esophageal motility,” and “high-resolution manometry.” Although no prospective or interventional studies directly evaluating AI in achalasia were identified, several retrospective proof-of-concept studies applied AI algorithms to HRM and FLIP data. These studies demonstrated the feasibility of automated classification of esophageal motility disorders, with high accuracy in differentiating motility subtypes potentially applicable to achalasia. Exploratory research on AI-assisted imaging and outcome prediction also showed encouraging results.

Summary: Current evidence suggests that AI-based models can accurately analyze complex esophageal motility data and reduce interobserver variability. While direct clinical evidence in achalasia remains limited, existing studies provide a solid methodological foundation for AI-assisted diagnosis, classification, and clinical decision support in this condition.

Outlook: Future research should focus on prospective validation, multicenter data collection, and multimodal integration of clinical, physiologic, and imaging data. With targeted development and ethical governance, AI has the potential to enhance diagnostic precision, support personalized treatment strategies, and advance precision motility care in patients with achalasia.

Keywords: achalasia; artificial intelligence; precision motility care; high-resolution manometry; machine learning; peroral endoscopic myotomy

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Introduction

Achalasia is a rare primary esophageal motility disorder characterized by impaired lower esophageal sphincter (LES) relaxation and the absence of peristalsis, leading to progressive dysphagia, regurgitation, and weight loss [1]. Despite its relatively low incidence, estimated at two to three cases per 100,000 individuals annually, it poses a significant clinical burden owing to diagnostic delays, frequent misclassification, and long-term complications, including aspiration, nutritional compromise, and an increased risk of esophageal cancer [1–5].

High-resolution manometry (HRM) is considered the gold standard for diagnosis, allowing classification into clinically relevant subtypes according to the Chicago Classification [6]. However, the technique requires specialized expertise and remains prone to interobserver variability, which limits its broader implementation and contributes to diagnostic delays that can exceed 24 months in certain cohorts [7]. Endoscopy and contrast studies are commonly employed to exclude mechanical causes of obstruction but often reveal nonspecific findings, especially in early disease stages [6].

In this context, artificial intelligence (AI) has emerged as a promising innovation in gastroenterology, with increasing applications in image analysis, physiologic data interpretation, and pattern recognition [8, 9]. Initial studies applying AI to esophageal motility disorders, including achalasia, demonstrated high accuracy in classifying HRM patterns and interpreting functional lumen imaging probe (FLIP) data [8, 10–13]. These systems have shown performance comparable to that of experienced clinicians in detecting disease and assigning phenotypes [12–15]. Such advances offer the potential to reduce diagnostic delays, enhance reproducibility, and support the shift toward precision motility medicine [16–18]. From a clinical perspective, this could translate into practical advantages such as earlier triage of patients with dysphagia, standardized HRM interpretation across operators, and optimized referral to expert centers.

At the biological level, achalasia is linked to degeneration of inhibitory neurons in the myenteric plexus, immune-mediated injury, and alterations in the esophageal microbiota, which together disrupt neuromuscular signaling and lower esophageal sphincter relaxation [3-5]. These molecular and cellular insights highlight the complex pathogenesis underlying a seemingly functional disorder. AI may serve as a bridge between these mechanistic findings and clinical phenotypes by integrating molecular biomarkers, manometric tracings, and imaging data into unified predictive models.

This narrative review aims to explore the current landscape and emerging potential of AI in the diagnosis and management of esophageal achalasia. We critically assess published studies, evaluate methodological strengths and limitations, and discuss future research priorities to support the integration of AI tools into clinical practice.

Methods

This narrative review was conducted to synthesize the literature on AI applications relevant to the diagnosis, classification, and management of esophageal achalasia. As a narrative review, this work does not adhere to PRISMA methodology, nor does it include formal bias assessment. The objective is conceptual mapping rather than systematic evidence synthesis. A structured literature search was carried out via three primary databases: PubMed, Scopus, and Web of Science, from 1 January 2020 to 30 June 2025, without language restrictions at the search stage. The search strategy combined terms related to AI, such as "artificial intelligence," "machine learning," "deep learning," and "neural networks," with terms related to esophageal motility and achalasia, including "achalasia", "esophageal motility disorders", "high-resolution manometry" and "esophageal imaging". Example PubMed string: ("achalasia" OR "esophageal motility" OR "high-resolution manometry" OR "HRM" OR "FLIP") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "CNN" OR "neural network").

Studies were considered eligible if they were peer-reviewed original research articles, reviews, or conference proceedings describing AI approaches relevant to esophageal motility disorders, with explicit or potential applicability to achalasia. Eligible works employed AI or machine learning (ML) techniques for diagnosis, classification, treatment planning, or outcome prediction via modalities such as HRM, FLIP, endoscopy, barium esophagram, or multimodal datasets. Publications in English from any year were eligible, although preference was given to those published within the last five years to reflect the most recent technological advancements. Both retrospective and prospective studies, including proof-of-concept and feasibility research, were considered.

Studies were excluded if they were unrelated to esophageal motility disorders or achalasia or if they described AI applications in gastroenterology without a clear link to esophageal diagnostics or therapeutics. Opinion pieces, editorials, and commentaries without primary data or systematic review methodology were also excluded.

Preclinical or animal studies lacking translational implications for human achalasia care, as well as non-English publications, were not considered.

Owing to the limited number of studies directly focused on achalasia, research involving related conditions or adjacent technologies was also considered to provide context and identify transferable methodologies.

Additional sources were identified through citation tracking and manual screening of the references within relevant articles and reviews. Data were extracted qualitatively and organized according to various themes, including AI in manometric interpretation, esophageal imaging, clinical decision support, and surgical outcome prediction. This methodology reflects the exploratory nature of a narrative review aimed at identifying current gaps and proposing a conceptual framework for future research.

Current applications of AI in esophageal motility disorders

Although no studies to date have focused specifically on the application of AI to esophageal achalasia, a growing body of research has investigated AI-driven tools in the broader context of esophageal motility disorders (Table 1). These developments primarily involve the automated interpretation of high-resolution esophageal manometry, a key diagnostic modality for achalasia and related conditions [19]. Several ML models, including support vector machines, convolutional neural networks, and deep learning frameworks, have been developed to classify motility patterns on the basis of manometric data [20]. These tools aim to replicate or surpass human interpretation by reducing interobserver variability and increasing diagnostic efficiency [21, 22].

Some studies have demonstrated the feasibility of AI-based algorithms in distinguishing among major motility disorders as defined by the Chicago Classification. These algorithms have shown promising accuracy in identifying type I, II, and III achalasia patterns, as well as other esophageal motility disorders, such as distal esophageal spasm and ineffective esophageal motility [23, 24]. The availability of large, annotated datasets remains limited, but pilot studies

Table 2: Potential clinical applications of AI in achalasia management.

Domain	AI application	Potential clinical benefit	Supporting references
Diagnosis	Automated HRM classification	Reduced interobserver variability	Surdea-Blaga et al. 2022 [23]; Kou et al. 2021 [24]
Diagnosis	Real-time FLIP interpretation	Early detection of subclinical disease	Ellison et al. 2023 [21]
Therapy selection	Prediction of response to POEM vs. pneumatic dilation	Personalized therapeutic strategies	Klontzas et al. 2024 [27]; Mela et al. 2025 [12]
Follow-up	Symptom monitoring via mobile apps and wearable sensors	Early detection of recurrence	Farah et al. 2025 [22]
Research	Multimodal data integration (HRM, imaging, genomics)	Novel phenotypic classification and targeted therapy development	Fass et al. 2024 [19]; Varghese et al. 2024 [10]

Table 1: Summary of published AI studies on esophageal motility disorders.

Author, year	AI approach	Diagnostic modality	Sample size	Objective	Main findings
Kou et al. 2021 [24]	Multistage ML model (CNN + XGBoost)	High-resolution manometry (HRM)	1,741	Subtype classification (Chicago classification)	Top-1 accuracy 81 %, Top-2 accuracy 92 % for esophageal motility disorders, including achalasia
Ellison et al. 2023 [21]	Machine learning–based analysis	Functional lumen imaging probe (FLIP)	229	Evaluation of FLIP panometry in motility practice	Demonstrated additional diagnostic yield beyond HRM, supporting integration of AI-assisted interpretation
Surdea-Blaga et al. 2022 [23]	Convolutional neural network (CNN)	HRM	2,084	Automated Chicago Classification	Accuracy up to 86 % in classifying major motility disorders (achalasia types I–III, DES, IEM)
Fass et al. 2024 [19]	Gradient Boosting + AI toolset	HRM	Narrative review of AI prototypes	Early pattern recognition, feasibility of automated diagnosis	Highlighted potential to reduce interpretation time and interobserver variability

using expert-labeled HREM tracings have laid the groundwork for future clinical implementation [24].

In addition to manometry, AI has been explored in the analysis of esophageal imaging. Techniques such as timed barium esophagography and endoscopic assessment are being revisited through the lens of computer vision [25]. Early investigations have applied deep learning models to detect structural abnormalities or impaired esophageal clearance, although these efforts are still in a preliminary stage [26].

Moreover, AI applications in clinical decision support and outcome prediction are emerging in esophageal surgery, including models designed to anticipate postoperative complications or predict therapeutic response [27, 28]. While these methods are not specific to achalasia, they illustrate the broader potential of AI technologies to inform treatment planning and follow-up strategies in patients with esophageal disorders [27, 28].

Together, these developments provide a conceptual and technical foundation that could be adapted to address the unique challenges of achalasia (Table 2). However, the lack of targeted research underscores a critical gap that warrants focused investigation.

Clinical cases and experimental AI prototypes

Although no large-scale clinical implementation has been achieved, several experimental prototypes provide insight into how AI could directly support achalasia management. For example, Kou et al. developed a multi-stage machine learning model trained on 1,741 HRM studies, achieving a top two accuracy of 92 % in distinguishing esophageal motility disorders, including achalasia subtypes [24]. Similarly, Surdea-Blaga et al. reported CNN-based classification of HRM data with accuracies of up to 86 % [23], demonstrating the feasibility of automated subtype recognition and a substantial reduction in interpretation time compared with expert review. In a related approach, Ellison et al. demonstrated that FLIP manometry provides complementary diagnostic insights when combined with HRM, supporting the potential for automated severity scoring [21]. Moreover, Farah et al. proposed integrating physiologic metrics with patient-reported outcomes through AI-assisted platforms, highlighting the feasibility of generating objective severity indices correlated with Chicago classification subtypes [22]. Case-based evaluations of these models have shown that AI can flag atypical motility patterns or borderline cases for expedited review, potentially reducing diagnostic delays. Kou et al. demonstrated that a multistage machine learning model achieved high diagnostic accuracy even in challenging HRM studies [24], whereas Surdea-Blaga et al. reported that CNN-based algorithms improved the reproducibility of Chicago classification assignments [23]. Although these systems are not yet integrated into commercial HRM platforms, they illustrate the technical feasibility and clinical promise of AI-assisted decision-making in real-world motility practice.

Knowledge gaps and unmet needs

Despite promising early results, the development of AI for esophageal achalasia faces substantial hurdles (Table 3). Achalasia is a rare disorder, and currently, no large, publicly available repositories of annotated images or physiologic tracings exist. In practice, most AI models rely on small single-center datasets. This scarcity of high-quality labeled data is a fundamental limitation: as one review noted, data scarcity and the lack of annotated examples in endoscopy can cause severe class imbalance and overfitting in AI models [29]. In particular, supervised learning methods are heavily data dependent; inadequate training samples lead to unreliable feature recognition and increase false positives or negatives [30]. In short, without large-scale, well-curated datasets (for example, endoscopic esophageal images, manometry charts, or FLIP outputs), algorithms cannot be robustly trained or compared, and progress will remain constrained [19, 22].

Equally important is the limited validation of existing AI systems. To date, most achalasia-related AI studies have

Table 3: Current knowledge gaps and research priorities.

Knowledge gap	Clinical implication	Research priority	Supporting references
Limited, single-center datasets	Bias and poor generalizability	Establish multi-center data consortia; explore federated learning	Fass et al. 2024 [19]; Farah et al. 2025 [22]
Lack of external validation	Risk of over-fitting, poor clinical reliability	Conduct prospective, multicenter validation studies	Surdea-Blaga et al. 2022 [23]; Kou et al. 2021 [24]
Minimal integration into clinical workflows	Limited adoption in practice	Develop interoperable AI platforms embedded in HRM/FLIP/EHR systems	Varghese et al. 2024 [10]; Mela et al. 2025 [12]
Ethical and legal uncertainties	Medico-legal risk, lack of accountability	Define ethical guidelines, governance frameworks, and liability policies	Fass et al. 2024 [19]; Aggarwal et al. 2024 [31]
Absence of long-term outcome studies	Uncertain durability of benefit	Perform longitudinal, outcome-oriented cohort studies	Klontzas et al. 2024 [27]; Mela et al. 2025 [12]

evaluated the performance on internal datasets or retrospective cohorts, often without prospective or multicenter testing. It is increasingly recognized that many AI papers merely compare model outputs to expert interpretations from the same dataset rather than validating against independent clinical end points [19]. For example, although AI models for manometry have demonstrated performance comparable to expert classification of achalasia subtypes, Fass et al. emphasized that such comparisons are limited, as they do not ensure predictive value for patient outcomes or therapeutic response [19]. In fact, as emphasized in recent reviews, the overwhelming majority of endoscopic and manometric AI studies rely on single-cohort validation, with little external testing, raising concerns of overfitting and limited generalizability [19, 23]. Small or nonrepresentative datasets may further bias model parameters, reducing their applicability to diverse patient populations [24]. Until AI tools are rigorously validated in large, heterogeneous cohorts, their clinical reliability in achalasia remains unproven.

Another major gap is that AI applications in achalasia patients have remained siloed by modality. To date, most models have been trained separately on manometry tracings, FLIP studies, or endoscopic images, with little effort to integrate across modalities. In real-world practice, however, diagnosis and management draw on multiple complementary data sources, including clinical history, barium studies, endoscopy, HRM, and FLIP. The integration of high-dimensional, multimodal datasets therefore represents an underexplored but promising opportunity [19, 22]. As experts have emphasized, data heterogeneity and multimodality remain critical unmet needs in gastrointestinal AI research [10]. The development of AI solutions that can integrate manometric, imaging, and clinical information could substantially improve achalasia phenotyping and treatment planning; however, this complex task has not yet been achieved.

Finally, there are nontechnical barriers to AI deployment in achalasia that remain unresolved. As in other areas of gastroenterology, AI raises ethical, legal, and logistical challenges. Key issues include data governance, privacy, and accountability: deploying AI widely requires multicenter data sharing, which involves strict privacy regulations and consent requirements [31]. Concerns also exist regarding algorithmic bias, as nonrepresentative datasets may lead to predictions that unfairly favor certain populations [19]. Moreover, liability for AI-driven decisions, such as a missed diagnosis, remains undefined, with uncertainty about how responsibility should be apportioned among clinicians, institutions, and developers [10, 31]. In summary, unresolved questions regarding data ownership, patient consent, and regulatory oversight must be addressed before AI can be responsibly implemented in achalasia care [19, 31]. Until these clinical and ethical governance issues are clarified, AI in achalasia is unlikely to progress beyond experimental settings. A comprehensive response to these knowledge gaps, including limited data availability, insufficient validation, poor integration across modalities, and unresolved ethical issues, is fundamental for advancing from conceptual frameworks to effective clinical applications. The next sections outline practical strategies and research priorities aimed at enabling the real-world implementation of AI in the management of achalasia.

Moreover, there is an almost complete absence of research integrating molecular or cellular biomarkers (e.g., immune signatures, neurodegenerative changes, or microbiome alterations) with motility and imaging data [3, 4]. Developing multimodal AI models that combine molecular-level information with physiologic parameters could enhance disease phenotyping, clarify pathogenesis, and open new therapeutic targets.

Emerging opportunities and challenges

A critical future direction is the assembly of large, well-annotated multicenter datasets to improve AI robustness and generalizability. In gastroenterology, consortium efforts already demonstrate the value of pooling data: for example, the *GastroNet-5 M* project aggregated over five million GI endoscopic images from eight centers to train deep learning models, finding that domain-specific pretraining on this broad dataset improved performance compared with natural image pretraining [32, 33]. In achalasia, similar multi-institutional registries should be pursued. Techniques such as federated learning can help overcome privacy barriers by enabling collaborative model training without sharing raw patient data [34]. Training on geographically and demographically diverse data will help ensure that AI algorithms perform reliably across different patient populations and care settings.

Equally important is the integration of multimodal patient data. AI methods that fuse physiological measurements, imaging findings, endoscopic observations, and clinical characteristics are likely to yield more precise diagnoses. For example, Fass and colleagues noted that "integration of patient presentation, demographics and alternate test results to individual motility test interpretation will improve diagnostic precision and prognostication" [19]. In achalasia, this could mean combining high-resolution manometry metrics with radiologic measurements (such as barium esophagram or FLIP metrics) and endoscopic findings. A recent multicenter study exemplifies this approach: unsupervised ML on combined HRM and esophagram data identified three distinct achalasia phenotypes (type I or II with a dilated esophagus and late-onset mixed types), which were correlated with different outcomes [35]. However, explainability and bias mitigation will be mandatory for clinical acceptance. Recent frameworks such as the EU AI Act and FDA guidance explicitly require transparent models and bias audits [36]. Federated learning and interpretable classifiers may help ensure both privacy and fairness. Such multimodal analysis may reveal disease subtypes and risk profiles that inform individualized management. For clinicians, this could mean more reliable subtype classification, earlier recognition of treatment-resistant cases, and more accurate prediction of response to interventions such as POEM or pneumatic dilation.

Explainability and transparency are crucial for clinician acceptance and regulatory approval of AI tools. Opaque "black box" models are unlikely to gain trust in decision-critical contexts such as achalasia management. Importantly, emerging regulations now mandate explainability: the European Union's AI Act (enforced 2024) requires that high-risk medical AI provide understandable rationales, either by design or via post hoc interpretability methods [36]. In parallel, the U.S. Food and Drug Administration's recent draft guidance on AI-enabled devices emphasizes transparency, bias mitigation, and detailed documentation of model design and outputs [37]. For example, the FDA guidance specifically calls for clear disclosures of model inputs, architecture, and performance and even suggests including visual demonstrations in submissions to help reviewers understand the system's operation [37]. Thus, future achalasia AI applications should incorporate interpretable models or visualization techniques, enabling clinicians to review the factors driving each prediction.

The development of predictive models for treatment response is another promising avenue. Early evidence suggests that ML can stratify achalasia patients by expected outcomes. For example, Takahashi et al. used a multicenter registry of 1778 treatment-naïve achalasia patients to train a predictive model of persistent symptoms (Eckardt score≥3) after peroral endoscopic myotomy (POEM), achieving an area under the ROC curve of 0.70 [35]. This model highlighted a high pre-POEM Eckardt score as the strongest predictor of treatment failure [35]. In the future, such models could be extended to predict other outcomes (e.g., postprocedure reflux or the need for reintervention) or to compare risks between alternative therapies (POEM vs. pneumatic dilation vs. surgical myotomy). By predicting individual risk profiles, AI-driven decision support could help tailor therapy selection, optimize intervention timing, and personalize follow-up strategies.

Finally, ethical and regulatory frameworks shape the trajectory of AI in achalasia care. Experts have cautioned that broad AI adoption raises issues of algorithmic bias, patient privacy, data ownership, and accountability [31]. For example, if training cohorts underrepresent certain demographic groups, an AI tool may perform poorly for those patients, potentially exacerbating disparities. Ensuring representative data and conducting rigorous bias audits will be essential to mitigate this risk. Data governance is also critical: some have proposed centralized repositories or federated data trusts to harmonize data collection and guard against bias [31]. Patient consent processes may need to adapt for secondary uses of clinical data, and clear policies must define liability for AI-assisted decisions. As regulatory agencies refine policies, exemplified by the EU AI Act and FDA guidance, ongoing ethical oversight and stakeholder engagement will be key to safely integrating AI into esophageal achalasia management.

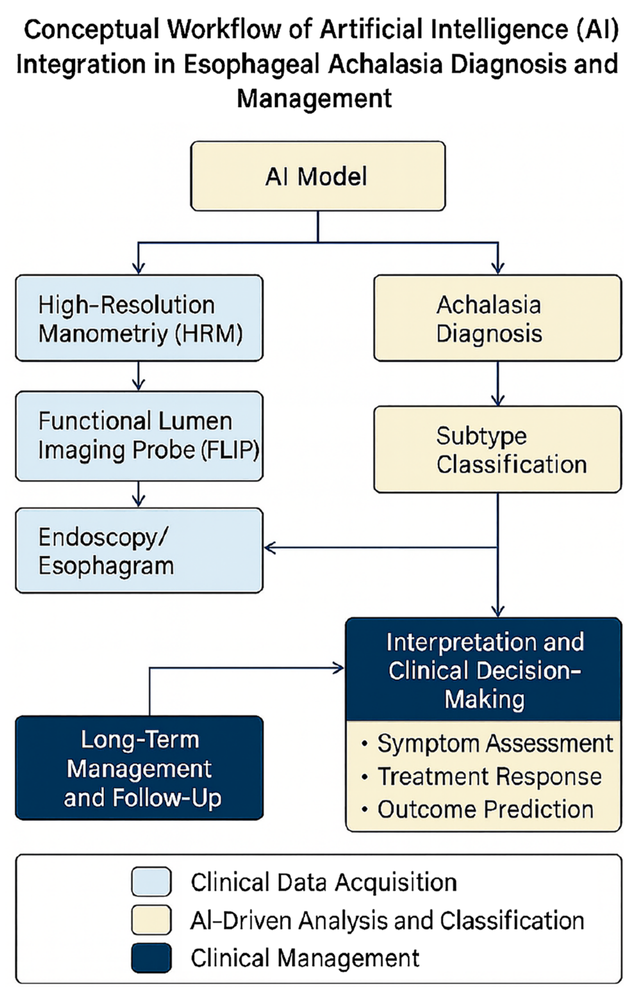

Figure 1: Conceptual workflow of AI integration in achalasia diagnosis and Management.

Discussion and implications for clinical practice

The exploration of AI in the context of esophageal achalasia reveals both promising milestones and significant obstacles. On the one hand, early AI applications to high-resolution manometry and esophageal imaging have demonstrated the feasibility of automated pattern recognition and diagnostic support [23, 24, 38]. These advances suggest that AI could enhance diagnostic consistency, reduce interpretation time, and potentially uncover novel phenotypes within the heterogeneous spectrum of achalasia (Figure 1) [23, 24, 38]. In real-world practice, early adoption of AI would likely begin with integrated decision-support modules in HRM and FLIP software. Over the next 5 years, tertiary centers could realistically apply AI for triage of complex tracings, telemonitoring of symptoms after POEM, and harmonization of motility reporting across operators. Nevertheless, implementation will also face practical barriers, including the cost of AI-enabled HRM/FLIP platforms, the need for staff training, and integration with existing hospital IT infrastructure.

On the other hand, the scarcity of large, well-annotated datasets and the absence of prospective multicenter validation studies represent critical barriers to clinical translation [22]. Without external benchmarking, models risk overfitting idiosyncratic local data and may fail to generalize across populations and equipment variations [22].

The integration of multimodal data, from manometry tracings to endoscopic videos and fluoroscopic images, offers a promising avenue to improve both the sensitivity and specificity of AI-driven diagnostics (Table 4) [24]. By correlating complementary data streams, researchers can develop more nuanced classifiers and predictive models that account for the complexity of achalasia presentations [24]. Future studies could expand beyond physiologic signals to include genomic, immunologic, or microbiome datasets, thereby connecting the molecular pathogenesis of achalasia with its clinical expression [3, 4]. AI-driven multimodal integration may uncover novel disease subtypes that are invisible to current diagnostic modalities and inform precision medicine strategies.

Table 4: AI application landscape across the achalasia care pathway.

Clinical phase	AI application	Examples
Symptom screening	Triage via app o NLP in EHR	Digital symptom checkers, referral optimization
Diagnostic work-up	HRM/FLIP/endoscopy image interpretation	Pattern recognition, subtype classification
Treatment planning	Therapy recommendation models	POEM vs. dilation vs. surgery prediction
Procedural guidance	Intraoperative decision support	AI-assisted robotics or navigation
Post-treatment monitoring	Symptom tracking, recurrence prediction	Wearables, mobile follow-up, risk alerts
Long-term outcome prediction	Prognostic modeling	Re-intervention risk, QOL estimation

Furthermore, incorporating explainable AI techniques is essential for fostering clinician trust, satisfying regulatory requirements, and facilitating shared decision-making [39]. Transparent models that elucidate their decision pathways can serve as valuable educational tools for trainees and guide more informed patient consent processes [24].

Predictive analytics for treatment response present another frontier with tangible clinical impact. Models capable of forecasting symptom resolution, procedural complications, or long-term quality of life could inform personalized therapeutic strategies and optimize resource allocation [24, 38]. Realizing this potential will require longitudinal data capture and rigorous outcome tracking alongside AI development. In parallel, ethical frameworks and governance structures must evolve to address liability, data ownership, and equity concerns [40]. Engaging stakeholders, including patients, clinicians, data scientists, and regulators, is vital to ensure that AI innovations do not inadvertently exacerbate disparities or compromise patient autonomy [40].

In summary, the convergence of AI and achalasia care is an emerging field poised for rapid growth. Future research must prioritize collaborative data sharing, multimodal model development, transparent algorithm design, and ethical oversight. By addressing these priorities, the community can harness AI to transform diagnosis, tailor treatment, and ultimately improve outcomes for patients with esophageal achalasia.

Given the rapid pace of AI innovation, the models and findings presented here may become outdated within a few years unless they are continuously updated with evolving data and methods.

Practical considerations for hospital workflow integration

The successful deployment of AI tools for achalasia will require seamless integration into existing hospital workflows. Embedding AI algorithms directly into HRM acquisition software, FLIP consoles, or endoscopic reporting systems could enable real-time decision support without disrupting standard clinical routines. Integration with electronic health records (EHRs) would allow AI models to access complementary patient data, enhancing diagnostic accuracy through multimodal analysis [39]. However, practical barriers remain [41].

Economically, acquiring AI-enabled diagnostic platforms may require significant capital investment, particularly for smaller or resource-limited centers [41]. Operationally, training personnel to interpret AI outputs, updating hospital IT infrastructure, and ensuring compliance with data security regulations represent non-trivial challenges [41]. Additionally, reimbursement policies for AI-assisted diagnostics remain undefined in many healthcare systems, potentially limiting adoption [41]. Overcoming these barriers will require not only technical innovation but also institutional commitment, clear regulatory guidance, and demonstration of cost-effectiveness in routine clinical care [41]. Thus, workflow integration should be considered in parallel with data validation, ensuring that technical advances translate into tangible benefits for patients and health systems.

Table 5: Clinical AI translation roadmap for achalasia limitations of the review.

Focus area	Near-term priorities	Long-term vision
Data infrastructure	Build large, multicenter datasets; explore federated learning to protect privacy	Establish global AI-ready motility databases
Model validation	Perform rigorous external and prospective testing	Continuous learning systems adapting to new data
Clinical integration	Embed AI tools into HRM/FLIP platforms and EHRs	Fully AI-assisted, real-time diagnostic and treatment workflows
Personalization	Predict treatment response and recurrence risk	Precision motility medicine integrating multimodal data
Accessibility	Expand AI-assisted telemedicine and remote monitoring	Equitable global access to expert-level motility diagnostics
Governance	Develop ethical guidelines and regulatory pathways	Harmonized international standards for AI in motility care

Roadmap for clinical translation

The crucial next steps include building large, multicenter esophageal motility datasets and validating AI models across diverse populations (Figure 2). Limited data availability is currently a major bottleneck in achalasia AI research, so collaborative data consortia or federated learning will be needed to aggregate broad cohorts while protecting privacy [34]. Equally important is rigorous external and prospective validation of any models in independent clinical cohorts to ensure reliability and generalizability [19]. The integration of AI into practice must also be addressed: future tools should be embedded as decision-support modules in manometry and endoscopy workflows, augmenting (not replacing) expert interpretation. Farah et al. noted that AI can standardize interpretation across centers and streamline diagnostic workflows, and Fass et al. emphasized that combining patient demographics, symptom profiles, and test results can substantially improve diagnostic precision over isolated motility data [19, 22]. In practice, this means evolving from isolated manometric interpretation toward systems that merge clinical context and physiologic measurements to make more accurate diagnoses (Table 5).

AI has the potential to transform the management of achalasia for diagnosis, treatment planning, and monitoring. For example, automated pattern recognition can speed up subtype classification via manometry or FLIP, and predictive models (trained on large datasets) could guide therapy choices or timing [38]. AI could predict which patients are likely to benefit most from myotomy vs. dilation or predict post-treatment symptom recurrence, enabling truly personalized therapy [24]. Moreover, AI-driven tools could support long-term follow-up: algorithms might analyze longitudinal symptom logs, follow-up motility tests, or even remote sensor data to flag early relapse or complications [40]. Farah et al. noted that AI's predictive capabilities extend to treatment outcome modeling and longitudinal tracking, enabling personalized care strategies over time [22]. Furthermore, we envision "precision motility care," where multimodal data (manometry, imaging, patient genetics and demographics, etc.) are integrated by AI to predict an individual's disease

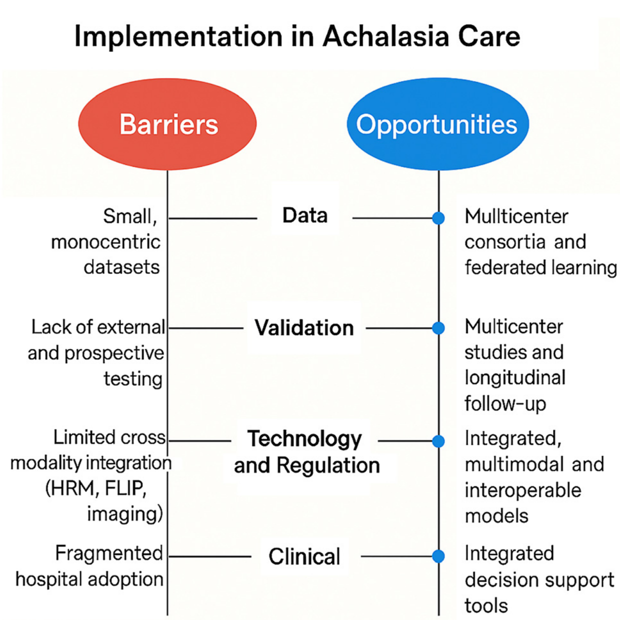

Figure 2: Barriers and opportunities for AI implementation in achalasia care.

trajectory and tailor interventions. In the broader health system, such AI advances could reshape care delivery, for instance, through AI-augmented telemedicine, remote symptom monitoring, and automated triage. These technologies may allow esophageal specialists to extend expertise beyond the clinic, improving early detection, risk stratification, and long-term patient monitoring [34]. By facilitating early warnings and more efficient care pathways, AI-driven precision may ultimately improve outcomes and efficiency across gastrointestinal healthcare [34].

This review is subject to several limitations inherent to its narrative design. Unlike systematic reviews, which follow predefined protocols for study selection and quality assessment, narrative reviews are more vulnerable to selection bias and subjective interpretation. The absence of a formal inclusion strategy may have led to the unintentional exclusion of relevant studies or overrepresentation of others, particularly in a rapidly evolving field such as AI in gastroenterology. Furthermore, the review was limited to English-language publications, introducing potential language bias and possibly overlooking valuable contributions reported in other languages. The heterogeneity of the studies included represents an additional limitation. The variability in population characteristics, AI methodologies, diagnostic endpoints, and outcome metrics precluded any attempt at quantitative synthesis or comparative meta-analysis, which in turn limited the strength of the overarching conclusions. Finally, the fast-paced evolution of AI technologies poses a temporal constraint; as new models, datasets, and computational strategies continue to emerge, the present analysis may not fully reflect the latest innovations, particularly those released after the literature cutoff point. Furthermore, as a narrative review, the synthesis remains interpretive and does not provide quantitative effect sizes or formal meta-analytic comparisons.

European and multicenter initiatives

In Europe, several initiatives are currently fostering the integration of AI into gastrointestinal motility research [9, 42]. The European Society of Neurogastroenterology and Motility (ESNM) has recently emphasized the need for standardized digital data repositories to support AI model development in rare motility disorders, including achalasia [43]. Moreover, collaborative projects such as GastroNet-EU and AI4GI aim to create shared, annotated databases of manometric and endoscopic data across multiple centers, following FAIR (Findable, Accessible, Interoperable, and Reusable) data principles [32]. These initiatives illustrate Europe's commitment to building the digital infrastructure required for clinically robust and ethically governed AI systems. In the specific field of esophageal motility, ongoing efforts in Italy, France, and Germany are exploring AI-assisted interpretation of HRM and FLIP datasets [43, 44]. Integrating such European multicenter experiences into future research will be essential to overcome data fragmentation and accelerate clinical translation of AI-based tools for achalasia.

Conclusions

AI holds strong promise for improving the diagnosis, classification, and management of esophageal achalasia. Early studies indicate that AI can enhance diagnostic consistency, support decision-making, and enable more personalized therapeutic strategies. Yet, progress remains constrained by limited annotated datasets, lack of external validation, and concerns about transparency, equity, and regulation. To realize its potential, future research should focus on collaborative data sharing, multimodal model development, prospective validation, and explainable, ethically governed frameworks. Interdisciplinary collaboration will be crucial to ensure that AI complements clinical expertise rather than replacing it, reducing diagnostic variability and facilitating personalized, data-driven care. Ultimately, AI may also help bridge clinical phenotypes with molecular insights, advancing precision and translational medicine in achalasia.

Key takeaways

– There is a striking absence of AI tools specifically trained for achalasia.
– Existing AI models in HRM and FLIP show strong potential for subtype recognition.
– Multicenter data collaboration is essential for overcoming data scarcity.
– Integration of multimodal inputs (HRM + imaging + symptoms) will improve precision.
– Regulatory clarity and explainability are vital for clinical adoption.

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References

1. Fernicola A, Palomba G, Calogero A, Sciarra A, Cavaliere A, Crocetto F, Sagnelli, et al. Achalasia and gut microbiota: is dysbiosis an overlooked factor in postoperative surgical outcomes? Surgeries 2025;6:63.
2. Domingues C, Cabral C, Jarak I, Veiga F, Dourado M, Figueiras A. The debate between the human microbiota and immune system in treating aerodigestive and digestive tract cancers: a review. Vaccines (Basel) 2023;11:492.
3. Baba Y, Tajima K, Yoshimura K. Intestinal and esophageal microbiota in esophageal cancer development and treatment. Gut Microbes 2025;17: 2505118.
4. Geng ZH, Zhu Y, Chen WF, Fu PY, Xu JQ, Wang TY, et al. The role of type II esophageal microbiota in achalasia: activation of macrophages and degeneration of myenteric neurons. Microbiol Res 2023;276:127470.
5. Jung DH, Youn YH, Kim DH, Lim CH, Lim HS, Moon HS, et al. Esophageal microbiota and nutritional intakes in patients with achalasia before and after peroral endoscopic myotomy. J Neurogastroenterol Motil 2022; 28:237–46.
6. Palomba G, Capuano M, Basile R, Sorrentino G, Fernicola A, Anoldo P, et al. Robotic surgery in achalasia: state of the art. Chirurgia 2023;118: 8–19.
7. Vittori A, Capovilla G, Salvador R, Santangelo M, Provenzano L, Nicoletti L, et al. Laparoscopic fundoplication improves esophageal motility in patients with gastroesophageal reflux disease: a high-volume single-center controlled study in the era of high-resolution manometry and 24-hour pH impedance. J Gastrointest Surg 2025;29: 101888.
8. Palomba G, Fernicola A, Corte MD, Capuano M, De Palma GD, Aprea G. Artificial intelligence in screening and diagnosis of surgical diseases: a narrative review. AIMS Public Health 2024;11:557–76.
9. Fernicola A, Palomba G, Capuano M, De Palma GD, Aprea G. Artificial intelligence applied to laparoscopic cholecystectomy: what is the next step? A narrative review. Updates Surg 2024;76:1655–67.
10. Varghese C, Harrison EM, O'Grady G, Topol EJ. Artificial intelligence in surgery. Nat Med 2024;30:1257–68.
11. Knudsen JE, Ghaffar U, Ma R, Hung AJ. Clinical applications of artificial intelligence in robotic surgery. J Robot Surg 2024;18:102.
12. Mela E, Tsapralis D, Papaconstantinou D, Sakarellos P, Vergadis C, Klontzas ME, et al. Current role of artificial intelligence in the management of esophageal cancer. J Clin Med 2025;14:1845.
13. Cizmic A, Mitra AT, Preukschas AA, Kemper M, Melling NT, Mann O, et al. Artificial intelligence for intraoperative video analysis in robotic-assisted esophagectomy. Surg Endosc 2025;39:2774–83.
14. Stam WT, Goedknegt LK, Ingwersen EW, Schoonmade LJ, Bruns ERJ, Daams F. The prediction of surgical complications using artificial intelligence in patients undergoing major abdominal surgery: a systematic review. Surgery 2022;171:1014–21.
15. Takeuchi M, Kawakubo H, Saito K, Maeda Y, Matsuda S, Fukuda K, et al. Automated surgical-phase recognition for robot-assisted minimally invasive esophagectomy using artificial intelligence. Ann Surg Oncol 2022;29:6847–55.
16. Rahmadian R, Qisthi M, Ariliusra Z. Artificial intelligence in surgery: role of AI in pre-operative, intra-operative, and post-operative. Surgery, Gastroenterology and Oncology 2024;29:189.
17. Ahmed FA, Yousef M, Ahmed MA, Ali HO, Mahboob A, Ali H, et al. Deep learning for surgical instrument recognition and segmentation in robotic-assisted surgeries: a systematic review. Artif Intell Rev 2025;58: 1.
18. Furube T, Takeuchi M, Kawakubo H, Noma K, Maeda N, Daiko H, et al. Usefulness of an artificial intelligence model in recognizing recurrent laryngeal nerves during robot-assisted minimally invasive esophagectomy. Ann Surg Oncol 2024;31:9344–51.
19. Fass O, Rogers BD, Gyawali CP. Artificial intelligence tools for improving manometric diagnosis of esophageal dysmotility. Curr Gastroenterol Rep 2024;26:115–23.
20. Sakai M, Saito H, Kuriyama K, Yoshida T, Kumakura Y, Hara K, et al. [High-resolution Manometry for Esophageal Motility Disorders]. Kyobu Geka 2018;71:894–9.
21. Ellison A, Nguyen AD, Zhang J, Mendoza R, Davis D, Podgaetz E, et al. The broad impact of functional lumen imaging probe panometry in addition to high-resolution manometry in an esophageal clinical practice. Dis Esophagus 2023;36:doac059.
22. Farah A, Abboud W, Savarino E, Mari A. Esophageal intelligence: implementing artificial intelligence into the diagnostics of esophageal motility and impedance pH monitoring. Neuro Gastroenterol Motil 2025;37. https://doi.org/10.1111/nmo.70038.
23. Surdea-Blaga T, Sebestyen G, Czako Z, Hangan A, Dumitrascu DL, Ismaiel A, et al. Automated Chicago classification for esophageal motility disorder diagnosis using machine learning. Sensors 2022;22: 5227.
24. Kou W, Carlson DA, Baumann AJ, Donnan EN, Schauer JM, Etemadi M, et al. A multi-stage machine learning model for diagnosis of esophageal manometry. Artif Intell Med 2022;124:102233.
25. Zhang P, She Y, Gao J, Feng Z, Tan Q, Min X, et al. Development of a deep learning system to detect esophageal cancer by barium esophagram. Front Oncol 2022;12:766243.
26. Islam MM, Poly TN, Walther BA, Yeh CY, Seyed-Abdul S, Li YJ, et al. Deep learning for the diagnosis of esophageal cancer in endoscopic images: a systematic review and meta-analysis. Cancers (Basel) 2022;14:5996.
27. Klontzas ME, Ri M, Koltsakis E, Stenqvist E, Kalarakis G, Boström E, et al. A. Prediction of anastomotic leakage in esophageal cancer surgery: a multimodal machine learning model integrating imaging and clinical data. Acad Radiol 2024;31:4878–85.
28. Poulos CM, Cassidy R, Khatibifar E, Holzwanger E, Schumacher L. The current state of artificial intelligence in robotic esophageal surgery. Mini-Invasive Surg 2025;9:6.

29. Ali S. Where do we stand in AI for endoscopic image analysis? Deciphering gaps and future directions. NPJ Digit Med 2022;5:184.
30. Yoo BS, Houston KV, D'Souza SM, Elmahdi A, Davis I, Vilela A, et al. Advances and Horizons for artificial intelligence of endoscopic screening and surveillance of gastric and esophageal disease. Artif Intell Med Imaging 2022;3:70–86.
31. Aggarwal N, Drew DA, Parikh RB, Guha S. Ethical implications of artificial intelligence in gastroenterology: the Co-pilot or the captain? Dig Dis Sci 2024;69:2727–33.
32. Jong MR, Boers TGW, Fockens KN, Jukema JB, Kusters CHJ, Jaspers TJM, et al. Barrett's oesophagus imaging for artificial intelligence (BONS-AI) consortium. GastroNet-5M: a multicenter dataset for developing foundation models in gastrointestinal endoscopy. Gastroenterology 2025. https://doi.org/10.1053/j.gastro.2025.07.030. S0016–5085(25)05797–X.
33. Boers TGW, Fockens KN, van der Putten JA, Jaspers TJM, Kusters CHJ, Jukema JB, et al. Foundation models in gastrointestinal endoscopic AI: impact of architecture, pre-training approach and data efficiency. Med Image Anal 2024;98:103298.
34. Liu SW, Li P, Li XQ, Wang Q, Duan JY, Chen J, et al. Recent advances in machine learning for precision diagnosis and treatment of esophageal disorders. World J Gastroenterol 2025;31:105076.
35. Takahashi K, Sato H, Shimamura Y, Abe H, Shiwaku H, Shiota J, et al. Achalasia phenotypes and prediction of peroral endoscopic myotomy outcomes using machine learning. Dig Endosc 2024;36:789–800.
36. Freyer N, Groß D, Lipprandt M. The ethical requirement of explainability for AI-DSS in healthcare: a systematic review of reasons. BMC Med Ethics 2024;25:104.
37. U.S. Food and Drug Administration. FDA issues artificial intelligence-enabled device software functions draft guidance. DLA Piper 2025. https://www.dlapiper.com/en-ca/insights/publications/2025/01/fda-issues-artificial-intelligence-enabled-device-software-functions-guidance [Accessed 20 September 2025].
38. Popa SL, Surdea-Blaga T, Dumitrascu DL, Pop AV, Ismaiel A, David L, et al. Gemini-assisted deep learning classification model for automated diagnosis of high-resolution esophageal manometry images. Medicina 2024;60:1493.
39. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med 2019;25:44–56.
40. Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. Briefings Bioinf 2018;19:1236–46.
41. Rajpurkar P, Chen E, Banerjee O, Topol EJ. AI in health and medicine. Nat Med 2022;28:31–8.
42. Quarto G, Benassai G, Fernicola A. Using artificial intelligence to enable safer laparoscopic cholecystectomy: a step toward a standardized critical view of safety and reduced bile duct injuries. Ann Ital Chir 2025;96:1279–81.
43. Tack J, Vanuytsel T, Serra J, Accarino A, Stanghellini V, Barbara G, ESNM Consensus Group. The leuven consensus group, the Italian consensus group, the Spanish consensus group on function testing in the COVID-19 pandemic era. European society for neurogastroenterology and motility recommendations for conducting gastrointestinal motility and function testing in the recovery phase of the COVID-19 pandemic. Neuro Gastroenterol Motil 2020;32:e13930.
44. Ugliono E, Buscemi S, Consalvo D, Iossa A, Tamburini N, Pernazza G, et al. Real-world management of achalasia and esophagogastric junction outlet obstruction in Italy: results from a national survey. Updates Surg 2025;77:2235–43.