applied sciences

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Investigating the Effect of Patient-Related Factors on Computed Tomography Radiation Dose Using Regression and Correlation Analysis

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Abstract: Computed tomography (CT) is a widely utilized diagnostic imaging modality in medicine. However, the potential risks associated with radiation exposure necessitate investigating CT exams to minimize unnecessary radiation. The objective of this study is to evaluate how patient-related parameters impact the CT dose indices for different CT exams. In this study, a dataset containing CT dose information for a cohort of 333 patients categorized into four CT exams, chest, cardiac angiogram, cardiac calcium score and abdomen/pelvis, was collected and retrospectively analyzed. Regression analysis and Pearson correlation were applied to estimate the relationships between patient-related factors, namely body mass index (BMI), weight and age as input variables, and CT dose indices, namely the volume CT dose index ($CTDI_{vol}$), dose length product (DLP), patient effective dose (ED) and size-specific dose estimate (SSDE), as output variables. Moreover, the study investigated the correlation between the different CT dose indices. Using linear regression models and Pearson correlation, the study found that all CT dose indices correlate with BMI and weight in all CT exams with varying degrees as opposed to age, which did not demonstrate any significant correlation with any of the CT dose indices across all CT exams. Moreover, it was found that using multiple regression models where multiple input variables are considered resulted in a higher correlation with the output variables than when simple regression was used. Investigating the relationships between the different dose indices, statistically significant relationships were found between all dose indices. A stronger linear relationship was noticed between $CTDI_{vol}$ and DLP compared to the relationships between each pair of the other dose indices. The findings of this study contribute to understanding the relationships between patient-related parameters and CT dose indices, aiding in the development of optimized CT exams that ensure patient safety while maintaining the diagnostic efficacy of CT imaging.

Keywords: radiation dose; computed tomography; regression and correlation analysis

Citation: AlShurbaji, M.; El Haout, S.; Chanchal, A.; Dhou, S.; Dalah, E. Investigating the Effect of Patient-Related Factors on Computed Tomography Radiation Dose Using Regression and Correlation Analysis. *Appl. Sci.* **2024**, *14*, 1071. https://doi.org/10.3390/app14031071

Academic Editor: Cosimo Nardi

Received: 31 December 2023
Revised: 21 January 2024
Accepted: 22 January 2024
Published: 26 January 2024

1. Introduction

X-rays, a form of energy similar to radio waves and light waves, have the ability to penetrate bone, tissue and organs unlike light and radio waves [1,2]. This characteristic allows X-rays to be used for medical imaging, including computed tomography (CT). However, the absorbed radiation during a CT scan contributes to the patient's radiation dose, raising concerns about potential health risks [3,4]. The number of CT scans performed annually in the United States was projected to increase from 75 million to 84 million by 2022 [5], highlighting the need to understand and mitigate radiation-related risks.

Dose indices vary between various X-ray-based imaging modalities such as mammography [6] and CT [7,8]. For instance, the volume CT dose index ($CTDI_{vol}$) and dose length product (DLP) are two commonly used dose indices in CT [7].

$CTDI_{vol}$ provides information about the dose intensity in a specific slice, while DLP quantity accounts for the scan length coverage by roughly multiplying $CTDI_{vol}$ with the scan length. In contrast, the effective dose (ED) integrates the dose contributions from various exposed organs or tissues, providing a comprehensive measure of radiation impact [9]. ED is used to assess the radiation absorbed by the patient's body. It is calculated as the sum of the organ-equivalent doses multiplied by the organ-weighting factors proposed by the International Commission on Radiological Protection (ICRP) [10]. ED takes into account the varying sensitivities of different tissues and organs to radiation, recognizing that the absorption during, for instance, an abdomen CT scan differs from that during a head CT scan [11]. Clinical scientists, radiologists and CT technologists consider these indices to optimize CT exams, striking a balance between dose and image quality while minimizing risks [12]. The correlation between $CTDI_{vol}$, DLP and ED depends on factors such as scan acquisition parameters, patient characteristics and dosimetric models used for calculation [12]. The SSDE index is another dose index that indicates that patient size (i.e., weight) was taken into consideration, unlike the CT dose index of $CTDI_{vol}$, resulting generally in more accurate dose estimates [13]. For more detail, the reader is referred to the American Association of Physicists in Medicine (AAPM) task group report no. 204 [14]. $CTDI_{vol}$ is affected by patient size and tissue composition; hence, high $CTDI_{vol}$ values are associated with obese patients, body parts made of more dense material like the bone, implemented metal and some types of pathologies [15].

While CT scans carry a potential risk that is associated with increasing cancer incidence, their medical benefits outweigh these risks by aiding in disease diagnosis, guiding procedures and evaluating injuries without invasive techniques [16]. Nonetheless, concerns about public health necessitate understanding the correlation between radiation dose indices and patient dose to develop strategies for dose optimization [17]. This study aims to investigate the impact of patient-related parameters, namely body mass index (BMI), weight and age as input variables, and reported CT dose indices, namely $CTDI_{vol}$, DLP, ED and SSDE as output variables, while considering different CT exams. Regression and correlation are suitable methods to achieve the aim of this study. Moreover, regression and correlation analysis are utilized in this work in accordance with similar studies found in the literature that investigated the relationship between patient-related parameters and different dose indices.

2. Materials and Methods

In this section, the study design is introduced in Section 2.1. A detailed description of the dataset is provided in Section 2.2. Section 2.3 discusses the regression analysis approach used in this work and the evaluation metrics.

2.1. Study Design

This study was performed retrospectively using CT data acquired from the University Hospital Sharjah, UAE, investigating the use of CT and the factors affecting radiation dose. This study was approved by the Ethics and Research Committee of the University Hospital Sharjah on 19 June 2017 (Ref. UHS-HERC-030-07062017). From all of the CT exams collected, the radiology team specified the images by the exam type and the patient gender. Each CT exam contains a set of information regarding the CT modality technical parameters, patient-related parameters and dose estimation parameters. From all of them, we were interested in extracting the parameters of $CTDI_{vol}$, DLP, ED, SSDE, BMI, weight and age. These parameters comprise the dataset used. Patients with missing data or outliers were excluded, which is a necessary step to make future results more reliable and robust. After that, Pearson correlation and linear regression were implemented to investigate the relationships between patient-related parameters and the different CT dose indices, aiming to answer the following research questions:

Q1. How much does each patient-related parameter impact each of the dose indices?

Q2. How do the relationships found in Q1 differ for different CT exams?

2.2. Dataset Description

The dataset consists of a total of 333 CT scans acquired from patients subjected to CT chest, CT cardiac angiogram, CT cardiac calcium score and CT abdomen/pelvis between June 2017 and April 2019. Seven pediatric cases were observed in the dataset and were excluded, leaving us with 326 CT scans available for analysis. The dataset was divided into 4 groups based on the performed CT exam, with 68 of them in the group of chest, 91 in the cardiac angiogram group, 94 in the cardiac calcium score group and the last 73 in the abdomen/pelvis group. In the present study, we considered the CT exams that could benefit from CT protocol optimization. Chest, abdomen and pelvis body part composition and thickness considerably vary across patient cohorts, which calls for kV and mAs modulation, i.e., CT protocol amendments. Table 1 lists the four groups of CT exams and provides patient-related information such as the patients' genders and their average (and range) age, weight and BMI.

Table 1. Population statistics of the dataset according to the groups of protocols.

CT Exam	No. of Patients (Male, Female)	Average Age (Range)	Average Weight (Range)	Average BMI (Range)
Chest	68 (37, 31)	65.3 (21–96)	66.4 (36–110)	25.5 (15.6–41.4)
Cardiac Angiogram	91 (49, 42)	55.7 (33–85)	83.8 (47–144)	31.2 (19.6–51.6)
Cardiac Calcium Score	94 (48, 46)	56.1 (33–85)	83.9 (52–144)	31.5 (19.6–51.6)
Abdomen/Pelvis	73 (31, 42)	48.4 (20–92)	72.9 (35–113)	27.4 (16–39.7)

2.3. Regression Analysis

The data in this study were analyzed using simple and multiple linear regression models. Regression analysis models the relationship between one output (dependent) variable and one or more input (independent) variable(s). Thus, linear regression is a technique that finds a line that best fits a dataset [18]. Simple linear regression model has one input feature as in (1):

$$\hat{y} = a + b_1 X_1 \tag{1}$$

where $\hat{y}$ is the predicted output variable, X_1 is the input variable, a is a scaler and b_1 is the slope of the line. Multiple linear regression model has multiple input variables $X_1 \ldots X_m$ as in (2):

$$\hat{y} = a + b_1 X_1 + b_2 X_2 + \cdots + b_m X_m \tag{2}$$

In this study, linear regression analysis was performed between each patient-related parameter (BMI, weight and age) as input variables and each CT dose measure ($CTDI_{vol}$, DLP, ED and SSDE as output variables) for each of the four CT exams. In addition, multiple linear regression analysis was performed on all input variables X_i altogether with each output variable separately.

In the evaluation process, several evaluation metrics are used to evaluate the resulting regression models, namely the coefficient of determination (R^2), mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). These metrics give an intuition of how much the line of a model fits the data [19]. Moreover, the Pearson correlation coefficient (r) and the two-tailed p-value are calculated to assess the strength of the correlation between the input and output variables. The metrics R^2, $RMSE$, MAE, $MAPE$ and r are calculated as in the following Formulas (3)–(7) [19]:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}, \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}, \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}, \tag{5}$$

$$MAPE = \frac{\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{n}, \tag{6}$$

where y_i is the true value of the output variable, $\hat{y}_i$ is the predicted value of the output variable, $\overline{y}$ is the mean of y_i values and n is the number of data points.

$$r = \frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \overline{x})^2 \cdot \sum_{i=1}^{n} (y_i - \overline{y})^2}} \tag{7}$$

where x_i is the input variable sample and $\overline{x}$ is the mean of x_i values.

3. Experimental Results

This study investigates the relationship between patient-related parameters (BMI, weight and age) and CT dose indices $CTDI_{vol}$, DLP, ED and SSDE using regression and correlation analysis. Table 2 displays the mean values and ranges within two standard deviations of each of $CTDI_{vol}$, DLP, ED and SSDE for each CT exam considered in the study. The table also provides the number of statistical outlier cases, defined as cases outside two standard deviations, with a maximum of seven outliers for each of the CT exams. The variation in mean dose indices is primarily influenced by the CT exam parameters and the relatively small size of the dataset.

Table 2. Dose indices' parameter range for each CT exam.

CT Exam	Statistics	DLP (in mGy.cm)	$CTDI_{vol}$ (in mGy)	ED (in mSv)	SSDE (in mGy)
Chest	Mean	316.76	9.03	3.32	8.53
	Range	69–1013	3.01–28.73	0.82–15.05	3.59–25.3
	Std.	197.16	5.42	2.12	3.7
	Number of Outliers	3	4	2	2
Cardiac Angiogram	Mean	654.1	37.1	-	-
	Range	222–1494	13.4–71.8	-	-
	Std.	241.1	11.5	-	-
	Number of Outliers	5	7	-	-
Cardiac Calcium Score	Mean	44.5	2.93	-	-
	Range	16–121	1.1–7.8	-	-
	Std.	22.62	1.44	-	-
	Number of Outliers	5	7	-	-
Abdomen/Pelvis	Mean	1156.4	27.5	11.53	22.71
	Range	58–2750	2.96–65.51	2.7–32.72	9.9–43.72
	Std.	660.5	14.39	6.23	7.2
	Number of Outliers	3	1	3	5

In this study, linear regression and Pearson correlation analysis were utilized to analyze the relationship between BMI, weight and age (as input variables) and each of $CTDI_{vol}$, DLP, ED and SSDE (as output variables). Additionally, multiple linear regression and correlation analysis models were employed to examine the relationship between all patient parameters as input variables and each of the dose indices. The evaluation results for each of the dose indices $CTDI_{vol}$, DLP, ED and SSDE are summarized in Sections 3.1–3.4, respectively. Section 3.5 presents the plots for the linear regression models generated.

Section 3.6 includes the regression and correlation analysis evaluation for each pair of the dose indices.

It is worth mentioning that polynomial regression models were investigated. However, it was found that the linear regression models outperformed the polynomial models. Therefore, the results from the polynomial regression analysis were not included in this study.

3.1. Computed Tomography Dose Index Volume ($CTDI_{vol}$) Correlations

The dataset includes $CTDI_{vol}$ values ranging from 1.1 mGy to 60.2 mGy. As shown in Table 3, linear and multiple linear regression and the Pearson correlation analysis were performed to analyze the relationship between $CTDI_{vol}$ and the patient parameters BMI, weight and age after removing a maximum of seven outliers.

Table 3. Regression and correlation analysis between $CTDI_{vol}$ as output variable and BMI, weight and age as input variables.

$CTDI_{vol}$ (mGy)					
CT Exam	**Evaluation Metric**	**Linear**			**Multiple Linear**
		X_1: BMI	**X_1: Weight**	**X_1: Age**	**All Parameters (X_1: BMI, X_2: Weight, X_3: Age)**
Chest	R^2	0.19	0.20	0.01	0.23
	RMSE	18.60	59.75	61.47	2.58
	MAE	17.82	57.88	58.04	1.76
	MAPE	70.13	93.81	86.87	23.57
	Eq.	$\hat{y} = 0.87\ X_1 + 18.80$	$\hat{y} = 2.44\ X_1 + 47.13$	$\hat{y} = 0.52\ X_1 + 61.73$	$\hat{y} = 0.81 + 0.09 * X_1 + 0.05\ X_2 + 0.01\ X_3$
	r	0.43	0.45	0.08	0.48
	p-value	9.38×10^{-4}	5.56×10^{-4}	5.46×10^{-1}	1.80×10^{-4}
Cardiac Angiogram	R^2	0.49	0.33	0.00	0.49
	RMSE	7.96	50.01	25.09	6.43
	MAE	6.12	47.56	20.73	4.92
	MAPE	19.99	56.65	34.55	14.09
	Eq.	$\hat{y} = 0.46\ X_1 + 14.60$	$\hat{y} = 1.20\ X_1 + 40.30$	$\hat{y} = 0.00\ X_1 + 55.25$	$\hat{y} = -0.14 + 1\ X_1 + 0.02\ X_2 + 0.05\ X_3$
	r	0.70	0.58	0.00	0.70
	p-value	1.70×10^{-13}	9.08×10^{-9}	9.78×10^{-1}	1.27×10^{-13}
Cardiac Calcium Score	R^2	0.58	0.41	0.01	0.59
	RMSE	28.17	80.59	54.40	0.62
	MAE	27.82	78.96	52.92	0.42
	MAPE	91.56	96.81	94.98	15.12
	Eq.	$\hat{y} = 0.15\ X_1\ -1.80$	$\hat{y} = 0.04\ X_1\ -0.43$	$\hat{y} = -0.01\ X_1 + 3.07$	$\hat{y} = -1.86 + 0.12\ X_1 + 0.01\ X_2 + 0\ X_3$
	r	0.76	0.64	−0.10	0.77
	p-value	1.24×10^{-17}	1.83×10^{-11}	3.40×10^{-1}	4.22×10^{-18}
Abdomen/Pelvis	R^2	0.10	0.13	0.00	0.17
	RMSE	13.01	46.90	32.44	12.34
	MAE	11.11	44.26	25.46	10.61
	MAPE	42.22	60.79	46.18	37.92
	Eq.	$\hat{y} = 0.12\ X_1 + 23.83$	$\hat{y} = 0.42\ X_1 + 60.38$	$\hat{y} = -0.02\ X_1 + 50.66$	$\hat{y} = -3.27 + -0.19\ X_1 + 0.4\ X_2 + 0.17\ X_3$
	r	0.32	0.36	−0.02	0.42
	p-value	8.69×10^{-3}	2.52×10^{-3}	8.86×10^{-1}	3.85×10^{-4}

A significant correlation was seen between patient weight, BMI and $CTDI_{vol}$ across all investigated CT exams. As can be seen in Table 3, there was a significant ($p < 0.05$) strong linear relationship between $CTDI_{vol}$ and BMI and weight, especially in the cardiac angiogram and cardiac calcium score exams, as indicated by the r and p-value. Age did not demonstrate any linear relationship with $CTDI_{vol}$ across all CT exams.

Using multiple regression resulted in a higher correlation with the output variables than when using simple regression in chest and abdomen/pelvis CT exams. This increase was evident when comparing the R^2, MAPE and r values of the multiple linear regression models with their values in the best respective simple linear regression models. The multiple linear regression models in cardiac angiogram and cardiac calcium score exams exhibited correlation values similar to those of the best respective simple linear regression models.

3.2. Dose Length Product (DLP) Correlations

The dataset includes DLP values ranging from 16 mGy.cm to 2498 mGy.cm. As shown in Table 4, linear and multiple linear regression models were used to examine the relationship between DLP as an output variable and BMI, weight and age as input variables after excluding up to five outliers.

Table 4. Regression and correlation analysis between DLP as output variable and BMI, weight and age as input variables.

DLP (mGy.cm)					
CT Exam	**Evaluation Metric**	**Linear**			**Multiple Linear**
		X_1: BMI	**X_1: Weight**	**X_1: Age**	**All Parameters (X_1: BMI, X_2: Weight, X_3: Age)**
Chest	R^2	0.15	0.24	0.00	0.24
	RMSE	278.74	241.19	261.54	115.94
	MAE	246.12	205.70	219.17	82.71
	MAPE	977.52	312.39	392.03	29.60
	Eq.	$\hat{y} = 0.02\ X_1 + 20.74$	$\hat{y} = 0.06\ X_1 + 49.76$	$\hat{y} = 0.00\ X_1 + 64.59$	$\hat{y} = -2.48\ -0.62\ X_1 + 4.11\ X_2 + 0.32\ X_3$
	r	0.39	0.49	0.03	0.49
	p-value	3.27×10^{-3}	1.48×10^{-4}	8.22×10^{-1}	1.22×10^{-4}
Cardiac Angiogram	R^2	0.35	0.21	0.00	0.35
	RMSE	605.98	554.89	583.90	138.45
	MAE	582.00	529.96	557.57	108.57
	MAPE	1895.46	653.77	1075.71	18.39
	Eq.	$\hat{y} = 0.02\ X_1 + 18.26$	$\hat{y} = 0.05\ X_1 + 52.01$	$\hat{y} = 0.00\ X_1 + 57.64$	$\hat{y} = 114 + 19.48\ X_1\ -0.91\ X_2\ -0.46\ X_3$
	r	0.59	0.46	−0.06	0.59
	p-value	1.86×10^{-9}	7.33×10^{-6}	6.08×10^{-1}	1.53×10^{-9}
Cardiac Calcium Score	R^2	0.68	0.48	0.00	0.68
	RMSE	16.31	43.79	26.17	9.76
	MAE	11.45	41.56	22.49	7.22
	MAPE	34.04	51.21	77.52	17.26
	Eq.	$\hat{y} = 2.42\ X_1\ -33.91$	$\hat{y} = 0.67\ X_1\ -14.26$	$\hat{y} = -0.05\ X_1\ -33.91$	$\hat{y} = -37.36 + 2.19\ X_1 + 0.09\ X_2 + 0.05\ X_3$
	r	0.82	0.69	−0.04	0.83
	p-value	3.39×10^{-23}	5.01×10^{-14}	7.26×10^{-1}	2.28×10^{-23}
Abdomen/Pelvis	R^2	0.11	0.16	0.02	0.17
	RMSE	1278.41	1236.02	1226.73	521.47
	MAE	1143.78	1098.39	1074.49	420.42
	MAPE	4200.92	1515.99	2551.55	36.68
	Eq.	$\hat{y} = 0.00\ X_1 + 24.04$	$\hat{y} = 0.01\ X_1 + 60.48$	$\hat{y} = 0.00\ X_1 + 53.77$	$\hat{y} = -93.35\ -9.31\ X_1 + 17.99\ X_2 + 4.3\ X_3$
	r	0.32	0.40	−0.13	0.41
	p-value	7.76×10^{-3}	9.25×10^{-4}	2.92×10^{-1}	5.49×10^{-4}

As can be seen in Table 4, among the CT exams, the cardiac calcium score exam exhibited a significant (p-value < 0.05) strong linear relationship between DLP and BMI. The cardiac angiogram exam showed a significant moderate linear relationship between DLP and BMI, while the other exams showed poor correlations. The patient's weight seems to have a significant (p-value < 0.05) relationship with DLP in all CT exams, especially in the cardiac calcium score exam. Similarly, as observed before, the patient's age did not display any linear relationship with DLP across all four CT exams.

Using multiple regression resulted in a higher correlation with the output variables than when using simple regression in the abdomen/pelvis exam. This enhancement was evident when comparing the R^2, MAPE and r values of the multiple linear regression models with the highest values among the respective simple linear regression models. The multiple linear regression models in the rest of the CT exams showed correlation values similar to those of the best respective simple linear regression models.

3.3. Effective Dose (ED) Correlations

The dataset includes ED values ranging from 0.8 mSv to 24.7 mSv. As shown in Table 5, linear and multiple linear regression models were used to investigate the relationship between ED as an output variable and BMI, weight and age as input variables after excluding up to three outliers.

Table 5. Regression and correlation analysis between ED as output variable and BMI, weight and age as input variables.

ED (mSv)					
CT Exam	Evaluation Metric	Linear			Multiple Linear
		X_1: BMI	X_1: Weight	X_1: Age	All Parameters (X_1: BMI, X_2: Weight, X_3: Age)
Chest	R^2	0.28	0.17	0.01	0.30
	RMSE	23.01	64.97	66.44	1.03
	MAE	22.39	62.97	63.64	0.86
	MAPE	88.14	95.35	94.90	28.79
	Eq.	$\hat{y} = 2.51\ X_1 + 17.88$	$\hat{y} = 5.48\ X_1 + 49.58$	$\hat{y} = 1.85\ X_1 + 60.15$	$\hat{y} = 0.18 + 0.12\ X_1 - 0.01\ X_2 + 0\ X_3$
	r	0.52	0.41	0.12	0.54
	p-value	3.28×10^{-5}	1.70×10^{-3}	3.40×10^{-1}	1.48×10^{-5}
Abdomen/Pelvis	R^2	0.16	0.15	0.06	0.17
	RMSE	16.90	62.76	44.54	4.90
	MAE	16.01	60.97	39.32	3.82
	MAPE	58.96	83.96	74.02	35.87
	Eq.	$\hat{y} = 0.39\ X_1 + 22.79$	$\hat{y} = 1.15\ X_1 + 59.23$	$\hat{y} = -0.83\ X_1 + 59.59$	$\hat{y} = 1.17 + 0.32\ X_1 + 0.03\ X_2 - 0.02\ X_3$
	r	0.40	0.38	−0.24	0.42
	p-value	9.22×10^{-4}	1.42×10^{-3}	4.83×10^{-2}	4.91×10^{-4}

In terms of BMI, ED exhibited a positive linear relationship across the given exams as indicated by the evaluation metrics (p-value less than 0.05). The relationship between ED and weight mirrored that of BMI. As observed earlier, age did not show any linear relationship with ED in any of the given exams.

Using multiple regression models resulted in a higher correlation with the output variables than when using simple regression in both CT exams. This increase was demonstrated by comparing the R^2, MAPE and r values of the multiple linear regression models with those of the respective best simple linear regression models.

3.4. Size-Specific Dose Estimate (SSDE) Correlations

In this section, linear and multiple linear regression is performed to investigate the relationship between SSDE as an output variable and BMI, weight and age as input variables. Table 6 shows the results of the regression and correlation analysis.

As can be seen in Table 6, for both BMI and weight, SSDE exhibited a positive linear relationship across the given exams as indicated by the evaluation metrics (the p-value < 0.05). As observed with the other dose indices, age did not show any linear relationship with SSDE in any of the given exams.

Using multiple regression models resulted in a higher correlation with the output variables than when using simple regression in both CT exams. This increase is noticed in the resulting R^2, MAPE and r values of the multiple linear regression models compared to those of the respective best simple linear regression models.

Table 6. Regression and correlation analysis between SSDE as output variable and BMI, weight and age as input variables.

SSDE (mGy)					
CT Exam	Evaluation Metric	Linear			Multiple Linear
		X_1: BMI	X_1: Weight	X_1: Age	All Parameters (X_1: BMI, X_2: Weight, X_3: Age)
Chest	R^2	0.30	0.28	0.01	0.40
	RMSE	18.02	59.88	60.94	1.92
	MAE	17.32	57.91	57.36	1.63
	MAPE	67.79	87.49	86.01	20.35
	Eq.	$\hat{y} = 1.30\ X_1 + 14.87$	$\hat{y} = 3.55\ X_1 + 37.38$	$\hat{y} = 0.98\ X_1 + 57.49$	$\hat{y} = 0.7 + 0.12\ X_1 + 0.04\ X_2 + 0.02\ X_3$
	r	0.55	0.53	0.12	0.63
	p-value	1.23×10^{-5}	2.30×10^{-5}	3.40×10^{-1}	1.57×10^{-7}

Table 6. *Cont.*

SSDE (mGy)					
CT Exam	Evaluation Metric	Linear			Multiple Linear
		X_1: BMI	X_1: Weight	X_1: Age	All Parameters (X_1: BMI, X_2: Weight, X_3: Age)
Abdomen/Pelvis	R^2	0.21	0.19	0.00	0.23
	RMSE	7.28	51.07	34.05	4.99
	MAE	5.76	49.25	27.83	3.98
	MAPE	21.47	68.06	49.68	17.97
	Eq.	$\hat{y} = 0.40\ X_1 + 18.04$	$\hat{y} = 1.15\ X_1 + 46.01$	$\hat{y} = -0.05\ X_1 + 50.71$	$\hat{y} = 6.25 + 0.32\ X_1 + 0.08\ X_2 + 0.03\ X_3$
	r	0.46	0.44	−0.01	0.48
	p-value	1.33×10^{-4}	3.20×10^{-4}	9.04×10^{-1}	5.23×10^{-5}

3.5. Plots of Linear Regression Models

In this section, plots of linear regression models are provided for each exam, considering BMI, weight and age as input variables and each of $CTDI_{vol}$, DLP, ED and SSDE as output variables. Figure 1 presents the plots of linear regression models for (a) the chest CT exam, (b) the cardiac angiogram CT exam, (c) the cardiac calcium score CT exam and (d) the abdomen/pelvis CT exam. As can be seen in Figure 1, the plots reflect the relationships found in Sections 3.1–3.4.

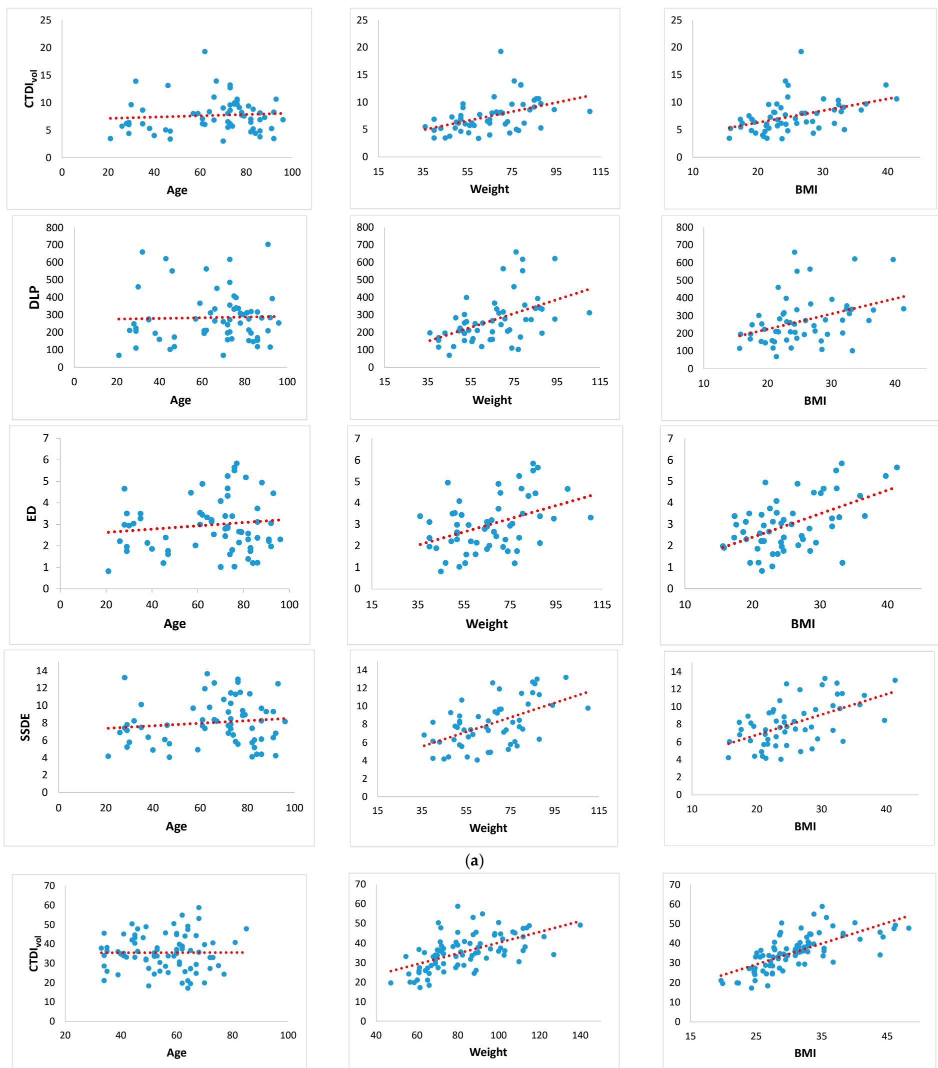

Figure 1. *Cont.*

Figure 1. Plots of the simple linear regression models for (**a**) the chest CT exam, (**b**) the cardiac angiogram CT exam, (**c**) the cardiac calcium score CT exam and (**d**) the abdomen/pelvis CT exam. The blue points represent the samples and the red dotted line represents the linear regression line.

3.6. Correlations between the CT Dose Indices

In addition, this study examined the relationship between the CT dose indices using linear regression models. Table 7 provides a summary of the correlation results between these indices.

Table 7. Regression and correlation analysis between the different CT dose indices.

CT Exam	Evaluation Metric	$CTDI_{Vol}$ as Output Variable ($\hat{y}$) with			DLP as Output Variable ($\hat{y}$) with		ED as Output Variable ($\hat{y}$) with
		X_1: DLP	X_1: ED	X_1: SSDE	X_1: ED	X_1: SSDE	X_1: SSDE
Chest	R^2	0.85	0.26	0.37	0.19	0.19	0.68
	RMSE	294.94	5.47	2.44	300.25	295.55	5.17
	MAE	268.43	4.83	1.94	273.25	268.32	4.94
	MAPE	97.06	193.59	25.89	98.84	96.80	63.28
	Eq.	$\hat{y} = 38.50\ X_1 - 22.14$	$\hat{y} = 0.21\ X_1 + 1.30$	$\hat{y} = 0.49\ X_1 + 4.08$	$\hat{y} = 45.05\ X_1 + 144.52$	$\hat{y} = 22.91\ X_1 + 96.15$	$\hat{y} = 1.61\ X_1 + 3.15$
	r	0.92	0.51	0.61	0.44	0.44	0.82
	p-value	4.86×10^{-26}	2.17×10^{-5}	1.55×10^{-7}	3.52×10^{-4}	3.66×10^{-4}	2.77×10^{-16}
Cardiac Angiogram	R^2	0.74	-	-	-	-	-
	RMSE	593.64	-	-	-	-	-
	MAE	572.96	-	-	-	-	-
	MAPE	94.13	-	-	-	-	-
	Eq.	$\hat{y} = 0.04\ X_1 + 7.83$	-	-	-	-	-
	r	0.86	-	-	-	-	-
	p-value	1.26×10^{-24}	-	-	-	-	-
Cardiac Calcium Score	R^2	0.90	-	-	-	-	-
	RMSE	39.48	-	-	-	-	-
	MAE	36.77	-	-	-	-	-
	MAPE	93.31	-	-	-	-	-
	Eq.	$\hat{y} = 15.60\ X_1 - 1.03$	-	-	-	-	-
	r	0.95	-	-	-	-	-
	p-value	3.07×10^{-44}	-	-	-	-	-
Abdomen/Pelvis	R^2	0.83	0.17	0.27	0.31	0.33	0.54
	RMSE	1199.77	19.67	11.93	1217.96	1208.01	11.65
	MAE	1070.05	16.24	10.18	1086.03	1074.99	11.04
	MAPE	97.39	192.24	49.83	98.81	97.25	52.41
	Eq.	$\hat{y} = 40.03\ X_1 + 32.66$	$\hat{y} = 0.16\ X_1 + 6.29$	$\hat{y} = 0.21\ X_1 + 15.95$	$\hat{y} = 62.26\ X_1 + 436.46$	$\hat{y} = 61.14\ X_1 - 226.39$	$\hat{y} = 0.77\ X_1 + 13.43$
	r	0.91	0.41	0.52	0.56	0.58	0.73
	p-value	8.48×10^{-26}	6.20×10^{-4}	1.08×10^{-5}	1.58×10^{-6}	5.05×10^{-7}	3.91×10^{-12}

In all CT exams, statistically significant relationships were apparent between all dose indices as indicated by the evaluation metrics (p-value < 0.05). The relationship between $CTDI_{vol}$ and DLP was found to be the most significant ($r > 0.85$ in all exams) compared to the relationships between each pair of the other dose indices. A relatively strong relationship between ED and SSDE was also noticed in the chest and abdomen/pelvis CT exams ($r = 0.82$ and $r = 0.73$, respectively).

4. Discussion

Several studies have investigated factors influencing CT radiation dose. Smith-Bindman et al. [20] conducted a study to determine patient, vendor and institutional factors that influence CT radiation dose. They employed linear regression and modified Poisson regression to identify the parameters contributing to dose variability. The authors found that CT dose varies within and across medical centers. Moreover, they found that patient size, institutional-specific protocols and multiphase scanning were the most important predictors of dose followed by manufacturer and iterative reconstruction.

The relationship between $CTDI_{vol}$ and patient parameters has been explored in the literature. Lange et al. [21] proposed a study to find associations between different CT dose estimates, namely $CTDI_{vol}$, DLP and SSDE, and patient age, BMI, scan length and technical parameters such as tube current, tube voltage, pitch, noise level and level of iterative reconstruction. It was found all dose estimates in all imaging protocols were affected by tube current. Garcia-Sanchez et al. [22] utilized machine learning techniques to predict CT radiation dose and discovered a relationship between the diagnostic reference level (DRL) and BMI, with increasing $CTDI_{vol}$ as BMI rises. As demonstrated in Section 3, it can be noted that our results are in agreement with the results found in [22]. Additionally, Christner et al. [23] conducted linear regression analysis on a dataset of 500 adult CT examinations and found a linear increase in $CTDI_{vol}$ with patient size, while SSDE remained independent of size.

With respect to DLP, McLaughlin et al. [24] investigated the relationship between radiation exposure and compositions of the abdominal cavity. They found that abdominal adipose tissue is the strongest contributor to DLP in abdominopelvic CT, followed by muscle volume. In [25], multivariate logistic regression analysis was performed to determine the factors affecting the radiation dose index (DLP) in pulmonary angiogram CT examinations. It was found that patients with high BMI and intensive care unit (ICU) referrals are associated with high CT radiation doses. These results are in agreement with our results, where the patient's BMI was found to correlate with the patient's DLP.

Factors affecting patient ED have also been studied in the literature. Cooper et al. [26] focused on factors increasing patient ED while undergoing CT exams, including gender, age, obesity (higher BMI), and multiphase/repeat scanning using Spearman correlation coefficients and penalized quantile regression on abdomen/pelvis CT scans of patients under 16 years. It was found that older age, female gender, obesity, and multiphase or repeat scanning are all associated with increased effective doses from abdomen/pelvis CT. In another study by Lee et al. [27], Pearson correlation analysis was conducted to explore the relationship between ED and the patient's BMI and abdominal fat in liver CT scans. A strong positive correlation between ED and both BMI (r = 0.715; p-value < 0.001) and TFA was found (r = 0.792; p-value < 0.001). The results above are in agreement with our results with respect to the patient's BMI, which was found to correlate with the patient's ED.

Several studies have explored the relationship between SSDE and patient parameters. Boos et al. [17] investigated the relationship between SSDE and patient related parameters, namely height, weight, effective diameter (Deff) and BMI, using linear regression models on a dataset of 400 thoracoabdominal CT adult examinations. Significant correlations were found between Deff, BMI and weight as surrogates for calculating SSDE. Their results are in agreement with our results with respect to patient BMI and weight, which were found to be correlated with the SSDE. Furthermore, O'Neill et al. [28] explored the potential of using BMI as a size-related metric alternative to the mid-slice effective diameter to estimate SSDE in abdominal CT using linear regression. It was found that there is a correlation between patient BMI and mid-slice effective diameter; thus, patient BMI can be used to accurately estimate mid-slice effective diameter, which is necessary for calculating SSDE for abdominal CT. Moreover, Svahn et al. [29] evaluated the effect of patient size on absorbed dose for ultra-low-dose and standard CT. They noted an inverse relationship between patient size and ultra-low-dose CT, while SSDE increased with larger patient size due to higher abdominal fatty tissue percentage. In [30], a study was proposed to analyze the correlation between patient weight, BMI and water-equivalent diameter and SSDE for chest and abdomen–pelvic CT examinations. Using linear regression analysis, it was found that both patient weight and BMI can be used to calculate SSDE in the chest and abdomen–pelvis CT exams. Similar results were found in [31], where higher BMI contributed to increased radiation dose and SSDE in patients who had undergone chest or abdomen–pelvis CT examination. The results of the aforementioned studies are in accordance with our results, where patient BMI and weight were found to be correlated with SSDE.

The relationship between several dose indices has been studied in the literature. In a study proposed by Binta et al. [12], the relationship between SSDE and both $CTDI_{vol}$ and DLP in chest CT exams was investigated. It was found that the $CTDI_{vol}$ value depends on the lateral diameter of the patient's body. The $CTDI_{vol}$ value varied as the lateral body diameter of each patient varied, which also resulted in greater variation in SSDE. Moreover, their results showed that different SSDE values were seen for patients with different BMI values. Garcia-Sanchez et al. [22] observed a high linear correlation between $CTDI_{vol}$ and SSDE. Similar results could be obtained using clustering algorithms [32] and numerical methods [33]. Sebelego et al. [34] proposed a study aiming to determine the factors that impact SSDE for chest–abdomen–pelvis and abdomen–pelvis CT exams. It was found that SSDE increased as the $CTDI_{vol}$ and patient BMI increased, respectively. The results of the aforementioned studies are in accordance with our findings, where statistically significant relationships were found between each pair of the CT dose indices (p-value < 0.05).

As discussed in this section, several studies have explored the relationships between patient parameters and CT dose indices and between the pair indices themselves. Other studies have been proposed in the literature for other purposes related to CT dose estimation and prediction. For example, the work in [35] explored deriving SSDE from BMI. Moreover, artificial neural networks (ANNs) were used to estimate the DLP in chest CT examinations [36], while convolutional neural networks (CNNs) were used to estimate SSDE in CT medical examinations [37]. In [22], several regression predictive models were used to predict the patient's CT dose in various CT protocols.

All in all, this study found that all CT dose indices correlated with BMI and weight in all CT exams with varying degrees. Age did not display any significant correlation with CT dose indices across all CT exams. All of the CT exams considered in the present study were either in the chest, abdomen, or pelvis area. Body thickness and composition in the body part mentioned were not affected by age, unlike the brain body part, which is affected by age, especially in the pediatric population. This explains the rationale behind the different age band groups to establish the diagnostic reference levels (DRLs) for pediatric CT brains. Our observation supports the recommendation of international commission on radiological protection (ICRP) Report 135 [38], which suggests DRLs to be established using weight criteria for both adult and pediatric populations.

The work presented in this paper investigated the correlation between different CT dose indices and patient-related parameters. One of the limitations of this work is the limited sample size. Moreover, the fact that the dataset was retrieved from a single CT machine and from a single institute does not address the different protocol setups between the different radiology departments. One cannot neglect the fact that CT detector configuration also varies across vendors, which could also contribute to CT exposure. The pediatric population is at more risk with the increased demand for requested CT. Our dataset was exclusively investigating adults. As a future work, this study can be applied to a larger dataset captured from a population with different age groups and collected from different institutions using different CT machines with different configurations.

5. Conclusions

This study investigated the correlations between different CT dose indices, namely $CTDI_{vol}$, DLP, ED and SSDE as output variables, and patient-related parameters, namely BMI, weight and age as input variables. Simple and multiple linear regression models and statistical tests were utilized to explore potential correlations. The study also examined the correlations between the CT dose indices themselves in different CT exams.

Using linear regression models, the study found that all CT dose indices correlated with BMI and weight in all CT exams with varying degrees. Age did not display any significant correlation with CT dose indices across all CT exams. Multiple linear regression models exhibited good relationships between input and output variables at least as much as the best respective simple linear regression models in all CT exams. Furthermore, the study investigated the relationships between the different CT indices and found that a strong linear relationship was apparent between $CTDI_{vol}$ and DLP compared to the relationships between each pair of the other dose indices. However, all dose indices exhibited statistically significant relationships. In conclusion, this study helps in better understanding how patient-specific parameters impact the reported CT dose indices and individuals' absorbed doses. Moreover, our observations are instrumental in the radiology field of medicine, as every radiology department is dedicated to optimizing radiation exposure while obtaining an adequate diagnosable image quality.

Author Contributions: Conceptualization, S.D. and E.D.; data curation, E.D.; formal analysis, M.A. and S.D.; investigation, M.A., S.E.H., S.D. and E.D.; methodology, S.D.; project administration, S.D.; resources, S.D. and E.D.; software, M.A., S.E.H. and A.C.; supervision, S.D.; validation, M.A., S.E.H. and A.C.; visualization, M.A. and S.E.H.; writing—original draft, M.A. and S.E.H.; writing—review and editing, M.A., S.D. and E.D. All authors have read and agreed to the published version of the manuscript.

Funding: The work in this paper was supported, in part, by the Open Access Program from the American University of Sharjah [Award #: OAPCEN-1410-E00274]. This paper represents the opinions of the authors and does not mean to represent the position or opinions of the American University of Sharjah.

Institutional Review Board Statement: The retrospective study was approved by the Ethics and Research Committee of the University Hospital Sharjah on 19 June 2017 (Ref. UHS-HERC-030-07062017).

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is contained within the article.

Acknowledgments: M.A. and S.E.H. would like to thank the Biomedical Engineering Graduate Program at the American University of Sharjah (AUS) for funding their graduate studies.

Conflicts of Interest: The authors declare no conflict of interest.

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