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Smartwatch-based algorithm for early detection of pulmonary infection: Validation and performance evaluation

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Abstract

Background: The proliferation of smart devices provides the possibility of early detection of the signs of pulmonary infections **(PI)**. This study validates a smartwatch-based algorithm to monitor the risk of PI in adults.

Methods: An algorithm that runs on smartwatches was developed and tested in 87 patients with **PI** and 408 healthy subjects. The algorithm examines heart rate variability, respiratory rate, oxygen saturation, body temperature, and cough sound. It was embedded into the Respiratory Health Study app for a smartwatch to detect the risk of PI and was further validated in the hospital. Doctors diagnosed PI using a clinical evaluation, lab tests, and imaging examination, the gold standard for diagnosis. The accuracy, sensitivity, and specificity of the algorithm predicting PI were evaluated.

Results: In all, 80 patients with PI and 85 healthy volunteers were recruited to validate the accuracy of the algorithm. The area under the curve of the algorithm for predicting PI was 0.86 (95% confidence interval: 0.82–0.91) ($P < 0.001$). Compared to the gold standard, the overall accuracy of the algorithm was 85.9%, the sensitivity was 81.4%, and the specificity was 90.4%. The algorithm for heart rate, respiratory rate, oxygen saturation, and body temperature had an accuracy of 68.2%, and the accuracy of the algorithm including cough sound was 82.6%.

Conclusion: Our wearable system facilitated the detection of risk of PI. Multi-source features were useful for enhancing the performance of the lung infection screening algorithm.

Trial Registration: Chinese Clinical Trial Registry of the International Clinical Trials Registry Platform of the World Health Organization ChiCTR2100050843; https://www.chictr.org.cn/showproj.html?proj = 126556

Keywords

Wearable device, Pulmonary infections, Cough sound analysis, Pneumonia

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Background

Pulmonary infections (PI), including both upper and lower respiratory tract infections (LRTI), are a major category of respiratory disease and also a leading burden of disease worldwide.[1,2] Whether acquired in the hospital or the community, PI are a global health concern with substantial morbidity and mortality.[3] Although PI tends to occur in susceptible populations, such as low immunity or young and middle-aged people in an often-temporary state of

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immune imbalance, clinical studies have consistently demonstrated the need for timely medical intervention. Delayed recognition of illness results in adverse outcomes and increased costs.[4,5] Furthermore, lung infection is usually highly specific, so its diagnosis needs to be combined with a consideration of symptoms, laboratory blood tests, imaging tests, and so on, which is not easy. The general public's understanding of the disease is poor. Early identification and intervention can prevent the disease from worsening and causing serious consequences. In a multicenter study of patients with acute cough, the area under the ROC (Receiver Operator Characteristics) curve for the diagnosis of pneumonia was only 0.77 using symptoms and signs plus serum C-reactive protein.[6] The search for biomarkers for early detection of lung infection will become a new prevention strategy and help timely treatment in susceptible people. Here, biomarkers are not necessarily molecular objects, such as proteins, metabolites, or RNA transcripts, but can also be digital signals of life. For example, wearable devices are used for the noninvasive and continuous monitoring of vital signs, analysis of high-density data, and detection of deviations between individuals and the baseline to identify PI in the early stages and provide targeted early treatment to avoid further harm.

Advances in electrical hardware design and data processing methods have led to the development of technology capable of detecting multiple physiological parameters in a continuous, noninvasive way. For example, changes in heart rate variability (HRV) are easy to evaluate using current commercial technologies. Some studies have used smartwatch technology to detect possible COVID-19 infection through monitoring changes in HRV or resting heart rate compared to baseline;[7–10] others have extended this to identify infection from 10 s to several days, adding a screening or prediction of the risk or severity of infection as well, using the degree of change in physiological data.[11–14] The measurement of physiological parameters can predict pneumonia in children, with a sensitivity of 96.6% and specificity of 96.4%.[15] Other wearable technologies can also contribute to the diagnosis and monitoring of respiratory diseases. For example, Health Care Origins (Rochester, New York) developed a wearable respiratory monitoring device for the observation and automatic management of asthma. It has the ability to detect abnormal breathing sounds in real time, from the wheezing usually associated with asthma to the local burst sounds heard in PI.[16] Research on the continuous tracking of respiratory behavior through wearable devices has proven the applicability of these devices in the field of chronic respiratory disease.[17,18] Although wearable monitoring technology cannot distinguish between bacterial and viral pathogens, it can warn of disease in advance and allow early detection and treatment to avoid serious illnesses requiring hospitalization.

While most wearable devices detect indicators such as heart rate and rhythm, sleep, and exercise, the monitoring of respiratory diseases, including the monitoring of potentially valuable signals such as blood oxygen saturation, body temperature, cough audio, and respiratory rate is rare. With regard to noninvasive evaluation of PI, some indicators of the CORB score, such as blood oxygen and respiratory rate, can be measured by wearable devices.[19] However, few studies have reported the diagnostic role of wearable sensor signals in PI in adults. Our previous studies demonstrated the accuracy of smart devices in detecting arrhythmia and OSA.[20–24] The aim of the present study was to establish an algorithmic model based on monitoring these signals in healthy adults and PI patients and then further verify the model in suspected patients with PI and healthy people, to prepare for population-level screening of pulmonary infectious diseases.

Methods

We designed a "Respiratory Health Study" platform application (Figure 1) that includes the following two parts: 1. Smartwatches (HUAWEI WATCH 3) measure physiological parameters including heart rate, blood oxygen, respiratory rate, body temperature, either for a single point in time (1 min) or for the whole sleep night (≥3 h) (Figure 2); Cough sounds were collected during wakefulness, 2–3 times in 15 s; 2. The measured physiological parameters are uploaded to the cloud through the mobile app Respiratory Health Research; the system was designed to seek deviations among the physiological parameters between PI patients and healthy volunteers. Using this system, we established and verified the algorithm for PI screening. All data were uploaded to the given research platform, and outside researchers had no access. The study was approved by the Ethics Committee of Chinese PLA General Hospital, Approval No. S2021–663–01. All participants signed informed consent before beginning the study. Furthermore, the study was registered in the Chinese Clinical Trial Registry, which is part of the International Clinical Trials Registry Platform of the World Health Organization (ChiCTR2100050843). The registration date was September 4, 2021.

Establishment of the training data sets

We enrolled 137 adult patients with suspected PI hospitalized in the PLA General Hospital from June 1, 2021, to November 30, 2021, and 408 asymptomatic healthy controls for the training dataset. All participants signed the informed consent. Data collection was based on a clinical questionnaire (**Supplementary Table 1**), electronic disease history, and physiological parameter measurement using a wearable smartwatch. The smartwatch presented to the patients monitored, recorded, and analyzed their heart rate, respiratory rate, body temperature, cough sound, and blood oxygen saturation when worn; these data were used to develop a screening algorithm for PI.

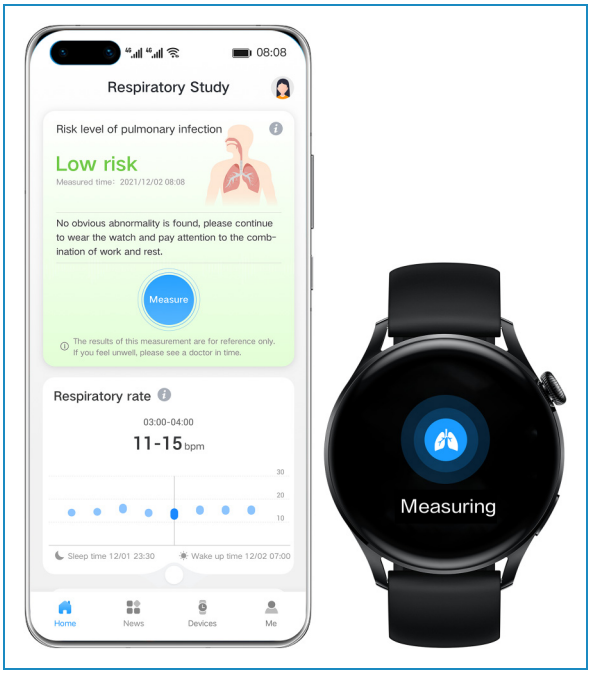

Figure 1. Respiratory health research app and HUAWEI smartwatch.

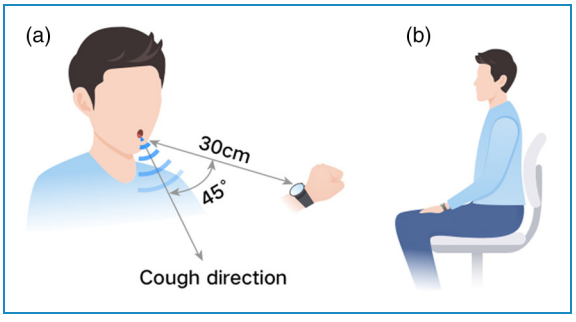

Figure 2. Collection of cough sound (a) and physiological parameters (b).

The PI diagnosis was made simultaneously by two independent physicians with respiratory specializations. After the exclusion of 50 subjects due to a final clinical diagnosis of non-pulmonary infection, incomplete data, or a poor signal (a low signal-to-noise ratio), 87 patients who were confirmed to have a PI diagnosis were used for the algorithm. 7 excluded pieces of data were due to the non-pulmonary infection diagnosis, and the rest 43 excluded data were either due to no valid physiological data (incomplete data) because the smartwatch fell off during the night wearing, or the low signal-to-noise ratio (poor data signal quality) of cough data due to excessive environmental noise. Combined with 408 healthy volunteers, 545 pieces of wearable data were collected (Figure 3).

Establishment of the algorithmic model

Features used for the screening algorithms were extracted from collected PPG signals, body temperature, and cough sound. First PPG signals and cough sounds were preprocessed (i.e., subjected to filtering and signal enhancement) to extract HRV, blood oxygen, respiratory rate, and cough features (**Supplementary Note**). Then aggregate features, including the median, variance, and coefficient of variation, were extracted from the original feature set.

By analyzing the differences between healthy controls and patients with pneumonia, we were able to extract relevant features to establish the classification algorithms **(Supplementary Note)**. The optimal parameters of the classification algorithms were determined through cross-validation on the training set, which contained 87 patients and 408 healthy controls. To verify the contributions of different features, we established three algorithms using different feature sets. The first algorithm (Algo-CS) used only features extracted from cough sound. The second algorithm (Algo-PP) used only features related to HRV, blood oxygen, respiratory rate, and body temperature features. The third algorithm (Algo-CSPP) used all the above features.

In addition, because features from different age groups are distributed differently, all algorithms contained several submodels for dealing with samples from different age groups.

Validation of the PI screening algorithm

The expected sensitivity and specificity of the proposed PI screening were 80% and 80%, respectively. We used the following formula to calculate the sample size:

$$n = \frac{Z_{1-\alpha}^2 P(1-P)}{\Delta^2} \quad .$$

In this formula, n is the sample size of the experimental or control group; $Z_{1-\alpha}$ is the quantile of the standard normal distribution, α=0.025 (one-sided), whose value is 1.96; P is the expected sensitivity or specificity; and Δ is the allowable error of P, which was 0.1 for this clinical study.

According to this formula, we needed to recruit 62 subjects with PI and 62 healthy control subjects (Table 3). We ultimately recruited 80 hospitalized patients with suspected PI and 85 healthy controls to form the validation dataset from the Chinese PLA General Hospital from September 10 to November 10, 2021. Then the established algorithms were evaluated on the validation set, which contained 80 patients and 85 healthy controls. In total, 297 pieces of data were collected, and 132 participants were measured repeatedly by the smartwatch. The diagnosis of PI took the final clinical discharge diagnosis as the gold standard for comparison with the results of monitoring to verify the accuracy, specificity, and sensitivity of the algorithm.

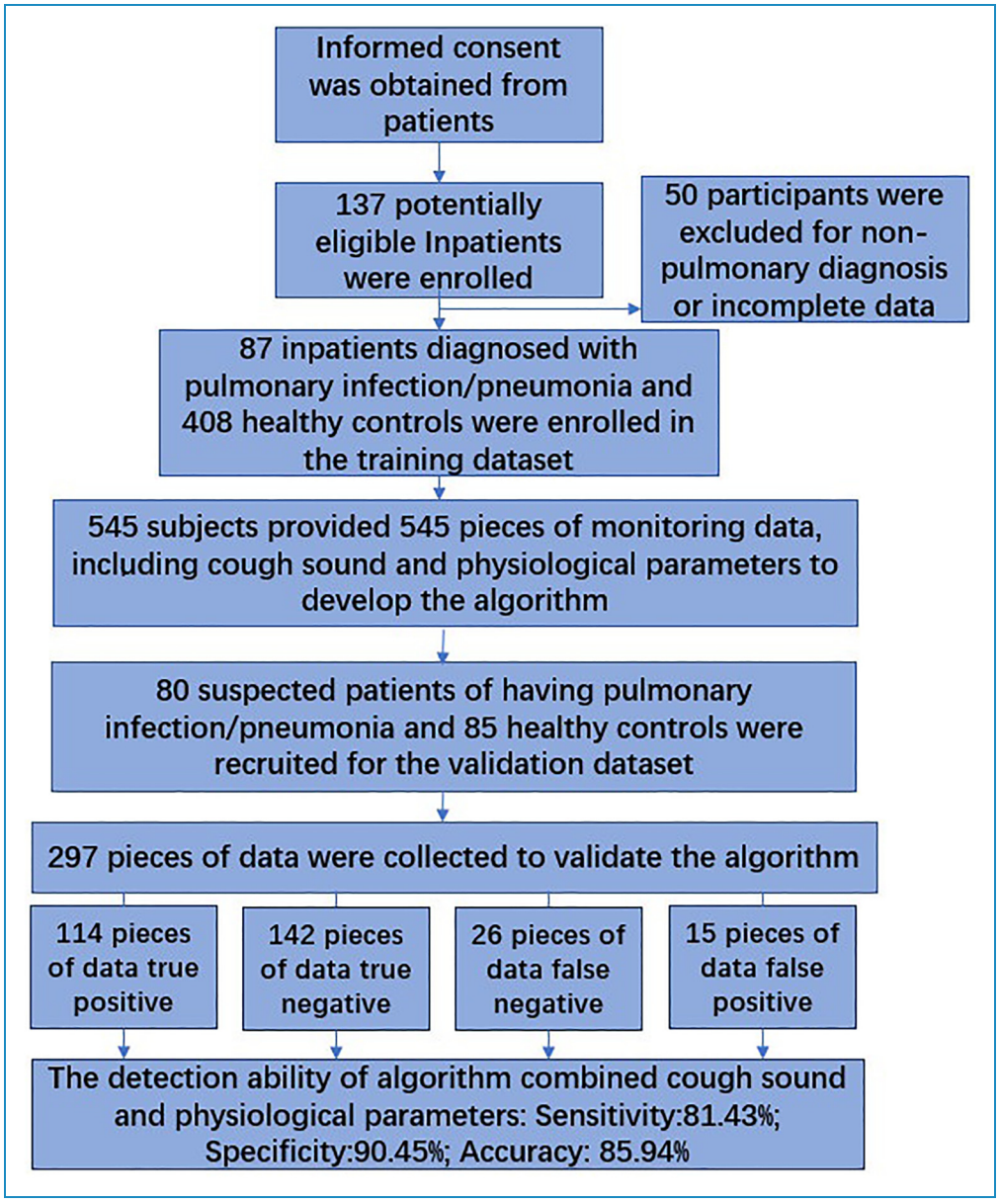

Figure 3. Flow diagram of the study.

Inclusion, exclusion, and diagnostic criteria for patients with PI

In this study, PI referred to lung infection or pneumonia caused by nonphysical or nonchemical factors (in other words, pathogens). Inclusion criteria: 1. age ≥ 18 years; 2. computed tomography (CT) identification of suspected pulmonary lesions; and 3. patient compliance with wearing a smartwatch.

Exclusion criteria: 1. patient not diagnosed with PI; 2. poor sensor signal quality on the smartwatch (low signal-to-noise ratio due to environmental noise or incomplete data due to dropping off the smartwatch); and 3. patient withdrawal before completion of data collection.

The PI diagnostic standard is as follows: 1. recent cough, expectoration, or aggravation of the original respiratory disease, with or without sputum production, chest pain, tachypnea, dyspnea, wheezing, or hemoptysis; 2. fever; 3. physical findings such as lung consolidation and/or wet rales; 4. peripheral blood leukocytes $> 10 \times 10^9$/L or $< 4 \times 10^9$/L, with or without left shift of nucleus; and 5. chest imaging examination via CT that shows new patchy infiltration, consolidation of leaves or segments, ground glass observation, or interstitial changes, with or without pleural effusion. PI was defined as meeting either criterion 1 or 2 above, which excludes the pathophysiological changes caused by pulmonary edema, atelectasis, pulmonary eosinophilic infiltration, and pulmonary vasculitis.

Physiological data acquisition using the smartwatch

The acquisition of physiological signals by a smartwatch was divided into two parts, and each patient collected the data for each part separately.

The first part was nocturnal monitoring. Patients wore their smartwatches in bed to collect data over the entire sleep period, including data on the motion of the body measured using an accelerometer; heart rate, respiratory rate, and blood oxygen data measured via PPG signals; and body temperature data (Figure 2A and 2B). The second part involved spontaneous measurement data. Wearing a smartwatch, patients were asked to take a deep breath and then cough serially and vigorously three times, repeating the entire process twice. Next, they wore the smartwatch for 1 min to collect physiological data including blood oxygen, respiratory rate, heart rate, and body temperature. Heart rate, blood oxygen, respiratory rate, and body temperature were collected at a sampling frequency of 25 Hz. Cough sounds were collected at a sampling frequency of 16 kHz;

After the data were acquired, the signal data were transferred through the Respiratory Health Research app to the research-specific platform.

Statistical analysis

Continuous variables were tested for normality with the Kolmogorov–Smirnov test. Data with normal distributions are presented as means ± standard deviations. Data with non-normal distributions were analyzed with the Mann–Whitney U test and are presented as medians (interquartile ranges). Categorical variables were analyzed with Pearson's chi-square test or Fisher's exact test. A two-sided $P < 0.05$ was considered statistically significant. Kappa coefficients were obtained, and statistical analysis of variables was performed with IBM SPSS Statistics, version 26.0 (IBM, Chicago, IL, USA).

Sensitivity and specificity were calculated based on the interpretation of the smart device compared to the physician's diagnosis. Finally, 95% confidence intervals and ROC curves were calculated and generated with MedCalc 19.0.4 (MedCalc Software, Ostend, Belgium).

Results

Creation of the PI algorithm (training dataset)

In all, 87 patients diagnosed with PI and 408 asymptomatic healthy controls were recruited. Patients' demographic statistics are presented in Table 1. Their symptoms and complications are presented in Table 2. In the training set, 2 patients reported abdominal distension and chest pain, and 2 patients in the validation set reported stomach aches and dizziness; 17 patients had no symptoms at all.

Table 1. Participants' demographic data (training set).

Characteristic	PI Patients (n = 87)		Healthy Controls (n = 408)		*P*
	n	Value (Mean ± SD)	n	Value (Mean ± SD)	
Male	56	-	218	-	
Female	31		190		
Age	87	58.82 ± 11.94	408	46.56 ± 19.21	0.000
Height (cm)	83	167.07 ± 7.40	379	166.76 ± 9.00	0.768
Weight (kg)	83	67.46 ± 11.60	376	62.89 ± 10.63	0.001
BMI (kg/m^2)	83	24.06 ± 3.14	376	22.54 ± 2.78	0.000
Hospital Days	87	13.15 ± 5.64	-	-	

Validation of the PI algorithm (validation dataset)

After the algorithm was developed, it was further validated in 165 newly recruited participants, including 80 patients with PI (54 males, 26 females) and 85 healthy volunteers (38 males, 47 females). Among these, 25 were asymptomatic. In some patients (n = 60) and healthy volunteers (n = 72), we collected physiological data from two smartwatches twice. Thus, a total of 297 sets of valid data were collected. The overall accuracy of the cough sound algorithm (Algo-CS) was 82.6%, the sensitivity was 83.57%, and the specificity was 81.53% **(Figure 4)** (**Supplementary Table 2**). The overall accuracy of the physiological parameter algorithm (Algo-PP) was 68.0%, the sensitivity was 37.86%, and the specificity was 98.09% **(Figure 5)**. The overall accuracy of the complete algorithm (Algo-CSPP) was 85.9%, the sensitivity was 81.43%, and the specificity was 90.45% (**Figure 6, Table 4**).

Discussion

Without medical training, PI is not easily recognizable merely from symptoms and intermittent measurement of body temperature. Wearable microsensors provide a convenient way of continuously detecting many physiological alterations besides cough or fever, such as heart rate, respiratory rate, oxygen saturation, and so on, that may indicate active PI. To the best of our knowledge, this is the first prospective study in China to differentiate adult PI patients and healthy controls based on data from smartwatch. The study provides new insights for the early identification of PI and lays a certain practical foundation for large-scale screening of PI among users of wearable devices.

Table 2. Symptoms and complications in pulmonary infection patients.

Symptoms	N = 87 (Training Dataset)	N = 80 (Validation Dataset)
Fever	10	13
Cough	50	41
Chill	4	6
Tachypnea	17	12
Sore Throat	7	10
Headache	4	5
Inappetence	8	8
Muscle Soreness	2	7
Nausea and Vomiting	4	4
Diarrhea and Stomach ache	0	5
Runny Nose, Sneezing, or Stuffed Nose	1	7
Fatigue	12	10
Sputum	50	44
Affecting Daily Life	54	45
Other symptoms	2	2
Complications	87	80
Lung Cancer	20	15
Obstructive Pulmonary Disease	5	5
Emphysema or Bullae	7	7
Kidney Dysfunction	2	4
Rheumatic Immune Disease	8	5
Bronchiectasis	12	7
Pulmonary Interstitial Disease	14	7
Asthma	3	4
Sleep Apnea	2	0
Nasal Sinusitis	4	4
Cardiovascular Disease	25	14
Hypertension	13	19
Mellitus Diabetes	20	9
Gastroesophageal Reflux	22	13
Leukopenia	11	9
Thrombocytopenia	4	8
Leukemia	1	1

Table 3. Participants' demographic data (validation set).

Characteristic	PI Patients (n = 80)		Healthy Controls (n = 85)		
	n	Value (Mean ± SD)	n	Value (Mean ± SD)	*P*
Male	54		38		–
Female	26		47		–
Age	80	53.32 ± 15.82	85	36.09 ± 12.06	0.000
Height (cm)	80	168.08 ± 7.73	85	164.99 ± 7.55	0.013
Weight (kg)	80	67.41 ± 9.64	85	60.03 ± 9.84	0.000
BMI (kg/m^2)	80	23.89 ± 3.34	85	21.96 ± 2.65	0.000
Hospital Days	80	14.00 ± 6.68	–		

Primary outcome

In our study, the physiological parameters of cough sound, heart rate, HRV, respiratory rate, oxygen saturation, respiratory rate, and body temperature were monitored to detect possible PI. We used physiological data collected at night and at a single point during the day to establish and verify the screening algorithmic model. The model

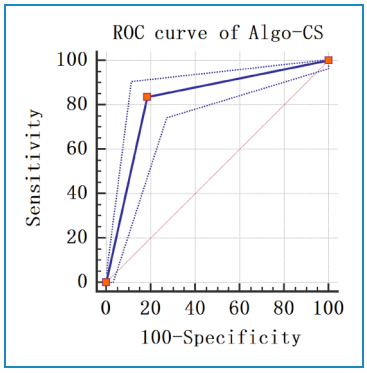

Figure 4. ROC curve of Algo-CS.
Solid blue line: ROC curve; dotted blue line: 95% confidence interval.

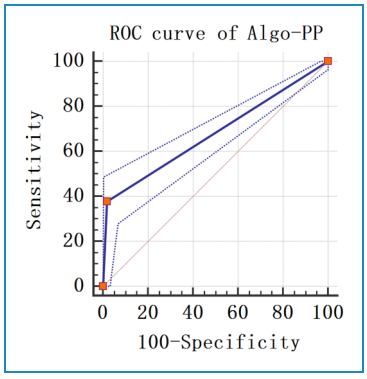

Figure 5. ROC curve for Algo-PP.
Solid blue line: ROC curve; dotted blue line: 95% confidence interval.

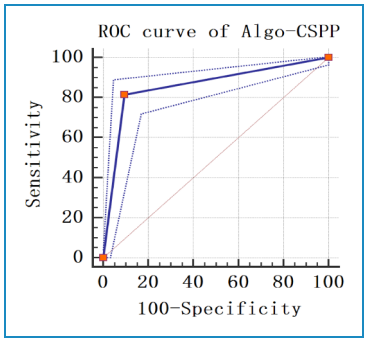

Figure 6. ROC curve of Algo-CSPP.
Solid blue line: ROC curve; dotted blue line: 95% confidence interval.

achieved 85.9% accuracy, 81.43% sensitivity, and 90.45% specificity, which indicates that this approach was effective at screening for PI and holds promise for large-scale screening of PI. Compared to a childhood pneumonia algorithm,[15] our algorithm exhibited lower efficacy for recognizing PI. This decreased efficacy was unsurprising, given the anatomical distinctions between the respiratory systems of children and adults. Children's lungs have shorter, narrower airways, and the transmission of cough sounds is more direct than in adults. Additionally, due to their smaller lung volume and high oxygen consumption, children exhibit a shallower, faster breathing pattern and rapid oxygen desaturation.

To investigate the contributing factors of the algorithm, we recorded the symptoms of each enrolled PI patient (Supplement 1). A total of 17 patients in the training dataset and 25 patients in the validating dataset lacked clinical symptoms, which posed a challenge to the traditional diagnosis of PI. Among symptomatic patients (Table 2), the most common symptoms were cough and expectoration, in 50 cases, followed by dyspnea and fatigue. Few patients had fever in either the training dataset or the validation dataset. This may be due to the features of the immune status of the patients and may have reflected the concealment of some PIs. Thus, body temperature did not play a crucial part in our algorithmic model. In a previous study,[25] the use of symptoms alone, such as cough symptoms, to identify lower respiratory tract infections (LRTIs) had a sensitivity of 90%, but low specificity of only 23%. The addition of other symptoms did not improve this. We located the research papers on terminal equipment-based lung infection screening. Cough sound[26–28] and physiological parameters (HRV, respiration rate, heart rate, etc.) screening[9,15,29] are the two main technical approaches for lung infection screening using terminal equipment. We discovered that while lung infection screening based on physiological indicators has poor sensitivity and high specificity, lung infection screening based on cough sounds has a high sensitivity and low specificity. We blend cough sounds and physiological metrics, which the smartwatch can collect, to ensure the algorithm's overall performance.

As cough is among the most important symptoms of PI, we used cough sound in an independent algorithm (Algo-CS) and found that its sensitivity and specificity can reach 83.57% and 81.53%, respectively. These results may be due to two facts: the control group in this study were all healthy volunteers, and 50 patients in the training dataset had cough symptoms, as did 41 patients in the validating dataset. The present understanding of cough sound is currently limited by human auditory sensitivity, with distinguishable sound usually falling within the limits of a 20 Hz to 20 kHz range. Cough sound contains important information on the lower respiratory tract. The power and energy of cough sound correlate strongly with physiological measures and subjective perceptions of cough strength.[30] When lung lesions, such as lung consolidation, edema, and airway obstruction due to increased secretion, occur, they can affect the transmission of airflow, thereby altering the acoustic features of the cough sound in both the time and frequency domains. Our study did not exclude patients

Table 4. Criterion values and coordinates of the algorithm ROC curve.

Algorithm	AUC	95%CI	Sensitivity	95%CI	Specificity	95%CI	Youden Index J	*P*	Z statistic
Cough Sound (CS)	0.826	0.777–0.867	83.57%	76.4–89.3	81.53%	74.6–87.3	0.6510	<0.001	14.731
Physiological Parameters (PP)	0.680	0.623–0.732	37.86%	29.8–46.4	98.09%	94.5–99.6	0.3595	<0.001	8.443
CSPP	0.859	0.815–0.897	81.43%	74.0–87.5	90.45%	84.7–94.6	0.7187	<0.001	17.738

with pulmonary lesions other than PI, such as tumors or fibrosis, which themselves may impact cough sound. Therefore, the ability to screen cough sounds may be affected and disturbed. Follow-up should be undertaken to further verify other respiratory diseases that have cough characteristics, such as cough variant asthma, chronic obstructive pulmonary disease, pulmonary fibrosis, and so on.

In addition to cough sound, a combination of other physiological parameters is used to screen for disease. Previous studies[11,31] have demonstrated the efficacy of multimodal infection screening systems using facial temperature, heart rate, and respiratory rate. Subtle changes in the above physiological parameters, as well as blood oxygen, may not be clinically detectable, but wearable devices can help to monitor and analyze them. The monitoring and analysis of 5700 patients hospitalized for COVID-19[32] showed the potential value of changes in RHR as early markers of COVID-19 infection: at admission, the proportion of patients with heart rate > 100 BPM (43.1%) was higher than that of patients with fever symptoms (30.7%). In the early stages of the disease, this slight change is likely to move the time of intervention forward to avoid serious disease consequences. In other studies of the early diagnosis of COVID-19 using wearable sensors,[33] key features included changes in sleep duration, total step count, Galvanic skin response, SpO_2, blood pressure, HR/HRV, respiratory rate, self-reported symptoms, and cough frequency. The accuracy of the algorithmic models used to detect COVID-19 varies greatly (20–88%), but they still show promising prospects. In our study, a separate screening algorithm was established that used only physiological parameters. Although the specificity of screening for PI was high, reaching 98.09%, the sensitivity was very poor, at 37.86%. This indicates that while the change was significant, its sensitivity in disease identification was insufficient. This may be related to individuals' specific physiological patterns, such as heart rate and sleep, as has previously been reported.[34,35]

The PI algorithm developed in this study was based on the XGBoost model (eXtreme Gradient Boosting), which is a kind of Boosted Trees implementation, and its advantages in classification discriminant analysis show significant advantages over traditional classification algorithms (e.g., Linear Discriminant Analysis, Support Vector Machine, etc.) in multimodal parameter fusion classification, especially in the handling of complex nonlinear relationships, automated feature selection, handling of noise and missing values, efficient parallelization of computation, and the ability to deal with the problem of class imbalance. This enables XGBoost to perform classification and discriminant analysis more effectively and achieve better classification results when facing multimodal parameters data.

Limitations

This study had numerous limitations. First, the inclusion criteria used to identify PI patients were not strict. The patients whose data were used to establish the algorithm generally exhibited more than one complication, most commonly cardiovascular disease, followed by gastroesophageal reflux, lung cancer, and diabetes mellitus. In addition, many patients had interstitial lung disease, bronchiectasis, COPD, and rheumatic immune disease. Previous studies have indicated that complications may be risk factors for pneumonia.[29,36] On the other hand, complications may affect physiological indicators, such as heart rate, blood oxygen, and respiratory rate, eventually causing deviation in the algorithm. We will conduct further research including a more diverse age range and varying health conditions, especially respiratory chronic diseases, such as chronic obstructive pulmonary disease (COPD) or asthma.

Although a larger set of healthy volunteers was available, the relatively small size of the training dataset may have introduced bias to the algorithm. Additionally, this study did not include baseline data from the patients; instead, healthy volunteers were used as controls. These are both common comparison methods, but the lack of control data for the patient group may have increased the individual bias of this study.

Third, although we collected symptoms of PI patients in a questionnaire because the volunteers were asymptomatic, it might have been better to add symptoms to the algorithm to distinguish PI, as was done in a previous study.[37] In the future, we intend to carry out a validation study on patients with respiratory disease symptoms and improve the ability

of the algorithm to identify PI in combination with symptoms and physiological parameters.

Fourth, the algorithm in this work depends on signal quality, hence there are particular signal quality requirements that must be met. 43 patients' data were consequently excluded, largely as a result of background noise. This feature imposed particular criteria for the algorithm's surroundings, which was also a limitation of the algorithm because we found during the study that external noise had a considerable impact on the cough sound characteristic.

Finally, all of the patients with PI recruited in this study were inpatients, and changes in activities were not included because patients' scope of activity was restricted to wards or hospitals, which was different from their patterns in daily life. Some studies have reported that behavior changes in patients may also help predict the occurrence of diseases.[38]

Future perspectives

The technology of wearable devices to measure various physiological parameters has significantly matured in recent years.[39] Although wearables cannot replace examination with medical devices, they may provide sufficient accuracy to provide an approximate assessment of an individual's condition.[40] Artificial intelligence has enabled us to detect and diagnose different respiratory diseases using cough sounds.[41] In future work, we plan to further validate the accuracy of our system in a real-world setting and conduct follow-ups with patients. Furthermore, it has the potential to help health care providers and patients themselves better track patient health outside regularly scheduled clinical visits, aiding rehabilitation and medication regimens. Consequently, screening by wearables may become the first step in the management of disease. The data provided by such devices also allow clinicians to provide patients with personalized tools and tailored solutions for improving their health moving forward. In summary, smartwatch-based screening has the potential to revolutionize personal health monitoring, but future efforts should focus on technology integration, sensor improvements, data security, and clinical validation.

Conclusion

The findings of this study indicate that, in contrast to conventional diagnostic techniques, it is feasible to utilize wearable devices to differentiate between adults with lung infections and healthy controls. As a screening instrument, the algorithmic model developed in this study integrates cough sounds and physiological parameters measured by smartwatches, thereby representing a more precise method than utilizing solely physiological parameters for the screening of lung infections.

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Authors' contributions: YB Chen collected and analyzed the data, and drafted the manuscript. D Li helped with data collection. DY She and YT Guo recruited the patients, conducted the examination, and made the diagnoses. LX Xie supervised the study. WJ Chen and J Li analyzed the data and built the algorithm model. All of the authors read and approved the final version of the manuscript. All authors contributed to the article's analysis, drafting, and revising, agreed on the journal for submission, gave final approval of the version to be submitted, and agreed to be accountable for all aspects of the work.

Availability of data and materials: The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available because of privacy or ethical restrictions.

Declaration of conflicting interests: The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Ethical statement: This study was performed according to the Declaration of Helsinki. The study protocol was approved by the Ethics Committee of the Chinese PLA General Hospital (Approval No. S2021–663–01). All participants provided written informed consent.

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