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Artificial Intelligence in Pediatric Bronchoscopy: Current Evidence and Future Perspectives

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ABSTRACT

Background: Artificial intelligence (AI) is rapidly advancing in medical endoscopy, with proven value in adult bronchoscopy for diagnostic enhancement and training. Pediatric bronchoscopy, with its unique anatomical and procedural challenges, is beginning to explore AI integration. This narrative review summarizes current evidence and anticipates future applications.

Methods: We searched PubMed and EMBASE for articles in English from inception to August 2025 using combinations of the terms "pediatric bronchoscopy," "artificial intelligence," "machine learning," and "deep learning." Additional relevant publications were identified by reviewing reference lists and conference abstracts. Inclusion was based on relevance to AI applications in pediatric or, when pediatric data were lacking, adult bronchoscopy. Areas of emphasis included AI-driven video image analysis, navigation guidance, diagnostic decision support, and training tools, along with challenges in data annotation, bias, and generalizability.

Results: Deep learning models can identify airway anatomy on bronchoscopy video with expert-level accuracy and, when integrated into simulators, improve novices' completeness, procedural structure, and speed. AI applied to chest radiographs shows high accuracy in predicting foreign body aspiration, potentially reducing unnecessary bronchoscopies. A validated pediatric bronchitis scoring tool standardizes airway inflammation assessment, supporting future AI automation. Limitations include small, single-center datasets and the need for pediatric-specific data to prevent bias.

Conclusions: AI in pediatric bronchoscopy is at an early stage, with most evidence extrapolated from adult practice. Available data suggest potential to improve diagnostic accuracy, safety, and training efficiency. Progress will require multi-center pediatric data collaboration, prospective trials, and workflow integration.

1 | Introduction

Advances in artificial intelligence (AI) are poised to transform bronchoscopy, a field historically dependent on the skill and experience of the operator. In adult gastrointestinal endoscopy, AI-based computer-aided detection/diagnosis (CADe/CADx) systems have already demonstrated increased tumor and polyp detection rates [1]. By analogy, bronchoscopy could benefit from AI assistance for identifying anatomical landmarks or airway lesions. Pediatric bronchoscopy stands to gain particularly, as children's airways are smaller and tolerance for prolonged or repeated procedures is low, making diagnostic yield optimization critical. Yet novice bronchoscopists often have lower diagnostic yields, higher complication rates, and longer procedure times [2].

AI has the potential to address these gaps by enhancing both the procedure process and diagnostic interpretation in bronchoscopy. For instance, AI vision algorithms could guide a bronchoscope to each lung segment or flag abnormal findings in real time, mitigating operator variability. AI could serve as a virtual assistant, classifying bronchoscopic images on the fly. Early studies and proofs-of-concept in adult bronchoscopy suggest that AI can perform on par with experts in select tasks and improve training outcomes [3, 4]. However, pediatric applications have been sparse due to limited data and the relative rarity of pediatric bronchoscopic conditions. To our knowledge, no comprehensive overview focusing on pediatric bronchoscopy and AI has been published to date.

This narrative review provides a broad, reflective overview of AI and machine learning (ML) principles relevant to bronchoscopy, highlights current applications with an emphasis on pediatric studies and tools, and discusses the limitations and challenges facing this emerging field. The goal is to inform pediatric pulmonologists and interventionalists of the state-of-the-art and what may be on the horizon, in order to inspire both cautious optimism and collaborative innovation in integrating AI into pediatric bronchoscopy.

2 | Search Strategy and Selection Criteria

We conducted a comprehensive literature search using PubMed and EMBASE databases for articles published in English from inception to August 2025. The search strategy employed combinations of the terms "pediatric bronchoscopy," "artificial intelligence," "machine learning," and "deep learning." To ensure the inclusion of the most recent and emerging evidence, we supplemented traditional database searching with AI-driven literature discovery tools.

Titles and abstracts were screened for relevance, prioritizing studies specifically addressing pediatric applications. Given the nascency of the field in pediatrics, we also selectively included pivotal "proof-of-concept" studies from adult bronchoscopy, specifically those demonstrating validated AI systems for navigation, lesion characterization, and skill assessment, to provide necessary context on technological maturity. Final inclusion was determined by manual review of the full text to ensure methodological quality and relevance to the review's scope (Box 1).

3 | Principles of AI and ML

3.1 | Basic Principles

AI broadly refers to computer systems able to perform tasks that normally require human intelligence. Contemporary medical AI is driven by ML algorithms that learn patterns from data. A subset, deep learning, uses multi-layered neural networks to automatically learn complex representations of input data. These techniques have particular relevance for bronchoscopy, which is a visually guided procedure: deep learning models (especially convolutional neural networks, CNNs) excel at image and video analysis. Bronchoscopic videos can be broken into individual image frames and analyzed by such neural networks. The network first learns what it should recognize from thousands of frames that experts have manually tagged as "carina," "right main bronchus," "foreign body," and so on. Once those labels are provided, the CNN itself works out the visual features (edges, colors, textures, and spatial relationships) that best distinguish each class—no hand-crafted feature engineering is required.

Although classic CNN workflows depend on fully supervised training- thousands of frames meticulously labeled by experts-current best practice often begins with self- or weak-supervised pre-training on hours of unlabeled videos to let the network learn generic feature representations. A smaller, carefully curated labeled subset then suffices for fine-tuning and validation, dramatically reducing annotation burden while maintaining (and sometimes improving) diagnostic accuracy in data-constrained settings.

3.2 | Bias and Generalizability

AI models are only as good as the data they learn from. If pediatric data are underrepresented, an AI trained mostly on adult bronchoscopic images might perform poorly in children (for instance, confusing the normal small-diameter pediatric airways for pathologically narrowed airways). Bias can also stem from imbalanced datasets (e.g., if healthy bronchoscopy videos greatly outnumber ones with pathology, a detection algorithm might be biased toward "normal"). It is crucial to use representative datasets and to test models across different populations and centers to ensure robust generalizability.

Building an AI for bronchoscopy involves: (1) defining a specific task (such as anatomical landmark identification, pathology detection, or skill assessment), (2) assembling a labeled dataset for that task, (3) training a model (often a deep CNN) on a portion of data, and validating on a separate set, and (4) comparing the AI's performance with human benchmarks. Performance metrics commonly include accuracy, sensitivity, specificity, and area under the ROC curve (AUC) for classification tasks, or correlation with experts for quantitative assessments [2].

A known limitation of deep learning is the "black box" nature of models—users cannot readily see how predictions are made,

BOX 1 | Why AI matters in pediatric bronchoscopy.

Domain	Key points
Pediatric challenges	Small airway size, limited tolerance for long procedures
Training	Novices show lower diagnostic yield and higher complication rates
AI potential	Real-time navigation, lesion detection, and structured feedback standardize performance

which can undermine trust. Efforts to improve interpretability include techniques like saliency mapping (e.g., Grad-CAM), which highlight regions of an image that most influenced the AI's decision. In one bronchoscopy study, saliency maps showed that the AI was focusing on key anatomical features (such as the carina ridge) when identifying bronchial branch points, providing reassurance that the model's behavior aligned with anatomical logic [5]. Such transparency will be important for physician acceptance of AI assistance.

4 | Current Applications in Pediatric Bronchoscopy

Applications of AI in bronchoscopy are summarized in Text Box 2, and can be broadly categorized into: (1) airway anatomy recognition and navigation, (2) lesion detection and diagnosis support, and (3) operator training and performance assessment. While most implementations to date have occurred in adult patient or simulation settings, we highlight existing pediatric-specific studies and consider their relevance to current practice. To contextualize this potential, it is essential to recognize the technological maturity already achieved in adult bronchoscopy, where AI has transitioned from theoretical models to validated clinical tools. Key examples include real-time navigation systems utilizing deep learning for precise localization, EBUS-based image analysis systems for lymph node characterization, and automated systems for objective skill assessment in simulation. These established frameworks serve as a rigorous “proof of concept” for pediatric applications. The challenge for the pediatric community is therefore not to invent new technologies from scratch, but to adapt these proven adult-centric models to the unique anatomical and pathological constraints of the pediatric airway.

4.1 | AI-Assisted Airway Anatomy Recognition and Navigation

One of the earliest successful bronchoscopy AI applications has been automatic identification of airway anatomy on video. Yoo et al. trained a deep CNN on over 8600 bronchoscopy images to classify them as carina, left mainstem, or right mainstem bronchi. Remarkably, the AI achieved 84% accuracy, outperforming five out of six human experts who were tested on the same images (expert accuracies ranged from 38% to 68% for anesthesiologists and up to 82% for the most experienced pulmonologist) [5]. This demonstrated that AI can learn to navigate the bronchial tree visually with near-expert proficiency. Maintaining uninterrupted orientation in the airway is fundamental in bronchoscopy, especially for trainees and for non-pulmonologist clinicians (e.g., anesthesiologists using bronchoscopes for intubation confirmation). Chen et al. demonstrated that a CNN could distinguish nine bronchoscopic airway anatomical positions with a mean accuracy of 91% and an area under the curve > 0.98, performing on par with or better than respiratory physicians in identifying these positions. These findings are noteworthy as they provide evidence that AI can match expert-level performance in key bronchoscopy tasks, supporting the potential of AI to standardize training and improve procedural quality in early-stage studies [6].

4.2 | AI for Lesion Detection and Diagnostic Support

Beyond navigation, AI has been applied to detect or characterize findings during bronchoscopy. In adult pulmonary medicine, a major focus has been assisting in the diagnosis of lung cancer. Several studies have trained AI on endobronchial ultrasound (EBUS) images of mediastinal lymph nodes to classify them as malignant vs benign. Classification performance in such studies has been high, achieving accuracies in the 74%–90% range for predicting malignancy [7–9]. Another emerging application is the use of AI for Rapid On-Site Evaluation (ROSE) cytology during flexible bronchoscopy. ROSE can improve biopsy adequacy and diagnostic yield, but its use is often limited by the availability of cytopathologists. A recently developed ROSE AI system, based on a deep CNN trained on over 6300 cytological images from 721 patients, was able to identify malignant cells with an accuracy of above 90%, comparable to experienced cytopathologists [10].

While pediatric pulmonologists rarely encounter primary lung cancer, they do perform bronchoscopy for conditions like tuberculous lymphadenopathy, lymphoma, or other tumors (e.g., inflammatory myofibroblastic tumors). In those rare scenarios, an AI that analyzes bronchoscopic video of endoluminal lesions could provide decision support (e.g., suggesting that a lesion “appears malignant” vs. “likely inflammatory”).

A particularly compelling pediatric-specific application of AI is in the evaluation of foreign body aspiration (FBA). Children (especially toddlers) frequently aspirate peanuts, seeds, or small objects, and bronchoscopy is the gold standard for diagnosis and removal. However, many children undergo bronchoscopy only to find no foreign body (negative bronchoscopy), which exposes them to procedural risks unnecessarily. Recently, Çoşkun et al.

BOX 2 | Key current applications.

Domain	Key points
Airway anatomy recognition	CNNs achieve ~84%–91% accuracy, comparable to experts
Lesion characterization	AI on EBUS distinguishes malignant vs benign nodes (74%–90% accuracy)
Foreign body aspiration	Pediatric CXR model reduces negative bronchoscopies (43% → 11%)
Bronchitis scoring	Pediatric BScore validated; future basis for automated AI scoring
Training tools	AI guidance improves completeness and shortens procedure time

developed a deep learning model to analyse pediatric chest X-rays for signs of airway foreign bodies [11]. Their CNN was trained on chest radiographs of children with and without confirmed FBA. The AI model achieved 97.3% accuracy in their dataset, with 94.1% sensitivity and 97.8% specificity for predicting the presence of an aspirated object. In practical terms, if the model strongly predicts "no foreign body," one might forego a bronchoscopy, whereas a high-risk prediction would reinforce the decision to perform a bronchoscopy. Notably, the deep learning predictor in this study outperformed a traditional multiple logistic regression model and would have reduced the negative (unnecessary) bronchoscopy rate from 43.3% to 11.1% in the retrospective cohort. This kind of AI tool, after further validation, could be integrated into emergency and clinic settings—as a second reader of the chest X-ray—to support pediatricians in determining which children truly need a bronchoscopy. Importantly, the authors caution that such AI should *augment* clinical judgment, not replace it, given the severe consequences of a missed foreign body. Still, this represents a promising step toward reducing invasive procedures in children using AI.

Pediatric bronchoscopy is often performed for chronic cough, suspicion of airway inflammation (endobronchial infection, bronchitis), or structural airway abnormalities (tracheomalacia, stenosis). One challenge has been the subjective nature of describing bronchoscopic findings—what one bronchoscopist calls "moderate inflammation" another might call "mild." To address this, Eg et al. developed the first standardized Bronchitis Scoring Tool (BScore) for children [12]. While not an AI study per se, it created an objective framework (scoring 0–3 or higher for features like mucosal edema, secretion amount and color, erythema, etc.) and validated it against bronchoalveolar lavage neutrophil counts. The BScore correlated significantly with airway neutrophilia ($r \sim 0.4$–0.5 for most features) and showed an AUC of 0.84 for identifying neutrophilic bronchitis. The development of BScore is highly relevant to AI: it provides a quantitative label that an algorithm could try to predict from bronchoscopic video. In the future, one can envision training a deep learning model on bronchoscopic videos labeled with BScore outcomes, so that the AI could automatically score the degree of bronchitis during a bronchoscopy. Early steps toward this might involve simpler tasks like automated detection of pus in the airways or redness of mucosa through color analysis—tasks suited for computer vision. Ultimately, integrating such AI could make bronchoscopy not only a diagnostic visual tool but also a semi-quantitative measure of airway disease severity, guiding therapy (e.g., deciding on antibiotics or anti-inflammatory treatments in chronic wet cough).

4.3 | Operator Training and Performance Assessment

Another application of AI—indirectly beneficial to patients—is training operators in procedure proficiency. An AI-driven bronchoscopy guidance system was developed, providing live feedback on which bronchial segment a trainee is viewing and whether they have systematically examined all segments. In a randomized controlled trial, 20 novice trainees practiced on a bronchoscopy simulator with or without the AI guidance system [4]. The AI group performed significantly better at the end of training: they visualized a median of 3.5 more bronchial segments and made 5 more correct sequential progressions than the control group, while completing the procedure 3.5 min faster. These differences were highly significant and demonstrated that AI guidance can accelerate learning of bronchial anatomy in a safe environment.

Tools have also been developed that analyze the bronchoscope's video feed and motion to provide objective metrics of skill. A notable example in adult bronchoscopy is an AI system that measures how completely and systematically a bronchoscopist examines the bronchial tree, as well as their efficiency (scope movement between segments). Cold et al. tested this AI assessment against expert raters' evaluations of bronchoscopist performance [3]. The AI's metrics—such as diagnostic completeness (percentage of segments visualized) and mean intersegmental navigation time—showed moderate correlation with experts' competency ratings (correlation coefficients ~0.4–0.57). These findings were replicated in a cohort of critical-care physicians, suggesting the potential to employ AI-based feedback for training in simulated settings [13].

For pediatric bronchoscopists, whose training opportunities may be less frequent (due to lower procedure volumes), such AI-based assessments could help ensure that essential skills are acquired and objectively verified before independent practice.

In summary, although most AI developments in bronchoscopy have occurred in adult-focused studies or simulation environments, the *concepts and tools are highly pertinent to pediatrics.* Table 1 provides an evidence summary of key studies, including a few pediatric-specific investigations. Collectively, current applications indicate that AI can identify anatomy, detect certain pathologies, guide trainees, and even interpret related imaging (like chest X-rays) with a high level of performance. However, translating these into routine pediatric bronchoscopy practice will require overcoming several limitations, as discussed in the next section.

5 | Limitations and Challenges

Despite the exciting successes of pilot studies, significant challenges, summarized in Box 3, must be addressed before AI can be widely implemented in pediatric bronchoscopy:

5.1 | Data Limitations

A recurring theme is the lack of large, diverse datasets in pediatric bronchoscopy. Many current AI models have been trained on adult data or small single-center datasets. Pediatric airway anatomy and diseases differ in important ways—for example, young children often have dynamic airway collapse (tracheomalacia) and smaller airways that may confound an AI not exposed to such data. Deep learning methods thrive on big data, yet in medicine, most models are trained on only hundreds of examples. This raises concerns about overfitting and limited applicability. There is a pressing need for multi-center collaboration to gather representative pediatric bronchoscopic

TABLE 1 | Key studies on AI applications in bronchoscopy (including pediatric-specific studies).

Clinical/ Training task	Representative AI system (year)	Study design and *N* (trainees/Patients/ Images)	Best-reported metrics[a]	Human benchmark	Key take-aways
Anatomical localization and navigation (training)	ResNet, Inception, MobileNet CNNs with transfer learning (Matava et al. [14])	775 videos (775 patients, aged 1–23 years)	Identification accuracy: 0.93–0.96. Specificity: 0.97–0.985 Sensitivity: 0.86–0.89.	NA	CNNs can classify key airway landmarks in real time, transfer learning markedly improves performance.
	EfficientNet + U-Net (Chen et al. [6])	1527 images supervised training (200 patients); 475 images for validation (72 patients)	Mean accuracy 91%, across 9 airway positions. AUC > 0.98	21 pulmonologists, variable experience	CNNs accurately identified and labeled major bronchial landmarks with higher precision than pulmonologists
	"AIBA" Image classifier (Cold et al. [3])	Prospective, single-session performance assessment, 52 doctors	Structured Progress (SP)—$r = 0.57$	Blinded expert ratings (validated 9-item anatomy + dexterity tool; interrater $r = 0.92\%$)	First AI to automatically and objectively assess bronchoscopy skills in simulation, supports mastery learning
	Real-time navigation/feedback console (Cold et al. [4])	20 novices, single-session RCT	Diagnostic-completeness ↑ +3.5 segments; structured-progress ↑ 14 points; procedure time ↓ 214 s	Written checklist	Mastery learning with AI feedback outperforms traditional directed practice
	AmbuBronchoSimulator-TrainingGUIDE v0.0.1 (Cold et al. [15])	Randomized crossover study; 101 participants grouped by experience	Diagnostic-completeness ↑ +6 segments; structured-progress ↑ +5.2 points. Strongest effect in novices.	Standard bronchoscopy without AI guidance	AI guidance improved completeness and structure of bronchoscopy across all experience levels
	"AI-co-pilot" bronchoscope robot (Zhang et al. [16])	Sim + porcine in-vivo; novice vs expert	Success rate 93%; path error 11.4 pixel	Senior bronchoscopist 92%, 16.3 pixel	Shared-control robot lets novices steer as safely as experts; potential to bridge workforce gaps
	Ambu Broncho Simulator bronchoscopy training (Agbontaen et al. [13])	Nonblinded, parallel group randomized controlled trial, 40 participants	MIT 8 s shorter, PT 77 s shorter in AI guided group	Expert tutored group	AI training resulted in faster and more efficient bronchoscopy performance by critical-care physicians

(Continues)

TABLE 1 | (Continued)

Clinical/ Training task	Representative AI system (year)	Study design and *N* (trainees/Patients/ Images)	Best-reported metrics[a]	Human benchmark	Key take-aways
Macroscopic airway inflammation	BScore (Eg et al. [12])	Prospective, 142 children	aROC 0.84 (BScore vs. BAL-neutrophilia > 10%)	None (biological gold standard)	Simple 6-item score (secretions amount & color, oedema, ridging, erythema & pallor) converts subjective impressions to reproducible severity grading
CADx for EBUS/ EB-OCT	EBUS-CAD system (Hotta et al. [8])	26,670 EBUS images (42 lesions)	Sens 95%, Spec 53%, AUC 0.84	Four experienced bronchoscopists Sens 80%, Spec 40%	Deep nets equal or surpass specialists for LN malignancy prediction; real-time overlay feasible
	CNN based EB-OCT image analysis (Zhou et al. [17])	17,820 OCT images (33 patients)	Dice similarity coefficient: 0.97 (Ai), 0.95 (Aw)	Manual EB-OCT measurements by clinicians	CNNs achieved expert-level accuracy in airway measurements, reducing workload and bias.
Foreign-body aspiration triage	Custom CNN on PA-CXR (Coskum et al. [11])	110 CXRs (47 suspected FBA)	Sens 94%, Spec 98%	MLR model Sens 77%, Spec 98%	CNN-DL demonstrated high accuracy significantly reducing negative bronchoscopies rate

Note: This table summarizes selected evidence on AI or related tool development in bronchoscopy, highlighting the study population, purpose, and main findings relative to human performance.
Abbreviations: AIBA, AI bronchoscopy assessment; CADx, computer aided diagnosis; CNN, convolutional neural networks; CXR, chest x-ray; DL, deep learning; EB, endobronchial; EBUS, endobronchial ultra-sound; FBA, foreign body aspiration; LN, lymph node; MIT, Mean intersegmental time; MLR, multiple logistic regression; OCT, optical coherence tomography; PA, postero-anterior; PT, procedure time.
[a]Highest values were reported for the primary end-point in each paper.

BOX 3 | Major challenges to implementation.

Challenge	Key points
Data scarcity	Few pediatric datasets; reliance on adult/single-center data
Annotation	Frame-by-frame labeling by pediatric experts is resource-intensive
Bias and generalizability	Variability in airway size, equipment, and populations limits robustness
Workflow integration	AI must be intuitive and non-obtrusive in the bronchoscopy suite
Regulation and ethics	Approval frameworks evolving; liability questions unresolved

video databases, including normal variants and a spectrum of pathologies. Efforts to share de-identified video data are hampered by data protection regulations and technical issues, but without such data, pediatric AI models will lag in accuracy. Çoşkun et al. explicitly note that larger multi-center datasets are needed to validate and improve their pediatric FBA model [11]—this applies across all pediatric AI endeavors.

5.2 | Annotation Bottleneck

Closely tied to data quantity is data quality and annotation. Bronchoscopic videos require laborious frame-by-frame or segment-by-segment labeling by experts for supervised learning. Getting multiple experts to label data (for consensus) is even harder. For pediatric cases, few people have the expertise (pediatric pulmonologists are relatively few), and their time for such tasks is limited. Innovative solutions like crowd-sourcing annotations to trainees or using semi-supervised learning will be needed. Additionally, establishing standard labeling criteria (e.g., what defines “significant secretions” in a video frame) is important so that AI models learn consistent patterns.

5.3 | Bias and Generalizability

AI models can inadvertently learn biases present in the training data. For instance, if all foreign body cases in a training set had right lung hyperinflation on X-ray, the model might latch onto “right lung looks bigger” as a sole criterion, potentially misclassifying other causes of air-trapping as foreign bodies. In a bronchoscopy video, differences in endoscope type, camera quality, angle, and lighting can all affect the visual appearance and introduce bias. A model trained in one tertiary pediatric hospital may underperform when applied to institutions with different patient populations, instruments, or procedural protocols. Rigorous external validation is essential—testing the AI on data from other hospitals or diverse patient groups—is critical to ensure generalizability. So far, very few bronchoscopy AI systems have undergone external validation. Dealing with bias also means making the models robust to variations: for example, Yoo et al. improved robustness by augmenting training images with random rotations and occlusions, since bronchoscopy can have any orientation and sometimes the view is partially obscured [5]. Future pediatric studies should similarly augment data (e.g., simulate mucus obscuring the lens, varying lighting) to ensure the AI is hardy against real-world conditions.

5.4 | Regulatory and Safety Hurdles

Introducing AI into a clinical tool requires regulatory approval and careful safety considerations. AI outputs in bronchoscopy (like a real-time alert or a navigation suggestion) could directly influence patient care; thus, they must be reliable. Regulatory frameworks (FDA, EMA, etc.) for AI in medical devices are still evolving [18, 19]. There is a need for clear standards on performance thresholds, validation requirements, and post-marketing surveillance for AI-driven bronchoscopic systems. For pediatric use, regulators will likely be even more cautious. Ensuring cybersecurity and patient data protection when AI systems possibly connect to hospital networks is another aspect. Implementation strategies will have to include clinician training on how to interpret AI feedback and what to do if the AI malfunctions (e.g., if an “anatomy guidance AI” fails mid-procedure, the bronchoscopist should be able to carry on safely).

5.5 | Integration Into Workflow

Even a perfectly accurate AI is of little use if it does not integrate smoothly into the bronchoscopy workflow. Bronchoscopists already manage a lot during procedures—visualizing the field, controlling the scope, attending to the patient's vital signs, communicating with the anaesthetist, instructing assistants, and so on. AI tools must present information in an intuitive and non-obtrusive manner. Early prototypes have tried heads-up displays or simple on-screen labels. There is a fine line between providing helpful assistance and distracting the operator. Human factors research will be needed to determine how best to deliver AI outputs (audio alerts? visual indicators? haptic feedback?) in pediatric bronchoscopy, where patient safety margins are smaller. Additionally, integration with existing systems (bronchoscope video processors, hospital PACS, etc.) will require technical development and standardization.

5.6 | Clinician Acceptance and Training

Pediatric bronchoscopists may naturally be cautious about AI. Some may worry that reliance on AI could deskill trainees or even threaten the role of specialists. A common question is, “Will AI replace bronchoscopists?” In reality, AI is expected to augment rather than replace clinicians. Bronchoscopists will remain crucial for their judgment, adaptability, and for tasks AI cannot handle (manual dexterity of scope manipulation, nuanced decision-making, management of complications, and the all-important communication with patients and families). Effective use requires training to understand AI's capabilities and limits. Endoscopy consensus guidelines provide a framework for validating AI tools, measuring their impact (e.g., lesion detection rate), and integrating them into clinical practice with safety and quality in mind [20]. But building trust will take time, supported by positive experiences and realistic expectations. This reflects the broader principle of "augmented intelligence," keeping physicians central while using AI as a supportive tool.

5.7 | Ethical and Medicolegal Issues

Using AI in pediatric care raises ethical considerations. Consent processes may eventually need to disclose AI involvement (e.g., "We will use an AI system to assist during your child's procedure"). Families might have questions about that—clinicians should be prepared to explain in simple terms. Medicolegal liability is also a gray zone: if an AI fails to detect something that a human also missed, is it considered standard error or product liability? Conversely, if an AI suggests a course (like "this area looks abnormal, biopsy here") that the physician ignores, and a lesion is later found, could not following the AI be seen as negligence? These scenarios will likely be adjudicated in time, but until then, a prudent approach is to use AI as confirmatory or adjunct information rather than a sole decision-maker. Professional societies and regulatory bodies are beginning to issue guidance on AI in clinical practice, which will help clarify responsibilities.

In summary, the road to routine AI deployment in pediatric bronchoscopy has obstacles ranging from data scarcity and bias to workflow integration and human acceptance. Each of these challenges is being actively addressed in ongoing research. Importantly, none appear insurmountable – they will require thoughtful engineering and close collaboration between clinicians, data scientists, and regulatory entities. The next section looks ahead to future directions, describing how these challenges may be overcome and painting a picture of an AI-assisted bronchoscopy service of the future.

6 | Future Directions and Utopian Vision

Given the current trajectory, the coming years are likely to bring rapid progress in AI for bronchoscopy. Here we outline future directions and present a forward-looking "utopian" scenario for pediatric bronchoscopy in the age of AI (see also Box 4).

6.1 | Near-Term Research Agenda

In the immediate future, priority should be given to validation and implementation studies. Thus far, most AI systems have been tested on retrospective data or in simulations. Prospective trials in real pediatric bronchoscopies are needed to answer questions like: Does an AI tool actually improve diagnostic yield or reduce procedure time in live cases? Does using AI guidance lead to better patient outcomes or fewer complications? Only with such evidence can widespread adoption be justified.

Simultaneously, efforts should focus on data infrastructure: establishing pediatric bronchoscopy video repositories, perhaps through international societies or registries, where data (with proper consent and de-identification) can be pooled. This will facilitate the training of pediatric-specific AI models and reduce bias. Techniques like federated learning (where an AI model is trained across multiple institutions' data without the data leaving each institution) could be leveraged to surmount data-sharing barriers while protecting privacy.

6.2 | Advances in AI Techniques

On the technical front, we anticipate more sophisticated models that can handle the full video stream in real-time, rather than single-frame analysis. This might involve combining computer vision with temporal models (e.g., LSTM or transformer networks) so that the AI considers the sequence of bronchoscopic views, much like an experienced bronchoscopist mentally notes where they have been and where to go next.

Multimodal AI is another exciting area—combining visual data with other inputs. For instance, an AI could integrate the live bronchoscopic video with the patient's chest radiograph, CT scan, vital signs, or other real-time sensor data (like the scope's orientation or ultrasound images in an EBUS) to provide a richer analysis. Another frontier is semi-supervised and unsupervised learning: AI that learns from unlabeled bronchoscopic videos by detecting patterns or anomalies on its own. This could alert clinicians to unusual findings that might not be part of a pre-defined classification (useful in rare pediatric diseases).

BOX 4 | Future directions.

Focus area	Key points
Validation	Prospective pediatric trials needed to prove clinical benefit
Data infrastructure	Multi-center repositories; federated learning to share models without moving data
Advanced models	Real-time video analysis, multimodal AI, unsupervised anomaly detection
Robotics	AI "co-pilot" could enable novice or remote bronchoscopy at expert safety levels
Augmented scope	Overlays showing anatomy, pathology, adequacy of biopsy

6.3 | Integration With Robotic Bronchoscopy

The line between AI and robotics is blurring. Robotic-assisted bronchoscopy platforms (such as the Monarch and Ion systems for adults) are already in use for reaching peripheral lung nodules, albeit not yet in pediatrics (due to scope size limitations and scarcity of indications). The study by Zhang et al. points to an AI-robot hybrid approach: an "AI co-pilot" that actively guides the robotic bronchoscope's movements [16].

In the future, pediatric-sized robotic bronchoscopes could be developed, incorporating AI to allow even novice operators to navigate delicate pediatric airways safely. This could dramatically extend specialized bronchoscopy services to areas lacking experienced pediatric bronchoscopists—a local physician could perform bronchoscopy on a child under the watchful eye of AI guidance and even tele-mentoring by an expert remotely. In a utopian vision, no child would need to be transferred far from home for a bronchoscopy; AI-enabled systems would ensure that the procedure can be done safely and effectively at regional centers with remote support. This once futuristic vision has already begun to materialize: a recent study demonstrated the successful removal of a foreign body from a pig's lung using a low-cost robotic bronchoscope enhanced by AI and connected via 5G, operated remotely from 1500 km away [21]. This striking proof-of-concept illustrates the disruptive potential of combining AI and tele-robotics in bronchoscopy.

6.4 | Real-Time Diagnostic Aids

The bronchoscope of the future might function as more than a camera—it could be a smart sensing device. One can imagine an "augmented bronchoscope" that not only shows the operator the airway but also overlays information: for example, "this lesion has an 85% chance of being granulomatous," "biopsy adequate—diagnostic cells identified" or "residual peanut fragment seen in right main bronchus." Achieving this will require tying together various AI components: computer vision, perhaps spectroscopy or other advanced imaging modalities (some research is exploring AI with bronchoscopy-linked optical coherence tomography or autofluorescence imaging to detect dysplasia) [17]. In pediatrics, a compelling application is AI's ability to quantify conditions that are difficult to grade visually, such as tracheobronchomalacia, and detect subtle airway changes in graft-vs-host disease that are currently not apparent on standard bronchoscopy.

6.5 | Personalized Bronchoscopy and Prediction

Another future direction is using AI to predict outcomes or tailor interventions. For example, by analyzing a combination of bronchoscopic findings and clinical data, an AI might predict which child with chronic suppurative lung disease is likely to benefit from a specific antibiotic or from a follow-up bronchoscopy. This crosses into the realm of big data and predictive analytics, integrating bronchoscopy results with electronic health records. It aligns with the trend toward personalized medicine—AI could help stratify pediatric patients by risk and need, ensuring bronchoscopies are done on those who truly need it and that the procedure yields actionable information.

6.6 | Human–AI Collaboration

In the ideal future scenario, pediatric bronchoscopists will work in tandem with AI systems to provide superior care. Picture a bronchoscopy suite in 2030: The bronchoscopist wears smart glasses that display the live video with AI annotations. As she navigates the child's airways, the AI quietly highlights each segment's name, notes areas that haven't been seen yet, and gently suggests, "Consider inspecting the right middle lobe bronchus before concluding—not fully visualized." A difficult-to-see peanut fragment hidden in the periphery is outlined by the AI in the video feed, alerting the physician to retrieve it, highlighting which device might be best suited for the procedure. Simultaneously, the AI is continuously monitoring oxygen saturation, heart rate, and end-tidal CO_2, as well as scope position, cautioning if a loss of stability is imminent. Once the bronchoscopy is done, the AI assembles a preliminary report: it documents which segments had inflammation, any dynamic collapse observed (with severity grading), and attaches annotated images of key findings. The physician reviews this draft, makes edits (thus also providing feedback to improve the AI's future performance), and finalizes the report within minutes after the procedure—a task that used to take much longer. Throughout, the pediatric patient experiences a smoother procedure with potentially shorter anesthesia time because the intervention was efficient and targeted.

In this envisioned setting, patient safety and comfort are maximized, diagnostic yield is near optimal (few things go unseen or unnoticed), and the bronchoscopist is empowered rather than replaced—focusing on medical decision-making and communication while the AI handles rote tasks and provides a safety net. Such a vision will require continued interdisciplinary

BOX 5 | Take home messages.

Theme	Key points
Stage of field	Promising but early; most data from pilot or adult studies
Evidence	AI matches or outperforms experts in anatomy ID, FBA detection, and training tasks
Barriers	Pediatric data scarcity, annotation bottleneck, and lack of external validation
Outlook	Collaboration across centers and disciplines essential
Clinical role	AI will augment, not replace, pediatric bronchoscopists

research and likely some breakthroughs, but the building blocks are already visible in today's early studies.

It is important to remain grounded: even the best AI will not eliminate all uncertainties or complications. And there will always be a need for clinical judgment—knowing when not to trust the AI, or when a patient's needs dictate a course of action contrary to algorithmic suggestion. However, if the current momentum continues, AI is set to become an invaluable partner in pediatric bronchoscopy. Embracing this technology and guiding its development with pediatric-specific insights will ensure that the unique needs of children—from smaller instruments to gentler procedures and a focus on long-term outcomes—are central in the AI revolution of bronchoscopy (Box 5).

Author Contributions

Patrick Stafler and Saharon Less Elazari conceived the article and collaboratively reviewed and interpreted the evolving literature on artificial intelligence in pediatric bronchoscopy. Patrick Stafler drafted the original manuscript, coordinated the overall scientific narrative, and integrated the clinical and technological perspectives presented in the review. Saharon Less Elazari provided substantial critical revision and contributed to the refinement of the manuscript's intellectual content and clinical interpretation. Both authors contributed to the final synthesis of the work, approved the submitted version, and accept responsibility for the integrity and accuracy of the manuscript. Patrick Stafler acted as the senior author and supervised the study conception and manuscript preparation.

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Ethics Statement

Because this work did not involve patient data, review and approval by an institutional review board were not required.

Conflicts of Interest

The authors declare no conflicts of interest.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used various models of Chat GPT (Open AI) to improve language and readibility. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Data sharing not applicable to this article as no datasets were generated or analyzed during the current study.

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