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Reduced Chest Computed Tomography Scan Length for Patients Positive for Coronavirus Disease 2019: Dose Reduction and Impact on Diagnostic Utility

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# Abstract

## Objective

This work aims to retrospectively evaluate the potential of dose reduction on chest CT examinations by reducing the longitudinal scan-length for patients positive for COVID-19.

## Methods

This study used the Personalized Rapid Estimation of Dose In CT (PREDICT) tool to estimate patient-specific organ doses from CT image data. PREDICT is a research tool that combines a linear Boltzmann transport equation solver for radiation dose map generation with deep learning algorithms for organ contouring. CT images from 74 subjects in the MIDRC-RICORD dataset (chest CT of adult patients positive for COVID-19) which included expert annotations including “infectious opacities” were analyzed. First, the full z-scan-length of the CT image dataset was evaluated. Next, the z-scan-length was reduced from the left hemidiaphragm to the top of the aortic arch. Generic dose reduction based on dose-length-product (DLP) and patient-specific organ dose reductions were calculated. The percentage of infectious opacities excluded from the reduced z-scan-length was used to quantify the effect on diagnostic utility.

## Results

Generic dose reduction, based on DLP, was 69%. The organ dose reduction ranged from ≈18% (breasts) and ≈64% (bone surface and bone marrow). On average, 12.4% of the infectious opacities were not included in the reduced z-coverage, per patient, of which 5.1% were above the top of the arch and 7.5% below the left hemidiaphragm.

## Conclusions

Limiting z-scan-length of chest CTs reduced radiation dose without significantly compromising diagnostic utility in COVID-19 patients. PREDICT demonstrated that patient-specific organ dose reductions varied from generic dose reduction based on DLP.

# Keywords

CT Organ Dose, Deterministic solver, Dose reduction, COVID-19

# 1. Introduction

Chest radiography and chest CT scans have been widely used during the Coronavirus disease 2019 (COVID-19) pandemic, particularly in patients with severe disease, complications, or prolonged symptoms1. Furthermore, patients with severe course of disease may develop premature fibrotic interstitial lung disease (ILD) and require follow up examinations to assess evolution of disease2. Although at the beginning of the pandemic chest CT scans have been used for COVID-19 diagnosis3, the United States Center for Disease Control (CDC) does not recommend the use of chest CT for diagnosis of COVID-19, since imaging findings are non-specific and overlap with other infections such as influenza4. However, chest CT has a relevant role in the assessment for COVID-19 progression and detection of its complications, such as acute respiratory distress syndrome, pulmonary embolism, superimposed pneumonia, or heart failure, and it can be used to assess additional suspected diagnosis other than COVID-195. Furthermore, several patients are subjected to repeated scans. One study on 782 patients positive for COVID-19 found that about 29% of them had two to eight chest CT examinations in less than 1 month6. With emerging variants and spread of disease through the younger populations, together with the stochastic risk of inducing cancer from CT examinations especially among children7–10, efforts for CT dose reduction become essential in the optimization of imaging protocols for enhancement of clinical utility of chest CT in patients with COVID-19 infection.

Studies of other chest conditions have shown that reducing the z-scan-length of a chest CT can significantly reduce radiation dose without reducing diagnostic accuracy11. While radiation dose reduction is important, patient-specific organ dose reduction may provide a more accurate risk assessment. This is particularly important for young patients with highly radiosentive thymic tissue7 and for patients undergoing repeated CT examinations for monitoring progression or resolution of pathology.

A chest CT extending from the lung apex to the lung base is the most frequently applied protocol found in literature for patients positive for COVID-193. According to multi-center study, the inferior chest CT scan length covered lung bases in 47% of the scans (370 of 782) and the adrenal glands in 41% of the scans (322 of 782), with no available data for other areas6. In our study we hypothesize that reducing z-axis scan length will reduce the patient-specific organ dose while maintaining diagnostic accuracy. As this project used a dataset annotated for findings of COVID-19, pathology aside from that associated with COVID-19 pneumonia which may be incidentally detected during CT examinations was not evaluated.

# 2. Materials and Methods

## 2.1. Chest CT dataset

The images for 74 patients positive for COVID-19 were taken from a publicly available dataset. The Radiological Society of North America (RSNA) has assembled the RSNA International COVID-19 Open Radiology Database (RICORD)12–14. The MIDRC-RICORD-1a (Medical Imaging Data Resource Center – RICORD release 1a) contains 120 chest CT examinations from four international sites from patients 18 years-old or older, all of whom were symptomatic from COVID-19. Two of the four sites were randomly selected, resulting in 75 patients for analysis. Written informed consent from all subjects in this study or waiver by IRB was not needed as imaging examinations and associated clinical information used in this work were de-identified by the contributing sites for inclusion in the RICORD database. One subject with CT images of size of 512 by 535 pixels, instead of usual size of 512 by 512 pixels, was excluded. Our final study cohort consisted of 74 patients (49 males, 25 females). Age was not available for one of the two sites. The average age for the 56 patients at the other site was 55.8 ± 30.3 years.

## 2.2. Reduced scan length protocol

Reduced z-scan-length from the top of the aortic arch to the left hemidiaphragm was chosen to represent the majority of the lung parenchyma that has diagnostic relevance for lung-related diagnosis11. Because the scout images were not provided for the analyzed patients, scouts were computationally generated from the CT image data as the antero-posterior projection of the linear attenuation coefficients. A MATLAB routine was employed to record the z-limits by clicking on the scout image of each patient at the top of the aortic arch and left hemidiaphragm (Figure 1).

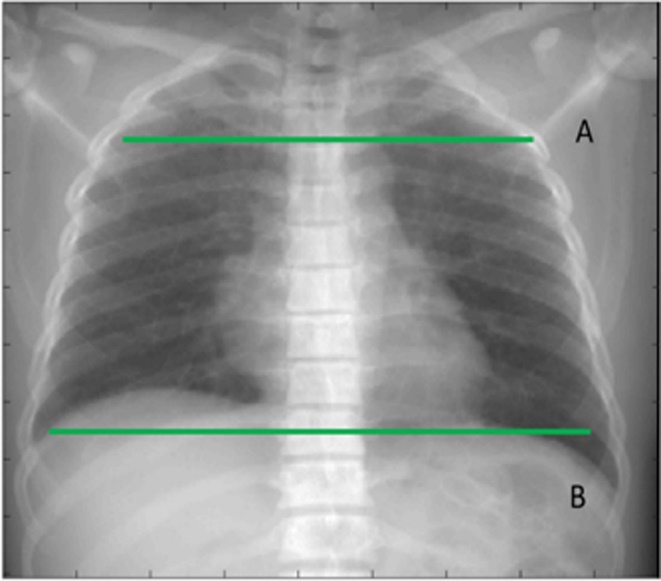
[](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9296570/figure/F1/)

Figure 1. Scout computationally generated from CT images. Line A represents the limit for the reduced z-scan-length at the level of the aortic arch, while line B represents the limit at the level of the left hemidiaphragm.

For each dataset, the z-scan-length was computed as a product of the slice thickness (3 mm for 56 patients, 1.5 mm for 17 patients, 1 mm for 1 patient, with no overlap or gap between slices) and the number of images per each case (Table 1, line 2). The number of images from the reduced z-scan-length (Table 1, line 3) was computed according to the selected limits at the top of the aortic arch and left hemidiaphragm. This calculation of the z-scan-length is an underestimate of the actual irradiated volume, because it does not account for the overrange, which is the scan length that extends beyond the volume of the reconstructed image that is required for helical scanning. However, this effect is expected to be small when comparing the full and reduced z-scan-length protocols.

Table 1: Z-scan-length: Median, maximum, minimum, 25th percentile (pctl), 75th percentile, and interquartile range (IQR) for full and reduced z-scan-length exams.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **Median** | **Max** | **Min** | **25th pctl** | **75th pctl** | **IQR** |
| **Full z-scan-length (cm)** | 32.70 | 44.85 | 24.00 | 30.30 | 34.95 | 4.65 |
| **Reduced z-scan-length (cm)** | 15.20 | 21.15 | 8.10 | 13.80 | 17.40 | 3.60 |

## 2.3. Evaluation of radiation dose

### *2.3.1. Estimates with Dose Length Product*

The dose reduction was first calculated in terms of percent change of Dose Length Product (DLP). The DLP, by definition, depends on both the z-scan-length and Volumetric CT Dose Index (CTDIvol). The CTDIvol is a measure of the scanner output, and accounts for the photons emitted by the x-ray source, which are proportional to the tube current. When tube current modulation (TCM) is applied, the tube current varies depending on slice position. In this case, the CTDIvol accounts for the average tube current across the whole scanned volume15. Therefore, the % DLP reduction is calculated as:

Where *FullScanLength* = (*nSlices* − 1) \* *dimZ* and *ReducedScanLength* = (*zAorticArch* − *zDiaphragmaticDome*) \* *dimZ*; *nSlices* is the number of image slices, *dimZ* is the slice thickness, *zAorticArch* and *zDiaphragmaticDome* are the *z* location of the top of the aortic arch and of the left hemidiaphragm, respectively.

accounts for the different average tube current for the reduced z-scan-length and the full z-scan-length, and both were calculated from the TCM profiles, that were generated by a previously validated custom MATLAB program16 (SmartmA, GE Healthcare, Chicago IL). The MATLAB routine is a proprietary model that takes as input the noise index and the scout and generates angular and longitudinal TCM profiles based on object attenuation, shape, and the desired noise index.

If the tube current were constant throughout the scan, the dose reduction calculated by means of the DLP would be affected only by the scan length reduction. However, since tube current modulation is applied, the average tube current decreases by avoiding denser structures than lungs, such as shoulders and upper abdomen, and the above considerations are needed.

### *2.3.2. Estimates with PREDICT*

Personalized Rapid Estimation of Dose in CT (PREDICT) tool is a fast and patient-specific estimator of computational dose maps and organ doses. It is a research tool developed though a collaboration of several academic institutions and Varian Medical Systems and combines a finite element solver for radiation dose maps generation with deep learning algorithms for organ segmentation17–19. Control of the data for this study was held by authors without a conflict of interest. The deep learning segmentation algorithms used by PREDICT have, to date, been trained on pediatric patients through age 16. A study was performed to validate that the deep learning segmentation models used by PREDICT provide sufficient accuracy for the adult subjects in the current study, with esophagus being the most challenging organ to segment. This validation study is described in Appendix A. PREDICT takes as input the images from the CT examination and scanner-specific specifications, and outputs the radiation dose to several organs.

The organs or tissues considered were lungs, breasts, esophagus, heart, bone marrow, and bone surface. The bowtie filter model, the overrange collimation, the tube current modulation (TCM), and spectral distribution of the x-ray beam, which are required for PREDICT, were not available from the MIDRC-RICORD dataset. The scanner type was not available for some of the patients. Therefore, this study modeled all patients as being scanned on a GE Discovery 750 HD (GE Healthcare) scanner, using a model that was previously validated as part of the PREDICT tool17, 18, 20. For all 74 patient cases, a 120 kVp beam with large (body) bowtie filter was modeled. PREDICT modeled all patients as scanned helically with a pitch of 0.9844 and nominal collimation of 40 mm.

For the tube current modulation, information on the noise index selected prior to the CT examination was not available. The standard deviation from the CT numbers of a region of surface of 5 cm2 at the center of the heart was then used to estimate the noise index. The TCM profiles, generated both for the full z-scan-length and for the reduced z-scan-length of the chest protocols, were used to scale the spectral distribution exiting the source for each z-position (Figure 2).

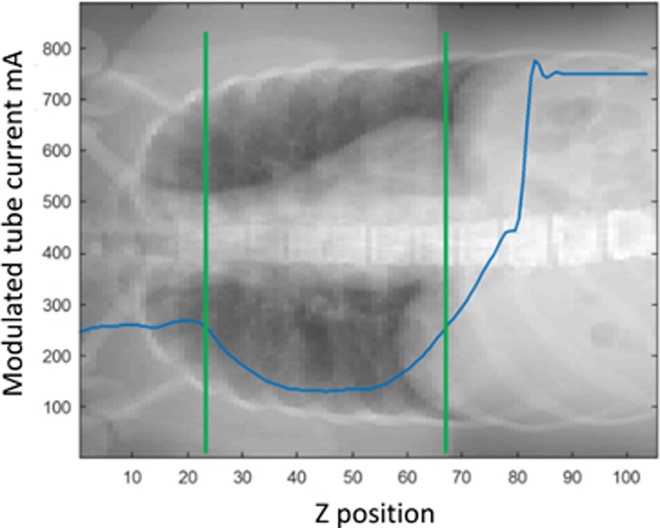
[](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9296570/figure/F2/)

Figure 2. Longitudinal (in blue) tube current modulation profile and delimitation lines of the reduced z-scan-length (in green), overlapped to a computationally generated scout image for one of the studied cases.

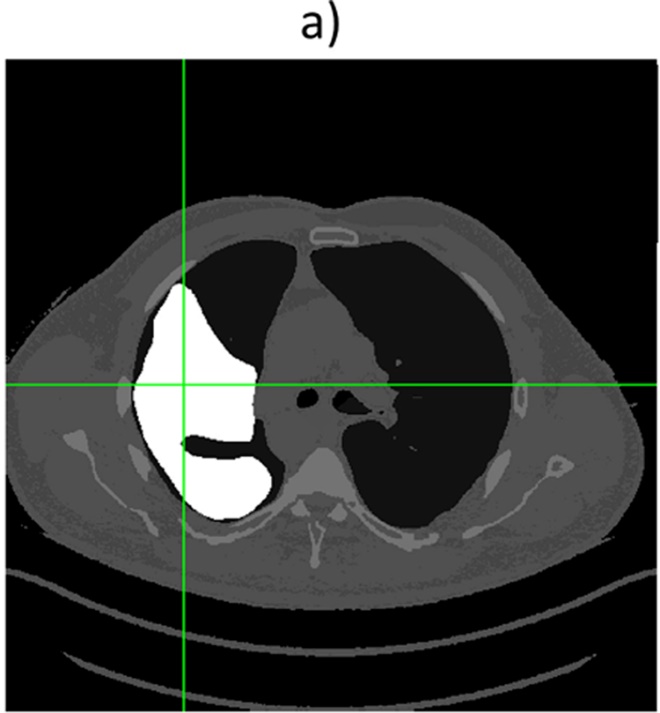
Dose maps and organ doses were estimated for full z-scan-length and reduced z-scan-length using the PREDICT tool. To quantify the dose reduction, the % dose difference for the contoured organs (heart, breasts, lungs, esophagus, bone surface and bone marrow) was computed as:

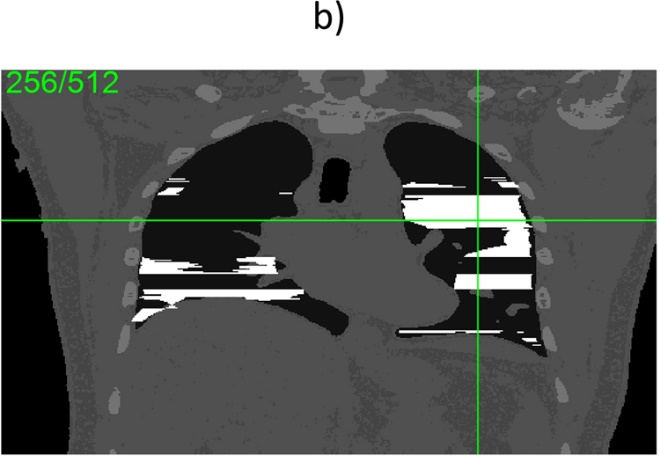
Where *OrganDoseFullScanLength* and *OrganDoseReducedScanLength* are the organ dose values for full z-scan-length and reduced z-scan-length using the PREDICT tool, respectively.

A Wilcoxon rank-sum test (Mann-Whitney U test) for all organ doses was performed for the null hypothesis that the organ doses estimated for full z-scan-length and reduced z-scan-length come from distributions with equal medians, where a p-value less than 0.05 is statistically significant.

## 2.4. Evaluation of diagnostic accuracy

The MIDRC-RICORD dataset includes expert annotations as discrete segmented areas labeled as “infectious opacities”. Vertices of each of the identified “infectious opacities” are available in the dataframe. We defined polygons from the vertices and reconstructed the opacity contours as binary masks (Figure 3). Binary masks were considered as belonging to the same opacity if they were contiguous along the z-axis. For the reduced z-scan-length exams, opacities that were completely outside the limits of the exam were considered excluded from the reduced scan-length.

[](https://www.ncbi.nlm.nih.gov/core/lw/2.0/html/tileshop_pmc/tileshop_pmc_inline.html?title=Click%20on%20image%20to%20zoom&p=PMC3&id=9296570_nihms-1779770-f0003.jpg)

[](https://www.ncbi.nlm.nih.gov/core/lw/2.0/html/tileshop_pmc/tileshop_pmc_inline.html?title=Click%20on%20image%20to%20zoom&p=PMC3&id=9296570_nihms-1779770-f0004.jpg)

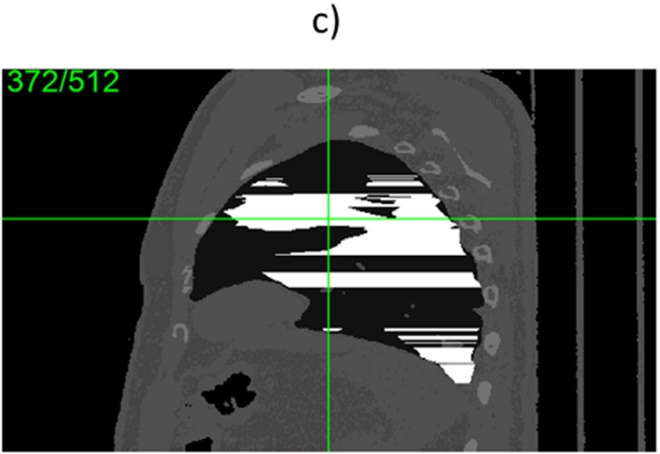
[](https://www.ncbi.nlm.nih.gov/core/lw/2.0/html/tileshop_pmc/tileshop_pmc_inline.html?title=Click%20on%20image%20to%20zoom&p=PMC3&id=9296570_nihms-1779770-f0005.jpg)

Figure 3. Binary mask example of infectious opacities (a) axial (b) coronal (c) sagittal views of one patient model, with infectious opacities shown in white.

Impact on diagnostic utility was calculated for each patient *i* as (*ExcludedOpacitiesi* \* 100/*TotalOpacitiesi*), and across all studied cases:

# 3. Results

## 3.1. Dose reduction

Table 2 shows the dose reduction from reduced z-scan-length exams, as calculated by DLP and by organ specific dose reduction. Median dose reduction by DLP was 68% while median organ dose reduction varied between 17.9% (breasts) and 63.4% – 64.8% (bone marrow - bone surface).

Table 2: Dose reduction from reduced z-scan-length exams compared to standard exam. Statistically significant decreases in dose reduction are indicated by bold and italic fonts. Pctl=percentile.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Dose reduction percentages** |  |  |  |  |  |  |
| **Percentage dose reduction by DLP (%)** |  |  |  |  |  |  |
|  | **Median** | **Max** | **Min** | **25th pctl** | **75th pctl** | **IQR** ***p-value*** |
| DLP | 68.0 | 92.3 | 42.9 | 61.8 | 75.9 | 14.1 *<0.001* |
| CTDIvol | 36.1 | 82.3 | 6.7 | 23.8 | 50.0 | 26.2 ***<0.001*** |
| z-scan-length | 51.8 | 73.0 | 37.6 | 47.4 | 56.9 | 9.6 ***<0.001*** |
| **Organ percentage dose reduction (%)** |  |  |  |  |  |  |
|  | **Median** | **Max** | **Min** | **25th pctl** | **75th pctl** | **IQR** ***p-value*** |
| Lungs | 40.7 | 72.2 | 25.4 | 34.9 | 46.8 | 11.9 ***<0.001*** |
| Breast | 17.9 | 65.7 | 0.24 | 13.4 | 27.9 | 14.4 ***1.09E-02*** |
| Esophagus | 55.9 | 89.3 | 18.0 | 46.7 | 62.1 | 15.4 ***<0.001*** |
| Heart | 33.7 | 73.5 | 17.5 | 27.4 | 41.3 | 14.0 ***<0.001*** |
| Bone marrow | 63.4 | 82.5 | 44.6 | 55.7 | 69.6 | 13.9 ***<0.001*** |
| Bone surface | 64.8 | 85.4 | 40.0 | 58.7 | 72.0 | 13.3 ***<0.001*** |

Figures 4 shows the dose maps for both the full scan and the reduced scan. Figure 5 plots the dose reduction factors for the six contoured organs and tissues across all cases.

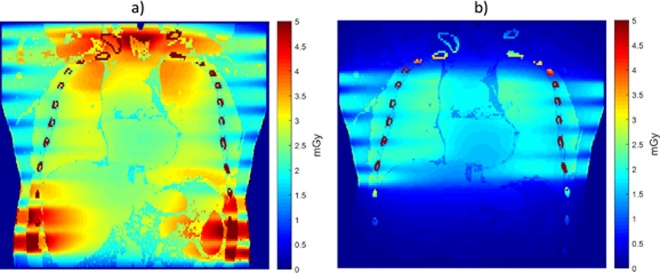
[](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9296570/figure/F4/)

Figure 4. Energy deposition maps (window 0, 0.1 eV/photon for (a) the original scan with full z-scan-length, (b) the reduced z-scan-length. eV = Electron Volt.

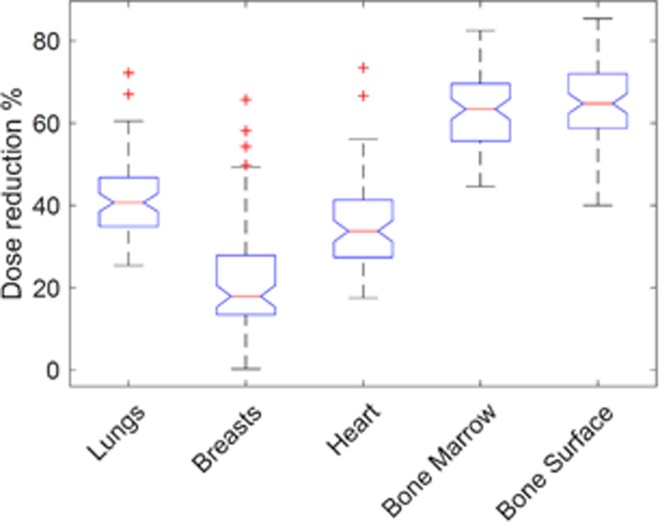
[](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9296570/figure/F5/)

Figure 5. Plot of the dose reduction factors for the six contoured organs and tissues across all studied cases. The red lines indicate the median value.

Figure 4. Dose maps (window 0, 5 mGy) for a patient helically scanned with (a) the original full z-scan-length, (b) the reduced z-scan-length. The dose map values in units of mGy were obtained by scaling the simulation output (in units of mGy per photon) using a conversion factor based on the CTDIvol provided in the DICOM header, according to the method used in Principi et al.18, 20

## 3.2. Diagnostic Accuracy

An average of 26.7 total unique opacities were contoured per patient for the full z-scan-range, of which 3.5 were excluded from the shortened z-scan-length. On average, reduced z-coverage resulted in missing 12.4% of infectious opacities per patient, of which 5.1% (1.5 per patient) were above the top of the arch and 7.5% (2 per patient) below the left hemidiaphragm. Due to extensive involvement of the areas of the lungs where the opacities were included, the diagnostic value of the examination was not significantly decreased, although we did not evaluate if any pathology or clinically concerning findings other than pneumonia were missed on the shorter z-axis scans. An example is given in Figure 6, where the distribution of the identified opacities is shown for one of the cases with higher percentage of excluded opacities. In this patient, 46 opacities were detected, of which 4 were excluded from the reduced z-coverage because above the top of the aortic arch, and 7 were excluded because below the left hemidiaphragm. The opacities excluded from the reduced z-scan-length are above and below the dotted blue and red lines, respectively.

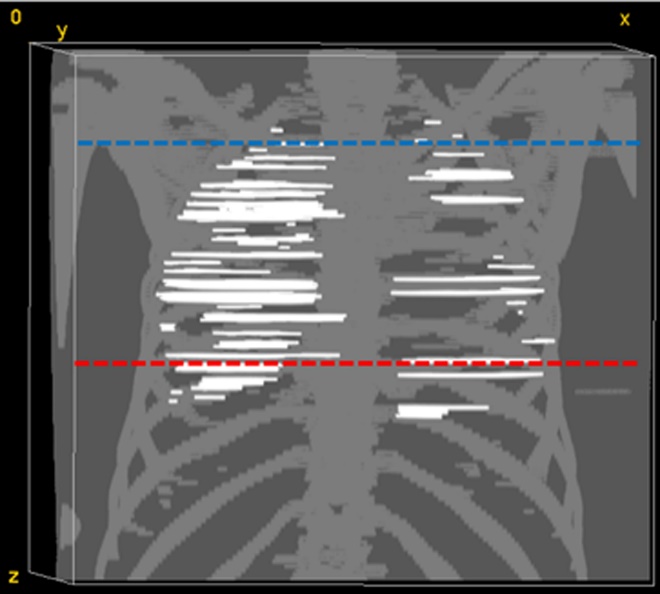
[](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9296570/figure/F6/)

Figure 6. Distribution of the infectious opacities in a patient where 11 out of 46 (24%) opacities were not included in the limited z-coverage. The opacities excluded from the reduced z-scan-length are identified by the red squares.

In 28% (21/74) of cases no opacity was excluded, neither above the top of the aortic arch nor below the left hemidiaphragm.

# 4. Discussion

This work demonstrates that a reduction in z-scan-length can significantly decrease radiation dose without a significant reduction in diagnostic accuracy in adult patients positive for COVID-19. Furthermore, the reduction is not evenly distributed, with a wide range of dose reduction amongst thoracic organs and tissues. To our knowledge, this is the first study to evaluate this potential dose reduction in COVID-19 patients. The widespread use of automatic exposure control, part of tube current modulation, has made z-scan-length decrease a prime target for dose reduction in chest CT. This is because the tube current used in the lung region is lower than the tube current used in the more highly attenuating regions of the shoulders and upper abdomen (Figure 4). Limiting the exam to the region between the top of the aortic arch and the left hemidiaphragm excluded the denser body regions, resulting in an average CTDIvol reduction of 37% (median ≈ 36%). When combined with a z-scan reduction of 52%, this reduced DLP by an average of 69% (median ≈ 68%). The median reduced scan-length of 15.2 cm in our work is in agreement with the reduced z-scan-length of 15 cm from Shahir et al. study on reduced scan length for when using CT to detect pulmonary emboli in pregnant patients11. However, the mean length of the original scan in their study was 26 cm (scan length reduced by a mean of 42.6%), and the dose was reduced on average by 70% (calculated as DLP reduction). A similar dose reduction factor was found in Litmanovich et al. work21, with a calculated dose reduction of 75% obtained again from DLP values in 26 pregnant patients who underwent CT Pulmonary Angiogram with a reduced scan range.

Due to differences in radiation sensitivity, the impact of radiation dose reduction on organs and tissues throughout the thorax will vary and thus radiation dose reduction should be evaluated on a tissue-by-tissue basis. Therefore, we estimated patient-specific organ dose by employing PREDICT. The average organ dose reduction varied between 17.9% (breasts) and 63.4% – 64.8% (bone marrow and bone surface), showing that reduced z-axis scan length impacts some organs more than others. This result highlights the fact that dose reduction based merely on the metric of DLP does not reflect the change of dose reduction across different organs and may overestimate the overall dose reduction. Also, our study demonstrated that reducing the scan length does not have a significant impact on diagnostic accuracy in COVID-19 patients. In fact, of the 27 infectious opacities found per patient on average for the full z-scan-range, only 3.5 were not included due to the reduced longitudinal exposure, on average. In Shahir et al. study on reduced scan length for pulmonary embolism11, no decrease in the diagnostic accuracy was observed, in fact no pertinent findings were missed (out of 60 across all cases), while four incidental findings were missed (of which three were thyroid nodules). While our method does exclude a small fraction of infectious opacities, the clinical significance is likely negligible given the typical diffuse distribution of COVID-19 pneumonia. On the other hand, the effect on diagnostic accuracy relative to findings not pertinent to the COVID-19 disease is beyond the scope of this study and was not evaluated.

Several papers have discussed the peripheral distribution of opacities within axial images of the lung22, 23, but there is little information about the longitudinal distribution. The results of this study demonstrate that opacities due to COVID-19 distribute across the longitudinal extent of the lung. This longitudinal distribution makes COVID-19 a good candidate for z-scan length reduction because, with an average of 88% of opacities located between the aortic arch and left hemidiaphragm, diagnostic utility can be maintained with the reduced scan length. This makes this technique useful in CT examinations assessing the severity of disease or monitoring the progression or resolution of disease in COVID-19 patients, as the distribution of their disease can be predicted. On the other hand, radiologists should be parsimonious in the usage of this technique, as other disease processes may not be as longitudinally distributed and diagnostic accuracy could suffer.

One limitation of this work is that portions of organs that extend beyond the chest volume, such as bone surface and bone marrow, were not accounted in the dose computation. Therefore, the organ dose is calculated only in respect to the volume of the organ, i.e. bone, that is within the scan length, even though it extends beyond the scanned image. Then, if the whole volume of bone and bone marrow were included in the calculations, the dose reduction for these tissues would be lower. Also, this study modeled all patients as being helically scanned on a GE Discovery 750 HD (GE Healthcare) scanner. As the objective of this work is not to provide the best estimate of dose for a specific scanner, but to quantify the relative dose reduction retrospectively, we considered that the use of our validated scanner model (GE Discovery 750HD) was adequate for the purpose of the study. Furthermore, contours for the adult organs in our study were generated by a deep learning algorithm trained on pediatric images. Due to the recent spike of COVID-19 infections among the younger population, an additional study using PREDICT for dose reduction quantification and protocol optimization for children and young adults would be particularly beneficial. Unfortunately, no dataset of patients positive for COVID-19 under 18 years of age is currently publicly available.

As known, radiation-induced cancer is a risk of stochastic nature. Risk models predict that approximately one in 100 individuals would be expected to develop cancer from a dose of 100 mSv, while approximately 42 of the 100 individuals would be expected to develop cancer from other causes24. However, the fact that there is no threshold above which cancers are induced makes it difficult to evaluate cancer risk due to exposure to ionizing radiation in humans and what are the effects of a dose saving of approximately 50% in terms of cancer incidences/death. A study at this regard is presented in Appendix B. Also, although reduction of radiation to thyroid is important especially for the younger population, the thyroid is not currently included in our training model, therefore contours and consequently absorbed dose were not available for this organ in the current study.

An additional limitation is that no information was available on the severity of the disease for each patient. However, the MIDRC-RICORD dataset Release 1c (MIDRC-RICORD-1c)25 that includes 998 Chest x-ray (CXR) examinations from 361 patients positive for COVID-19 classified mild, moderate, and severe cases according to the following criteria:

Mild- Opacities in 1–2 lung zones

Moderate- Opacities in 3–4 lung zones

Severe - Opacities in 5–6 lung zones

Where the lungs are divided on frontal chest x-ray into 3 zones per lung (6 zones total), of which the upper zone extends from the apices to the superior hilum, the mid zone spans between the superior and inferior hilar margins, and the lower zone extends from the inferior hilar margins to the costophrenic sulci. In our study, 52 cases out of the 73 studied patients have opacities distributed across six lung zones, and can be considered severe cases of COVID-19 pneumonia, whilst the other patients are moderate cases, according to the mentioned criteria. It is worth noting that since CT is more sensitive to subtle findings than CXR, the classification criteria provided here is likely overestimating the severity of disease in our cohort.

In conclusion, limiting z-scan-length of chest CTs reduced radiation dose without compromising diagnostic utility in COVID-19 positive patients, as approximately 90% of the infectious opacities are still detected despite the reduced scanned volume. The results from this study could be extrapolated to chest CT examinations for conditions beyond COVID-19 pneumonia that have similar longitudinal distribution throughout the lungs or have a central distribution of pathology.

# Conflicts of Interest and Source of Funding

This work was supported by NIH U01EB023822. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The authors also declare that the PREDICT tool was developed via collaboration with Varian Medical Systems.

Authors S. Principi, T. G. Schmidt, and S. D. O’Connor collaborate through the NIH grant U01 EB023822 with Varian Medical Systems on the development and validation of the PREDICT tool. No authors receive research funding from Varian Medical Systems. The core algorithms of the PREDICT tool were developed by Varian Medical Systems and were validated as part of the PREDICT tool by authors S. Principi and T. G. Schmidt as well as other multi institutional collaborators. The PREDICT tool is not commercially available and was developed as a research tool. Varian Medical Systems was not involved in the research of this COVID study.

# Appendix A

The deep learning algorithm used in the PREDICT tool was trained and validated on a pediatric dataset (average age of 7 ± 4.5 years)19, therefore its performance on adult patients was preliminary tested in this study. At this regard, reference ground truth contours for adult patients for heart, lungs, and esophagus from the “Lung CT Segmentation Challenge 2017” available in The Cancer Imaging Archive (TCIA) were employed26, 27. The test, performed on 24-patient dataset, showed that the average dice scores were 0.87 and 0.96 for heart and lungs respectively which considered good segmentation performance. A significantly lower average dice score of 0.38 was obtained for the esophagus. In order to further investigate the appropriateness of the PREDICT tool for the adult subjects in the current study, we evaluated the percent dose error from using deep learning contours and ground truth contours. Despite its low dice coefficient, the dose error in the esophagus due to segmentation error was ≈2%, calculated for the case with dice score equal to the first quartile (≈0.22). These results suggest that the segmentation algorithm used by the PREDICT tool has sufficient accuracy for low organ dose error for the adult subjects in this study, when considering lungs, heart, and esophagus. However, due to a lack of ground truth contours for breast tissue, we do not know if the performance of PREDICT deep learning contouring for breast segmentation in adults is good. The PREDICT tool can be further improved for adults in the future by retraining the deep learning segmentation algorithms with adult subjects.

# Appendix B

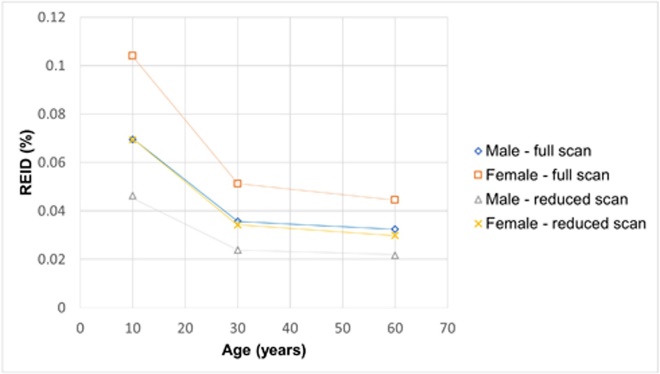
The BEIR (Biological Effects of Ionizing Radiations) VII committee24 developed models based on epidemiologic data, i.e. from atomic bomb survivors, for estimating the risk that an individual exposed to radiation will develop cancer. The BIER lifetime risk model predicts that approximately one individual in 100 persons would be expected to develop cancer from a dose of 100 mSv, while approximately 42 of the 100 individuals would be expected to develop cancer from other causes.

In our study, the risk in terms of death due to radiation-induced cancer was evaluated with the tool PCXMC28. PCXMC adopts the mathematical risk models developed by the BEIR committee, that accounts for sex and age at the exposure. PCXMC takes as input the dose to several organs (such as lungs, colon, liver), age, gender and ethnicity of the patient, and outputs the risk of exposure-induced cancer death (REID).

Because we do not have estimates of the dose to all required organs, we extrapolated them using data from the literature for chest CT29, 30. In order to quantify the risk saving when reducing the z-scan-length, we applied our dose reduction factor, obtained through organ-based calculation, to each organ dose, and we repeated the simulation with PCXMC. The results are shown in Figure B.7.

The results show that females are more radiosensitive than males, and that the older the patient the more radioresistant he/she is. In terms of benefit from the reduced scan length, we observe that the REID is approximately 50% lower when reducing the z-scan-length. However, among all cases the maximum REID is 0.104% (10-year-old female, full scan length), which is well below the cancer mortality rate for other causes not related to radiation exposure, that is 22.2% and 18.5% for male and female, respectively. It is worth mentioning that the REID would be further increased if repeated scans are required.

Figure B.7.



Plot of risk of exposure-induced cancer death (REID %) as a function of age, gender and scan length.

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