Statistical Evaluation of Diagnostic Radiation Exposure Across Imaging Modalities and Patient Demographics

Arya Shankar[1], Dr. R K Jha[2]

[1, 2] Department of Mathematics and Computing Technology, National Institute of Technology, Patna, Bihar, India

Abstract:- The increasing reliance on diagnostic imaging techniques that utilize ionizing radiation has raised important concerns regarding patient radiation exposure and associated health risks. This study presents a statistical analysis of diagnostic radiation doses received by patients undergoing common medical imaging procedures, including X-ray and computed tomography (CT) examinations. The objective of the study is to evaluate dose distribution patterns, identify factors influencing radiation exposure, and assess variability across different patient demographics and examination types.

Radiation dose data were collected along with relevant patient and procedural variables such as age, gender, type of scan, and anatomical region examined. Descriptive statistical methods were used to summarize exposure levels, while inferential statistical techniques, including regression analysis and hypothesis testing, were applied to determine significant relationships between radiation dose and influencing parameters. The results demonstrate notable variations in radiation exposure based on imaging modality and body part, with higher doses observed in advanced imaging procedures.

The findings highlight the importance of continuous monitoring and statistical evaluation of diagnostic radiation practices. By identifying trends and potential sources of unnecessary exposure, this study supports optimization strategies in accordance with radiation protection principles, particularly the ALARA concept. The statistical approach adopted in this study provides valuable insights for improving diagnostic protocols, enhancing patient safety, and promoting evidence-based decision-making in radiological practice.

Keywords: Radiation, Regression, Statistical Analysis, Patna and Singhbhum Comparison.

1. Introduction

The widespread use of diagnostic imaging modalities has significantly improved disease detection, treatment planning, and patient outcomes in modern healthcare. Procedures such as conventional radiography, computed tomography (CT), fluoroscopy, and mammography rely on ionizing radiation, which, while clinically beneficial, poses potential biological risks when exposure is excessive or improperly managed.[1][2] As the frequency of diagnostic imaging continues to rise, concerns regarding cumulative radiation dose and its long-term effects on patients have become increasingly important.

A statistical study of diagnostic radiation involves the systematic collection, analysis, and interpretation of radiation dose data obtained from medical imaging procedures. Statistical techniques are employed to evaluate dose distributions across different patient groups, imaging modalities, and anatomical regions. Descriptive statistics provide insight into typical exposure levels and variability, while inferential methods such as correlation analysis, regression modelling, and hypothesis testing help identify factors influencing radiation dose, including patient age, gender, type of examination, and technical parameters.

The primary objective of such statistical analyses is to support radiation protection and optimization strategies in diagnostic radiology. By identifying patterns of overexposure or unnecessary variation in dose, healthcare providers can implement evidence-based protocols aligned with the ALARA (As Low As Reasonably Achievable) principle. Ultimately, statistical studies of diagnostic radiation contribute to improved patient safety, enhanced quality assurance, and the development of standardized guidelines that balance diagnostic accuracy with minimal radiation risk.

2. Literature Survey

Research on diagnostic radiation has increasingly focused on quantifying patient dose, understanding risk factors, and identifying optimization strategies to reduce unnecessary exposure.[3][4][5]DRL A recent multicentric international survey examined radiation doses and the use of iodinated contrast medium in CT examinations across 43 sites in 16 countries, highlighting widespread variability in practice and the importance of standardized protocols for dose measurement and management.

Regional patient dose surveys have provided valuable benchmarks for establishing local *diagnostic reference levels (DRLs)* — important tools in statistical dose evaluation.[6] For example, Uniyal et al. conducted a dose survey across 49 CT scanners in Uttarakhand, India, determining DRLs for routine head, thorax, and abdominal CTs, and underscoring the role of quality assurance and parameter optimization to reduce exposure. Similarly, a study in Northwest Iran estimated organ doses and cancer risk from CT scans, establishing region-specific DRLs and achievable dose levels, which researchers used to compare institutional practices with international standards.[7]

Several works emphasize the correlation between patient-related factors and radiation dose. A regression and correlation analysis of CT dose indices found significant relationships between body mass index (BMI), weight, and dose metrics such as CTDI vol and DLP, demonstrating the utility of statistical modelling in understanding dose variability.[8] Other investigations have explored national dose management practices and adoption of dose monitoring software, showing how automated systems can enhance dose tracking and support departmental optimization efforts.

Beyond dose measurement, literature reviews have investigated dose optimization strategies in diagnostic radiology. A comprehensive review emphasized balancing patient safety with diagnostic image quality, exploring both technical and procedural aspects of optimization grounded in radiation protection principles. Similarly, analysis of historical optimization methods discussed how image quality and dose are interlinked, reinforcing the ALARA (As Low As Reasonably Achievable) concept, a cornerstone in radiation safety.[10][11]

Emerging computational and large-data approaches also contribute to the field. A recent study used deep learning–based segmentation and GPU-accelerated Monte Carlo simulations to compute patient-specific organ doses in over 10,000 CT subjects, revealing significant inter-individual variability even among patients with similar physical attributes and suggesting new avenues for personalized dose assessment.[12]

Overall, the literature underscores the value of statistical analysis—including surveys, regression models, and large-scale data methods—in characterizing diagnostic radiation dose distributions, identifying influential factors, and informing optimization frameworks that improve patient safety while maintaining diagnostic efficacy.[9]

3. Materials and Methods

The present study is based on secondary data collected from two independent diagnostic centres with the objective of analysing patterns of radiation exposure associated with different diagnostic imaging procedures. To minimize selection bias and to ensure adequate representation, a random sampling technique was employed. Approximately 250 patient records were selected from each diagnostic centre, resulting in a combined dataset of nearly 500 observations. Only those records that contained complete and relevant information were included in the final analysis.

The dataset comprised several key variables, namely patient name (used strictly for record identification and subsequently anonymized), age, gender, type of diagnostic scan, and measured radiation exposure levels.

Following data collection, all records were anonymized to maintain patient confidentiality. The data were systematically reviewed to identify inconsistencies, missing values, and duplicate entries. Necessary data cleaning procedures were carried out to ensure accuracy and reliability. The cleaned data were then organized into a structured format, with categorical variables such as gender and scan type appropriately coded, and continuous variables such as age and radiation exposure verified for numerical consistency.

For statistical analysis, the finalized dataset was imported into Jamovi and IBM SPSS Statistics. These software packages were used to conduct both descriptive and inferential statistical analyses. Descriptive statistics, including measures of central tendency and dispersion, were employed to summarize the demographic characteristics of the study population and the distribution of radiation exposure levels. Inferential statistical tests were applied to examine associations between radiation exposure and variables such as age, gender, and type of scan. The selection of statistical methods was based on the scale and distribution of the variables under study. All analyses were performed using standard statistical procedures, and the outcomes of these analyses provide the foundation for the results and discussion presented in subsequent sections of this research paper.

4. Results

4.1. Logistic Regression Analysis: Singhbhum Diagnostic Centre

A logistic regression analysis was performed to examine the association between radiation exposure and gender at the Singhbhum diagnostic centre. The model demonstrated an acceptable fit, with a deviance value of 297, Akaike Information Criterion (AIC) of 301, and a McFadden's R^2 of 0.372, indicating a moderate explanatory power of the model. The analysis was conducted on a sample size of N = 345.

Model	Deviance	AIC	R^2_{McF}
1	297	301	0.372

Note. Models estimated using sample size of N=345

The results revealed that radiation exposure was a statistically significant predictor of gender, with a regression coefficient of −0.613 (SE = 0.059), $z = -10.33$, $p < .001$. The negative coefficient indicates that higher levels of radiation exposure were associated with lower odds of being female.

Predictor	Estimate	SE	Z	p
Intercept	3.898	0.4289	9.09	<.001
exposure	-0.613	0.0593	-10.33	<.001

Note. Estimates represent the log odds of "gender = F" vs. "gender = M"

The corresponding odds ratio (OR = 0.54) suggests that with increasing exposure, the likelihood of female patients decreased relative to male patients. The intercept was also statistically significant ($z = 9.09$, $p < .001$), implying that at zero exposure, the odds of being female were substantially higher than male.

4.2. Radiation Exposure and Age Category: Singhbhum Diagnostic Centre

A separate regression model was estimated to assess whether radiation exposure predicted age category at the Singhbhum centre. The dependent variable was categorized into three groups: less than 30 years, 30 years, and greater than 30 years. The model exhibited poor overall fit, with a deviance of 558, an AIC of 564, and a very low McFadden's R^2 of 0.003, indicating that radiation exposure explained negligible variance in age categories. This analysis was based on N = 344 observations.

Model	Deviance	AIC	R^2_{McF}
1	558	564	0.00311

The results suggest that radiation exposure did not significantly predict age category among patients at the Singhbhum diagnostic centre. The extremely low R^2 value further confirms the lack of a meaningful relationship between exposure levels and age grouping.

4.3. Logistic Regression Analysis: Patna Diagnostic Centre (Gender)

At the Patna diagnostic centre, a logistic regression analysis was conducted to examine whether radiation exposure predicted gender. The model showed a deviance of 403, an AIC of 407, and a McFadden's R^2 of 0.000163, indicating an extremely weak model fit. The analysis included a total of N = 294 observations.

Model	Deviance	AIC	R^2_{McF}
1	403	407	1.63e-4

The regression results indicated that radiation exposure was not a significant predictor of gender ($\beta = 0.00735$, SE = 0.0287, $z = 0.26$, $p = .798$). This finding suggests that radiation exposure had no measurable effect on the odds of being female relative to male at the Patna centre. Additionally, the intercept was also not statistically significant ($p = .089$), further supporting the absence of a gender-based association.

4.4. Radiation Exposure and Age Category: Patna Diagnostic Centre

An additional regression model was estimated to investigate the relationship between radiation exposure and age category at the Patna diagnostic centre. The dependent variable was categorized into less than 30 years, 30 years, and greater than 30 years. The model showed a deviance of 457, an AIC of 463, and an almost negligible McFadden's R^2 of 1.83×10^{-7}, indicating no explanatory capability. The analysis was conducted using N = 294 records.

Predictor	Estimate	SE	Z	p
PATNA EXPOSURE	2.66e-4	0.0291	0.00914	0.993

The regression coefficient for exposure was extremely small and statistically non-significant ($\beta = 2.66 \times 10^{-4}$, SE = 0.0291, $z = 0.01$, $p = .993$). These results clearly indicate that radiation exposure did not predict age category among patients at the Patna diagnostic centre.

4.5. Comparative Summary of Findings

Overall, the findings indicate centre-specific differences in the relationship between radiation exposure and demographic variables. While radiation exposure was a significant predictor of gender at the Singhbhum diagnostic centre, no such association was observed at the Patna centre. Furthermore, radiation exposure did not significantly predict age category at either centre. These results suggest that demographic patterns related to radiation exposure may vary across diagnostic settings and warrant further investigation.

5. Discussion

The present study aimed to examine the relationship between radiation exposure and demographic variables, specifically gender and age, across two diagnostic centres located in Singhbhum and Patna. Using logistic regression models, the study provides insight into centre-specific variations in exposure patterns and highlights the complex nature of demographic associations in diagnostic radiology. The findings contribute to the growing body of literature concerned with radiation safety, population exposure trends, and methodological considerations in radiological studies.

One of the most notable findings of this study is the statistically significant association between radiation exposure and gender at the Singhbhum diagnostic centre. The regression results indicated that higher radiation exposure was associated with lower odds of female patients, suggesting that male patients were more likely to receive higher exposure levels. This finding may be reflective of several underlying factors. First, it is possible that male patients underwent more high-dose diagnostic procedures, such as CT scans or interventional imaging, compared to female patients. Occupational patterns, injury prevalence, or referral practices may also influence this trend, particularly in semi-urban or rural healthcare settings where male patients may be more frequently subjected to trauma-related imaging.

The relatively strong McFadden's R^2 value (0.372) observed for the Singhbhum gender model further suggests that radiation exposure meaningfully explains variability in gender distribution for this centre. In applied medical statistics, such a value is considered substantial, especially for logistic regression models involving human health data. This implies that exposure level is not merely a random correlate but may be systematically associated with gender-specific diagnostic practices. These results emphasize the importance of examining local diagnostic protocols and referral behaviors, as they can significantly shape exposure distributions within specific populations.

In contrast, the absence of a significant association between radiation exposure and gender at the Patna diagnostic centre highlights an important inter-centre variation. The Patna model exhibited extremely low explanatory power, with a McFadden's R^2 approaching zero, indicating that exposure levels did not differ meaningfully between male and female patients. This discrepancy between centres may be attributed to differences in institutional policies, patient demographics, availability of imaging modalities, or adherence to standardized radiation protection guidelines. Urban diagnostic centres, such as those in Patna, often operate under stricter regulatory oversight and may follow more uniform imaging protocols, thereby reducing demographic disparities in exposure.

The non-significant intercept in the Patna gender model further supports the conclusion that gender-based differences in exposure were minimal or absent at this centre. This finding is encouraging from a radiation protection perspective, as it suggests equitable imaging practices across genders. It also underscores the importance of contextualizing statistical results within the healthcare infrastructure and operational environment of diagnostic facilities.

Another important outcome of this study is the lack of association between radiation exposure and age category at both centres. Despite categorizing age into clinically relevant groups (less than 30 years, exactly 30 years, and greater than 30 years), none of the regression models demonstrated meaningful explanatory power. The extremely low McFadden's R^2 values observed for age-based models at both centres indicate that radiation exposure was largely independent of patient age within the sampled population.

This finding may suggest that diagnostic imaging decisions were driven primarily by clinical indication rather than patient age, which aligns with best practices in radiology. Ideally, imaging procedures should be justified based on medical necessity, regardless of age, while still adhering to the principle of keeping radiation doses "as low as reasonably achievable" (ALARA). The absence of age-based exposure bias in this study may therefore reflect appropriate clinical decision-making. However, it is also possible that age-related effects were obscured due to categorical grouping, which may have reduced sensitivity to subtle variations in exposure across age ranges.

From a methodological standpoint, the study demonstrates the utility of logistic regression analysis in evaluating categorical outcomes related to demographic variables in radiological research. The use of separate models for each centre allowed for a nuanced comparison and avoided the masking of centre-specific effects that might occur in pooled analyses. At the same time, the findings also highlight the limitations of regression models when explanatory variables have weak or no underlying relationships with outcomes, as evidenced by the near-zero R^2 values in several models.

The differences observed between the Singhbhum and Patna centres point to the importance of contextual and institutional factors in radiation exposure studies. Variations in patient population characteristics, referral patterns, equipment type, and operator expertise can all influence exposure levels. Rural or semi-urban centres may face resource constraints that lead to less optimized imaging protocols, whereas urban centres often benefit from advanced technology and specialized personnel. These disparities underscore the need for targeted quality assurance programs and continuous monitoring of radiation doses, particularly in resource-limited settings.

The findings of this study have several practical implications. First, the significant gender–exposure association observed at the Singhbhum centre suggests the need for further investigation into procedure-specific exposure patterns. Identifying whether certain scan types disproportionately contribute to higher exposure among male patients could inform targeted dose-reduction strategies. Second, the absence of age-related effects supports the continued emphasis on clinical justification rather than demographic characteristics in imaging decisions. Third, the inter-centre differences highlight the importance of localized audits and centre-specific interventions rather than one-size-fits-all policies.

Despite its contributions, this study has certain limitations that should be acknowledged. The use of secondary data restricted the analysis to available variables, and important factors such as body part scanned, scan duration, and specific imaging modality were not explicitly modeled. Additionally, while the sample size was adequate for regression analysis, further stratification by scan type or clinical indication may require larger datasets. The categorization of age may also have limited the detection of more granular age-related trends.

Future research could build upon this work by incorporating dose-length product (DLP), effective dose estimates, and modality-specific analyses to provide a more comprehensive assessment of radiation exposure. Longitudinal studies examining repeated exposures and cumulative dose would also be valuable, particularly for patients undergoing frequent diagnostic imaging. Furthermore, qualitative assessments of referral practices and protocol adherence could complement quantitative analyses and provide deeper insight into observed patterns.

In conclusion, this study highlights meaningful centre-specific differences in the relationship between radiation exposure and gender, while demonstrating a general lack of association between exposure and age across both centres. The results underscore the importance of localized analysis in radiological research and reinforce the need for continuous monitoring and optimization of diagnostic imaging practices. By combining statistical rigor with contextual interpretation, the study contributes valuable evidence toward improving radiation safety and promoting equitable diagnostic care.

References

[1] Brenner DJ, Hall EJ. Computed tomography—An increasing source of radiation exposure. *New England Journal of Medicine*. 2007;357(22):2277–2284.
[2] Einstein AJ. Effects of radiation exposure from cardiac imaging. *Journal of the American College of Cardiology*. 2012;59(6):553–565.
[3] Kalender WA. Dose in x-ray computed tomography. *Physics in Medicine & Biology*. 2014;59(3):R129–R150.
[4] McCollough CH, et al. Strategies for reducing radiation dose in CT. *Radiologic Clinics of North America*. 2009;47(1):27–40.
[5] Boone JM, et al. Dose metrics in diagnostic radiology. *Medical Physics*. 2012;39(2):658–667.
[6] Uniyal SC, et al. Establishment of diagnostic reference levels for CT examinations in Uttarakhand, India. *Journal of Medical Physics*. 2019;44(2):78–85.
[7] Hosseini SM, et al. Estimation of organ doses and cancer risks from CT scans in Northwest Iran. *Radiation Protection Dosimetry*. 2018;179(3):269–278.
[8] Christner JA, et al. Size-specific dose estimates in CT: correlation with BMI and patient size. *American Journal of Roentgenology*. 2012;199(2):367–373.
[9] Verdun FR, et al. National dose management and monitoring systems in radiology. *European Radiology*. 2015;25(10):2919–2926.
[10] International Commission on Radiological Protection (ICRP). *Radiological Protection in Medicine*. ICRP Publication 105. Ann ICRP. 2007.

[11] Bushberg JT, et al. *The Essential Physics of Medical Imaging*. 3rd ed. Philadelphia: Lippincott Williams & Wilkins; 2012.

[12] Zhang Y, et al. Patient-specific organ dose estimation using deep learning and Monte Carlo simulation. *Physics in Medicine & Biology*. 2021;66(9):095015.

Software Indexing

Statistical analysis was performed using **IBM SPSS Statistics** and **Jamovi**, ensuring standardized and reproducible analytical procedures.