Influence of Gaussian White Noise on Medical Students' Capacity to Accurately Identify Pulmonary Sounds

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Abstract

Background: The effect of background noise on auscultation accuracy for different lung sound classes under standardised conditions, especially at lower to medium levels, remains largely unexplored. This article aims to evaluate the impact of three levels of Gaussian white noise (GWN) on the ability to identify three classes of lung sounds. **Methods and materials:** A pre-post pilot study assessing the impact of GWN on a group of students' ability to identify lung sounds was conducted. The three intensities were applied to the three classes of lung sounds: no GWN, signal-to-noise ratio (SNR), SNR-40 (medium level) and SNR-20 (high). This resulted with three exams, each containing nine questions. Fifty-two participants underwent a 4-day training programme and were tested on their identification of lung sound classes under the three levels of GWN, but seven subjects were excluded for not completing all three assessments. Statistical analysis was performed on 45 subjects, using non-parametric tests to analyse the data. A *P*-value of 0.05 was considered statistically significant. **Results:** The GWN did not impact the overall lung sound identification capacity of medical students, with consistent scores of 66.7% across the three noise levels for all three lung sound classes combined. However, when considering sound classes separately, GWN affected the identification of normal (NAS) and discontinuous (DAS), but not continuous (CAS) types. Exam scores for NAS varied significantly across the three noise levels, with respective scores of 66.7%, 100% and 66.7%. Scores for DAS also varied, revealing 66.7%, 33.3% and 66.7%. **Conclusion:** This study introduces a standardised simulation-based approach to investigate the effect of GWN on the accuracy of auscultation amongst medical students. Findings indicate that whilst CAS sounds are robust to background noise, the identification of NAS and DAS sounds can be compromised. The medium noise levels (SNR-40) of noise pollution had the greatest effect on the DAS lung sounds.

Keywords: Aauscultation, Gaussian, lung sounds, noise, pulmonology

Key Messages

(1) The study results show that discontinuous lung sounds are the most heavily impacted by Gaussian white noise (GWN).
(2) Medium levels (SNR-40) of Gaussian white noise impair students' ability to recognise discontinuous lung sounds more than higher levels (SNR-20).
(3) Continuous class of lung sound were not affected by different levels of GWN.
(4) White noise needs to be incorporated into training of medical students.

Access this article online

Quick Response Code:

Website: www.noiseandhealth.org

DOI: 10.4103/nah.nah_98_24

Introduction

Lung auscultation is a crucial aspect of pulmonary system examination.[1] The stethoscope has been a common tool in healthcare for over 200 years, but it has notable shortcomings.[2] One important issue is the negative effect

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Received: 27 May 2024 **Revised:** 22 October 2024
Accepted: 25 October 2024 **Published:** 30 December 2024

How to cite this article: Razvadauskas H, Razvadauskienė J, Aliulis M, Aliulytė Rūta, Naudžiūnas A, Paukštaitienė R, Sadauskas S. Influence of Gaussian White Noise on Medical Students' Capacity to Accurately Identify Pulmonary Sounds. Noise Health 2024;26:474-82.

of background noise, including noise from the stethoscope itself.[3]

Medical wards often have high levels of ambient noise due to staff activities, treatment carts and the surrounding environment.[4] However, standardised and easily replicable studies that examine how background noise impacts the ability of an examiner to identify lung sounds correctly are notably few. Most existing research is limited, over 5 years old, and performed in various settings or focused on paediatric patients.[5,6] A literature review from the last 5 years identifies only two articles that examine or discuss the impact of noise on the auscultation ability of subjects (only by Ye *et al.*[7] and Seah *et al.*[8]).

In 2022, the first study by Ye *et al.*,[7] assessed the ability of 56 participants to accurately auscultate a type of discontinuous lung sound (crackles) in the presence of fake crackles. These fake crackles were produced when the stethoscope membrane glided over the skin. The article concluded that such crackles can lead to misdiagnosis.

Furthermore, in 2023, a review paper by Seah *et al.*[8] primarily focussed on advancements in stethoscope technology for auscultation. Whilst their study acknowledged the impact of extreme noise in disaster zones, chaotic situations and helicopters, they failed to provide detailed insights into the effects of different classes of respiratory lung sounds, leaving a gap in our understanding of how background noise influenced auscultation.

Older research articles present contradictory conclusions, indicating that the ability of most examiners to hear heart and lung sounds is insignificantly impacted by background noise, with only remarkably high levels of noise in emergency departments having a negative effect on auscultation.[6]

Additionally, research, with the exception of Ye *et al.*,[7] does not use standardised background noise or patient conditions.[5,6,8] Simultaneously, studies show that noise levels in hospital settings are rising, with daytime values ranging from 37 to 88.6 dB.[4] These factors make it difficult to test hypotheses through replicable methods and to improve the diagnostic accuracy of pulmonary auscultation, which is an important clinical skill.[9]

Furthermore, not all lung sounds are alike. Two main types of auscultation sounds are available: normal (NAS) and pathological. Pathological auscultation sounds can be further classified into continuous (CAS) and discontinuous (DAS). DAS are characterised by fine and coarse crackles, whilst CAS are audible as wheezes and bronchial sounds. CAS typically have frequencies ranging from 80 to 1600 Hz, lasting more than 250 ms and are associated with asthma and chronic obstructive pulmonary diseases. In contrast, DAS are shorter, typically less than 20 ms in duration, have a wide frequency range from 100 to 2000 Hz and are associated with congestive heart failure and pneumonia.[10] Some ambiguity is encountered in defining crackles on a spectrogram compared to wheezes due to the wide frequency range caused by intermittent airway closure and opening.[11]

Gaussian white noise (GWN) was selected for the study because it was synthetic noise with equal energy distribution across frequencies, therefore, muffling different classes of lung sounds uniformly, unlike real-life noise. Additionally, GWN had been used in previous research to analyse the accuracy of machine-learning models in auscultation.[12]

Medical students were chosen for the study, as auscultation training typically began with them. Younger subjects were also less likely to experience hearing impairments.[13] Furthermore, confounding variables such as age, subjects' environment and training hours could be more easily controlled.

The null-hypothesis of the study was that GWN at three different levels of signal-to-noise ratio (SNR) would have no effect on the ability of medical students to recognise three different classes of lung sounds.

Materials and Methods

Kaunas' Regional Bioethics Committee approved the study (P1-BE-2-57/2021), and informed consent was obtained from all subjects.

The study used a pre-post, prospective intervention design to train and assess the ability of medical students to accurately identify three classes of lungs sounds under three levels of GWN (no GWN, SNR-40 and SNR-20).

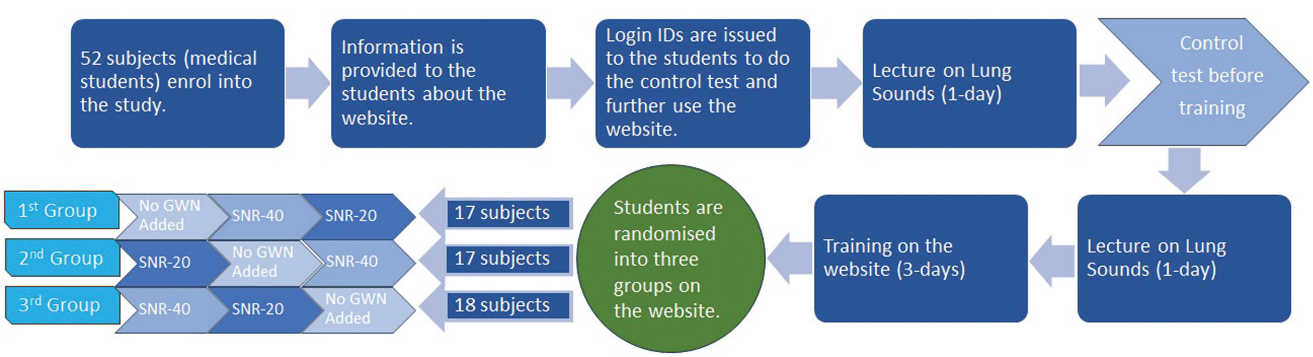

Figure 1: Study flowchart. Schematic diagram of all 52 subjects' participation steps, showing the studying stages from subject enrolment to exam completion in the set order in three different groups.

The primary objective of the study was to measure medical students' accuracy in identifying all three classes of lung sounds (combined) under three levels of GWN. The secondary objective was to measure medical students' accuracy in identifying all three classes of lung sounds separately (NAS, CAS and DAS) under three levels of GWN.

The study comprised of two parts: the first involved education (training students to identify three classes of lung sounds), whilst the second stage required students to identify lung sounds under the three levels of GWN (no GWN, SNR-40 and SNR-20). After training, students were randomly divided into groups, with each group taking three exams in different orders [Figure 1].

The study methodology comprised of eight stages: lung sound recording at a medical hospital, double-blind selection, database creation, development of teaching tools, subject enrolment, education, examination and data collection and analysis. An internal medicine physician recorded 654 lung sounds from 109 patients using a 3M™ Littmann(R) CORE digital stethoscope (3M Company, St Paul, MN, USA), Microsoft (R), Windows (R) 10 Operating System (Microsoft Corporation, Redmond, WA, USA) based HP ProBook 450 G4 (HP Inc., Palo Alto, CA, USA) Intel(R) Core™ i5 i5-7200U Laptop (Intel Corporation, Santa Clara, CA, USA) to store audio files via 3M™ Littmann(R) StethAssist – 1.3.230 software (3M Company, St Paul, MN, USA). All eligible patients in the ward were offered to participate in the study to prevent selection bias. The recordings were conducted over a period of approximately 3 months. The electronic stethoscope settings were as follows: the diaphragm mode was activated, and the sound amplification was set to level 3 (with a maximum level of 9). The investigator made the recordings in wards that typically contained two to four patients, all of whom were in stable condition and receiving treatment for their underlying disorders. During the procedure, patients were asked to remain quiet, and the ward doors were kept closed. If noise levels rose to the point of hindering auscultation, such as when a trolley passed or a nurse entered the room, the lung sounds were re-recorded. Each recording lasted 15 seconds long each and was stored in waveform audio file format (WAV). A team of family and internal medicine physicians conducted a double-masked review to assess the sounds for DAS, CAS and NAS, as well as their quality. The types of sounds selected for each class were as follows: crackles represented DAS, wheezes represented CAS and vesicular and bronchovesicular sounds represented NAS. The quality of the sounds was rated as either 'audible' or 'inaudible' for teaching purposes. Internal medicine and family physicians had to independently agree that a sound was 'audible' and classified it correctly as NAS, DAS or CAS to allow its inclusion in the respiratory sounds database. Of the 109 patients, 84 (504 lung sounds) were deemed suitable for teaching and examination. The lung sound descriptions and WAV files from the 84 patients were securely stored in an encrypted Microsoft(R) Excel(R) (Microsoft Corporation, Redmond, WA, USA) database and audio folder, respectively. This database contained only following essential patient information: age, gender, clinical diagnosis, audio file name and lung sound description. The data were stored on a password-locked laptop in the Internal Medicine Clinic, ensuring safety and confidentiality. The recordings were then transferred to a team member for the addition of GWN and subsequent upload to a proprietary website. Access to the website was restricted to enrolled participants through a password. GWN was added using Anaconda (R) (Austin, TX, USA) with Jupyter Notebook 6.4.7 utilising the LibROSA Python library, applied to each 15 seconds audio file used for assessment. The recordings were processed at the following levels: no GWN, SNR-40 (medium GWN level at 5 dB) and SNR-20 (high GWN level at 25 dB) [Figure 2]. The SNRs were as follows: no GWN had a signal of approximately 45 dB and noise at 0 dB; SNR-40 had a signal of approximately 45 dB and noise at 5 dB; and SNR-20 had a signal of approximately 45 dB and noise at 25 dB. The GWN was added across the frequency spectrum from 31.25 to 1968.75 Hz. Audacity(R) (Muse Group, Limassol, Cyprus) was used to visualise waveforms and spectrograms.

The SNR was calculated in accordance with the following formula:

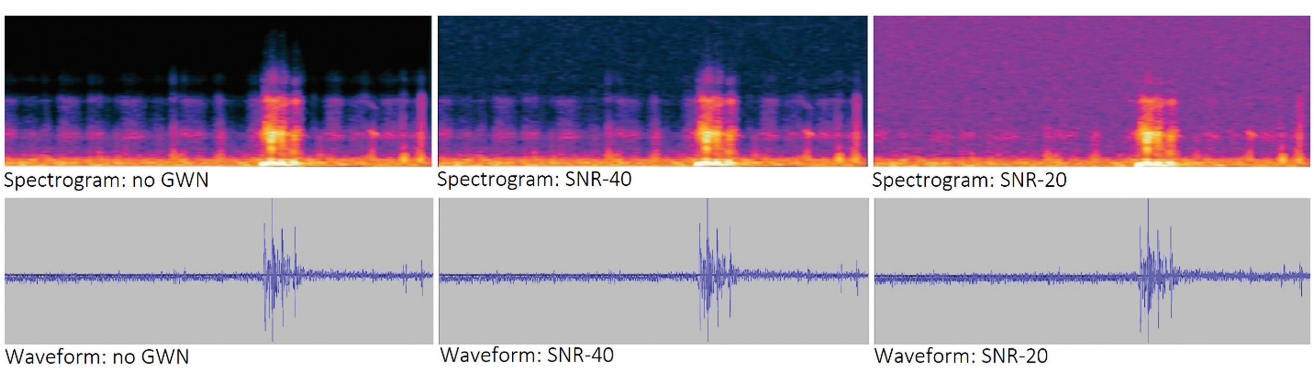

Figure 2: Visualisation of GWN levels added to lung sounds. Spectrogram (top row) and waveform (bottom row) analysis from one 15 seconds recording. Brighter backgrounds in the spectrogram indicate increasing Gaussian white noise (GWN) intensity from lowest (no GWN), medium signal-to-noise ratio (SNR) −40, to highest SNR-20 (left to right column).

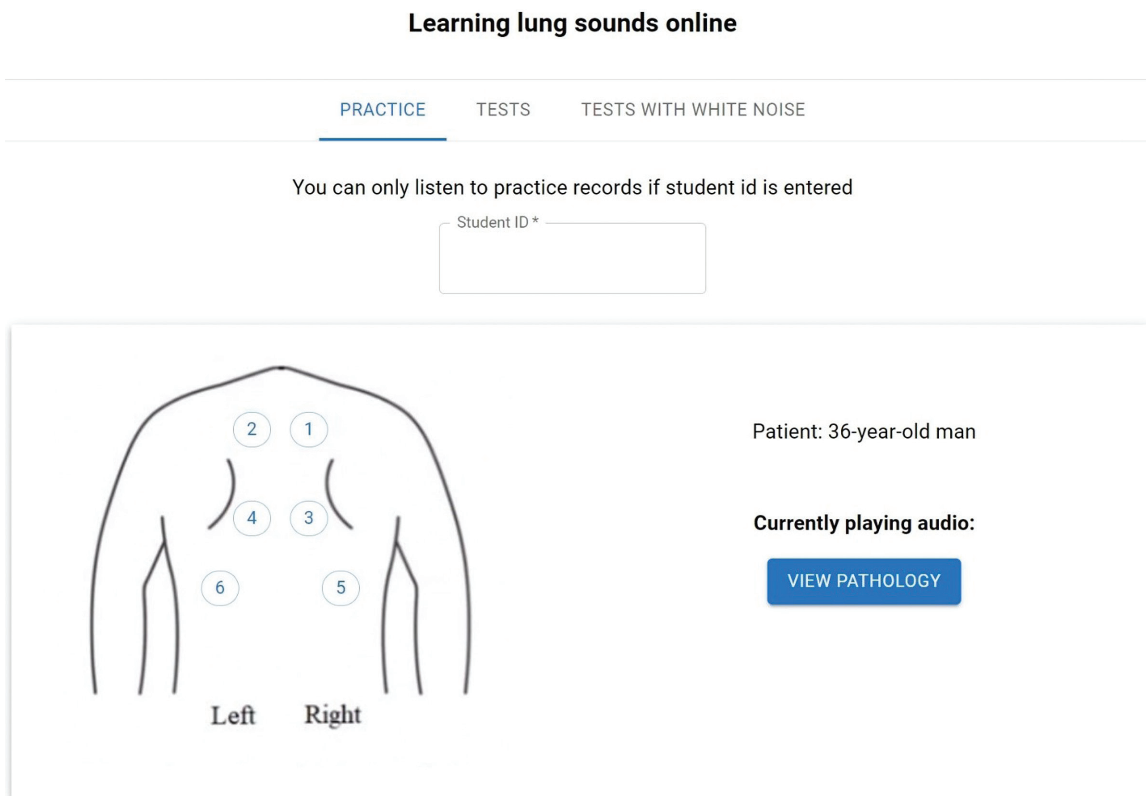

Figure 3: Website virtual patient ausculation section. Screenshot showing the top part of the website's practice section, where six auscultation points with 15 seconds lung recordings are related to anatomic sites of the human body (back of the thorax).

$SNR = Power\ of\ the\ signal\ (dB) / \ Power\ of\ the\ noise\ (dB).$

A website created with training and examination sections for the subjects, as this platform had been successfully utilised in previous study.[14] The training section of the website featured a pictogram of a chest with six clickable points, allowing students to listen to lung sounds, effectively creating web-based virtual simulated patients [Figure 3]. The information presented to the students was anonymised; only the patient's age and gender were included, along with details regarding the lung sound. The training section contained 101 lung sound recordings, of which 54% were DAS and CAS. The examination section was randomised and included 54 sound recordings, comprising equal proportions of NAS, CAS and DAS classes of lung sounds.

Prior to the pilot study, the website was tested with 15 students to assess its functionality during a dry run and to collect data for sample size calculation. A pulmonologist reviewed the website. Enrolment involved 52 out of 629 second- and third-year medical students who met specific criteria and provided informed consent.

The sample size was determined using G*Power software (ver. 3.1.9.4; Heinrich-Heine-Universität Düsseldorf, Düsseldorf, Germany) by selecting the following means: Wilcoxon signed-rank test (matched pairs) function. The following assumptions were applied: power ($1-\beta$ error probability) at 0.95 and an α error probability of 0.05. The effect size (Cohen dz) was calculated from the pilot study to be 0.61, based on pre- and post-training means and standard deviations (SDs) of 4.80 ± 0.49 and 5.07 ± 0.36, respectively. These values were inputted into the function, resulting in a sample size of 33 subjects. The pilot study had an attrition rate of 30%. Therefore, accounting for attrition, the total final number of subjects required was 48.

The criteria for enrolment were as follows: participants had to be over 18 years old, enrolled as medical students in their second or third year, have no prior experience with auscultation and agree to participate. Students with hearing impairment or loss, those over 40 years old or those who did not sign the consent forms were excluded.

Subjects were educated about lung sounds in a 30–35 minutes lecture, which introduced normal and adventitious sounds. The lectures and illustrations were created using Microsoft(R) PowerPoint(R) (Microsoft Corporation, Redmond, WA, USA). The 3-day learning process began with students advised to spend between 45 and 90 minutes daily learning the lung sounds on the simulated website. Students had the opportunity to listen to six recordings of the simulated patient's chest and 'view pathology' related to the simulation [Figure 3].

A description of each lung sound, along with a single recording for each, was provided at the bottom of the practice section of the website to assist students in learning lung sounds [Figure 4].

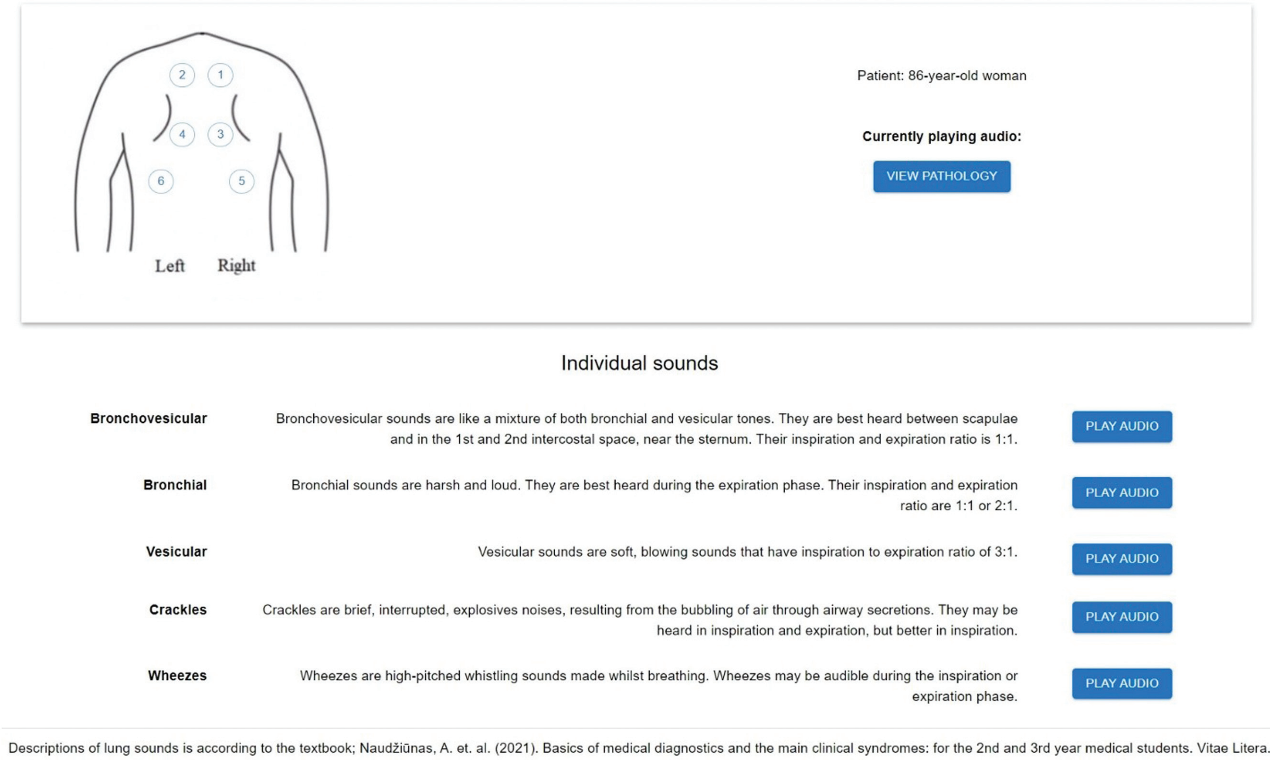

Figure 4: Website individual sounds practice section. Screenshot showing the lower part of the website's practice section, where the subject would study each lung sound individual before moving on to the cases.

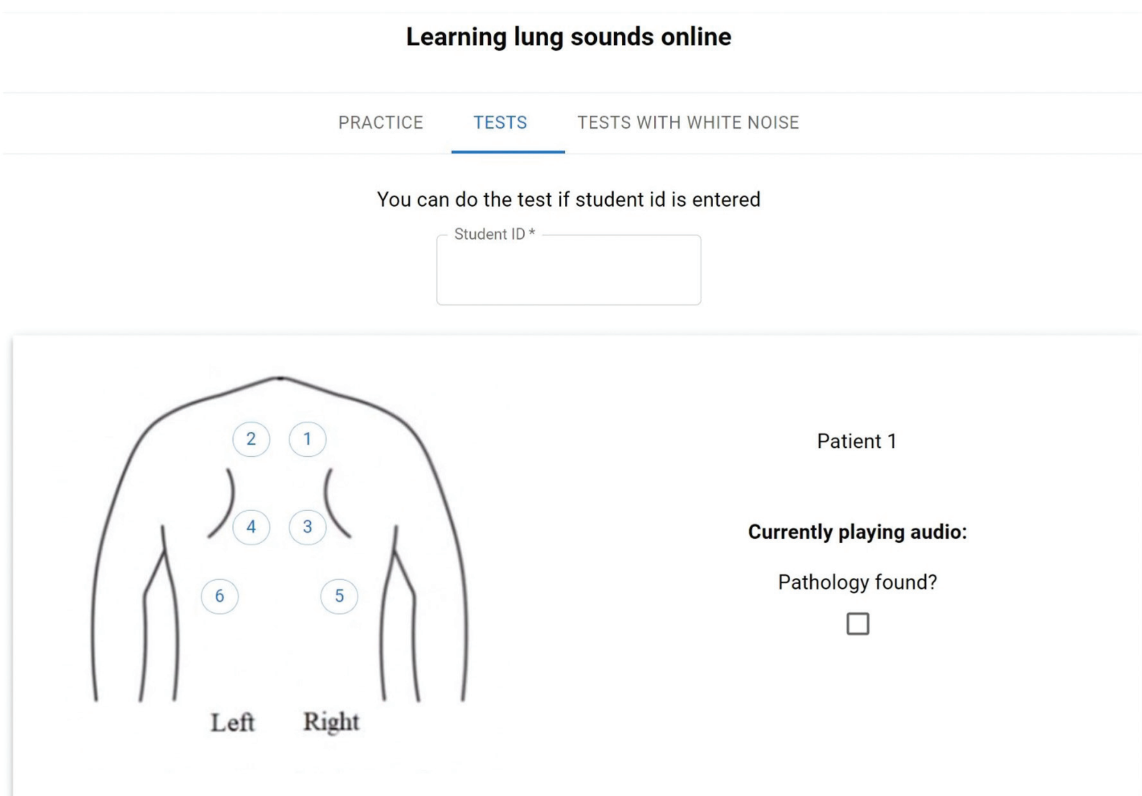

Figure 5: Website test section. Screenshot showing the test section of the website.

On the fifth day, students were assessed through three randomised multiple-choice exams at three different GWN levels. During the examination, students listened to nine cases categorised into NAS, CAS and DAS. The maximum score for each exam was 9 points, and the scores were converted to percentages in further data analysis. Students who did not hear any pathology were instructed not to check the 'pathology found' box and to continue to the next question. Conversely, students who identified pathological sounds or believed they did in the virtual patient had to check the 'pathology found' box and selected the types of pathology by choosing 'crackles' or 'wheezes' [Figure 5].

The examination room was quiet, and earphones were used to prevent distortion of the lung sounds. Although students were not time-limited, they were informed that they should aim to finish the test within 15 minutes. The student examination times for all students were monitored, and each student completed the test within 30 minutes. Research data were collected using MongoDB(R) (MongoDB, Inc., New York City, NY, USA) software and entered into a Microsoft(R) Excel(R) (Microsoft Corporation) spreadsheet for statistical analysis. The medical students' enrolment started in February 2023, and study finished in April 2023.

Statistical analysis

The data were analysed using a Microsoft(R) Excel(R) (Microsoft Corporation) spreadsheet and the JASP (ver. 0.18.3; Jeffreys' Amazing Statistics Programme, The Jamovi project, Sydney, Australia) statistical package. A *P*-value of 0.05 or below was considered statistically significant. The results were presented in tables and summarised in a box-and-whisker plot.

During data cleaning, seven subjects were excluded from further statistical analysis for not completing all three assessments. Therefore, statistical analysis was performed on 45 out of 52 subjects.

The results did not adhere to a normal distribution; therefore, nonparametric tests were used for further analysis of median values. The Wilcoxon rank-sum test assessed the effect of training on the ability of students to discern lung sounds accurately, whilst Friedman's test was used to analyse the impact of the three GWN levels on different lung sound classes with two degrees of freedom. Finally, a Conover post hoc comparison was performed to evaluate the ability of medical students to recognise the lung sound classes (NAS, CAS and DAS) separately under the three different levels of GWN.

Results

A descriptive analysis of the 45 subjects showed that the majority were female ($n = 32$), representing 71.1% of the total ($n = 45$). The average age of the students was 21.80 ± 2.57 years.

The pre–post training results were analysed, revealing that the ability of the examiner to distinguish lung sounds improved by 11.1% after 4 training days, with a median score of 66.7% (55.6%, 66.7%) ($P < 0.001$).

The exam scores of students showed no significant difference between the different GWN levels when lung sound classes were combined ($P = 0.358$) [Table 1]. Further statistical analysis was performed by splitting examination questions into NAS, CAS and DAS, evaluating the ability of students to recognise each class of lung sound under different levels of GWN, as shown in the bottom of Table 3 (fourth to sixth row). The results indicated a statistically significant influence of GWN on the ability of subjects to identify NAS and DAS lung sounds ($P = 0.042$, 0.021, respectively). However, no statistically significant influence of GWN on CAS ($P = 0.311$) was observed.

Finally, Conover's post hoc comparison was performed to evaluate the influence of the three levels of GWN on the ability to recognise NAS and DAS [Table 1]. Statistically significant differences were found in lung sound recognition between no GWN and SNR-40 for NAS ('a'), between no GWN and SNR-40 ('b') and between SNR-40 and SNR-20 for DAS ('c') ($P = 0.016$, 0.013, 0.023, respectively).

The results of three levels of GWN's impact on the ability of students to identify different lung class sounds were visually summarised in a box-and-whisker plot [Figure 6]. The plot illustrated the greatest variability in the recognition of DAS lung sounds due to noise pollution.

Discussion

The study's primary outcome was to determine the accuracy of medical students in identifying all three classes of lung sounds (combined) under three levels of GWN. The

Table 1: Medical students' exam scores for all classes of lung sounds under different levels of GWN [*M* (P25, P75)]

Lung sound classes	Number of questions	Number of subjects (*n*)	Exam scores at no GWN	Exam scores at SNR-40	Exam scores at SNR-20	*Z*-value	*P*-value
Classes combined	9	45	66.7 (55.6, 66.7)	66.7 (55.6, 66.7)	66.7 (55.6, 77.8)	2.056	0.358
NAS	3	45	66.7 (66.7, 100)	100 (66.7, 100)[a]	66.7(66.7, 100)	6.326	0.042
CAS	3	45	66.7 (33.3, 66.7)	66.7 (33.3, 66.7)	66.7 (33.3, 66.7)	2.337	0.311
DAS	3	45	66.7 (33.3, 66.7)	33.3 (33.3, 66.7)[b]	66.7 (33.3, 66.7)[c]	7.748	0.021

Notes: Lung sound recognition scores [*M* (P25, P75)] for 45 subjects under three Gaussian white noise (GWN) levels. GWN is measured signal-to-noise ratio (SNR) from lowest levels (no GWN), medium (SNR-40) and to highest levels (SNR-20). Scores are presented overall (combined) and separately for continuous (CAS), discontinuous (DAS) and normal (NAS) classes. The letters 'a', 'b', and 'c' refer to the sound classes and noise levels where statistical significance was found after applying the post hoc test for NAS at SNR-40, DAS at SNR-40 and DAS at SNR-20 levels, respectively.

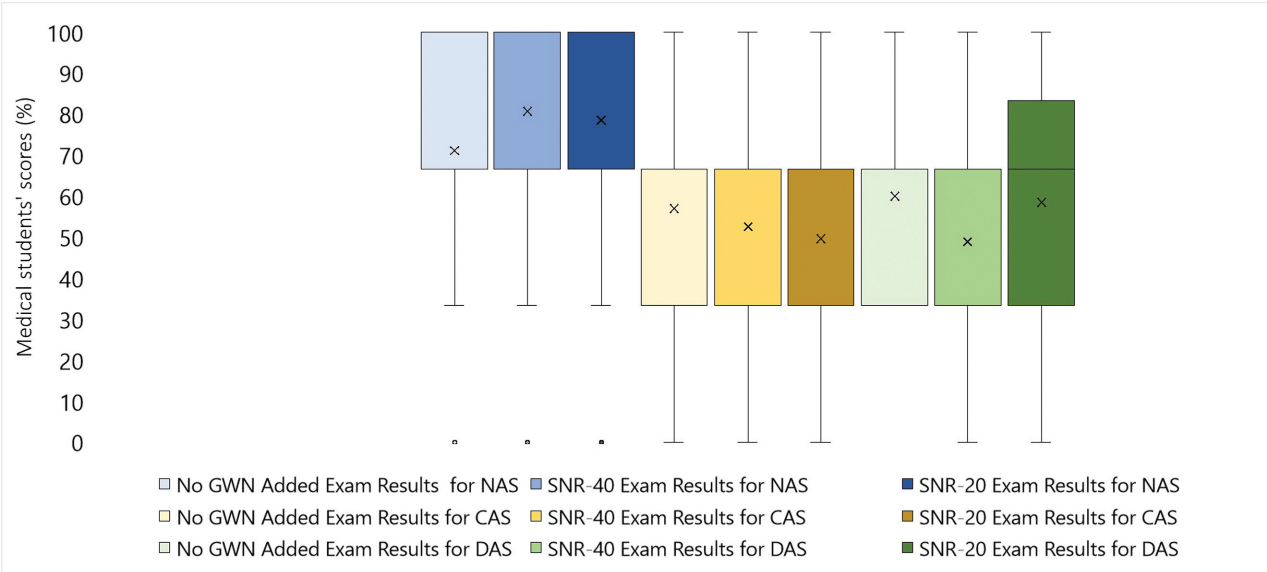

Figure 6: Medical students' exam scores for three classes of lung sounds under different levels of GWN. Impact of three levels of Gaussian white noise (GWN) on the ability of students to recognise continuous (CAS), discontinuous (DAS) and normal (NAS) lung sound classes. The noise levels are expressed in signal-to-noise ratio (SNR) from lowest levels (no GWN), medium (SNR-40) and to highest levels (SNR-20).

secondary outcome aimed to assess their accuracy in identifying the three classes of lung sounds separately under the same conditions.

The results for the primary outcome did not show a significant difference in identifying the classes of lung sounds across the three different GWN levels ($P = 0.358$).

Secondary outcome results showed that GWN had a statistically significant impact on the ability of subjects to recognise specific classes of lung sounds. This ability to identify NAS and DAS significantly varied ($P = 0.042$, 0.021, respectively) at the three levels of GWN, whilst no significant impact of GWN levels on CAS sounds was observed ($P = 0.311$).

Post hoc analysis of the NAS and DAS classes revealed a statistically significant difference in students' scores for the NAS class between no GWN and SNR-40 ($P = 0.016$). For the DAS class, significant differences were found between no GWN and SNR-40 ($P = 0.013$) and between SNR-40 and SNR-20 ($P = 0.023$).

The hypothesis that ambient noise uniformly impacted all lung sound classes was rejected. The findings indicated that background noise especially affected DAS, which were the most difficult to identify at SNR-40 level of noise pollution.

Existing research shows that crackles are more difficult to identify correctly than wheezes, which belong to the DAS and CAS classes of lung sounds respectively.[15] Particularly, research by Ye *et al*.[7] examined the ability of 56 subjects to distinguish fake crackles from real ones and concluded that the former has a statistically significant impact on misdiagnosis. This research indicates another contributing factor, noise, as demonstrated by different levels of GWN. This factor is concerning because DAS lung sounds are associated with heart failure and pneumonia; therefore, a lack of early diagnosis could adversely impact the care of these patients.

Assessing acoustic properties is a key to understanding why DAS is affected more than CAS. Amongst the two classes, adventitious lung sounds and wheezes are continuous, high-pitched sounds with a frequency of 400 Hz, lasting more than 80 ms. In contrast, crackles are discontinuous, exhibiting a wider frequency range of 100–2000 Hz but with a notably shorter duration of less than 20 ms.[11]

Fine crackles are hard to hear due to their short duration. In a previous study by Moriki *et al*.,[16] which included 296 physicians with different specialities and levels of expertise, only 55.2% correctly identified fine crackles, compared to 72.2% who correctly recognised wheezes. They can also be more easily confused with the rubbing of the stethoscope membrane.[7] The study used only five audio-recorded respiratory sounds that physicians had to listen to and document their responses.

Whilst CAS appears not to be impacted by GWN, this condition may not hold true if different types of background noise, such as babbling or car sounds, are used.

Another major reason why CAS is least affected by GWN is that wheezes have the most distinct audio qualities amongst the three classes. Whilst NAS could potentially be confused with DAS, especially when GWN is introduced, students misidentify these lung sounds even at no GWN and SNR-20 levels.

Regarding the DAS class of sounds, a fascinating observation is obtained: identifying lung sounds at SNR-40 is more difficult compared to SNR-20. Previous research has already identified crackles as problematic to identify and easy to confuse, particularly due to fake crackles, a wide frequency range and their short duration.[7,11] This research indicates that not only is the DAS class harder to identify, but it is also the most affected by noise pollution. Interestingly, this class is impacted most at the medium noise level (SNR-40) rather than at higher intensity (SNR-20).

The authors acknowledge several limitations of the study. Firstly, the sample size was small, comprising only 45 medical students. Whilst the age group, student type and training period were kept narrow, participants were selected to have no prior experience with auscultation to reduce any confounding factors that might influence the results. Secondly, the majority of the medical students were female, reflecting the higher proportion of women in the medical population from which the sample was drawn. Thirdly, the enrolled subjects comprised only medical students, who were highly motivated, as only 8.3% of the total 629 eligible students chose to participate in the study. Further research involving a more diverse group, including physicians and nurses, are necessary to better establish the impact of noise pollution on lunch auscultation. Lastly, the study only used GWN as background noise, omitting real-life background sounds such as mumbling, babbling and noise from street vehicles.[17]

This unique research study establishes a reliable, replicable and scalable virtual auscultation simulation that trains and assesses medical students in accurately identifying three classes of lung sounds under three levels of GWN.

Future research should incorporate noise from more representative real-life healthcare settings, such as mumbling, babbling and sounds from street vehicles.[17,18] Additionally, including nurses and physicians in the study would enhance its applicability in clinical settings.

Conclusion

This study introduces a standardised simulation-based approach to investigate the effect of GWN on the accuracy of auscultation amongst medical students. The findings indicate that whilst CAS sounds are robust to background noise, the identification of NAS and DAS sounds can be compromised. Notably, medium levels of noise pollution (SNR-40) have the greatest effect on the recognition of DAS lung sounds.

Author Contributions

Haroldas Razvadauskas (guarantor): Concepts, Design, Clinical Studies, Manuscript preparation, Data analysis, Manuscript editing; **Jurgita Razvadauskienė:** Concepts, Manuscript preparation, Data analysis; **Rūta Aliulytė:** Literature search, Manuscript preparation**; Martynas Aliulis:** Data analysis, Data acquisition; **Saulius Sadauskas:** Manuscript review, Manuscript editing; **Albinas Naudžiūnas:** Manuscript review, Manuscript editing; **Renata Paukštaitienė:** Data analysis, Statistical analysis.

Acknowledgements

The authors want to thank the heads of the Internal Medicine Department and Cardiology Department at Kaunas Hospital of Lithuanian University of Health Sciences, Irena Šidiškienė and Laima Jankauskiene, for creating suitable conditions for recording lung sounds for the database. They would also like to mention 15 LSMU students studying medicine in class 2021 from the 12th and 5th groups who participated in testing the website in the dry run trial. The authors would also like to thank the following persons and companies for their letters of support: James Schofield of TopMD Precision Medicine Ltd., Giedre Brandao of Abbaltis Ltd., and Stéphane Favier of eKuore Chip Ideas Electronics S.L. Mobility Insights Manager Fransua Razvadauskas at Euromonitor for reviewing the article for readability.

Financial support and sponsorship

The research received a grant from the Lithuanian University of Health Sciences and Kaunas Technology Innovation Funds (project number: PP2023/39/4) for collecting lung sounds and creating an annotated database.

Conflict of interest

There are no conflicts of interest.

Ethics Approval and Consent to Participate

The study was approved by Kaunas' Regional Bioethics Committee. Study was issued approval identification number: P1-BE-2-57/2021. All participants that enrolled into the study, done so voluntarily and signed the consent forms. The study was registered on Clinical Trials website (ID NCT05731193).

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