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The rise of artificial intelligence in respiratory primary care and pulmonology: a scoping review

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Artificial intelligence (AI) is rapidly advancing respiratory disease management, from diagnosis to population lung health. This scoping review synthesizes the most promising uses of AI in respiratory medicine, with a particular focus on pulmonologists and family physicians interested in lung health. In diagnostics, deep-learning systems streamline chest-imaging workflows by triaging radiographs, detecting COVID-19 pneumonia, and classifying lung nodules on CT. In pulmonary function testing, algorithms detect technical errors and classify spirometric patterns, some claiming to outperforming pulmonologists. Acoustic analysis of cough, breathing, and speech captured on smartphones or wearables offers non-invasive decision support. For monitoring and prediction, AI helps shorten weaning from mechanical ventilation and guides closed-loop strategies for acute respiratory distress. In chronic care, connected devices integrated with environmental data help to forecast asthma and COPD exacerbations, while telehealth and predictive models enable earlier, more personalized interventions. Additional gains are emerging in paediatrics, sleep medicine, lung ultrasounds, and public health. Realizing these benefits will require rigorous multicentre validation and real-world evidence. It will also require proactive bias detection and mitigation with inclusive sampling and equity audits. High-quality, interoperable data and explainable models are needed to enable human oversight. Practical issues such as digital literacy, device access, and usability for children, older adults, and other vulnerable populations also matter for applications requiring patient interaction. With sustained collaboration among clinicians, engineers, AI experts, industry, regulators, and scientific societies, AI can increase the time invested in a satisfactory clinician-patient relationship. With all likelihood, AI can also measurably improve efficiency and accuracy across multiple domains of respiratory care.

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FROM EXPERT SYSTEMS TO LARGE LANGUAGE MODELS: A BRIEF TIMELINE OF AI IN RESPIRATORY MEDICINE

Artificial Intelligence (AI) is triggering a profound transformation across all industries, including medicine. And pulmonology is no exception. AI is set to redefine diagnostic processes, treatment selection, prevention programme design, and chronic disease management. With ever-growing computing power and increasingly sophisticated algorithms, these systems can detect subtle patterns in the vast volumes of complex and heterogenous medical data now available, enabling more accurate and timely clinical decisions.

AI is formed by a plethora of tools, and virtually all of them have been applied to medicine in general and respiratory medicine in particular. For instance, expert systems, one of the fist techniques of symbolic AI[1], were developed focusing on automated clinical diagnosis[2]. These models were later refined by the introduction of probabilistic consideration, which allowed for instance applications to ICU ventilation monitoring[3]. Later, machine learning (ML) shifted the paradigm to extract patterns directly from the data rather than relying on expert-defined rules[4]. Within the available models in this realm, decision trees have been particularly useful for solving classification problems (such as assigning a diagnosis) as a series of transparent questions. More powerful classifiers, such as artificial neural networks (ANN), have been adapted to deal with complex data, such as in the case of convolutional networks (like those applied to the pixels in a medical image) or recurrent networks (which can deal with time series).

Natural language processing (NLP) opened another door, making it possible to convert the unstructured information of electronic health records (EHR) into structured data that could be analysed with the same statistical tools as those used for conventional numerical variables. Generative AI and large language models (LLMs) have recently opened new horizons. Trained on extensive corpora of medical text, these systems can extract structured information from unstructured clinical notes, assist in drafting documentation, synthesize clinical evidence, and support decision-making.

Respiratory medicine presents a uniquely fertile ground for AI innovation due to its wealth of intrinsically complex data sources, either unimodal or multimodal. The field is rich in high- or low-resolution imaging data from CT scans and X-rays, objective and standardized PFT waveforms, and analyzable respiratory acoustics like cough and breath sounds. Furthermore, the chronic and episodic nature of many respiratory diseases generates extensive longitudinal monitoring data from wearables and population-level surveillance data for illnesses like influenza and COVID-19. This convergence of diverse, mostly structured, and often time-series data provides an ideal substrate for developing and validating sophisticated AI models that can assist in diagnosis, phenotyping, prediction, and personalized management.

In respiratory medicine overall, a growing body of applications already demonstrate the remarkable potential of AI to transform clinical practice[5,6], This scoping review examines these developments in detail, identifies emerging opportunities for innovation, and considers the limitations and challenges that must be

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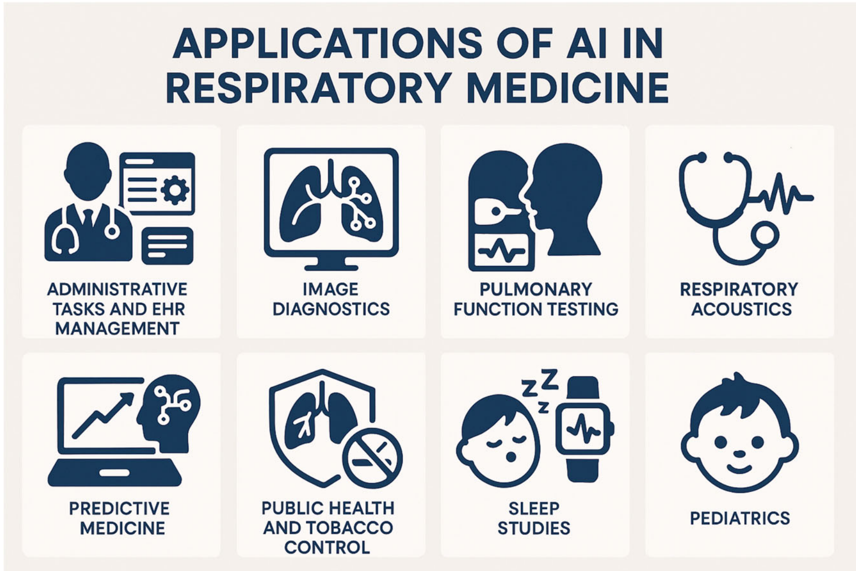

Fig. 1 Applications of AI in Respiratory Medicine. This figure was generated by Microsoft copilot.

overcome to ensure AI is safe, effective, and can have an equitable integration into respiratory care.

A scoping review maps the landscape of evidence on a research topic differently than a systematic review. The goal is to identify the volume, variety, and characteristics of the evidence. Therefore, scoping reviews do not follow EQUATOR's PRISMA guidance[7,8], Importantly, the primary purpose of scoping reviews is to identify gaps, clarify concepts, or examine how research is conducted. Most importantly, the search strategy is extensive and iterative, but the goal is representativeness, not absolute completeness. Finally, synthesis for scoping reviews is narrative and descriptive of the body of literature, presenting an overall overview, not a combined result as per a systematic review and certainly without meta-analyzing any quantitative outcomes.

The search terms that we used to obtain evidence were organized in two large blocks, where each is composed of several other sub-terms. The first block describes the technology and the second the application. The specific terms were: ('Artificial Intelligence*' OR 'AI' OR 'Machine Learning' or 'ML' OR 'Expert System' OR 'Pattern Recognition' OR 'Voice analysis' OR 'Large Language Models') AND ('Pulmonary.' OR 'Respiratory care research.' OR 'critical care' OR 'ICU' OR OR 'Public Health' OR 'Smoking' OR 'Respiratory acoustics' OR 'Sleep' OR 'Pulmonary Function Testing' OR 'Tobacco' OR 'Paediatrics' OR 'Diagnosis' OR 'Treatment) (See Online Appendix). We searched in Google Scholar and PubMed for publications in English up to June 2025. These terms were not defined at once at the beginning of the search, but were iteratively enlarged while studying the identified literature, with the aim of enhancing representativeness (e.g. after finding an article commenting on respiratory acoustics, the term was added in order to find other similar papers). Searches were performed by subset in the OR blocks to guarantee the representation of all the terms considered. Although results were retrieved both in terms of citations and relevance, our final criterion for selection was interest, potential impact and representativity[9].

APPLICATIONS OF AI IN RESPIRATORY MEDICINE: A WIDE LANDSCAPE OF OPPORTUNITY

Respiratory innovations have already translated into a broad range of applications with substantial potential—from imaging diagnostics to remote monitoring and personalized medicine—even if some have not been widely adopted in clinical practice, as most remain at the research stage, illustrating the promise of what AI could achieve in the mid to long-term. Strategic investment in refining these technologies and addressing their technical and ethical challenges, discussed later in this review, could lead to substantial improvements in the practice of respiratory care. Find next an abridged list (Fig. 1),

Efficiency gains in administrative tasks may not appear exciting. However, they represent a major opportunity for immediate impact. Estimates vary, but recent studies suggest that U.S. physicians spend nearly 50% of their time interacting with EHRs[10]. AI, particularly generative AI, can reduce this burden by enabling systems that can transcribe clinician–patient conversations, generate preliminary EHR entries, and streamline documentation. Once verified by the physician, these systems could significantly enhance workflow efficiency and reduce time spent on administrative tasks.

Image diagnostics have seen impressive advances across all medical specialties, including respiratory diseases. As early as 2019, it has been widely claimed that AI already performs comparably to clinicians in most diagnostic settings[11].

AI has proven highly effective in respiratory care for screening and early detection within radiology workflows. Deep neural networks can pre-screen chest radiographs to identify likely-normal studies, allowing urgent cases to be prioritized. This has achieved performance comparable to expert radiologists and reduced reporting time for critical cases from an average 11.2 to only 2.7 days (Fig. 2)[12]. Very recently, fast and accurate contour propagation with deep learning-based methods in lung cancer improved significantly the efficiency of MR imaging-guided radiotherapy. (Fig. 3)[13].

One of the most recognized examples of AI-aided diagnosis emerged in 2020, when ML helped identify COVID-19 from chest X-rays. This supported the detection of pneumonia patterns during high clinical demand, especially when PCR testing was unavailable[14].

In thoracic CT, advanced architectures now accurately classify lung nodules, improving early lung cancer detection and enabling more standardized interpretations. For instance, TransUnet has demonstrated excellent performance in distinguishing benign from malignant nodules on CT[15]. Similar results were reported by integrating a clinical and a radiomic model based on deep learning to predict the malignancy of pulmonary nodules,

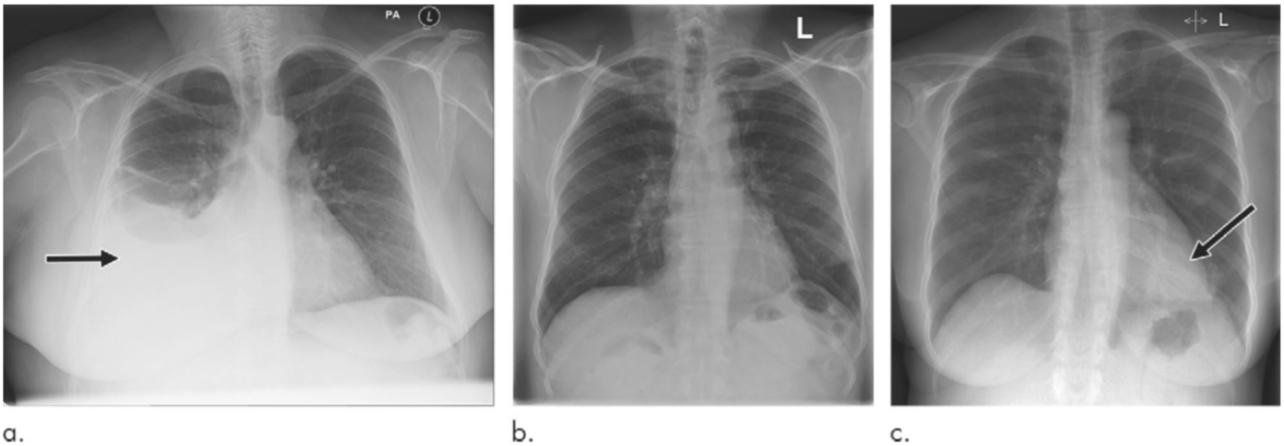

Fig. 2 Examples of correctly and incorrectly prioritised radiographs (from ref. [12]). a Radiograph was reported as showing large right pleural effusion (arrow). This was correctly prioritised as urgent. **b** Radiograph reported as showing “lucency at the left apex suspicious for pneumothorax.” This was prioritised as normal. On review by three independent radiologists, the radiograph was unanimously considered to be normal. **c** Radiograph reported as showing consolidation projected behind heart (arrow). The finding was missed by the artificial intelligence system, and the study was incorrectly prioritized as normal.

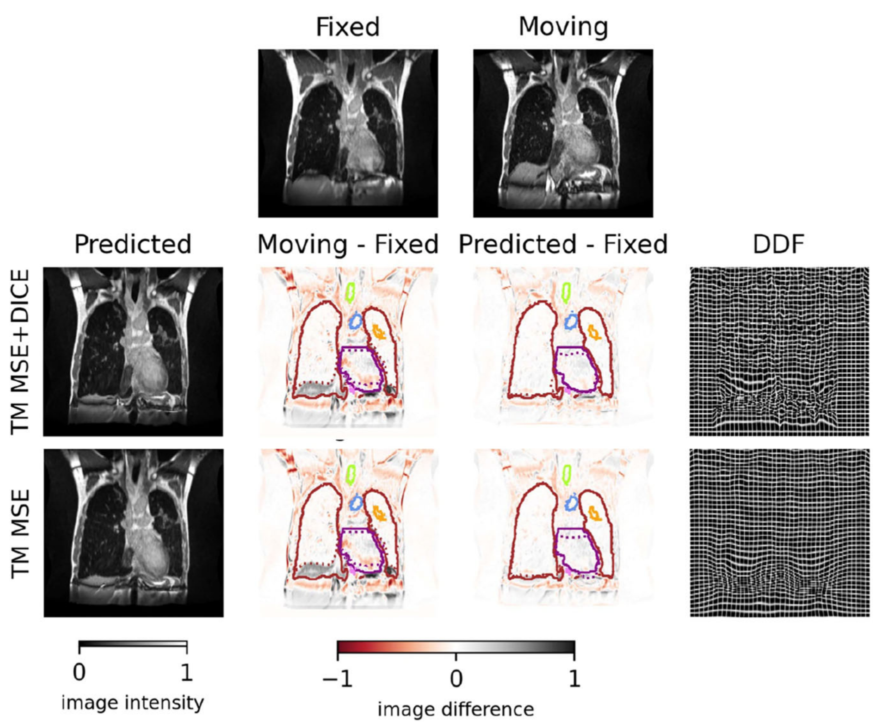

Fig. 3 Deformations of an example test patient (from ref. [13]). The fraction image was fixed, and the planning image was registered to the fraction image as a moving image. The differences between moving and fixed images and predicted and fixed images are shown in the center, where the dashed lines represent the moving or predicted contours and the solid lines represent the fraction contours. The right column shows a grid image warped by the deformation fields (DDF).

boosting predictive performance and significantly improving lung cancer diagnosis[16].

ML also shows promise in diagnosing respiratory conditions with overlapping symptoms, such as asthma and COPD[17].

However, noted by Shen and colleagues, most AI diagnostic tools lack rigorous external validation, not fulfilling observational research STROBE[18] or TRIPOD minimums[19], which can lead to serious issues. As we will discuss later, stricter development protocols will be essential to fully harness AI’s diagnostic potential and foster effective collaboration between humans and machines.

Pulmonary function testing (PFT), especially spirometry, shows significant promise for improvement through AI. Although PFTs are essential for diagnosing and monitoring disease, their accuracy depends heavily on patient effort (often incomplete), technician skill (frequently inconsistent in enforcing a maximal effort, correct posture, a tight mouth seal and nose clip, or other protocolised minimums), and precise equipment handling. These dependencies contribute to frequent errors that affect spirometry conducted either in lung function laboratories or at Primary Care, harming key indicators such as FVC, FEV_1, and the FEV_1/FVC ratio[20].

AI can be trained on large, carefully curated datasets to recognize and correct common error patterns. Topalovic M, et al.[21], showed that AI outperformed pulmonologists in classifying obstructive, restrictive, and mixed spirometric patterns.

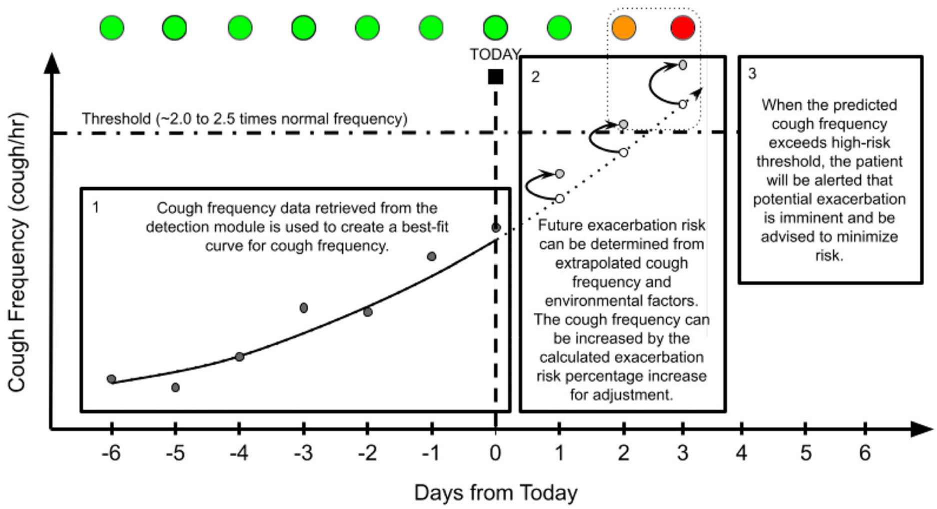

Fig. 4 Illustration of the procedures implemented within the prediction module that forecasts the expected progression of the condition of the patient in the days ahead (from ref. [32]). This final step in the multi-modal architecture combines the results from the respiratory sound analysis performed by the machine learning model of the detection module, and the environmental and meteorological factors and trends analysis conducted by the environmental module. By extrapolating the cough frequency trends by taking cough frequencies in future days from a best-fit curve, along with the predicted exacerbation risks due to the environmental and meteorological data, the system can alert the patient and caregivers of the imminent risks and pre-empt medical interventions to potentially reduce hospitalization costs. A green circle represents a day where the adjusted cough frequency is lower than the threshold, orange represents a day when the adjusted frequency is higher than the threshold, and red represents a day when the original cough frequency exceeds the threshold. Orange and red are "danger" zones.

AI is also advancing quality assurance. A deep learning-based system can detect suboptimal manoeuvres during forced spirometry (for example, incorrect FVC efforts), ensuring more standardized and reliable measurements[22]. Recently, an AI-powered evaluation of lung function significantly improved diagnosis of interstitial lung disease, more accurately and earlier[23].

Respiratory acoustics offer a non-invasive approach to diagnosis by analysing recordings of coughs, breathing sounds, and speech. These recordings can be captured using everyday devices such as mobile phones or wearable microphones and analysed automatically. Recent work has shown that audio-based diagnostics perform well across a range of respiratory conditions and are progressing toward clinical use through commercial tools. For example, ResApp, a smartphone application acquired by Pfizer in 2022[24], demonstrates the potential of such tools to provide low-cost alternatives to in-person visits and to enable continuous remote monitoring.

A representative application of respiratory acoustics is automatic cough detection. You et al., developed an AI-based system to identify cough episodes from real-world audio recordings[25]. Beyond cough detection, researchers are investigating features of both speech and breathing sounds as digital biomarkers of respiratory function. These methods allow algorithmic analysis of acoustic signals from both the upper and lower airways, supporting the identification and diagnosis of various respiratory conditions[26]. However, in real-life conditions, even with the assistance of AI tools, accurately identifying respiratory sounds such as crackles and wheezing remains challenging. And so far unreliable for medical decision-making[27].

In predictive medicine, AI is increasingly used to predict future onset of clinical events and tailor therapy across various care settings. A particularly notable application is in critical care. For instance, Liao et al., developed a system to optimize the weaning process from mechanical ventilation. Their system successfully reduced the average duration of mechanical ventilation by half a day[28]. Complementing this, optimized closed-loop ventilation strategies—which model lung mechanics in real time—can minimize transpulmonary driving pressure in patients with acute respiratory distress syndrome (ARDS). Intelligent Adaptive Support Ventilation, developed by Buiteman-Kruizinga et al., maintains optimal settings more consistently, reduces episodes of low blood oxygen (hypoxemia), and accelerates the return to spontaneous breathing[29].

For chronic respiratory diseases, such as asthma and chronic obstructive pulmonary disease (COPD), remote monitoring through wearable and connected devices—including portable spirometers, respiratory rate sensors, oxygen saturation monitors, and cough trackers—can be integrated with environmental data such as temperature, humidity, airborne allergens, pollution, and ozone levels to forecast disease risk. Within this ecosystem, platforms like myAirCoach combine mobile health (mHealth) tools with home-monitoring sensors and AI to predict asthma exacerbations. Early studies show potential for reducing the severity of these episodes and improving quality of life[30,31], Methodologically, hybrid spatio-temporal AI models, which analyze clinical and environmental data, have shown promise in forecasting respiratory disease exacerbations (Fig. 4)[32]. Very recently, by using routinely collected longitudinal health records of Scottish primary care data for 21,250 asthma patients were used to help predicting (Area under the Curve of 0.75) the risk of asthma attacks in the following year.[33].

On the care coordination side, telehealth platforms and medical chatbots support timely patient evaluation and clinical escalation. Earlier tries included 24-hour, 7-day a week doctor and nursing support of Telemedicine[34]. The patient-clinician relationship has been deeply affected by the emergence of these new tools for self-management[35]. A particularly relevant example is the Global Initiative for Asthma (GINA), which emphasizes structured cycles of personalized self-management. These include identifying individual triggers, adjusting medication, and receiving remote support for long-term asthma control (Fig. 5)[36].

In **public health**, apps like HEpiTracker have supported hospital-based COVID-19 monitoring, enabling syndromic surveillance and protecting healthcare workers[37]. Beyond surveillance, AI enhances logistics and facilitates targeted health-promotion campaigns[38]. ML helps identify priority audiences, and recent studies underscore the value of positive, resonant messaging for lung health at the population level[39].

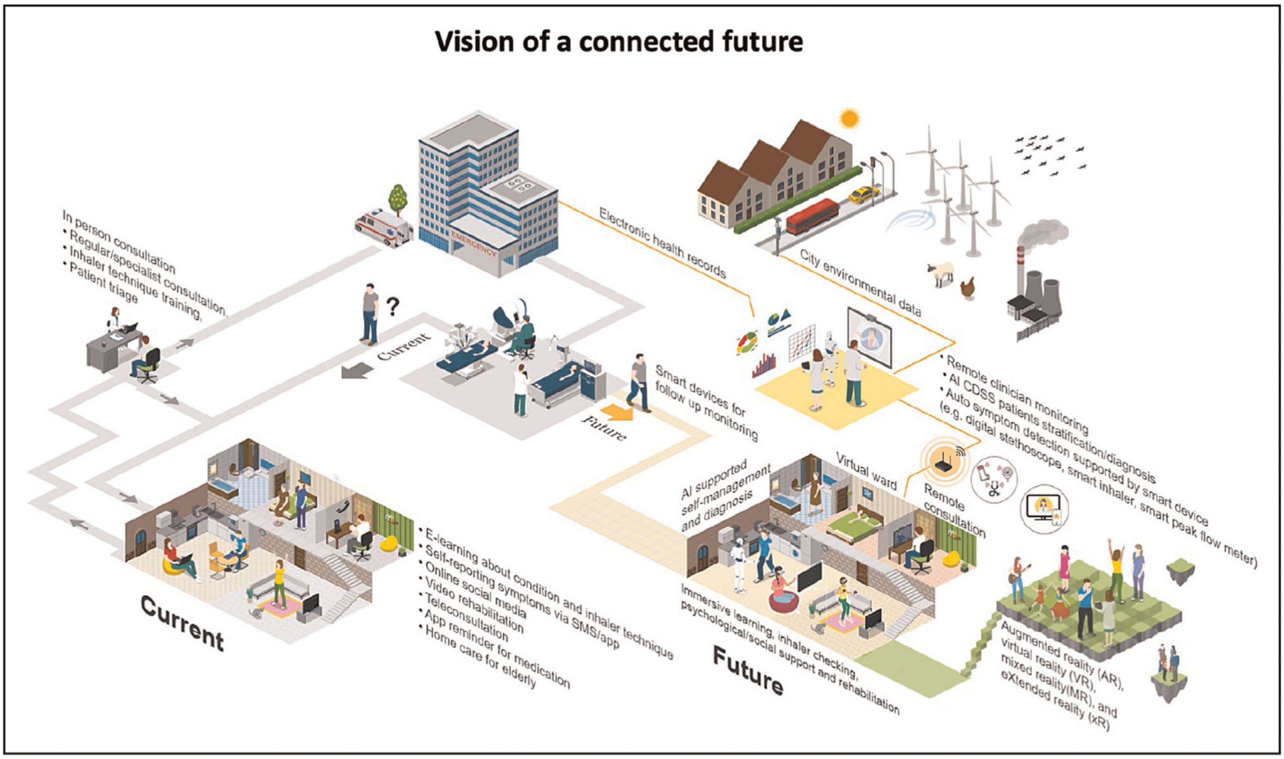

Fig. 5 Vision of a connected future (from ref. [36]). On the left is the traditional referral pathway as the patient attends a clinic, may be referred to a hospital for tests or treatment and discharged home. Promising digital innovations exist (tele-consultations, on-line information, social fora, apps and reminders) are available but typically stand alone. Primary care and hospital use EHRs but interoperability with different sectors or with patients is limited/non-existent. On the right is a vision of an interconnected system in which AI-supported self-management advice and clinical decision support is informed by a fully interoperable system. AI can use data from all these sources to tailor information provision and health promotion, monitor disease and environmental status and alert to increased risk, detect attacks and advise self-management actions, deliver home-based treatments (such as rehabilitation, hospital at home, psychological treatments) and provide social support and monitoring.

In **tobacco control**, ML models identified unique population-level predictors for U.S. adolescents for vaping use and associated behaviours across a spectrum of populations[40]. AI complemented standard epidemiologic survey data and identified a potential to explore personal experiences with cannabis, ENDS, and tobacco products[41]. ML was used to determine the risks of ever-vaping and daily vaping in youngsters, and enabled the identification of essential correlates and complex intersections to customize public health policies for targeted population subgroups[42]. As a first step toward personalized care for smoking cessation, by using a novel ML approach with baseline measures of clinical and executive functioning, researchers were able to predict smoking cessation outcomes following a group enrolled in cognitive behavioral therapy[43].

AI is increasingly applied in **sleep studies**, either in laboratory polysomnography (PSG) or in wearable devices. Since the early 1990s, computer-aided tools have reduced inter-rater variability in sleep staging and enabled automatic detection of sleep features, such as spindles, sleep depth, delta duration, and even predicted awakenings[44]. The Somnolyzer 24 × 7, an e-health solution for automated sleep classification, has shown strong reliability and clinical applicability[45]. Extending beyond the lab, wearable systems now detect abnormal respiratory events during home sleep apnea testing, supporting screening and at-home evaluation[46].

In **lung ultrasounds**, there are also uses of AI in enhancing them as a way to provide low-radiation, hand-held, real-time assessments in low-resource or austere environments, and possibly by non-experts, such as in pleural effusions[47], or more generally to discern normal versus abnormal lung parenchima[48].

Finally, AI may be especially promising in **Paediatric Pulmonology**, where more homogeneous patient populations can improve model performance. Current applications focus on three main areas: respiratory sound analysis, chest image interpretation, and pulmonary function test evaluation[49]. For instance, CAD4Kids achieved over 85% sensitivity in diagnosing childhood pneumonia from chest X-rays, aligning with WHO-defined endpoints[50]. AI tools also predict asthma control deterioration, with reported sensitivity and specificity above 70%[51]. Finally, such technology can be used to significantly enhance asthma adherence (Fig. 6)[52].

Ultimately, AI can relieve Primary to Tertiary clinicians of repetitive work, enabling them to refocus on the art of the doctor-patient relationship[53], and improve performance by shortening turnaround times, increasing accuracy in triage and image interpretation, and improving quality control. These gains could translate into faster, more precise, and more individualized care. However, realizing this promise requires rigorous external validation on multicentre datasets; proactive bias detection and mitigation with inclusive sampling and equity audits; high-quality, interoperable data under strong governance aligned with initiatives such as the European Health Data Space; privacy-preserving approaches like federated learning and high-fidelity synthetic data; and explainable, auditable models kept under human oversight. Any post-deployment surveillance of AI models in respiratory medicine should consider data drift, or changes in the input data distribution over time, such as shifts in the demographics of patients with asthma or variations in the technical specifications of new CT scanners. Further, concept drift might involve a change in the underlying relationship between inputs and outputs, such as when a model trained to predict

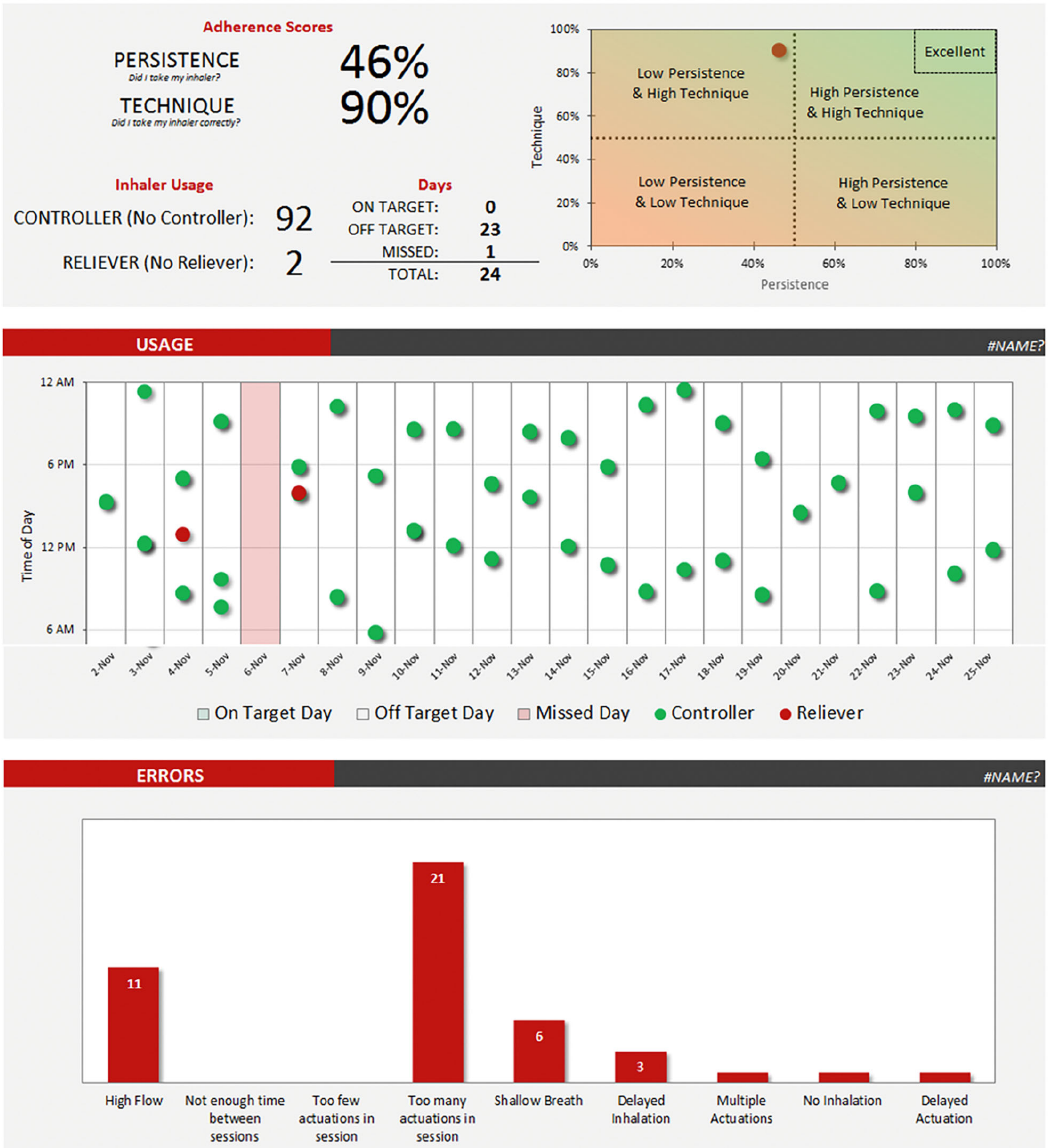

Fig. 6 Adherence scores for inhalers usage (from ref. [52]). An example of the output of a smart spacer data visualisation is shown. To assess this output, the memory card from the smart spacer needs to be manually removed and the data file should be transferred to a computer to be analysed using a Microsoft Excel file. Together with the patient, the adherence report is then analysed by the nurse. Using this output, tailor made inhalation education can be given. As such, patients will be asked to bring their smart spacer to the study visits.

severe COVID-19 outcomes becomes less accurate because new viral variants alter the clinical presentation of the disease. Proactively monitoring for both types of drift is crucial to ensure these models remain reliable, safe, and effective in dynamic clinical environments.

From a clinical perspective in respiratory medicine, the potential for errors and even hallucinations in LLMs and generative AI poses significant safety risks, such as fabricating plausible but incorrect medication dosages, misinterpreting nuanced radiology findings, or suggesting contraindicated therapies for conditions like severe COPD or ILD. These errors could directly harm patients and erode clinicians' trust. Therefore, robust guardrails and a multi-layered evaluation framework are imperative. This must include rigorous pre-deployment validation on real-world clinical cases, continuous monitoring with clinician-in-the-loop oversight, clear system transparency about uncertainty, and strict protocols ensuring AI outputs are always reviewed and contextualized by a qualified healthcare professional before influencing patient care decisions.

Practical barriers also matter: digital literacy, access to devices, and usability for children and older adults are key for applications that interact directly with patients. Sustained collaboration among primary care doctors and nurses, pulmonologists, engineers, AI experts, commercial developers, regulators, and scientific societies is essential to translate AI's promise into a safe, equitable, and clinically effective transformation of respiratory care.

DATA AVAILABILITY

No datasets were generated or analysed during the current study.

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Both authors did all.

COMPETING INTERESTS

The authors declare no competing interests.

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