AI
(Artificial Intelligence)
in
Respiratory
Medicine

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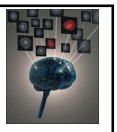
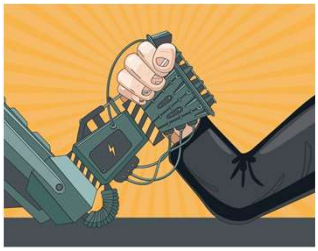
Chairperson, Family Physician Airways Group of Canada
Vice President Respiratory Effectiveness Group
Chair ACDC Asthma COPD App development program

Learning Objectives

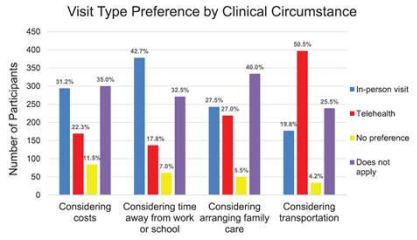


- Describe the main applications of artificial intelligence and machine learning within respiratory medicine.
- Explain how AI/machine learning use fits into everyday clinical practice.
- Describe how issues of patient safety and physician liability should be addressed.

Medicine is changing

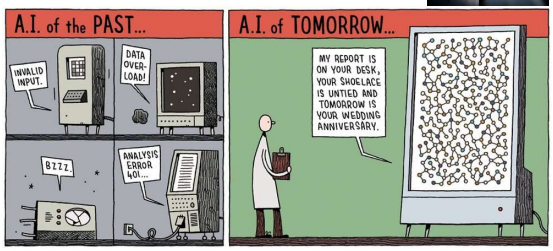


Example: Telehealth vs In-person?

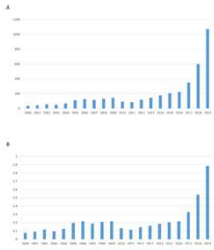


Ugalde IC, et al. Preference for and impact of telehealth vs in-person asthma visits among Black and Latinx adults. Ann Allergy Asthma Immunol. 2023 Nov;131(5):614-627.e2. doi: 10.1016/j.anai.2023.07.012. Epub 2023 Jul 23. PMID: 37490981.

Where have we come from?



Exploding area of interest



State of the art review

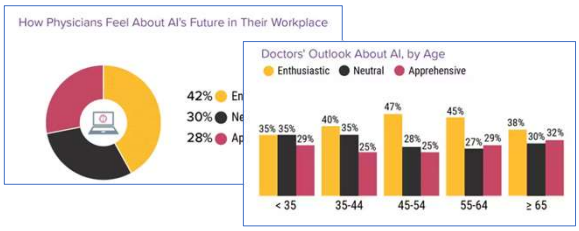
Applications of artificial intelligence and machine learning in respiratory medicine

Sherif Gonem ,[1,2] Wim Janssens,[3,4] Nilakash Das,[1] Marko Topalovic[1,5]

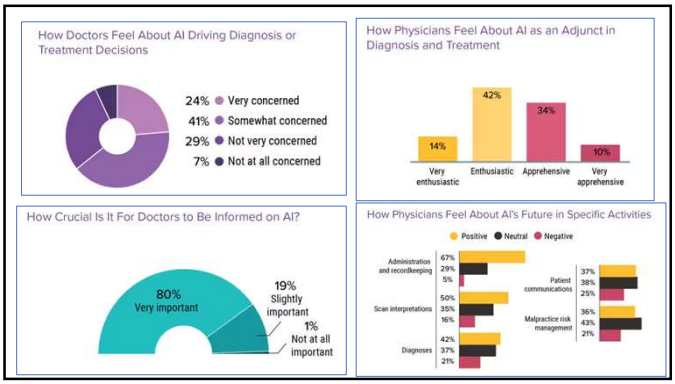
Figure 1 Published articles on artificial intelligence and machine learning in respiratory medicine shown as raw numbers (panel A) and as a percentage of all articles on respiratory medicine (panel B) from 2000 to 2019. Panel A shows the number of retrieved articles on the PubMed database published from 2000 to 2019 using the search terms specified for this review (artificial intelligence related term and respiratory-related term). Panel B shows this number expressed as a percentage of all articles retrieved using just the respiratory-related search terms.

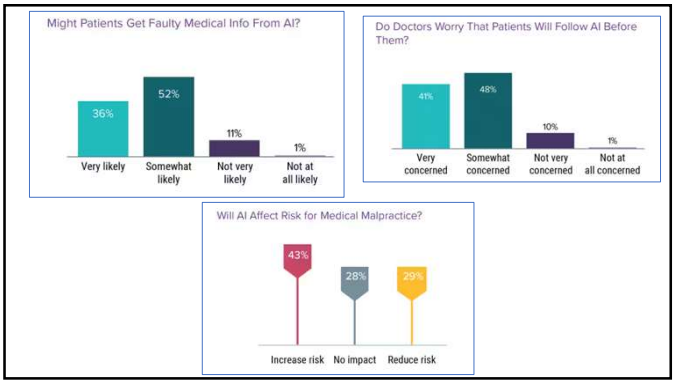
Gonem S, Janssens W, Das N, Topalovic M. Applications of artificial intelligence and machine learning in respiratory medicine. Thorax. 2020 Aug;75(8):695-701. doi: 10.1136/thoraxjnl-2020-214556. Epub 2020 May 14. PMID: 32409611.

Medscape survey on attitudes to AI



https://www.medscape.com/slideshow/2023-artificial-intelligence-6016743#10 Accessed Nov 5, 2023





"You caught a virus from your computer, and we had to erase your brain. I hope you've got a back-up copy!"

AI growing in many areas!

Knee Surgery, Sports Traumatology, Arthroscopy
https://doi.org/10.1007/s00167-020-06227-w

KNEE

Machine learning can reliably identify patients at risk of overnight hospital admission following anterior cruciate ligament reconstruction

Yining Lu[1] · Enrico Forlenza[2] · Matthew R. Cohn[2] · Ophelie Lavoie-Gagne[2] · Ryan R. Wilbur[1] · Bryant M. Song[1] · Aaron J. Krych[3] · Brian Forsythe[2]

Received: 30 July 2020 / Accepted: 2 October 2020
© European Society of Sports Traumatology, Knee Surgery, Arthroscopy (ESSKA) 2020

Abstract

Purpose Overnight admission following anterior cruciate ligament reconstruction has implications on clinical outcomes as well as cost benefit, yet there are few validated risk calculators for reliable identification of appropriate candidates. The purpose of this study is to develop and validate a machine learning algorithm that can effectively identify patients requiring admission following elective anterior cruciate ligament (ACL) reconstruction.

Methods A retrospective review of a national surgical outcomes database was performed to identify patients who underwent elective ACL reconstruction from 2006 to 2018. Patients admitted overnight postoperatively were identified as those with length of stay of 1 or more days. Models were generated using random forest (RF), extreme gradient boosting (XGBoost), linear discriminant classifier (LDA), and adaptive boosting algorithms (AdaBoost), and an additional model was produced as a weighted ensemble of the four final algorithms.

Results Overall, of the 4,709 patients included, 531 patients (11.3%) required at least one overnight stay following ACL reconstruction. The factors determined most important for identification of candidates for inpatient admission were: operative time, anesthesia type, age, gender, and BMI. Smoking history, history of COPD, and history of coagulopathy were identified as less important variables. The following factors supported overnight admission: operative time > 200 min, age < 35.8 or > 53.5 years, male gender, BMI < 25 or > 31.2 kg/m^2, positive smoking history, history of COPD and the presence of preoperative coagulopathy. The ensemble model achieved the best performance based on discrimination assessed via internal validation (AUC = 0.76), calibration, and decision curve analysis. The model was integrated into a web-based open-access application able to provide both predictions and explanations.

Conclusion Modifiable risk factors identified by the model such as increased BMI, operative time, anesthesia type, and comorbidities can help clinicians optimize preoperative status to prevent costs associated with unnecessary admissions. If externally validated in independent populations, this algorithm could use these inputs to guide preoperative screening and

Modifiable risk factors identified by the model such as increased BMI, operative time, anesthesia type, and comorbidities can help clinicians optimize preoperative status.

(AUC = 0.76)

Where and how to be used?

- Radiologic interpretation
- Pulmonary function interpretation
- Asthma vs COPD clinical, biomarker and spirometry
- Others: TB, pneumonia prediction, the list goes on…
- Digital inhalers
- Action Plans

PLOS ONE

A systematic review of the diagnostic accuracy of artificial intelligence-based computer programs to analyze chest x-rays for pulmonary tuberculosis

Miriam Harris, Amy Qi, Luke Jeagal, Nazi Torabi, Dick Menzies, Alexei Korobitsyn, Madhukar Pai, Ruvandhi R. Nathavitharana, Faiz Ahmad Khan

Published: September 3, 2019 • https://doi.org/10.1371/journal.pone.0221339

Article | Authors | Metrics | Comments | Media Coverage

Abstract
Introduction
Methods
Results
Discussion
Box 1. Recommendations for CAD accuracy study design elements
Supporting information
Acknowledgments
References

Abstract

We undertook a systematic review of the diagnostic accuracy of artificial intelligence-based software for identification of radiologic abnormalities (computer-aided detection, or CAD) compatible with pulmonary tuberculosis on chest x-rays (CXRs). We searched four databases for articles published between January 2005-February 2019. We summarized data on CAD type, study design, and diagnostic accuracy. We assessed risk of bias with QUADAS-2. We included 53 of the 4712 articles reviewed: 40 focused on CAD design methods ("Development" studies) and 13 focused on evaluation of CAD ("Clinical" studies). Meta-analyses were not performed due to methodological differences. Development studies were more likely to use CXR databases with greater potential for bias as compared to Clinical studies. Areas under the receiver operating characteristic curve (median AUC [IQR]) were significantly higher in Development studies AUC: 0.88 [0.82–0.90]) versus Clinical studies (0.75 [0.66–0.87], p-value 0.004); and with deep-learning (0.91 [0.88–0.99]) versus machine-learning (0.82 [0.75–0.89], p = 0.001). We conclude that CAD programs are promising, but the majority of work thus far has been on development rather than clinical evaluation. We provide concrete suggestions on what study design elements should be improved.

Reader Comments (0)

How about urgent care and CXR interpretation?

ERS EUROPEAN RESPIRATORY SOCIETY INTERNATIONAL CONGRESS 2023 MILAN Italy, 9-13 September

CheXED artificial intelligence to detect radiographic pneumonia in urgent care clinic patients.

N. Dean (Salt Lake City, United States), J. Hart (Salt Lake City, United States), K. Kuttler (Salt Lake City, United States), C. Van Uden (Palo Alto, United States), C. Langlotz (Palo Alto, United States), C. Carman (Utah Valley, United States), T. Sakata (Salt Lake City, United States)

Introduction Chest imaging is needed for diagnosis and treatment of patients suspected of pneumonia. Radiologist interpretations are delayed and may not specify findings. CheXED processes digital chest Xray images using artificial intelligence (Irvin J Thoracic Imaging 2022), but needed development and validation for urgent care clinics (UCC).
Methods CheXED was trained with PA and Lateral CXR images from 9,174 patients, categorized by review of radiologist reports from 28 Utah (USA) UCCs 2019-2021. After the updated CheXED was deployed to 5 UCCs, we compared radiologist reports to CheXED for radiographic pneumonia on PA and Lateral CXRs done 21.12.22 to 5.1.23 in consecutive patients >12 years old. Two CXRs where CheXED and reports differed were resolved by image and clinical note review by a Pulmonologist (ND) to determine presence/absence of radiographic pneumonia.
Results Study population had a median age of 45 +/- 19.1 years; 15.7% were diagnosed with pneumonia by the UCC clinician. CheXED and the radiologist agreed on 38 of 40 CXRs; CheXED was judged correct once and the radiologist in the other. Kappa agreement = 0.84.
Conclusion CheXED accurately identified radiographic pneumonia in UCC patients <1 second after image uploading. CheXED embedded within ePNa electronic clinical decision support (Dean AJRCCM 2022 205:1330) is likely to improve UCC diagnosis and treatment of patients suspected of pneumonia.

CheXED artificial intelligence to detect radiographic pneumonia in urgent care clinic patients

N Dean, J Hart, K Kuttler, C Van Uden, C Langlotz, C Carman
Intermountain Healthcare, University of Utah, and Stanford University
Salt Lake City Utah and Palo Alto California, USA

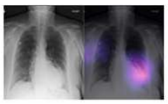
Introduction

- Chest imaging is necessary for diagnosis and treatment of patients suspected of pneumonia.
- Radiologist interpretations are often delayed and may not specify needed information.

CheXED provides real-time processing of chest Xray images using artificial intelligence but needed development and validation for urgent care clinic patients.

- Chest Xrays in urgent care clinics are Posterior/Anterior and Lateral images

Limitations of Radiology and Natural Language Processing



Time delay — Patient and provider dissatisfaction

Free text — Errors in critical element extraction

Physician variability — Disagreement and inconsistency in radiologist interpretation

Methods

CheXED additionally trained on PA and Lateral CXR images taken from 9174 patients suspected of pneumonia, categorized by physician review of clinical radiologist reports from 28 Utah (USA) urgent care clinics 2019-2021.

Urgent care clinic accuracy compared with radiology report: AUROC 0.91

After deployment of the updated CheXED to 5 clinics, we compared radiologist interpretations to CheXED for radiographic pneumonia likely/possible/unlikely on CXRs done 21.12.22 to 5.1.23 in 40 consecutive patients >12 years old.

Studies where CheXED and radiologist reports differed were resolved by image and clinical note review by a pulmonologist (ND) to determine the presence of radiographic pneumonia

Results

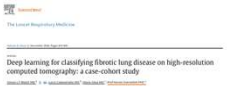
Study population had a median age of 45 +/- 19.1 years; 7 (17.5%) were diagnosed with pneumonia by the clinic physician. 6 of 40 (15%) had radiographic pneumonia

In 38/40 patients, CheXED was congruent with radiologist interpretation

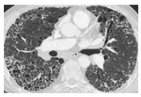
Where discordant, the radiolog was judged correct once, CheXED once

Kappa agreement = 0.84

Fibrotic lung diseases


Deep learning for classifying fibrotic lung disease on high-resolution computed tomography: a case-cohort study

- The accuracy of the algorithm on test set A was 76·4%, with 92·7% of diagnoses within one category.
- The algorithm took 2·31 s to evaluate 150 four slice montages (each montage representing a single case from test set B).
- The median accuracy of the thoracic radiologists on test set B was 70·7% (IQR 65·3–74·7), and the accuracy of the algorithm was 73·3% (93·3% were within one category), **outperforming** 60 (66%) of 91 thoracic radiologists.



Walsh SLF, Humphries SM, Wells AU, Brown KK. Imaging research in fibrotic lung disease; applying deep learning to unsolved problems. Lancet Respir Med. 2020 Nov;8(11):1144-1153. doi: 10.1016/S2213-2600(20)30003-5. Epub 2020 Feb 25. PMID: 32109428.

Does my cough sound like COVID? There could be an app for that

It could be possible to detect whether someone has COVID-19 or not, just from the sound of their coughing.

That's the conclusion of testing of an artificial intelligence (AI) algorithm developed by the Massachusetts Institute of Technology (MIT), which was able to detect around 98% of cases of COVID-19 from a forced cough delivered down a cell phone – confirmed by coronavirus testing.

Almost unbelievably, the neural network was also 100% effective in correctly diagnosing COVID-19 in people with no symptoms but who had tested positive for the virus, according to the MIT researchers, although the trade-off was a false positive rate of around 17% in this group.

The MIT Open Voice algorithm was put through its paces in more than 5,300 patients, finding a 97.1% accuracy rate overall, with 98.5% sensitivity and 94.2% specificity.

The finding ties in with anecdotal reports that COVID-19 causes a very distinctive sounding cough, although it will have to be thoroughly tested in additional studies to see if it could be useful as a screening tool.

https://pharmaphorum.com/news/does-my-cough-sound-like-covid-there-could-be-an-app-for-that/

Perspective

Artificial intelligence and machine learning in respiratory medicine

Evgeni Mekov, **Marc Miravitlles** & Rosen Petkov

Pages 559-564 | Received 20 Sep 2019, Accepted 12 Mar 2020, Accepted author version posted online: 13 Mar 2020, Published online: 17 Mar 2020

Download citation https://doi.org/10.1080/17476348.2020.1743181

Full Article | Figures & data | References | Citations | Metrics | Reprints & Permissions | Get access

ABSTRACT

Introduction

The application of artificial intelligence (AI) and machine learning (ML) in medicine and in particular in respiratory medicine is an increasingly relevant topic.

Studies identified corresponded to the area of chronic obstructive pulmonary disease (COPD), in particular to **COPD and chest computed tomography scans**, interpretation of **pulmonary function tests**, exacerbations and treatment, **diagnosis of interstitial lung disease**, and a few other studies were identified on the fields of mechanical ventilation, **interpretation of images on chest X-ray** and **diagnosis of bronchial asthma**.

Man vs Machine?

Expert opinion:

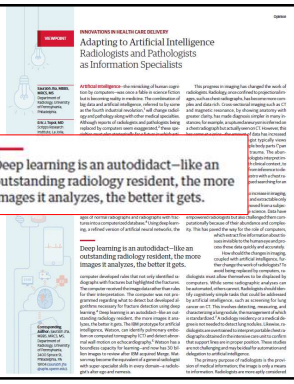
- ML may help to make clinical decisions but will not replace the physician completely.
- Human errors in medicine are associated with large financial losses, and many of them could be prevented with the help of AI and ML.
- AI is particularly useful in the absence of conclusive evidence of decision-making.

Mekov E, Miravitles M. Artificial Intelligence and machine learning in respiratory medicine
Expert Review of Respiratory Medicine. Volume 14, 2020; 559-564

Clinical response predictions

- Comparing what we can do in practice
- How much more (and faster) a computer can process
- If trained correctly (big issue, more to come!) then can be of huge help!

But,



INNOVATIONS IN HEALTH CARE DELIVERY

Adapting to Artificial Intelligence
Radiologists and Pathologists as Information Specialists

Deep learning is an autodidact—like an outstanding radiology resident, the more images it analyzes, the better it gets.

children

MDPI

Article

Predicting Treatment Outcomes Using Explainable Machine Learning in Children with Asthma

Matija Lovrić [1], Ivana Banić [1], Emanuel Lacić [1], Kristina Pavlović [1], Roman Kern [2,3,*] and Mirjana Turkalj [4,5,*]

Variable Group		Description
demographics		gender, age
subjective clinical data		at baseline (B0)-p… rhinitis (AR), ato…
objective clinical data		at baseline (B0) an… severity of exac… (FVC, FEV1, M… medication use; … to inhaled allerg… measures (height… suggestive histor… impedanc… gastroesophag… obstructive sleep… venom alle…
genetic data		genotypes for rs… rs1876828 (CRHB… Fig…

AR: allergic rhinitis, AD: atopic dermatitis, … second, MEF50: maximal expiratory flow at … SPT: skin prick test, IgE: immunoglobulin E, ENT: ear/nose/throat, GLCCI1: glucocorticoid-induced 1, TBX21: t-box 21, CRHR1: corticotropin releasing hormone receptor 1, ADRB2: beta-2 adrenergic receptor and MMP9: matrix metallopeptidase-9. A full variable list is given in the supplementary file (see Table S3).

Table 2. Patient stratification according to their response to treatment (target variables). Response to treatment is defined into more detail in the supplementary file. Ppb: parts per billion.

Class	FEV_1	MEF_{50}	FENO	Asthma Control
Responders	Increase ≥ 10% predicted	Increase ≥ 15% predicted	Decrease < 20% for values > 35 (50) ppb or < 10 ppb for values < 35 (50) ppb	Improvement in asthma control
Non-Responders	Change < 10% predicted	Change < 15% predicted	Decrease ≤ 20% FENO ≤ 20% for values over 35 (50) ppb or ± 10 ppb for values < 35 (50) ppb or increase >20% for values > 35 (50) ppb or > 10 ppb for values < 35 (50) ppb	No changes in partial asthma control or deterioration in asthma control

FEV1—forced expiratory volume in one second, MEF50—maximal expiratory flow at 50% of the vital flow capacity, FENO—Fractional Exhaled nitric oxide.

Lovrić M, Banić I, Lacić E, Pavlović K, Kern R, Turkalj M. Predicting Treatment Outcomes Using Explainable Machine Learning in Children with Asthma. Children (Basel). 2021 May 10;8(5):376. doi: 10.3390/children8050376. PMID: 34068718; PMCID: PMC8151683.

Artificial intelligence in diagnosis of obstructive lung disease: current status and future potential

Authors: Das, Nilakash; Topalovic, Marko; Janssens, Wim
Source: Current Opinion in Pulmonary Medicine, Volume 24, Number 2, March 2018, pp. 1
Publisher: Wolters Kluwer
DOI: https://doi.org/10.1097/MCP.0000000000000459

- Machine learning has been successfully used in automated interpretation of pulmonary function tests for differential diagnosis of obstructive lung diseases.
- Deep learning models such as convolutional neural network are state-of-the art for obstructive pattern recognition in computed tomography.
- Machine learning has also been applied in other diagnostic approaches such as forced oscillation test, breath analysis, lung sound analysis and telemedicine with promising results in small-scale studies.

CrossMark

Artificial intelligence outperforms pulmonologists in the interpretation of pulmonary function tests

Marko Topalovic[1], Nilakash Das[1], Pierre-Régis Burgel[2,3], Marc Daenen[4], Eric Derom[4], Christel Haenebalcke[5], Rob Janssen[6], Huib A.M. Kerstjens[7], Giuseppe Liistro[8], Renaud Louis[9], Vincent Ninane[10], Christophe Pison[11], Marc Schlesser[12], Piet Vercauster[13], Claus F. Vogelmeier[14], Emiel Wouters[15], Jokke Wynants[16,17] and Wim Janssens[1] on behalf of the Pulmonary Function Study Investigators

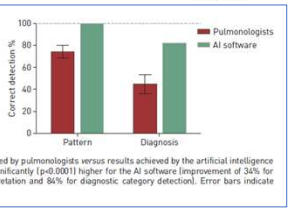
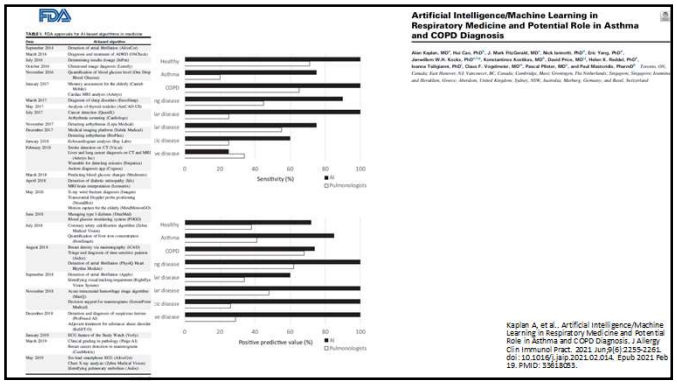


FIGURE 2 Comparison of results obtained by pulmonologists versus results achieved by the artificial intelligence (AI) software. Correct detections are significantly ($p<0.0001$) higher for the AI software (improvement of 34% for pulmonary function test pattern interpretation and 84% for diagnostic category detection). Error bars indicate standard deviation.

Topalovic M, et al; Pulmonary Function Study Investigators; Pulmonary Function Study Investigators:. Artificial intelligence outperforms pulmonologists in the interpretation of pulmonary function tests. Eur Respir J. 2019 Apr 11;53(4):1801660. doi: 10.1183/13993003.01660-2018. PMID: 30765505.



Artificial Intelligence/Machine Learning in Respiratory Medicine and Potential Role in Asthma and COPD Diagnosis

Alan Kaplan, MD[a], Hui Cao, PhD[b], J. Mark FitzGerald, MD[c], Nick Iannotti, PhD[d], Eric Yang, PhD[e], Jaewallen W.H. Kocks, PhD[f,g], Konstantinos Kostikas, MD[h], David Price, MD[i], Helen K. Reddel, PhD[j], Ioanna Tsiligianni, PhD[k], Claus F. Vogelmeier, MD[l], Pascal Philon, MD[m], and Paul Mastoridis, PharmD[n]

Kaplan A, et al.. Artificial Intelligence/Machine Learning in Respiratory Medicine and Potential Role in Asthma and COPD Diagnosis. J Allergy Clin Immunol Pract. 2021 Jun;9(6):2255-2261. doi: 10.1016/j.jaip.2021.02.014. Epub 2021 Feb 19. PMID: 33618053.

Unmet medical needs

Asthma and COPD burden

Disease		Asthma	COPD
Prevalence		8.6%[1]	11.7%[7]
Mortality		346k[2]	3M (4th leading death cause) *By 2030: 4.5M (3rd leading death cause)* [7]
Social burden		24M DALYs[3]	63M DALYs[3]
Economic burden (total cost = direct + indirect)	Europe	€17.7bn[4]	€38.6bn [7]
	US	$81.bn[5]	$52.4bn[7]
Misdiagnose	**Overdiagnosis**	**30–61%[6]**	**33%[8]**
	Underdiagnosis	**20–73%[6]**	**60–86%[8]**

1. To T, Stanojevic S, et al. BMC Public Health. 2012;12:204. 2. Global Initiative for Asthma. 2018. Available from: www.ginasthma.org; 3. Global Burden of Disease Collaborative Network. Seattle, United States: Institute for Health Metrics and Evaluation 2017; 4. Braman SS. Chest. 2006;130:4-12; 5. Numagambetov T, et al. The Economic Burden of Asthma in the United States, 2008–2013. ATS. 2018;15(3); 6. Aaron SD, et al. AJRCCM. 2018; 7. Global Initiative for Chronic Obstructive Lung Disease. 2018. Available from: https://goldcopd.org; 8. Gershon AS, et al. Chest. 2018;153(6):1336-1346.

Figures presented are estimations per year

26

Misdiagnosis of Asthma and COPD

Reasons

Spirometry not performed / difficulty interpreting results

It is estimated that only **16–43%** of patients with asthma[1] and around **33%** of patients with COPD[2] undergo lung function testing

Difficulties in differential diagnosis

Symptoms of asthma and COPD can be very similar making them difficult to differentiate[3]

Underreporting

of respiratory symptoms to physicians[2]

Reasons for misdiagnosis

No single diagnostic tool

Poor diagnostic sensitivity of spirometry[4]; FeNO results can be context dependent[5]

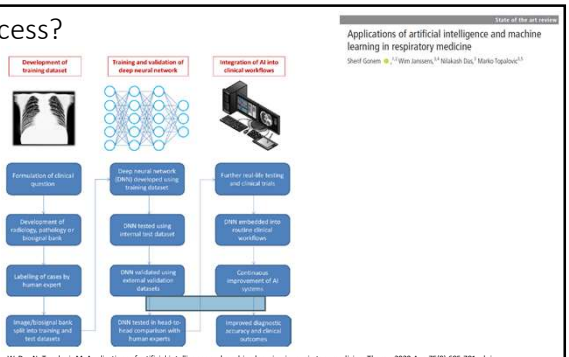
Asthma and COPD are evolving diseases

For example, sustained remission in young patients with asthma[2] and patients with asthma can display COPD later in life

1. Aaron SD, et al. AJRCCM 2018; 2. Lamprecht et al. Prim Care Respir J 2013;
3. De Marco JE et al. JAO 2002; 4. Schermer TR, et al. NPJ Prim Care Respir Med 2016;
5. GINA 2020. Available from: www.ginasthma.org 6. Nissen F, et al. Br J Gen Pract 2018

27

Process?



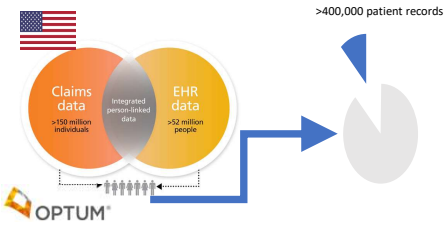
Gonem S, Janssens W, Das N, Topalovic M. Applications of artificial intelligence and machine learning in respiratory medicine. Thorax. 2020 Aug;75(8):695-701. doi: 10.1136/thoraxjnl-2020-214556. Epub 2020 May 14. PMID: 32409611.

Our Solution: ACDC

Machine Learning-Assisted
Asthma **C**OPD **D**ifferentiation **C**lassification

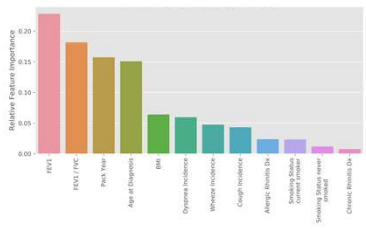
On-the-ground support for **general practitioners** to help diagnose **Asthma from COPD**

Where does ACDC data come from?



>400,000 patient records

Top Features of Importance: Cohorts I, II, and III



1. FEV_1
2. FEV_1/FVC
3. Pack Year
4. Age
5. BMI
6. Dyspnea
7. Wheeze
8. Cough
9. DX Allergic Rhinitis
10. Current smoker
11. Never smoked
12. DX Chronic Rhinitis

Confusion Matrix: Cohorts I, II and III

Deep optimization

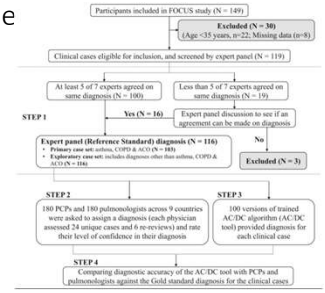
	precision	recall	f1-score	support
aco	0.92	0.78	0.84	4116
asthma	0.97	0.98	0.98	21562
copd	0.97	0.98	0.98	36057

Precision (positive predictive value)
Recall (also known as sensitivity)
F1-score (a measure of a test's accuracy) is the weighted average of Precision and Recall, therefore, this score takes both false positives and false negatives into account.
Support=number of patients holdout

Limitations in the Training Model!!!

- Post BD FEV1 was not done frequently, so not included in the data
- Age of onset of illness not captured
- FENO done even LESS frequently, so not included in the data
- Background medication use

So, we studied the algorithm again

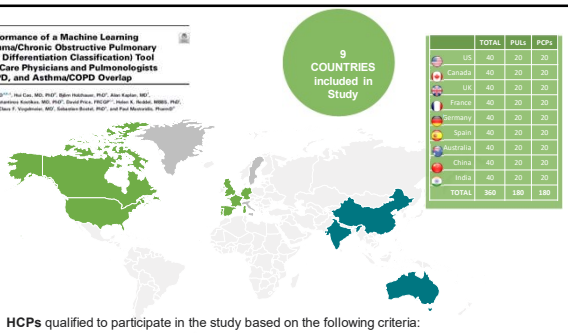


Kochs JW, Cao H, Holzauer B, Kaplan A, et al. Diagnostic performance of a machine-learning algorithm (Asthma/COPD Differentiation Classification; AC/DC) tool versus primary care physicians and pulmonologists in asthma, COPD and ACO JACI published January 27, 2023 DOI:https://doi.org/10.1016/j.jaip.2023.01.017

Original Article

Diagnostic Performance of a Machine Learning Algorithm (Asthma/Chronic Obstructive Pulmonary Disease (COPD) Differentiation Classification) Tool Versus Primary Care Physicians and Pulmonologists in Asthma, COPD, and Asthma/COPD Overlap

Jamelleen W.H. Kochs, MD, PhD[a,b,c], Hui Cao, MD, PhD[d], Björn Holzhauer, PhD[d], Alan Kaplan, MD[e], J. Mark FitzGerald, MD[f,g], Konstantinos Kostikas, MD, PhD[h], David Price, FRCGP[i,j], Helen A. Reddel, MBBS, PhD[k], Ioanna Tsiligianni, MPH, PhD[l], Claus F. Vogelmeier, MD[m], Sébastien Bosnic, PhD[d], and Paul Mastoridis, PharmD[d]



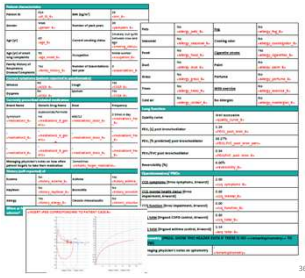
	TOTAL	PULs	PCPs
US	40	20	20
Canada	40	20	20
UK	40	20	20
France	40	20	20
Germany	40	20	20
Spain	40	20	20
Australia	40	20	20
China	40	20	20
India	40	20	20
TOTAL	360	180	180

HCPs qualified to participate in the study based on the following criteria:

- Board certified or eligible (US only)
- Practicing at least 2 years post-residency
- Spend at least 50% of time in direct clinical practice/ patient care
- See at least 1 patient with respiratory diseases

Patient Features Parameters

Patient Features Shown to Steering Committee/PULs/PCPs
~50 Parameters

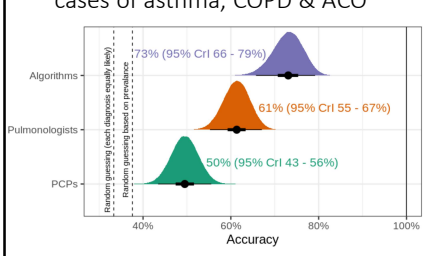


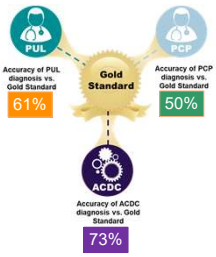
Patient Feature Shown to AC/DC
~12 Parameters

- Age
- BMI
- FEV1 pre bronchodilator values
- FEV1 pre bronchodilator percentages
- Current smoking status
- Never smoked
- Pack years
- Chronic sinusitis
- History of hayfever
- Dyspnea (ACQ4)
- Cough (CCQ5)
- Wheeze (ACQ5)

***In cases where ACQ and CCQ values weren't available, MRC values were utilized.*

Average Diagnostic Accuracy in evaluating clinical cases of asthma, COPD & ACO





37

Study results

AC/DC meets all Primary Endpoints

- ☑ 1. Superiority to PCPs
- ☑ 2. Non-Inferior to Pulmonologists
- ☑ 3. Superiority to Pulmonologists

Kochs JW, Cao H, Holzauer B, Kaplan A, et al. Diagnostic performance of a machine-learning algorithm (Asthma/COPD Differentiation Classification; AC/DC) tool versus primary care physicians and pulmonologists in asthma, COPD and ACO JACI published January 27, 2023 DOI:https://doi.org/10.1016/j.jaip.2023.01.017

38

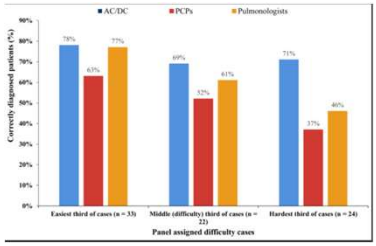
GOLD Standard Summary

- Total patient cases from FOCUS study = 119
- Steering Committee members came to consensus on diagnoses of **116 cases**
- Breakdown by diagnosis:
  Asthma: **53** COPD: **43** ACO: **7** Other: **13**
- Breakdown by difficulty:
  Easy: **39** Moderate: **39** Hard: **38**

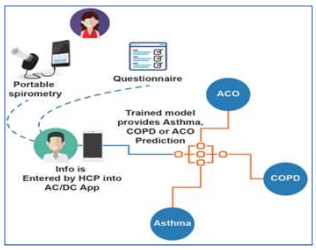
	Asthma	COPD	ACO	Other	Total
Easy	10	27	2	0	39
Moderate	20	13	3	3	39
Hard	23	3	2	10	38
Total	53	43	7	13	116

39

ACDC vs others in different difficulties?



Future? App currently being purchased by a US company…we shall see….

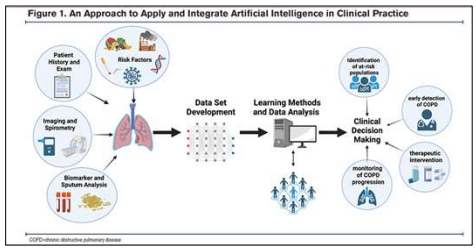


This is now the model for AI diagnostics

Chronic Obstructive Pulmonary Diseases: Journal of the COPD Foundation

Perspective

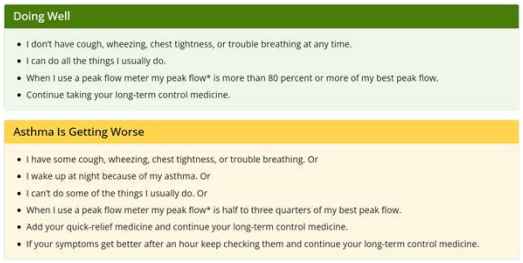
Integrating Artificial Intelligence in the Diagnosis of COPD Globally: A Way Forward



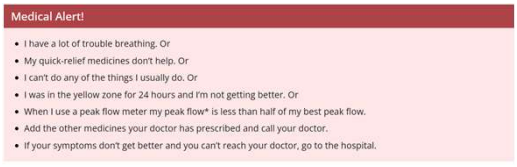
Robertson NM, Centner CS, Siddharthan T. Integrating artificial intelligence in the diagnosis of COPD globally: a way forward. Chronic Obstr Pulm Dis. 2024; 11(1): 114-120. doi: http://dx.doi.org/10.15326/jcopdf.2023.0449

How often are action plans given in the US?

NO good data on line; Answer is likely NOT MUCH!!!

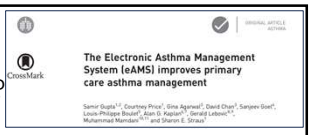


https://www.cdc.gov/asthma/actionplan.html Accessed Nov 12, 2023

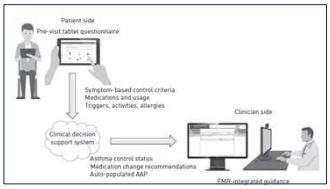


https://www.cdc.gov/asthma/actionplan.html Accessed Nov 12, 2023

Utilize the EMR
How often do you give an Asthma Action Plan?

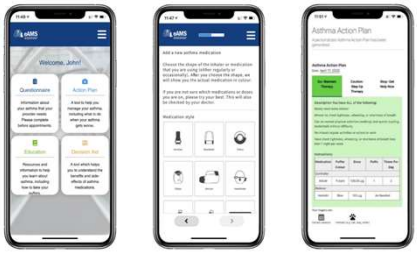


Action plan delivery (primary outcome) improved from zero out of 412 (0%) to 79 out of 443 (17.8%) eligible patients (absolute increase 0.18 (95% CI 0.14–0.22)).

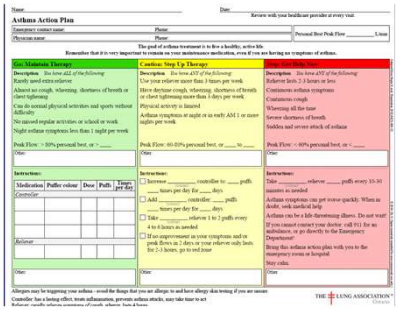


Gupta S, Price C, Agarwal G, Chan D, Goel S, Boulet LP, Kaplan AG, Lebovic G, Mamdani M, Straus SE. The Electronic Asthma Management System (eAMS) improves primary care asthma management. Eur Respir J. 2019 Apr 25;53(4):1802241. doi: 10.1183/13993003.02241-2018. PMID: 30765503; PMCID: PMC6482383.

Auto-populates the Action plan based on input



https://apps.health/featured/eams/

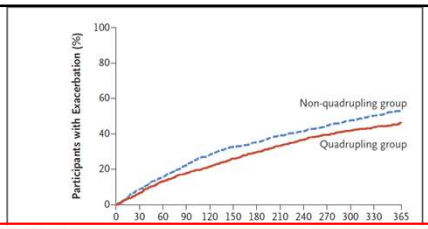


The NEW ENGLAND JOURNAL of MEDICINE

ORIGINAL ARTICLE

Quadrupling Inhaled Glucocorticoid Dose to Abort Asthma Exacerbations

Tricia McKeever, Ph.D., Kevin Mortimer, Ph.D., Andrew Wilson, M.D., Samantha Walker, Ph.D., Christopher Brightling, Ph.D., Andrew Skeggs, B.Sc., Ian Pavord, F.Med.Sci., David Price, F.R.C.G.P., Lelia Duley, M.D., Mike Thomas, Ph.D., Lucy Bradshaw, M.Sc., Bernard Higgins, Ph.D., Rebecca Haydock, B.Sc., Eleanor Mitchell, B.A., Graham Devereux, Ph.D., and Timothy Harrison, M.D.



CONCLUSIONS

In this trial involving adults and adolescents with asthma, a personalized self-management plan that included a temporary quadrupling of the dose of inhaled glucocorticoids when asthma control started to deteriorate resulted in fewer severe asthma exacerbations than a plan in which the dose was not increased. (Funded

Figure 2. Kaplan–Meier Curves for the Time to the First Severe Asthma Exacerbation, According to Assigned Group.

ASTHMA ACTION PLAN YELLOW ZONE FORMULATION TABLE (≥ 16 YEARS OLD)

Medication in Green Zone			Change in Yellow Zone (*all inhaler recommendations are for 7-14 days*)	
DEVICE	MAXIMUM DOSING FOR DEVICE	DOSING REGIMENS	YELLOW ZONE ESCALATION	
ICS MONOTHERAPY				
Flovent HFA (Fluticasone propionate)	2000 mcg	50 mcg 1 puff BID	Increase to 4 puffs BID	
		125 mcg 1 puff BID	Increase to 4 puffs BID	
		250 mcg 1 puff BID	Increase to 4 puffs BID	
Flovent Diskus (Fluticasone propionate)	2000 mcg	50 mcg 1 puff BID	Increase to 4 puffs BID	
		100 mcg 1 puff BID	Increase to 4 puffs BID	
		250 mcg 1 puff BID	Increase to 4 puffs BID	
		500 mcg 1 puff BID	Increase to 2 puffs BID	
Arnuity Ellipta (Fluticasone furoate)	200 mcg	100 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
		200 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
Pulmicort Turbuhaler (Budesonide)	2400 mcg	100 mcg 1 puff BID	Increase to 4 puffs BID	
		200 mcg 1 puff BID	Increase to 4 puffs BID	
		400 mcg 1 puff BID	Increase to 3 puffs BID	
QVAR MDI (Beclomethasone)	800 mcg	50 mcg 1 puff BID	Increase to 4 puffs BID	
		100 mcg 1 puff BID	Increase to 4 puffs BID	
		100 mcg 2 puffs BID	Prednisone 30-50 mg daily*	
Alvesco MDI (Ciclesonide)	800 mcg	100 mcg 1 puff OD	Increase to 4 puffs OD	
		200 mcg 1 puff OD	Increase to 4 puffs OD	
		200 mcg 2 puffs OD	Increase to 4 puffs BID	
Asmanex Twisthaler (Mometasone)	800 mcg	200 mcg 1 puff OD	Increase to 4 puffs OD	
		400 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
Aemmony Respiclick (fluticasone propionate)	2000 mcg	55 mcg 1 puff BID	Increase to 4 puffs BID	
		113 mcg 1 puff BID	Increase to 4 puffs BID	
		232 mcg 1 puff BID	Increase to 4 puffs BID	

ASTHMA ACTION PLAN YELLOW ZONE FORMULATION TABLE (≥ 16 YEARS OLD)

lung health foundation

Medication in Green Zone			Change in Yellow Zone *(all inhaler recommendations are for 7-14 days)*	
DEVICE	MAXIMUM DOSING FOR DEVICE	DOSING REGIMENS	YELLOW ZONE ESCALATION	
ICS/LABA COMBINATION THERAPY				
Advair Diskus (Fluticasone propionate/Salmeterol)	1000 mcg of fluticasone propionate and 100 mcg of salmeterol	100/50 mcg 1 puff BID	Add Flovent Diskus 100 mcg 3 puffs BID	
		250/50 mcg 1 puff BID	Add Flovent Diskus 250 mcg 3 puffs BID	
		500/50 mcg 1 puff BID	Add Flovent Diskus 500 mcg 1 puff BID	
Advair HFA (Fluticasone propionate/Salmeterol)	1000 mcg of fluticasone propionate and 100 mcg of salmeterol	125/25 mcg 2 puffs BID	Add Flovent HFA 125 mcg 3 puffs BID	
		250/25 mcg 1 puff BID	Add Flovent HFA 250 mcg 3 puffs BID	
		250/25 mcg 2 puffs BID	Add Flovent HFA 250 mcg 2 puffs BID	
Symbicort Turbuhaler (Budesonide/Formoterol)	2400 mcg of budesonide and 48 mcg of formoterol fumarate dihydrate	100/6 mcg 1 puff BID	Increase to 4 puffs BID	
		200/6 mcg 1 puff BID	Increase to 4 puffs BID	
		200/6 mcg 2 puffs BID	Add Pulmicort Turbuhaler 400 mcg 2 puffs BID	
Zenhale MDI (Mometasone/Formoterol)	The maximum daily recommended dose is 800 mcg mometasone furoate and 20 mcg micronized fumarate dihydrate	50/5 mcg 2 puffs BID	Change to Zenhale MDI 200/5mcg 2 puffs BID	
		100/5 mcg 2 puffs BID	Option 1: Change to Zenhale MDI 200/5 mcg 4 puffs BID[1]	Option 2: Prednisone 30-50 mg daily[1]
		200/5 mcg 2 puffs BID	Prednisone 30-50 mg daily[1]	
Breo Ellipta (Fluticasone furoate/Vilanterol)	The maximum recommended dose is 200 mcg of fluticasone furoate and 25 mcg of Vilanterol	100/25 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
		200/25 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
Wixela Inhub (fluticasone propionate/salmeterol) *No version of Inhub with just ICS available*	1000 mcg of fluticasone propionate and 100 mcg of salmeterol	100/50 mcg 1 puff BID	Add Flovent Diskus 100 mcg 3 puffs BID	
		250/50 mcg 1 puff BID	Add Flovent Diskus 250 mcg 3 puffs BID	
		500/50 mcg 1 puff BID	Add Flovent Diskus 500 mcg 1 puffs BID	
Atectura Breezhaler (mometasone/indacaterol)	The maximum recommended dose is 320/160 micrograms once daily (based on limit of 320 for mometasone) Max for mometasone alone is 800mcg	80/160 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
		160/160 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*
		320/160 mcg 1 puff OD	Option 1: Increase to 4 puffs OD*	Option 2: Prednisone 30-50 mg daily*

ASTHMA ACTION PLAN YELLOW ZONE FORMULATION TABLE (≥ 16 YEARS OLD)

lung health foundation

Medication in Green Zone			Change in Yellow Zone *(all inhaler recommendations are for 7-14 days)*	
DEVICE	MAXIMUM DOSING FOR DEVICE	DOSING REGIMENS	YELLOW ZONE ESCALATION	
ICS/LABA/LAMA Triple Therapy				
Trelegy Ellipta (fluticasone furoate/umeclidinium/vilanterol)	The recommended and maximum dose is 62.5 mcg of umeclidinium.	100/62.5/25mcg 1 puff OD	Option 1: add Amuity Ellipta 100mcg 3 puffs daily[1]	Option 2: Prednisone 30-50mg daily for 5-7 days[1]
		200/62.5/25mcg 1 puff OD	Option 1: add Amuity Ellipta 200mcg 3 puffs daily[1]	Option 2: Prednisone 30-50mg daily for 5-7 days[1]
Enerzair Breezhaler (indacaterol/glycopyrronium/mometasone)	The maximum recommended dose is ENERZAIR BREEZHALER 150/50/160 mcg once-daily.	150/50/160mcg 1 puff OD	Option 1: add Atectura Breezhaler 320/150mcg 3 puffs OD*	Option 2: Prednisone 30-50mg daily for 5-7 days[1]
Special considerations				
In patients with a history of sudden and severe exacerbations, and/or presenting with PEF or FEV1 ≤60% of personal best/predicted				Prednisone 30-50mg daily for 5-7 days as first line therapy[1]
If patient fails to improve clinically within 2-3 days of increase in inhaled medication, and/or has a rapid clinical deterioration, and/or has a peak expiratory flow or FEV1 that falls to ≥60% of their personal best value				Prednisone 30-50mg daily for 5-7 days as rescue (second line) therapy[1]

† This dose exceeds product monograph total daily dose limits intended for chronic daily use. A short-term dose increase beyond these limits is unlikely to carry any significant safety risks, however formal safety testing data are not available and the decision to pursue

Gupta S, Kaplan A, Kouri A, in press

THERAPEUTIC ADVANCES in *Chronic Disease*

Review

The emerging role of digital health in the management of asthma

Alan Kaplan, Michael Boivin, Jacques Bouchard, James Kim, Sean Hayes and Christopher Licskai

Ther Adv Chronic Dis
2023, Vol. 14, 1–19
DOI: 10.1177/20406223231209329

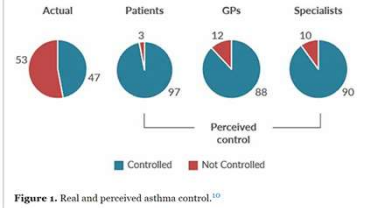


Figure 1. Real and perceived asthma control.[10]

Kaplan A, Boivin M, Bouchard J, Kim J, Hayes S, Licskai C. The emerging role of digital health in the management of asthma. Therapeutic Advances in Chronic Disease. 2023;14. doi:10.1177/20406223231209329

So why is the Asthma not controlled??

- Patient related
- Physician related
- Disease severity
- Comorbidities
- Triggers

Kaplan A, Boivin M, Bouchard J, Kim J, Hayes S, Licskai C. The emerging role of digital health in the management of asthma. Therapeutic Advances in Chronic Disease. 2023;14. doi:10.1177/20406223231209329

Table 2. Factors influencing asthma control.

Patient related
- Adherence[7,74–78]
  - Inadequate knowledge about asthma and its management
  - Missing maintenance and rescue inhalers
  - Forced inhaler changes
  - Patient inertia
    - Low acceptance of asthma diagnosis or severity
    - Clinical fatigue/frustration over lack of improvement
    - Apathy to treat preventively
- Inhaler technique[74,77,79,80]
  - Education and reinforcement of proper technique
  - Type of inhaler
  - Motivation to master technique
- Older age[81,82]
- Duration of asthma[81,82]
- Asthma severity[74,83]
- Smoking history[74,75,83,84]
- Female sex[85,86]
- Low socioeconomic status[73,74,76]
- Stress[87]
- Medication access/cost[74,76]

Physician related
- Lack of specialist care[81,84]
- Suboptimal adherence to asthma guidelines[82–84]
- Underexamination of asthma severity[81,87,88]
- Poor communication of asthma and its management to patients and caregivers
- Clinical fatigue/frustration over lack of improvement
- Apathy to treat preventively

Respiratory
- Low FEV_1 (especially < 60% predicted)[73,74,78,83]
- Elevated blood eosinophils[7]
- Elevated $FeNO$[83]

Other medical conditions
- Obesity[74–76,85,89]
- Chronic obstructive pulmonary disease[87]
- Chronic rhinosinusitis[83,84]
- Allergic rhinoconjunctivitis[74,77]
- Gastroesophageal reflux disease[74,78]
- Allergies[83,84]
- Major psychological issues[73,74]
- Alcohol or other substance abuse[76]
- Pregnancy[74]

Environmental
- Air pollution[83]
- Weather[83]
- Exposure to dust, gas, vapor, fumes, or other allergens[83,89]
- Second-hand tobacco smoke, including e-cigarettes[73,74,78]

$FeNO$, fractional concentration of exhaled nitric oxide, FEV_1, forced expiratory volume in 1 s.

- What can digital health assist with?

- Diagnosis
- Adherence
- Technique

Kaplan A, Boivin M, Bouchard J, Kim J, Hayes S, Licskai C. The emerging role of digital health in the management of asthma. Therapeutic Advances in Chronic Disease. 2023;14. doi:10.1177/20406223231209329

Digital Health Technology in Asthma

Table 3. Key findings for DHT in management of the patient with asthma.

Adherence and outcomes
- Significant improvement in asthma control with high-frequency (more often than once monthly) behavioral support using DHT *versus* low-frequency (less often or equal to once monthly) HCP-directed behavioral support, HCP-directed educational support, or usual care[108]
- Higher achievement of clinically meaningful asthma improvement *versus* standard of care inhaler[109]
- Increase in HCP-reported patient interactions[109]
- Improved adherence[110,111]

Environmental scan and quality review
- Several asthma management apps have demonstrated the ability to change user behaviour[112]

User-specific perspectives
- Patients and physicians generally have a positive view of DHT[91,113]

User-centered design
- Most important design criteria:[51]
  - Simplicity of use for both inhaler device and software
  - Interface similar to smartphone technology with which users are already accustomed
  - Software should inform, engage, and motivate users
  - Device should be unobtrusive, affordable, and provide accurate and objective measurements
  - Interface language/terminology should be concrete and understandable by persons at a Grade 6–7 reading level[114]

DHT, Digital health technology; HCP, healthcare provider.

Kaplan A, Boivin M, Bouchard J, Kim J, Hayes S, Licskai C. The emerging role of digital health in the management of asthma. Therapeutic Advances in Chronic Disease. 2023;14. doi:10.1177/20406223231209329

Barriers

Table 5. Common barriers to incorporating DHT into clinical practice.

- Time
- Training
- Interpretation of information obtained from the device
- Lack of consensus or standards for interpretation of DHT data
- Adherence to the technology
- Resistance to change
- Fear of being watched, monitored, and/or reprimanded
- Lack of perceived need for technology as the belief that patient is well controlled
- No compensation for potentially more work
- Overwhelmed with technology
- Cost and insurance coverage for the device and technology
- Medicolegal concerns

DHT, digital health technology.

Kaplan A, Boivin M, Bouchard J, Kim J, Hayes S, Licskai C. The emerging role of digital health in the management of asthma. Therapeutic Advances in Chronic Disease. 2023;14. doi:10.1177/20406223231209329

SMART inhalers in USA

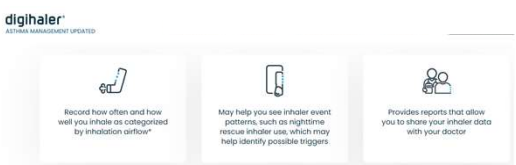
- Smart inhalers help people with chronic lung conditions to use their inhalers more effectively[1].
- There are currently seven FDA-cleared or FDA-approved smart inhalers. Some are all-in-one devices, and others are sensors you attach to a traditional inhaler[1].
- Studies that use digital inhaler systems to collect objective real-time data on medication-taking behavior via electronic medication monitors and feed this data back to patients on their mobile asthma app, and to health care professionals on the clinician dashboard to counsel patients, show positive outcomes[2].

1. https://www.goodrx.com/conditions/asthma/smart-inhalers-review
2. Mosnaim GS, Greiwe J, Jariwala SP, Pleasants R, Merchant R. Digital Inhalers and Remote Patient Monitoring for Asthma. J Allergy Clin Immunol Pract. 2022 Oct;10(10):2525-2533. doi: 10.1016/j.jaip.2022.06.026. Epub 2022 Jun 29. PMID: 35779779.

Digihaler by Teva:

ProAir Digihaler (albuterol sulfate)
ArmonAir Digihaler (fluticasone propionate)
AirDuo Digihaler (fluticasone/salmeterol)

The medication and the technology are already assembled. All you have to do is link the inhaler to the app. Once the Digihaler is out of doses, you discard the entire device. Each new inhaler needs to be linked to the app when you start using it.
You don't have to connect the Digihaler to the app to use it. The inhaler will still provide medication even if you're having technical difficulties.



Propeller

- Propeller is a FDA-cleared smart sensor that you attach to your inhaler.
- The sensors fit most FDA-approved inhalers.
- When you finish all doses in an inhaler, you remove the sensor and attach it to a new inhaler.
- Each sensor has a non-rechargeable battery that should last for about a year.
- Once the battery dies, you'll need a new sensor.
- To get started with Propeller, your healthcare provider needs to enroll you to use the device and app.
- Company located in Madison Wisconsin

Breath Suite

- BreatheSuite uses a non-rechargeable battery, typical battery life for one sensor is about 1 ½ years.
- As with Propeller, BreatheSuite doesn't know which brand inhaler you're using. While setting up the app, you'll have to add your inhaler details.
- Senses:
- How long you shook your MDI before using
- If you were holding your inhaler correctly during a dose
- How long you breathed in your dose
- If you pushed down on your inhaler as you started breathing in

CapMedic

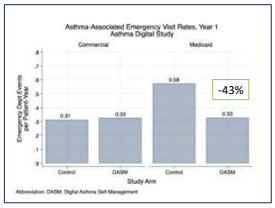
- The prescription-only sensor is rechargeable and fits on most MDIs.
- CapMedic's unique feature is that the sensor talks to you while you're using it.
- If you're not holding your MDI upright, the device will tell you.
- It lights up and plays music to let you know when to push down on your inhaler.
- As soon as you're done with your puff, the lights will be either red or green in color to tell you how well you did with your dose.

Hailie

- MDI and DPI

Does Digital AI work?

- 41 US states
- The DASM program uses consumer–grade devices for passive biometric monitoring.
- A smart phone app provides "smart nudges," symptom logging, trigger tracking, evidence-based education, and other resources



Harris B, Silberman J, Sarlati S, et al. Digital asthma self-management tool reduced emergency visit rates in a Medicaid population. Ann Allergy Asthma Immunol. 2023; 131(5):S230-1 (LB005). doi.10.1016/j.anai.2023.10.021

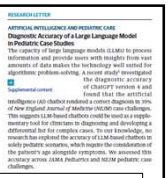
New technologies?

- Parameters (wheezes, rhonchi, coarse and fine crackles, HR, RR, I/E) measured by a device such as an AI-aided home stethoscope allows for the detection of exacerbations without the need for performing PEF measurements.

Emeryk A, et al. . Home Monitoring of Asthma Exacerbations in Children and Adults With Use of an AI-Aided Stethoscope. Ann Fam Med. 2023 Nov-Dec;21(6):517-525. doi: 10.1370/afm.3039. PMID: 38012028; PMCID: PMC10681685.

What about ChatGPT?

- One of many Artificial intelligence language processing models
- I have NO experience in these.
- BUT, I have concerns



RESEARCH LETTER

ARTIFICIAL INTELLIGENCE AND PEDIATRIC CARE

Diagnostic Accuracy of a Large Language Model in Pediatric Case Studies

The capacity of large language models (LLMs) to process information and provide users with insights from vast amounts of data makes the technology well suited for algorithmic problem-solving. A recent study[1] investigated the diagnostic accuracy of ChatGPT version 4 and found that the artificial intelligence (AI) chatbot rendered a correct diagnosis in 39% of *New England Journal of Medicine* (*NEJM*) case challenges. This suggests LLM-based chatbots could be used as a supplementary tool for clinicians in diagnosing and developing a differential list for complex cases. To our knowledge, no research has explored the accuracy of LLM-based chatbots in solely pediatric scenarios, which negates the consideration of the patient's age alongside symptoms. We assessed this accuracy across *JAMA Pediatrics* and *NEJM* pediatric case challenges.

Supplemental content

Text from 100 cases was pasted into ChatGPT version 3.5 with the following prompt: "List a differential diagnosis and a final diagnosis."

Two physician researchers scored the chatbot-generated diagnosis as "correct," "incorrect," or "did not fully capture diagnosis."

ChatGPT version 3.5 reached **an incorrect diagnosis in 83 out of 100 pediatric** case challenges.

So, careful what you trust!!

Barile J, et al "Diagnostic Accuracy of a Large Language Model in Pediatric Case Studies" JAMA Pediatr 2024; DOI: 10.1001/jamapediatrics.2023.5750.

Performance of ChatGPT compared to clinical practice guidelines in making informed decisions for Lumbosacral Radicular Pain: A cross-sectional study

Silvia Gianola [1], Silvia Bargeri [1], Greta Castellini [1], Chad Cook [2 3 4], Alvisa Palese [5], Paolo Pillastrini [6 7], Silvia Salvalaggio [8 9], Andrea Turolla [6 7], Giacomo Rossettini [10]

- Compared the accuracy of an artificial intelligence chatbot to clinical practice guidelines (CPGs) recommendations for providing answers to complex clinical questions on lumbosacral radicular pain.
- Accuracy between ChatGPT answers and CPGs recommendations was slight, demonstrating agreement in **33%** of recommendations.

Gianola S, Bargeri S, Castellini G, Cook C, Palese A, Pillastrini P, Salvalaggio S, Turolla A, Rossettini G. Performance of ChatGPT compared to clinical practice guidelines in making informed decisions for Lumbosacral Radicular Pain: A cross-sectional study. J Orthop Sports Phys Ther. 2024 Jan 29:1-18. doi: 10.2519/jospt.2024.12151.

JAMA Network

From: **Using Artificial Intelligence to Improve Primary Care for Patients and Clinicians**

Table. Potential Use Cases for AI in Primary Care

Use case	Examples of AI role
Inbox management	• Prioritize patient messages • Generate draft responses • Edit physician messages to optimize communication, including for literacy appropriateness
Clinician documentation	With transcription software: • Draft progress notes in real time during visits • Draft prior authorization, disability, and durable medical equipment requests • Draft a list of billing codes for visits
Between-visit panel management	• Accurately identify patients in need of cancer screening using unstructured and structured EHR data to determine exclusions • Identify patients with incomplete cancer screening (such as missed appointments), automate communication with patients, and provide scheduling and/or staff notification • Generate tailored messages to patients related to needed between-visit care needs
Individualized decision support	• Identify relevant information in structured and unstructured EHR data to prioritize differential diagnoses for new symptoms • Recommend medication options for chronic conditions, considering prior medication prescriptions, allergies, and intolerances noted in structured and unstructured EHR data

Abbreviations: AI, artificial intelligence; EHR, electronic health record.

JAMA Intern Med. Published online February 12, 2024. doi:10.1001/jamainternmed.2023.7965

The Perils of Artificial Intelligence in a Clinical Landscape

1) AI's assistance with inbox management and documentation may dehumanize the clinician-patient relationship
2) The volume of documentation that is generated by AI may contribute to clinician burnout
3) AI's output is only as good as the training that it receives; this may lead to critical information being overlooked.
4) AI has the potential to fabricate information or confabulate.

Ostrer I, Aronson L. The Perils of Artificial Intelligence in a Clinical Landscape. JAMA Intern Med. Published online February 12, 2024. doi:10.1001/jamainternmed.2023.7962

Will we be replaced by AI?

CrossMark

No need for pulmonologists to interpret pulmonary function tests

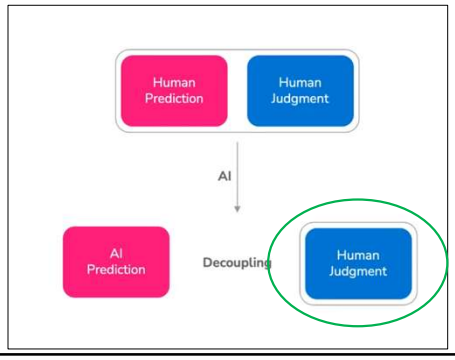
Christophe Delclaux[1,2,3]

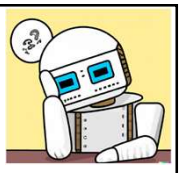
Computers can easily make these functional diagnoses based on the availability of z-scores, but one may wonder if it is necessary given the simple rules of interpretation.

Thus, almost 100% of pulmonologists would give a correct PFT interpretation, at least in university centres that are responsible for medical student teaching. However, it must be pointed out that a FEV1/VC ratio <5th percentile is not necessarily abnormal; it is only atypical because 5% of the normal subjects exhibit this atypical feature.

It is up to the physician interpreting the functional exploration to provide this kind of nuance depending on the clinical context.

Delclaux C. No need for pulmonologists to interpret pulmonary function tests. Eur Respir J. 2019 Jul 18;54(1):1900829. doi: 10.1183/13993003.00829-2019. PMID: 31320479.





Summary

- Artificial intelligence in Respiratory Medicine is growing
- Real opportunities in real-time issues of
  - Imaging
  - Prediction models
  - Improving diagnostic models
  - Making our lives easier with things like auto-populating Action Plans
  - Digital devices for assessing technique and adherence
- Future is exciting
- Good news, Live Clinicians are STILL NEEDED!! ☺

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