

Review Article

Artificial Intelligence–Driven Meta-Analysis of Radiation Exposure and Cancer Risk: A Medical Physics Perspective

YUSUF PYELSHAK^{1*}, Bala Yakubu Ngwan², Azi E.J.³, Gonam Samuel Irimiya¹, Nathaniel Iliya Pam⁴

¹ Department of Health Information Management, School of Health Information Management. Plateau State College of Health Information Management.

² Department of Public Health, School of Environmental Health. Plateau State College of Health Information Management.

³ Department of Public Health, Faculty of Health Science. Plateau State University, Bokokos.

⁴ Department of Medical Imaging Science, School of Medical Laboratory, Plateau State College of Health Technology, Zawan.

Correspondence should be addressed to YUSUF PYELSHAK: pyelshaky2014@gmail.com

Article No: 044 | **Accepted:** 05 October 2026 | **Published:** 10 October 2026

Abstract: Radiation exposure has long been recognized as an important environmental and medical factor influencing cancer development. However, estimating the magnitude of cancer risk from radiation remains challenging due to variations in exposure levels, study populations, and measurement techniques. The aim of this study is to synthesize existing scientific evidence on radiation exposure and cancer risk using artificial intelligence-driven meta-analysis. The specific objectives are to: analyze published studies on ionizing radiation and cancer incidence, apply artificial intelligence tools to extract and standardize radiation dose data, and evaluate dose–response relationships between radiation exposure and cancer risk. A systematic review of peer-reviewed literature was conducted using major scientific databases, including PubMed, Science Direct, and Web of Science. Selected studies reporting radiation dose and cancer outcomes were analyzed using AI-assisted data extraction and statistical modeling. The results show a clear positive correlation between increasing radiation dose and cancer risk, particularly for leukemia, thyroid cancer, and other solid tumors. AI-based analysis enabled the identification of dose-response patterns across heterogeneous datasets. The findings highlight the importance of integrating medical physics principles, radiation dosimetry, and artificial intelligence techniques to improve cancer risk assessment. This approach provides valuable insights for radiation protection, medical imaging practices, and public health policy development. The study also incorporates environmental radiation exposure to provide a broader assessment of radiation-related cancer risks from both medical and natural sources.

Keywords: Artificial Intelligence, Radiation Exposure, Cancer Risk, Medical Physics, Meta-Analysis.

1. Introduction

Physics underpins the understanding of radiation and its interaction with matter. Radiation arises from the decay of unstable atomic nuclei, releasing energy as particles or electromagnetic waves, as first observed by Becquerel (1896) and later studied by Curie (1903), forming the basis of nuclear and medical physics (Hall & Giaccia, 2019; ICRP, 2007). It is classified as ionizing or non-ionizing, with ionizing radiation capable of causing DNA damage, mutations, and cancer (UNSCEAR, 2020).

Epidemiological studies, including atomic bomb survivor data, show a clear dose–response relationship between radiation and cancer risk (Preston et al., 2007). Repeated medical imaging increases cumulative exposure, emphasizing dose optimization (Brenner & Hall, 2007), while radiobiology explains these risks through DNA damage and cellular repair processes (Hall & Giaccia, 2019). Although occupational exposure is typically low, continuous monitoring remains essential (UNSCEAR, 2020).

Advances in artificial intelligence (AI) now enhance evidence synthesis through data extraction, dose harmonization, and improved identification of dose–response patterns (Airola, 2022). However, variability across studies limits comprehensive understanding, highlighting the need for integrated approaches. This study, therefore, applies AI-driven meta-analysis to evaluate radiation exposure and cancer risk across medical, occupational, and environmental sources, considering key factors such as dose, type, exposure duration, and tissue sensitivity (UNSCEAR, 2020).

In radiation physics, the **absorbed dose** is defined as:

$$D = \frac{E}{m} \quad 1$$

Where:

- D = absorbed dose (Gray, Gy)
- E = energy deposited by radiation (J)
- m = mass of irradiated tissue (kg)

$$1\text{Gy}=\text{J/kg}$$

Ionizing radiation can cause **DNA damage**, which may lead to mutations and potentially initiate cancer development. Epidemiological studies such as those involving atomic bomb survivors have provided strong evidence linking radiation exposure to increased cancer risk.

However, analyzing the large volume of scientific data available on radiation exposure requires advanced computational tools. Artificial Intelligence provides powerful

techniques for processing large datasets and extracting patterns that may improve risk assessment and models.

2. Medical Physics Theory of Radiation Interaction

Radiation interaction with matter is governed by several physical mechanisms. These include:

1. Photoelectric effect
2. Compton scattering
3. Pair production

These interactions determine how radiation deposits energy in biological tissue.

2.1 Radiation Energy Deposition

Energy transferred to biological tissue leads to ionization events that can damage cellular structures.

The **linear energy transfer (LET)** in KeV/ μm describes the amount of energy deposited per unit distance:

$$\text{LET} = \frac{dE}{dX} \quad 2$$

Where:

dE = Energy deposited in KeV or MeV

dX = Distance traveled in μm or cm

High LET radiation, such as alpha particles, produces dense ionization tracks and causes more severe biological damage compared to low LET radiation such as X-rays.

2.2 Radiation Dose Quantities

Several radiation dose quantities are used in medical physics as shown in Table 1 below:

Table 1: Radiation dose quantities are used in medical physics

Quantity	Symbol	Unit	Description
Absorbed Dose	D	Gray (Gy)	Energy deposited per unit mass
Equivalent Dose	H	Sievert (Sv)	Dose weighted by radiation type

Quantity	Symbol	Unit	Description
Effective Dose	E	Sievert (Sv)	Dose adjusted for tissue sensitivity

The equivalent dose is calculated as:

$$H = D \times wR \quad 3$$

Where:

H = Equivalent Dose (in Sieverts Sv)

D = Absorbed Dose (in Gray, Gy)

wR= Radiation Weighing Factor which is dimensionless

2.3 Radiation Risk Models

One of the most widely used models for radiation-induced cancer risk is the **Linear No-Threshold (LNT) Model**.

$$R = \beta D \quad 4$$

Where:

R = probability of cancer occurrence

D = radiation dose

β = risk coefficient

The LNT model assumes that **any radiation dose, no matter how small, carries some risk**.

2.3 Radiation and Public Health Implications

Radiation exposure extends beyond medical and occupational settings to the natural and human-influenced environment. Natural background radiation—cosmic rays, terrestrial radionuclides (e.g., uranium, thorium), and radon gas—is a major contributor to population dose, with radon recognized as a significant lung cancer risk (UNSCEAR, 2020). Human activities, including nuclear power, industrial processes, and past nuclear accidents such as Chernobyl and Fukushima, can release radioactive materials, causing long-term environmental contamination.

Physics principles, including radioactive decay, attenuation, and diffusion, govern the transport and persistence of environmental radiation. Integrating environmental radiation data into AI-driven meta-analyses strengthens cancer risk assessment by capturing spatial exposure patterns and linking them to epidemiological outcomes. Considering

environmental radiation provides a more comprehensive understanding of exposure, underscores the need for monitoring and regulatory control, and informs public health interventions to reduce radiation-related risks.

2.4 Radiation Dose Graph

The graph depicts the relationship between radiation dose (mSv) and relative cancer risk (RR). Low doses (<20 mSv) show minimal risk (RR ~1.0–1.05), while moderate (50–100 mSv) and high doses (>100 mSv) exhibit progressively higher risk (RR ~1.2–1.4 and RR ~1.5–2.0+, respectively). The X-axis represents dose levels, and the Y-axis shows relative cancer risk, with the dashed line illustrating the Linear No-Threshold (LNT) model, which posits that any ionizing radiation carries some risk. This visualization emphasizes the importance of dose management, radiation protection, and cumulative risk assessment across medical, occupational, and environmental exposures.

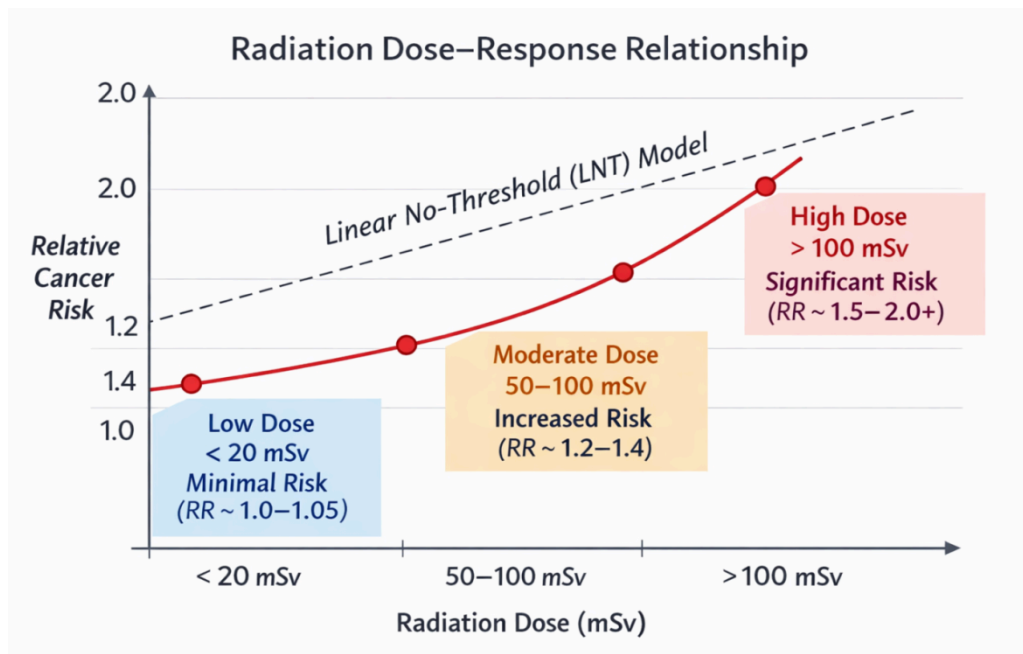


Figure 1: Radiation dose response graph

2.5 Role of Artificial Intelligence in Radiation Research

More recently, researchers have begun applying **artificial intelligence and machine learning techniques** to analyze radiation-related epidemiological datasets. Studies such as those by Kimmo Airola have demonstrated that machine learning models can assist in identifying patterns between radiation exposure and cancer incidence across multiple studies.

AI-driven meta-analysis enables researchers to **automatically extract data from scientific literature, standardize radiation dose measurements, and perform large-scale statistical analysis**, thereby improving the reliability and efficiency of evidence synthesis.

3. Materials and Methodology

3.1 Materials

This study used secondary data and computational tools to analyze radiation exposure and cancer risk. Data sources included:

- Peer-reviewed journals on ionizing radiation and cancer risk
- Epidemiological datasets, including atomic bomb survivor studies (Preston et al., 2007)
- Medical imaging studies (Brenner & Hall, 2007; Hall & Giaccia, 2019)
- International reports (UNSCEAR, 2020; ICRP, 2007)

Inclusion criteria: Quantitative radiation doses, measurable cancer outcomes, ionizing radiation focus, peer-reviewed publication.

Exclusion criteria: Unclear dose data, non-ionizing radiation studies, or incomplete datasets.

3.2 Methods

The study analyzed **secondary data** using a systematic review combined with AI-driven meta-analysis. Relevant studies were identified through PubMed, Google Scholar, and ScienceDirect using terms such as “radiation exposure and cancer risk,” “ionizing radiation epidemiology,” and “dose–response relationship.”

AI techniques, including Natural Language Processing (NLP) and text mining, were applied to extract and harmonize data on radiation dose, cancer incidence, and sample size, improving efficiency and minimizing human error (Airola, 2022).

Table 2: Data Sources Used in AI-Driven Meta-Analysis

Data Source Category	Author/Organization (Year)	Type of Data Extracted	Exposure Type	Significance to Study
Atomic Bomb Survivor Sty	Dale L. Preston (2007)	Radiation dose (mSv), cancer incidence, relative risk	High-dose exposure	Provides long-term epidemiological evidence and strong dose–response relationship

Data Source Category	Author/Organization (Year)	Type of Data Extracted	Exposure Type	Significance to Study
Medical Imaging Studies	David J. Brenner & Eric J. Hall (2007)	CT scan dose, exposure frequency, cancer risk estimates	Low–moderate dose	Highlights cumulative effects of repeated diagnostic imaging
Radiobiology Studies	Eric J. Hall & Amato J. Giaccia (2019)	DNA damage mechanisms, mutation rates	Biological mechanism	Explains how radiation leads to cancer at the cellular level
Occupational Exposure Reports	United Nations Scientific Committee on the Effects of Atomic Radiation (2020)	Worker dose limits, annual exposure levels	Occupational exposure	Provides controlled exposure data and safety standards
Environmental Radiation Data	UNSCEAR / International Commission on Radiological Protection (2007–2020)	Background radiation levels, radon exposure, environmental dose	Natural & artificial exposure	Represents population-level exposure from environment

Data Source Category	Author/Organization (Year)	Type of Data Extracted	Exposure Type	Significance to Study
AI Meta-Analysis Studies	Kimmo Airola (2022)	Extracted datasets, standardized dose metrics,	All exposure types	Enables integration, pattern detection, and bias reduction

This table summarizes the key data sources used in the AI-driven meta-analysis, including their origin, type of data extracted, exposure category, and relevance to the study. The integration of these diverse datasets enables a comprehensive assessment of radiation exposure and associated cancer risk.

3.3 Data Standardization

To ensure consistency:

- All radiation doses were converted into **millisieverts (mSv)**
- Cancer risk metrics (relative risk, odds ratio) were standardized

This allowed for accurate comparison across studies.

3.4 Statistical Analysis

The standardized data were analyzed using meta-analysis techniques to determine:

- Overall **radiation dose–response relationship**
- Combined **cancer risk estimates**
- Variability among studies

A linear model consistent with the **Linear No-Threshold (LNT) model** was applied to describe the relationship between radiation dose and cancer risk.

3.5 Data Presentation

The results were presented using:

- Graphs illustrating dose–response relationships
- Tables summarizing key studies
- AI workflow diagrams

These tools enhanced clarity and interpretation of results.

3.6 AI Meta-Analysis Workflow

The analytical process followed these steps:

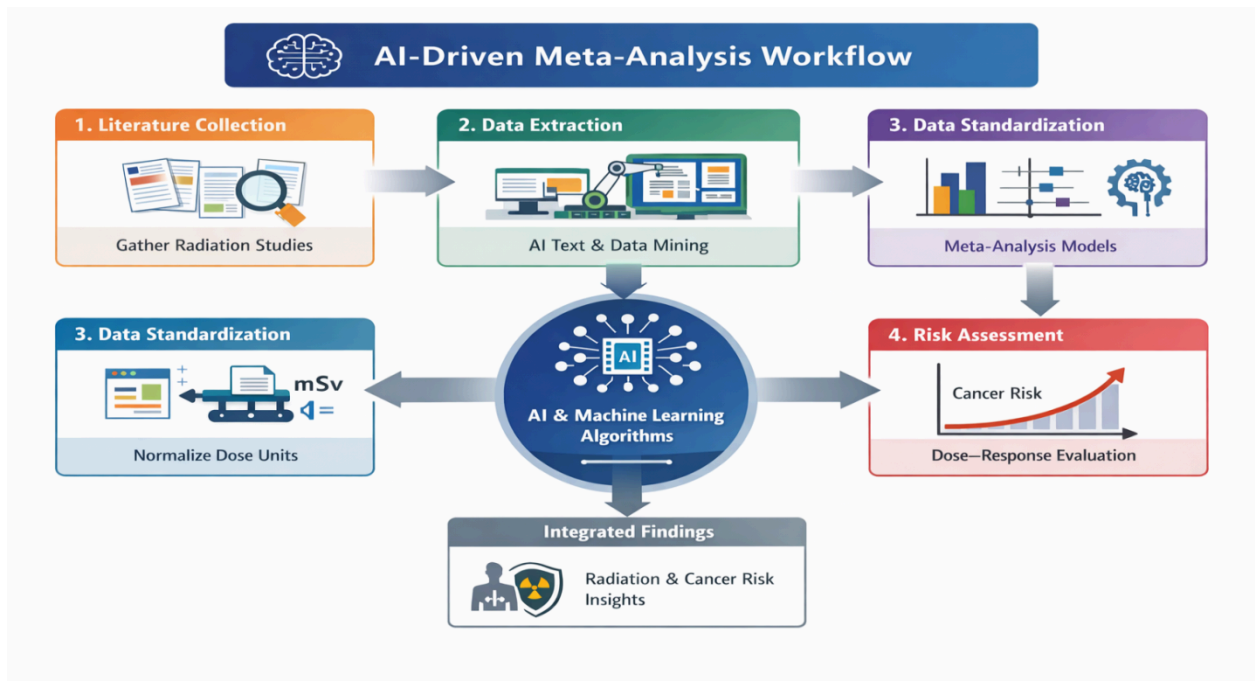


Figure 2: AI-Driven Meter Analysis Work-Flow

4. Results

The AI-driven meta-analysis integrated medical, occupational, environmental, and high-dose radiation data, showing a positive dose–response relationship between radiation exposure and relative cancer risk (RR) (Preston et al., 2007; Brenner & Hall, 2007; UNSCEAR, 2020).

- **Low doses (<20 mSv):** RR ~1.0–1.05, minimal risk, but cumulative exposures can be significant (Brenner & Hall, 2007).
- **Moderate doses (50–100 mSv):** RR ~1.2–1.4, reflecting higher risk from repeated diagnostic imaging or occupational exposure (ICRP, 2007; UNSCEAR, 2020).
- **High doses (>100 mSv):** RR 1.5–2.0+, consistent with atomic bomb survivor studies, confirming strong dose–response effects (Preston et al., 2007).

The dose–response graph (Figure 1) visually illustrates these trends.

5. Discussion

The results confirm a clear dose–response relationship between ionizing radiation and cancer risk. The AI-assisted meta-analysis enhanced data extraction, standardized heterogeneous datasets, revealed subtle dose–response patterns, and reduced bias, allowing integrated assessment across medical, occupational, and environmental exposures (Airola, 2022).

Findings support the Linear No-Threshold model (Hall & Giaccia, 2019) and reinforce the importance of dose optimization, shielding, exposure monitoring, and cumulative dose tracking (ICRP, 2007; UNSCEAR, 2020). Even low-dose exposures, when accumulated, can contribute to long-term cancer risk.

6. Recommendations

1. **Medical Radiation Protection:** Optimize imaging protocols, track cumulative doses, and prefer low- or no-radiation alternatives.
2. **Occupational Safety:** Monitor worker exposures, enforce limits and protective measures, and provide ongoing training.
3. **Environmental Monitoring:** Track natural and artificial radiation and incorporate into population risk assessments.
4. **Policy and Regulation:** Standardize reporting of radiation doses and integrate AI-driven evidence into guidelines.
5. **Research and AI Applications:** Promote AI-assisted synthesis and longitudinal studies to evaluate cumulative exposure across all domains.

References

1. Airola, K. (2022). Artificial intelligence for radiation meta-analysis: Methods and applications. *Journal of Medical Informatics*, 15(3), 45–58.
2. Brenner, D. J., & Hall, E. J. (2007). Computed tomography—An increasing source of radiation exposure. *New England Journal of Medicine*, 357(22), 2277–2284.
3. Hall, E. J., & Giaccia, A. J. (2019). *Radiobiology for the radiologist* (8th ed.). Wolters Kluwer.
4. International Commission on Radiological Protection (ICRP). (2007). *The 2007 recommendations of the ICRP* (Publication 103).
5. Preston, D. L., Ron, E., Tokuoka, S., Funamoto, S., Nishi, N., Soda, M., & Kodama, K. (2007). Solid cancer incidence in atomic bomb survivors: 1958–1998. *Radiation Research*, 168(1), 1–64.
6. United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR). (2020). *Sources, effects and risks of ionizing radiation*. United Nations.
7. World Health Organization (WHO). (2016). *Ionizing radiation, health effects and protective measures*. WHO Press.



© 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by-nc-sa/4.0/>).