



Systematic Review

Radiation Dose Reduction in CT Exams with Iterative and Deep Learning Reconstruction: A Systematic Review

Sandra Coelho, Maria de Lurdes Dinis, Marco Freitas and João Santos Baptista



Systematic Review

Radiation Dose Reduction in CT Exams with Iterative and Deep Learning Reconstruction: A Systematic Review

Sandra Coelho ^{1,*} , Maria de Lurdes Dinis ¹ , Marco Freitas ²  and João Santos Baptista ³ 

¹ Center for Natural Resources and Environment (CERENA), Faculty of Engineering, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal; mldinis@fe.up.pt

² Radiology Department, School of Health, Polytechnic Institute of Porto, 4200-072 Porto, Portugal; mfr@ess.ipp.pt

³ Associated Laboratory of Energy, Transports and Aerospace (LAETA), Faculty of Engineering, University of Porto, Rua Dr Roberto Frias, 4200-465 Porto, Portugal; jsbap@fe.up.pt

* Correspondence: up202401123@up.pt

Abstract

This systematic review evaluated the effectiveness of iterative reconstruction (IR) and deep learning reconstruction (DLR) in reducing radiation dose in computed tomography (CT) while preserving diagnostic image quality. We systematically searched PubMed, Scopus, and Web of Science (last search 22 March 2025); the protocol was registered in the OSF (DOI: 10.17605/OSF.IO/TUQDS). Eligible studies were English-language adult (≥ 18 years) investigations published between 2020 and 2025 that used IR or DLR and reported radiation-dose outcomes; studies on paediatric, phantom, cadaver, cone-beam, and spectral CT were excluded. In accordance with PRISMA 2020 guidelines, 4371 records were identified, and 30 met the inclusion criteria. Risk of bias was assessed using the NIH Quality Assessment Tool; most studies were deemed to be at low risk. Data were narratively synthesised and structured by a reconstruction approach and anatomical region. Across the 30 studies, IR achieved a dose reduction of 24–50% (mean $\approx 45\%$) and a DLR reduction of 34–89% (mean $\approx 58\%$); several DLR protocols enabled reductions of $\geq 75\%$ without impairing diagnostic quality. Thirty studies in total were included (total $N = 2581$; range 24–289). It was determined that both approaches substantially reduce radiation exposure while maintaining diagnostic image quality; DLR generally demonstrates greater noise suppression and dose efficiency, especially in ultra-low-dose applications. However, heterogeneity in methods, designs, and scanner technologies limits the ability to draw uniform conclusions. Standardised protocols, multi-vendor prospective studies, and long-term evaluations are needed.

Keywords: radiation dose reduction; computed tomography; iterative reconstruction; deep learning



Academic Editor: Salvatore Gallo

Received: 7 December 2025

Revised: 22 December 2025

Accepted: 26 December 2025

Published: 28 December 2025

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Ionising radiation poses stochastic and deterministic risks; in CT, protocol optimisation is therefore a central focus to minimise radiation dose while preserving diagnostic accuracy. The repercussions of this form of radiation may manifest as either stochastic effects or deterministic effects, which are contingent upon the dosage and duration of exposure. Since the introduction of computed tomography (CT) in the 1970s, it has become a widely used and integral diagnostic tool in medicine. However, this technological advancement has also contributed to a significant increase in radiation exposure across global populations. In

light of ongoing discussions regarding the stochastic effects of ionising radiation, including potential carcinogenic risk, the optimisation of CT protocols has become an important focus in clinical imaging to reduce radiation dose while preserving image quality [1,2].

The concept of keeping radiation “As Low As Reasonably Achievable” (ALARA) is a basis of medical imaging safety, and radiation dose optimisation has become a central topic in CT research and clinical practice. Iterative Reconstruction (IR) and Deep Learning (DLR) techniques have emerged as two promising solutions for dose reduction. IR methods, such as sinogram-affirmed iterative reconstruction (SAFIRE), offer significant noise reduction by reconstructing images iteratively rather than relying solely on traditional filtered back projection [3,4]. Similarly, as reported in the literature, DL-based reconstruction algorithms leverage data training to suppress noise and improve image quality even at substantially reduced radiation doses, offering robust performance across varied clinical scenarios [5,6]. Evidence suggests that IR with techniques like automatic Tube Voltage Modulation (e.g., CARE kV) can achieve radiation dose reductions of up to 41% without compromising image quality [3,4].

Despite significant technological progress, substantial variability in CT radiation doses persists internationally, and it is often attributable not to patient or machine factors but to institutional choices regarding protocol settings [1,2]. Such variability underscores the importance of standardising dose-reduction strategies and promoting wider adoption of advanced reconstruction techniques. The objective of this systematic review is to evaluate human adult CT studies investigating radiation dose reduction achieved by iterative reconstruction and deep learning reconstruction and to compare their dose efficiency and diagnostic image quality across anatomical regions.

2. Materials and Methods

The systematic review followed a predefined methodology and is reported according to the Preferred Reporting Items for Systematic Review and Meta-Analyses Extension for Systematic Reviews Guidelines (PRISMA 2020) [7,8]. To ensure methodological transparency and facilitate reproducibility, the protocol has been registered and is publicly available in the Open Science Framework (OSF) under the DOI: 10.17605/OSF.IO/TUQDS. Full methodological details are transparently reported in accordance with PRISMA 2020 guidelines.

2.1. Eligibility Criteria

Peer-reviewed human adult studies (≥ 18 years), 2020–2025, in English, evaluating IR or DLR for CT dose reduction and reporting radiation dose metrics (e.g., CTDIvol, DLP, ED) and/or diagnostic image quality (noise, SNR/CNR, lesion detectability). Paediatric, phantom, cadaver, cone-beam or spectral-CT reviews, guidelines, and non-original research were excluded.

2.2. Information Sources

A comprehensive electronic database search was conducted from February to 22 March 2025, to identify relevant articles published between 2020 and 2025. Searches were performed in PubMed (last searched 22 March 2025), Scopus (22 March 2025) and Web of Science (22 March 2025) using the same predefined queries in all databases.

2.3. Search Strategy

The search strategy development process involved conducting a brief overview of the subject through a preliminary Google search complemented by the author’s expertise and an examination of keywords used in relevant publications. From this process, the following candidate terms were identified: “Computed Tomography”, “CT Exam”, “Dose Reduction”, “Radiation Risk”, “Radiation Dose Reduction”, “Iterative Reconstruction”, “Tube Voltage

Modulation”, “Automatic Exposure”, “Tube Current Modulation”, “Noise-based tube current”, and “Innovation”. Each term was individually tested across databases to assess retrieval performance, after which different combinations were evaluated for eligibility.

The final search strategy applied free-text terms to titles and abstracts using three complementary conceptual strings focused on computed tomography, radiation dose reduction, and acquisition-related optimisation techniques. These core search strings were intentionally designed to be broad and vendor-neutral to capture a wide range of reconstruction-based dose optimisation studies. Although deep-learning reconstruction-specific terms were not included as primary search keywords, this approach was adopted to avoid restricting retrieval to particularly proprietary or rapidly evolving algorithm nomenclature. Studies employing deep learning-based reconstruction were nonetheless retrieved through broader reconstruction-related indexing and were included when they met the predefined eligibility criteria. This strategy ensured sensitivity while minimising bias associated with algorithm-specific terminology. Full database-specific strategies are provided in Appendix A Table A1. Filters applied, where available, were humans, article, English, and publication years 2020–2025.

2.4. Selection Process

All retrieved articles were imported into Mendeley (Mendeley Reference Manager—Mendeley, London, UK) [9] and to Rayyan Software (Rayyan Systems Inc., Cambridge, MA, USA) [10]. Duplicate records were identified and removed using Rayyan Software to ensure data integrity. Two reviewers (S.C. and M.L.D.) independently screened the titles and abstracts of 208 records according to the predefined inclusion criteria. Potential relevant studies were retrieved in full text for further assessment. Disagreements were resolved through discussion or, when necessary, by consultation with a third reviewer (J.S.B.). Automation tools were not used during the selection process. Studies were included if they reported radiation dose reduction in CT examinations using IR or DLR. Exclusion criteria comprised studies involving phantoms, paediatrics, cadavers, cone-beam CT, or Spectral CT, as well as studies with incorrect publication types, outcomes, or populations.

2.5. Data Collection

Thirty full-text articles met the inclusion criteria and were screened for data extraction using Rayyan software. The data charting process was conducted with a structured Excel-based data extraction form via SciSpace software (SciSpace; PubGenius Inc., Milpitas, CA, USA) [11]. This process involved systematic extraction of predefined data items initially performed with the support of SciSpace and subsequently verified by two researchers (S.C. and M.L.D.) to ensure accuracy and consistency. In this data form, each line corresponds to a different study. Corresponding authors were contacted if data were missing or unclear.

2.6. Data Items

Eligible outcomes were radiation dose reduction, iterative reconstruction, deep learning, machine learning, dose length product (DLP), CT dose reduction, and CT radiation risk reduction. Any measurement of these outcomes was eligible for inclusion, with no restrictions on the type of measurement. The researcher anticipated that outcomes would be grouped by reconstruction type and anatomic region to facilitate the most comprehensive analysis of the information. If multiple outcomes existed, the result that provided the most complete information was chosen. A formal critical appraisal of the included studies was conducted using the NIH Quality Assessment Tool across multiple domains relevant to observational and before-and-after study designs.

For each selected study, data were extracted regarding the report (author, year, title, and country), study characteristics (research focus and objectives), methodology (study

type, population, anatomical region, analysis group, standard/control group, protocol used for screening, reconstructed protocol, standard protocol, equipment type/vendor/model, variables measured, reconstruction type) and research outcomes (radiation dose, dose reduction achieved, image achievements with IR/DLR, most dose reduction vs. image quality, radiation dose reduction achieved with IR/DLR, noise DLR, contrast DLR, main findings regarding radiation dose reduction, conclusions, limitations, future research, detected bias, observations).

2.7. Risk of Bias

The methodological quality of included studies was assessed using the NIH Quality Assessment Tool for observational cohort and before-and-after study designs, which is appropriate for the non-randomised imaging designs included in this review. The tool covers nine domains: clarity of study question, definition of the study population and eligibility criteria, group comparability or intra-individual design, reporting of CT acquisition parameters, validity of outcomes measurements, blinding of image reviewers, inter-observer agreement, data completeness, and potential funding/vendor bias. Each domain was rated as low, moderate, or high risk. Items not reported were judged based on their potential to introduce bias. An overall rating was assigned using a conservative worst-case rule, where a domain was considered high if any domain was rated high, moderate if at least one domain was rated moderate, and low when all domains were rated low.

Retrospective design was not automatically penalised, and use of different scanners was not considered a source of bias when inherent to the technology being evaluated (e.g., DLR/IR available only on specific hardware). Funding bias was rated high only when direct industry sponsorship of the study was declared; authors working with vendors without direct study funding were not downgraded.

2.8. Effect Measures

The primary effect measure was the percentage reduction in radiation dose relative to the standard dose protocol. Percentage dose reduction was extracted as reported in each study. It was calculated by comparing reduced-dose acquisitions or reconstruction techniques with the reference protocol used within the same study or institution. As no standardised reference protocol was applied across all included studies, reference dose levels varied according to scanner type, clinical indication, and institutional practice. Secondary effect measures included the mean differences in image noise, signal-to-noise ratio (SNR), contrast-to-noise ratio (CNR), and qualitative image quality ratings between reconstruction techniques.

2.9. Synthesis of Results

Given the heterogeneity of the included studies, a narrative synthesis was performed. Data were organised by reconstruction techniques (IR or DLR), anatomical region, and reported dose reduction. We tabulated study-level estimates with 95% confidence intervals when reported—region/vendor conducted planned subgroup analyses. Results are presented in tables and organised by the outcome domain within which the studies were conducted.

2.10. Reporting Bias and Certainty Assessment

Potential reporting biases were evaluated qualitatively by examining completeness of outcomes, funding statements, and patterns of publication. Selective reporting, or publication bias, was considered suspected when authors had industry affiliations, although only direct industry funding was considered in the risk-of-bias rating.

Certainty of evidence for each outcome was evaluated using the GRADE (Grading of Recommendations Assessment, Development, and Evaluation) framework across five domains: risk of bias, inconsistency, imprecision, indirectness, and publication bias. Overall certainty for each outcome was rated as high, moderate, or low according to the standard GRADE guidance.

3. Results

The selection process was done according to the PRISMA methodology. Figure 1 presents an overview of the articles identified in each step.

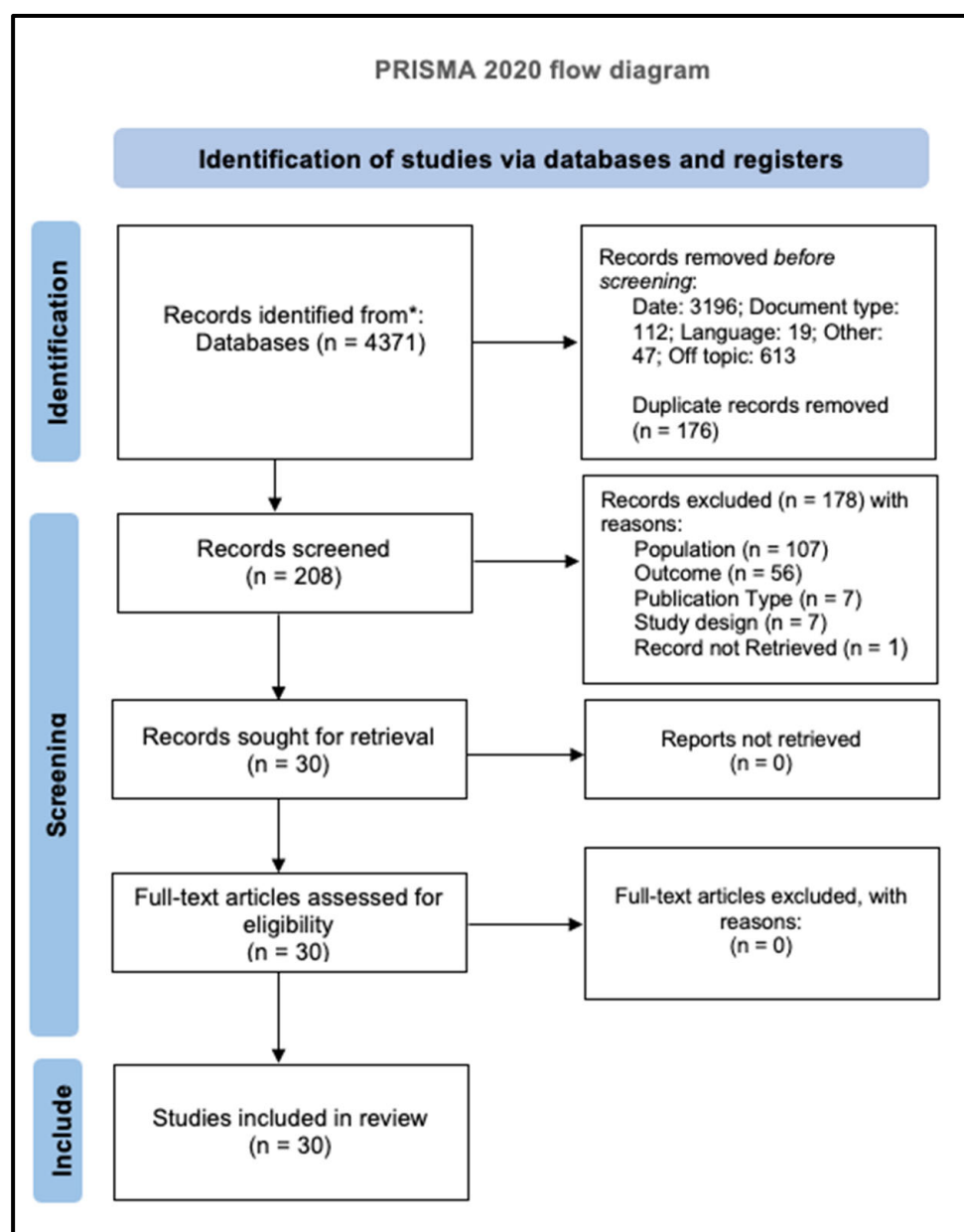


Figure 1. PRISMA 2020 flow diagram: records identified (n = 4371); after deduplication (n = 4195); screened (n = 208); full text assessed (n = 30); included (n = 30). No records were excluded after full-text assessment [8].

3.1. Study Selection

The initial database search retrieved 4371 articles. Subsequently, filters were applied, excluding 3196 by publication date, 112 by document type, 19 due to language criteria, 47

for other reasons (non-human/phantom, non-diagnostic outcomes, or non-CT modalities), and 613 by out-of-topic criteria. This process resulted in 384 articles, from which duplicates were removed using the Rayyan software, resulting in the exclusion of 176 records. During title and abstract screening, 178 of the remaining 208 articles were excluded, as they did not meet the inclusion criteria. During the screening process, some studies initially appeared eligible but were excluded because they did not involve human adult populations [12–20]. Of the 30 full-text articles, all were retrieved with full text, and none were excluded at this stage, as all met the eligibility criteria.

3.2. Study Characteristics

Study Characteristics Overview

A total of 30 studies were included in this systematic review, which were published between 2020 and 2025. Most publications were concentrated in 2021 ($n = 9$), followed by 2022 and 2024, with each contributing eight studies. In contrast, 2020 and 2023 had only three and two studies, respectively. Geographically, most investigations were conducted in China ($n = 10$), followed by Japan ($n = 5$) and Korea ($n = 4$), indicating a significant prevalence in East Asia. A few studies originated from Europe (Italy, France, Germany, Sweden, and the United Kingdom), the Middle East (Iran and Saudi Arabia), and the United States.

Study Design and Duration

Although all studies were comparative, some heterogeneity existed in study designs. The majority were prospective comparative studies ($n = 12$), followed by retrospective comparative studies ($n = 9$). A smaller portion consisted of comparative designs without specified temporal directions ($n = 6$). In addition, one study used a mixed comparative design, combining prospective, and retrospective cohorts ($n = 1$) [21], and one study employed a cross-sectional comparative approach ($n = 1$) [22]. One study was classified as a prospective multi-institutional comparative study ($n = 1$) [23]. Overall, the evidence base is characterised by non-randomised, comparative designs, reflecting real-world clinical and feasibility constraints in CT dose-reduction research. The duration of the included studies ranged from 2 to 42 months, with an average duration of approximately 10 months, reflecting medium-term investigations into imaging practices and outcomes.

Other variables that may influence interpretation.

Information on funding varied across the included studies. Two studies reported financial support from scanner manufacturers, representing a potential source of industry-related influence [23,24]. Twelve studies were funded by academic or public institutions, including universities, hospitals, foundations, or national research programmes, with no apparent commercial conflicts of interest [2,4,21,25–33]. Four studies did not provide funding information [34–37]. The remaining studies explicitly declared no funding, suggesting a low likelihood of external influence on their findings [22,38–47].

Figure 2 provides a visual overview of key study characteristics, including publication trends, funding status, and geographical distribution. Detailed methodological and clinical characteristics of the included studies are summarised in Table 1.

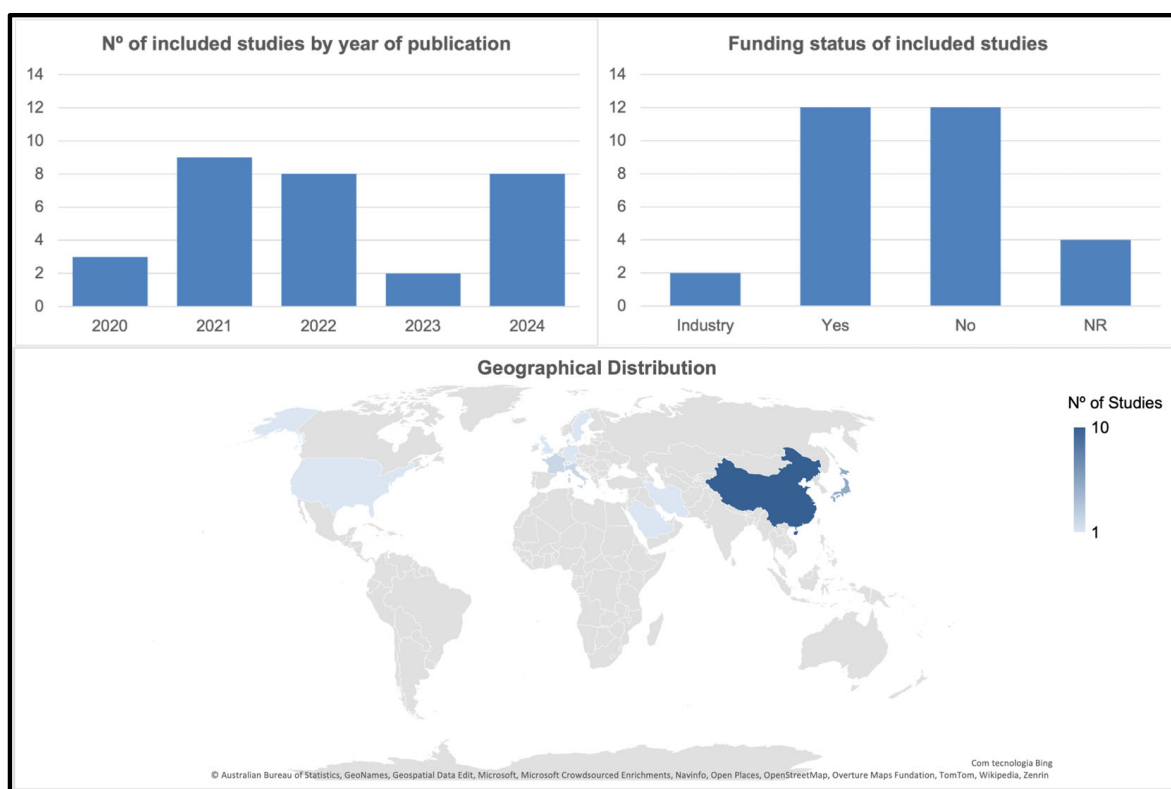


Figure 2. Visual summary of study characteristics, number of publications per year, funding classification, and geographical distribution of the included studies.

3.3. Risk of Bias in Studies

The methodological quality of the included studies was evaluated using the NIH Quality Assessment Tool. Overall, the evidence base demonstrated acceptable methodological robustness, with 21 of 30 studies (70.0%) judged to be at low risk of bias, 5 (16.7%) at moderate risk, and 4 (13.3%) at high risk of bias. Most low-risk studies employed intra-individual designs, which minimised confounding and ensured strong internal validity. The moderate-risk design rating was primarily attributed to between-group comparisons without randomisation, limited blinding of image reviewers, or incomplete reporting of inter-observer reliability. High-risk ratings occurred in studies with substantial methodological constraints, including unblinded assessments and the absence of standardised image-quality methods. Importantly, the reporting of radiation dose (CTDIvol, DLP, ED) was consistently comprehensive across all studies. The overall risk-of-bias profile supports the credibility of the observed improvements in dose reduction and image quality.

Table 1. Characteristics of the 30 included studies, including publication year, country, study design, population, anatomical region, scanner model, reconstruction technique, standard protocol, low-dose protocol, and dose reduction achieved.

Ref.	Year	Authors	Country	Study Design	N	Anatomical Region	Scanner	Recon. Type	Standard Protocol	Low-Dose Protocol	Dose Reduction
[2]	7.2022	Jeong-A Yeom, Ki-Uk Kim, et al.	Korea	Prospective Comparative	32	Chest	NR	DLR	120 kV, 60–120 mAs	ULDCT at 120 kVp/10 mAs	DLIR: 32–65% reduction
[4]	11.2021	Karolin J Paprottka, Karina Kupfer, et al.	Germany	Retrospective Comparative	131	Brain	Philips—128-row	HIR	120 kV, 300 mAs	SDCT (120 kVp, 300 mAs) vs. LDCT (120 kVp, 200 mAs)	IR methods reduced dose; ~33% reduction reported
[21]	9.2024	Weitao He, Ping Xu, et al.	China	Comparative (Prospective + Retrospective)	76	Abdomen	Canon—320-row	DLR	AIDR 3D	Plain and dual-phase contrast CT using two 320-row CT scanners	AiCE reduced dose > 54%; AIDR-3D increased noise
[22]	3.2024	Sarah Prod'homme, Roger Bouzerar, et al.	France	Cross-sectional Comparative	57	Abdomen and Pelvis	Ge—256-row	DLR	IR (100 kV, 50–200 mAs)	LDCT (100 kVp, 50–200 mAs) vs. ULDCT (100 kVp, 10–60 mAs) reconstructed using ASIR-V 70% and DLIR-H	Low-dose CT < 3 mSv; dose consistently reduced by DLR/IR
[23]	3.2020	Ramandeep Singh, Subba R Digumarthy, et al.	United States	Prospective Multi-institutional Comparative	59	Chest and Abdomen	Canon—64-row	DLR	AIDR 3D	SDCT (120 kVp/20 mAs) vs. LDCT (100 kVp, 30–50 mAs)	DLR enabled up to 36% reduction in CCTA
[24]	1.2021	Yuko Nakamura, Keigo Narita, et al.	Japan	Comparative (Not Specified)	72	Abdomen	Canon	DLR	IR	Hepatic arterial and equilibrium phase CT; SDCT: 250 mAs vs. LDCT: 175 mAs	30% total dose reduction; DLR superior at low dose
[25]	3.2024	Yanshan Chen, Zixuan Huang, et al.	China	Comparative (Not Specified)	270	Abdomen and Pelvis	Canon—64-row	DLR	CTC at 120 kVp and reconstructed using IR (RD-IR).	LDCT at 100 kVp reconstructed with IR (LD-IR) and DLR (LD-DLR)	83% dose reduction with LDCT; DLR superior to IR
[26]	9.2024	Liyong Zhuo, Shijie Xu, et al.	China	Prospective Comparative	156	Cardiac	Canon—320-row	DLR	120 kVp/30 mAs	SDCT (120 kVp/30 mAs), LDCT (120 kVp/20 mAs), and ULDCT (80 kVp/20 mAs)	Group A: 31%; Group B: 83% reduction depending on kVp/mAs; CTDIvol reduced by 50%
[27]	5.2022	Akio Tamura, Eisuke Mukaida, et al.	Japan	Retrospective Comparative	71	Abdomen	Canon—320-row	DLR HIR	AIDR 3D	LDCT with AiCE vs. routine-dose CT with AIDR-3D	43–45% reduction in CTDIvol, ED, and SSDE with AiCE
[28]	12.2021	Ali Chaparian, Mohamadhosin Asemanrafat, et al.	Iran	Prospective Comparative	40	Abdomen	Toshiba—160-row	IR	120 kV; mA 80–500; N 8	Routine-dose and reduced-dose CT with FBP vs. AIDR-3D	~48% reduction with low-dose AIDR-3D
[29]	11.2024	Huiyuan Zhu, Zike Huang, et al.	China	Prospective Comparative	102	Chest	GE—256-row	DLR	NR	SDCT vs. LDCT, with LDCT reconstructed using DLIR-H	LDCT achieved 84% reduction; DLIR-H superior to IR
[30]	6.2022	Ruijie Zhao, Xin Sui, et al.	China	Prospective Comparative	70	Chest	Canon—320-row	DLR	120 kV, automatic tube current	Chest HRCT vs. LDCT at 120 kVp; LDCT performed with 30 mAs	58–62% reduction depending on BMI group
[31]	9.2024	Shumeng Zhu, Baoping Zhan, et al.	China	Comparative (Not Specified)	60	Abdomen	United Imaging—320-row	DLR	100 kV, 213 mAs	Group A: 100 kVp (AEC); Group B: 80 kVp (AEC)	Deep IR enabled ~70% reduction; 80 kVp scans reduced dose by 57–65%
[32]	2.2021	Nieun Seo, Mi-Suk Park, et al.	Korea	Prospective Comparative	32	Abdomen	GE/Philips—128-row	DLR	Asir-V	Portal venous CT (120 kVp, 100–350 mAs) with optional pre-contrast or arterial phases	ULDCT achieved 68–72% dose reduction in CTDIvol and DLP
[33]	1.2023	Peijie Lyu, Zhen Li, et al.	China	Prospective Comparative	80	Head, chest, and abdomen	GE—Dual-energy	DLR	Full-dose single-energy CT (SECT) at 120 kVp, tube current of 400 mA	Reduced-dose DECT with virtual monochromatic images (40–60 keV, 350 mAs)	34% reduction achieved

Table 1. Cont.

Ref.	Year	Authors	Country	Study Design	N	Anatomical Region	Scanner	Recon. Type	Standard Protocol	Low-Dose Protocol	Dose Reduction
[34]	3.2022	Tetsuro Kaga, Yoshifumi Noda, et al.	Japan	Prospective Comparative	106	Abdomen	GE—Dual-energy	DLR	IR-Veo	Unenhanced abdominal LDCT using DLIR; comparison with SDCT reconstructed with ASIR-V	>75% dose reduction with DLIR vs. SDCT
[35]	3.2021	E Hettinger, M.-L Aurumskjöld, et al.	Sweden	Retrospective Comparative	39	Abdomen and Pelvis	Philips—256-row	IR iDose 4	100 kV, 233 mAs	CT urography with three phases: LD unenhanced scan + two SD contrast phases (100 kVp / 120 mAs)	35% reduction using MIR
[36]	6.2022	Hayato Tomita, Kenji Kuramochi, et al.	Japan	Retrospective Comparative	24	Brain	Canon—320-row	MIR IR	120 kV	100 kV	LDCT achieved 44% reduction vs. SDCT
[37]	3.2024	Xu Lin, Yankun Gao, et al.	China	Prospective Comparative	86	Abdomen and Pelvis	Ge—256-row	DLR	Fast kVp switching DECT (80/140 kVp), auto-mA (200–250 mA), NI = 8	Fast kVp switching DECT (80/140 kVp), auto-mA (200–250 mA), NI = 12	50% reduction
[38]	10.2023	Abdul Rauf, Saqib Javed, et al.	United Kingdom	Comparative (Not Specified)	121	Abdomen	Canon/GE-660	DLR	non-IA/IR-Veo	Comparison between Canon Genesis (AiCE) and GE Optima 660 (non-AI)	AI-based CT KUB and CTU protocols achieved substantial dose reduction
[39]	1.2021	Angélique Bernard, Pierre-Olivier Comby, et al.	France	Retrospective Comparative	289	Brain and Cardiac (Stroke)	Canon—320-row	DLR	NR	Brain CT protocol including unenhanced CT, perfusion CT, CTA, and CCTA (120 kVp, automatic mA modulation)	~28% reduction with AiCE
[40]	9.2020	L E Cao, Xiang Liu, et al.	China	Prospective Comparative	40	Abdomen	GE—256-row	DLR ASIR	120 kV, NI 11	SDCT (120 kVp, NI 11) vs. LDCT (NI 24) with ASIR-V	76% reduction in delayed-phase CT with DLIR
[41]	1.2022	June Park, Jaeseung Shin, et al.	Korea	Retrospective Comparative	123	Abdomen and Pelvis	GE	DLR IR	h-IR	LDCT reconstructed with DLIR vs. SDCT with hybrid IR (h-IR)	DLIR maintained image quality with ~76% dose reduction
[42]	6.2024	Emilio Quaia, Elena Kiyomi, et al.	Italy	Retrospective Comparative	83	Chest and Abdomen	NR	DLR	FBP	CT from lower neck to costophrenic angle (100–120 kVp, auto-mA)	DLIR achieved reduced ED vs. FBP and IR (ED: 18.45 vs. 22.06 mSv)
[43]	7.2022	Sungeun Park, Jeong Hee Yoon, et al.	Korea	Retrospective Comparative	80	Abdomen	Siemens—Dual-source	DLR	IR	Split-dose protocol: dual-tube acquisition (66.7% vs. 33.3% dose), 90 kVp, auto-mA	67% reduction with DLD vs. SDCT
[44]	11.2022	Dominik C Benz and Sara Ersözlü, et al.	Switzerland	Prospective Comparative	50	Cardiac	Ge—256-row	DLR	Asir-V	Coronary calcium score LDCT with ECG triggering (60% tube current)	43–56% reduction with DLIR in CCTA
[45]	1.2021	Lingming Zeng, Xu Xu, et al.	China	Comparative (Not Specified)	207	Abdomen	NR	DLR	IR	SDCT vs. LDCT comparison	LDCT with DELTA: ~49% reduction vs. HIR
[46]	6.2021	Davide Ippolito, Cesare Maino, et al.	Italy	Retrospective Comparative	125	Chest and Abdomen	NR—256-row	MIR	IR	Contrast-enhanced LDCT (100 kVp) vs. SDCT (120 kVp)	MBIR protocol reduced DLP by 42% and CTDIvol by 49%
[47]	5.2020	A Sulieman, H Adam, et al.	Saudi Arabia	Comparative (Not Specified)	111	Abdomen	NR	IR	NR	Standard imaging protocol vs. LDCT using 3D Sure Exposure	LDCT achieved ~48% reduction
[48]	2.2021	Yoshifumi Noda, Tetsuro Kaga, et al.	Japan	Prospective Comparative	59	Chest and Abdomen	GE—Dual-energy	DLR	120 kV; auto mA; N 7	LDCT protocol (120 kVp, auto-mA, noise index 14)	Hybrid-IR: 58%; Full-IR: 75%; DLIR >75%

Detailed domain-level assessments are provided in Appendix A Table A2 and Figure A1, with the overall distribution of risk of bias shown in Figure 3.

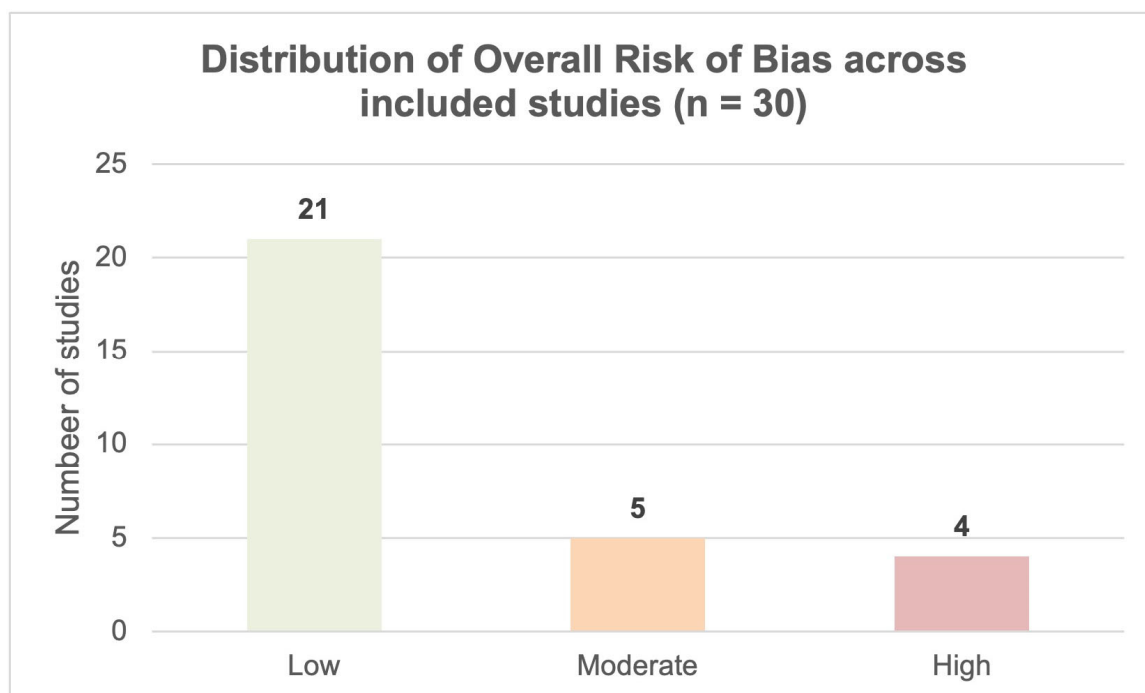


Figure 3. Distribution of overall risk of bias ratings across the 30 included studies; based on the NIH Quality Assessment Tool (21 low, 5 moderate, and 4 high risk).

3.4. Results of Individual Studies

To support transparency and allow comparison across heterogeneous study designs, the detailed results of each study are presented in Table 2. This table reports the absolute dose metrics, percentage dose reduction, and key findings related to image quality metrics.

The review summarises multiple studies assessing radiation dose reduction in CT exams using IR or DLR. IR was analysed in 6 studies and DLR in 24 studies. Some studies mentioned the commercial name of the reconstruction tool, but for standardisation and comparison, they were categorised into IR or DLR.

All included studies achieved dose reduction while maintaining diagnostic image quality [2,31,35,40]. In most studies, preservation of diagnostic image quality was inferred from objective image quality metrics and radiologist-based assessment rather than from formal diagnostic accuracy testing. On average, iterative reconstruction achieved a 45.4% dose reduction, whereas deep learning reconstruction achieved a mean decrease of 58.4%. As shown in Table 3, IR protocols reported dose reductions ranging from 24% to 50%, while DLR yielded substantially wider and higher reductions, ranging from 34% to 89%, with several studies exceeding 75% [25,34]. Deep learning reconstruction consistently allowed greater dose reduction than conventional IR while maintaining or improving image quality, as supported by marked noise suppression and enhanced SNR/CNR performance across multiple studies [2,21,32]. Image quality assessment varied across the included studies: the majority reported objective, quantitative metrics, including noise measurements, SNR, CNR, and related parameters. Subjective image quality evaluation by radiologists using Likert or Visual grading scales was also frequently employed, often in combination with objective measures. Only one study relied exclusively on subjective image assessment without reporting quantitative image quality metrics [35].

Table 2. Summaries of absolute dose metrics, percentage dose reduction, and key findings related to image quality metrics. Funding codes: NR = not reported; No = no funding declared; Yes = funding received but not from manufacturers; Industry = manufacturer-funded.

Ref.	Authors	Study Duration (Months)	Dose Metrics	Radiation Dose Reduction (%)	Confidence Intervals (%)	Image Quality Metrics	Main Dose-Related Finding	Funding
[2]	Jeong-A Yeom, Ki-Uk Kim, et al.	8	ED ULDCT = 0.39 ± 0.03 mSv ED SDCT = 3.43 ± 0.57 mSv	89.0	95	DLIR preserved diagnostic quality in ULDCT, matching SDCT performance in emphysema quantification.	Ultra-low-dose CT achieved substantial reductions in exposure while maintaining acceptable image quality.	Yes
[4]	Karolin J Paprottka, Karina Kupfer, et al.	10	Tube current = 300 → 200 mAs → NR	24.0	NR	Model-based IR improved CNR and lesion demarcation in ischemic imaging.	Low-dose cerebral CT achieved meaningful radiation reduction while maintaining image quality.	Yes
[21]	Weitao He, Ping Xu, and Mengchen Zhang, et al.	NR	ED LDCTE = 2.21 ± 0.23 mSv ED SDCTE = 4.82 ± 1.48 mSv	54.1	95	AiCE improved image quality over FBP and MBIR, maintaining diagnostic efficiency.	LDCT urography protocols reduced radiation dose meaningfully relative to standard CTU.	Yes
[22]	Sarah Prod'homme, Roger Bouzerar, et al.	NR	ED ULD CT = 0.59 mSv ED LD CT = 1.96 mSv	70.0	NR	DLR maintained diagnostic quality at <3 mSv, with improved SNR.	Ultra-low-dose CT achieved strong radiation reduction, with preserved clinical interpretability.	No
[23]	Ramandeep Singh, Subba R Digumarthy, et al.	NR	NR (only % reported)	36.0	NR	DLR improved image quality in abdominal and chest LDCT.	DLR supported meaningful dose reductions across coronary CT imaging.	Industry
[24]	Yuko Nakamura, Keigo Narita, et al.	2	SD CTDIvol = 7.2 ± 2.3 mGy LD → NR	30.0	95	DLR produced higher quality images than SD hybrid-IR, with superior noise and CNR.	Low-dose abdominal CT achieved notable exposure reduction with preserved diagnostic confidence.	Industry
[25]	Yanshan Chen, Zixuan Huang, et al.	12	ED LDCT = 0.86 mSv ED SDCT = 5.18 mSv	83.2	95	DLR showed superior SNR, CNR, and subjective quality compared with LD-IR.	Low-dose CT colonography achieved substantial radiation dose reduction while maintaining diagnostic image quality.	Yes
[26]	Liyong Zhuo, Shijie Xu, et al.	9	CTDIvol: 4.2 → 2.0 mGy	82.7	95	DLR improved noise suppression and CNR, maintaining diagnostic image quality in ULDCT.	Low-dose and ultralow-dose protocols markedly reduced radiation exposure without impairing evaluation.	Yes
[27]	Akio Tamura, Eisuke Mukaide, et al.	11	NR (only % reported)	40.0	NR	AiCE provided lower noise and better diagnostic quality than AIDR-3D.	AiCE consistently lowered radiation exposure while preserving overall image quality.	Yes
[28]	Ali Chaparian, Mohamadhosein Asemanrafat, et al.	12	NR (only % reported)	48.0	NR	IR improved objective image quality and reduced noise vs. FBP.	Reduced-dose abdominal CT protocol meaningfully lowered radiation exposure relative to routine CT.	Yes
[29]	Huiyuan Zhu, Zike Huang, et al.	4	ED LDCT = 0.86 mSv ED SDCT = 5.37 mSv	84.0	95	DLIR-H improved detection rates of subsolid nodules and overall quality.	LDCT enabled very large exposure reductions while maintaining diagnostic acceptability.	Yes
[30]	Ruijie Zhao, Xin Sui, et al.	7	NR (BMI categories only)	61.9	NR	DLR improved image quality in ILD evaluations compared with hybrid-IR.	In ILD imaging, DLR markedly reduced dose compared with HRCT while sustaining adequate quality.	Yes
[31]	Shumeng Zhu, Baoping Zhan, et al.	4	ED Deep IR = 1.53 ± 0.37 mSv ED SDCT = 5.09 ± 0.91 mSv	69.9	NR	Deep IR improved SNR, CNR, and subjective quality over hybrid-IR.	Deep IR substantially decreased radiation exposure with improved image quality metrics.	Yes
[32]	Nieun Seo, Mi-Suk Park, et al.	42	NR (only % reported)	71.8	95	ULDCT with IMR preserved diagnostic quality with higher CNR and lower noise.	Ultra-low-dose protocols achieved large dose reductions with maintained diagnostic utility.	Yes

Table 2. Cont.

Ref.	Authors	Study Duration (Months)	Dose Metrics	Radiation Dose Reduction (%)	Confidence Intervals (%)	Image Quality Metrics	Main Dose-Related Finding	Funding
[33]	Peijie Lyu, Zhen Li, et al.	19	NR (only % reported)	34.0	NR	DLIR enhanced resolution, contrast, and lesion conspicuity compared with IR.	Reduced dose with DLIR lowered radiation exposure while maintaining adequate perceptual quality.	Yes
[34]	Tetsuro Kaga, Yoshifumi Noda, et al.	6	NR (only % reported)	75.0	NR	DLIR preserved image quality with lower noise and comparable lesion detectability to SDCT.	DLIR enabled major radiation dose reductions compared with standard-dose hybrid IR.	NR
[35]	E Hettinger, M.-L Aurumskjöld, H Sartor, et al.	NR	NR (only % reported)	35.0	95	IMR improved low-contrast resolution compared with iDose and maintained diagnostic quality.	IMR-based abdominal CT enabled relevant dose reductions without compromising diagnostic value.	NR
[36]	Hayato Tomita, Kenji Kuramochi, et al.	10	NR (only % reported)	44.2	NR	FIRST improved noise reduction and image quality compared with FBP and AIDR-3D.	Low-dose paranasal CT achieved notable radiation savings compared with standard protocols.	NR
[37]	Xu Lin, Yankun Gao, et al.	7	Early enteric ED = 6.31 mSv Late-enteric ED = 3.01 mSv	50.0	NR	DLIR provided higher noise suppression, SNR, and overall quality compared with ASIR-V.	Late-enteric-phase imaging resulted in lower radiation exposure compared with early-phase acquisition.	NR
[38]	Abdul Rauf, Saqib Javed, et al.	NR	CT KUB = 78 mGy·cm CTU = 401.9 mGy·cm	~82.0	NR	DLR achieved diagnostic-quality CT KUB/CTU images at reduced exposure.	AI-based CT KUB/CTU protocols substantially reduced radiation dose compared with conventional techniques.	No
[39]	Angélique Bernard, Pierre-Olivier Comby, et al.	4	ED AiCE = 1.5 ± 0.7 mSv ED AIDR = 2.5 ± 0.5 mSv	40.0	95	DLR improved noise and diagnostic quality in cardiac CTA compared with AIDR-3D.	AiCE reduced radiation dose across multiphase stroke imaging, with preserved diagnostic utility.	No
[40]	L E Cao, Xiang Liu, et al.	NR	Delayed-phase ED = 0.76 ± 0.09 mSv Arterial-phase ED = 3.18 ± 0.48 mSv	76.0	NR	DLIR-H produced image quality comparable to routine-dose ASIR-V, with improved noise and confidence.	Delayed-phase CT achieved a pronounced dose reduction compared with standard arterial-phase imaging.	No
[41]	June Park, Jaeseung Shin, et al.	NR	SSDE LDCT = 6.6 ± 1.0 mGy SSDE SDCT = 10.3 ± 1.6 mGy	35.1	95	DLIR-M reduced noise and maintained diagnostic quality even at lower dose levels.	LDCT protocols reduced radiation exposure, with preserved image quality in abdominal imaging.	No
[42]	Emilio Quaia, Elena Kiyomi, et al.	16	ED DLIR = 18.45 ± 13.16 mSv ED FBP = 22.06 ± 9.55 mSv	16.0	NR	DLIR improved noise, SNR, and diagnostic confidence over IR and FBP.	DLIR demonstrated a lower effective dose compared with IR while maintaining image quality metrics.	No
[43]	Sungeun Park, Jeong Hee Yoon, et al.	5	NR (only % reported)	67.0	95	DLD maintained diagnostic image quality with improved contrast-to-noise ratio compared with SDCT.	Deep-learning liver CT achieved major dose reductions while maintaining non-inferior quality.	No
[44]	Dominik C Benz and Sara Ersözlü, et al.	NR	NR (only % reported)	43.0	95	DLIR improved CCTA image quality, SNR, and noise versus ASIR-V.	DLR meaningfully reduced radiation exposure in CCTA without impairing plaque or stenosis assessment.	No
[45]	Lingming Zeng, Xu Xu, et al.	2	NR (only % reduction)	49.0	NR	LDCT-DELTA preserved image quality and improved SNR/CNR compared with HIR.	DLR reconstruction allowed significant radiation savings compared with hybrid iterative methods.	No

Table 2. Cont.

Ref.	Authors	Study Duration (Months)	Dose Metrics	Radiation Dose Reduction (%)	Confidence Intervals (%)	Image Quality Metrics	Main Dose-Related Finding	Funding
[46]	Davide Ippolito, Cesare Maino, et al.	16	NR (only % reported)	42.0–49.0	NR	MBIR produced higher SNR/CNR and better quality than HIR while maintaining diagnostic value.	MBIR enabled substantial radiation dose reductions while enhancing image quality.	No
[47]	A Sulieman, H Adam, et al.	NR	CTDIvol SD = 7.2 ± 2.3 mGy, LD → NR	48.0	NR	Low-dose IR preserved diagnostic quality with acceptable noise levels.	Low-dose Sure Exposure protocols reduced radiation meaningfully without compromising the evaluation.	No
[48]	Yoshifumi Noda, Tetsuro Kaga, et al.	2	NR (only % reported)	75.0	NR	DLIR showed higher SNR and lower noise than SD-IR and LD-IR across metrics.	DLIR provided a substantial dose reduction superior to hybrid and full IR approaches.	No

Table 3. Comparison of hybrid iterative reconstruction (HIR), model-based iterative reconstruction (MBIR), and deep learning reconstruction (DLR) across standard CT quality and dose metrics.

Metric	HIR	MBIR	DLR
Dose Reduction Range (%)	24–50	35–75	34–89
Noise Reduction	Moderate	High	Very High
Image Noise (SD)	↓ 30–40%	↓ 50–60%	↓ 65–83%
SNR	Moderate	High	Very High
CNR	Moderate	High	Very High
Reconstruction Speed	Fast	Slow (3–7 min)	Fast *

HIR—hybrid iterative reconstruction; MBIR—model-based iterative reconstruction; DLR—deep learning reconstruction; ↓—indicates a reduction relative to standard-dose protocols. SNR—signal-to-noise ratio; CNR—contrast-to-noise ratio. * Reconstruction speed for DLR may vary depending on vendor-specific implementation and available computational resources, particularly GPU acceleration.

Eight anatomical regions were represented across the included studies. The abdomen was the most frequently investigated site (12/30; 40%) [23,27,32], followed by combined abdomen and pelvis (5/30; 16.7%) and combined chest and abdomen examinations (4/30; 13.3%). Chest-only studies accounted for 10% (3/30), while brain and cardiac examinations were each represented by two studies (6.7%). Highly specific protocols, such as Brain and Cardiac (Stroke) and whole-body Head–Chest–Abdomen acquisitions, were reported only once each [33,39]. This distribution reflects the broad clinical applications of low-dose CT techniques across emergency, oncological, thoracic, abdominal, and cardiovascular settings. Table 4 summarises the mean dose reduction achieved within each anatomical region, together with the reconstruction technique applied and its typical clinical contexts.

Table 4. Summary of radiation dose reduction by anatomical region across 30 studies. It integrates study counts, reconstruction techniques, mean percentage dose reduction, and main clinical applicability.

Anatomical Region	No. of Studies	Techniques Used	Mean Dose Reduction (%)	Clinical Applicability (Examples)
Abdomen	12	DLR, IR	57.8	Oncology, hepatic imaging
Chest	3	DLR	78.3	Emphysema, thoracic imaging
Chest–Abdomen	4	DLR, IR	43.6	Contrast-enhanced studies
Abdomen–Pelvis	5	DLR, IR	54.7	Follow-up exams, pelvic oncology
Cardiac	2	DLR	62.9	Coronary angiography, CACS
Brain	2	IR	34.1	Acute stroke/emergency imaging
Brain–Cardiac (Stroke)	1	DLR	40.0	Stroke pathway, perfusion CT
Head, Chest, and Abdomen	1	DLR	34.0	Whole-body oncology or trauma pathway

Sample sizes across the studies ranged widely, ranging from 24 to 289 participants, with an estimated mean of 86 patients per study. Across all 30 studies, population sizes were sufficient to support comparative analyses of reconstruction algorithms and dose-reduction strategies. However, demographic details such as age, sex, or BMI were inconsistently reported and therefore not used for table standardisation. Regarding image reconstruction techniques, iterative reconstruction was used in approximately 20% of the studies ($n = 6$), while deep learning-based reconstruction was notably more prevalent, featuring in 70% of the studies ($n = 21$). Three studies used both methods. This highlights the growing adoption of DLR technologies in dose-reduction strategies.

Among studies reporting quantitative dose reduction, the average reduction achieved was 58.4% ($\pm 21.2\%$), underscoring the substantial potential of advanced reconstruction methods, particularly DLR, to lower radiation exposure while maintaining diagnostic

image quality. Table 2 presents the dose reduction achieved in each study, along with the reconstruction technique employed.

A broad range of CT scanners and reconstruction systems was represented across the included studies. Canon Medical (Ottawa, Japan) and GE Healthcare (Chicago, IL, USA) accounted for most of the datasets, using systems ranging from 64- to 128-slice scanners to 320-detector Aquilion One and Revolution Apex platforms. Philips Healthcare (Amsterdam, The Netherlands) and Siemens Healthineers (Erlangen, Germany) systems were also represented, although less frequently, together with isolated examples from Toshiba and United Imaging. Reconstruction approaches included conventional IR families (ASIR, ASI-V, AIDR, iDOSE, IMR); model-based IR; and several DLR implementations such as TrueFidelity, DLIR, AiCE, and Precise DL (Beta). Some studies used generic or custom reconstruction pipelines where vendor information was not reported. Overall, this diversity reflects the rapid evolution of reconstruction technologies and the growing interest in optimising CT dose efficiency across manufacturers, as summarised in Table 5.

Table 5. Vendors, scanner models, iterative reconstruction (IR) algorithms, and deep learning reconstruction (DLR) version represented in the 30 included studies.

Manufacturer	Scanner Model	IR Type(s)	DLR Version	No. of Studies
GE Healthcare	Revolution CT (Apex, Evo), Optima	ASIR, ASIR-V	TrueFidelity/DLIR	11
Canon Medical	Aquilion One, Aquilion Precision	AIDR 3D	AiCE (DLR)	9
Siemens Healthineers	SOMATOM Force	SAFIRE/ADMIRE (IR) *	—	1
Philips Healthcare	Brilliance, Ingenuity CT One	iDose, IMR	Precise DL (Beta)	3
Toshiba	Aquilion Prime SP	AIDR 3D	—	1
United Imaging	NR	Generic IR	—	1
Mixed/Not Stated	—	Generic IR	Custom/unspecified	5

IR Types and DLR implementations are listed as reported by each manufacturer or study. “Mixed/Not Stated” refers to studies where vendor information was unclear or multiple platforms were used. * SAFIRE and ADMIRE, both from Siemens, represent different generations of iterative reconstruction techniques.

3.5. Reporting Biases and Certainty of Evidence

Based on the assessment of publication bias, no strong evidence of selective reporting or publication bias was identified. Although a small number of studies involved authors affiliated with scanner manufacturers, only two studies reported direct industry funding, and these were appropriately accounted for in the risk-of-bias and GRADE assessment. Most studies were classified as undetected for publication bias, suggesting that there are no indications of unpublished negative results. This assessment provides confidence that the reported effects are not driven by the selective non-publication of studies with negative findings.

Certainty of evidence, evaluated using the GRADE framework, was predominantly high across core outcomes. Twenty-six studies (86.7%) were graded as high certainty, reflecting effects, precise estimates, and well-reported methodologies. Two studies (6.7%) were graded as moderate certainty, typically due to residual confounding or limited sample sizes, and two studies (6.7%) were graded as low certainty, mainly because of high risk of bias or inconsistency. Certainty was particularly strong for radiation dose reduction and image quality metrics (noise, SNR, CNR) and moderate for lesion detection due to sample size variations. These findings indicate that the evidence supporting the benefits of dose reduction and image quality preservation in low-dose CT protocols is reliable and robust. An overall distribution of risk of bias is presented in Figure 4, and the synthesis of the GRADE certainty assessment is provided in Appendix A Table A3, with study-level linkage provided in Table A4.

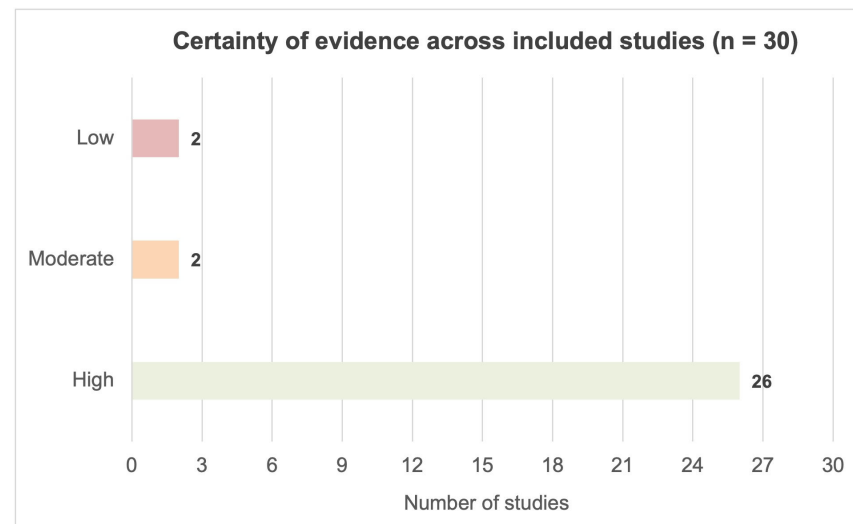


Figure 4. Summary of certainty across the 30 studies.

4. Discussion

This systematic review summarises the existing literature on radiation dose reduction in CT examinations with IR and DLR. The research findings demonstrate considerable variability across studies in the assessment of reconstruction algorithms, including differences in technical characteristics, clinical applications, and reported outcomes related to dose reduction and image quality. Overall, the review highlights the ongoing evolution and clinical impact of advanced image reconstruction techniques—particularly iterative reconstruction and deep learning-based reconstruction in supporting radiation dose optimisation in computed tomography.

It is important to note that IR and DLR techniques do not directly reduce radiation dose in isolation. Instead, the dose reductions reported across the included studies reflect the extent to which these reconstruction methods enable the optimisation of acquisition parameters—such as tube voltage, tube current, automatic tube current modulation, noise index, and protocol design—while maintaining diagnostic image quality. Within this context, DLR and IR were generally associated with meaningful radiation dose reductions in optimised CT protocols across the 30 included studies while preserving diagnostic image quality. Several studies reported that low-dose or ultra-low-dose CT protocols incorporating DLR maintained both subjective and objective image quality, with improvements in noise, SNR, and CNR when compared with IR [27,35,40,41].

The results reinforce the emerging consensus in the literature: deep learning reconstruction techniques were generally associated with better performance than iterative reconstruction approaches in achieving radiation dose reduction across various clinical applications. In this review, DLR achieved larger dose reductions (median $\approx 58\%$) than IR ($\approx 45\%$), with several DLR protocols enabling $\geq 75\%$ reduction while preserving diagnostic quality [25,34,35,43]. In the present review, DLR consistently achieved larger reductions (median $\approx 62\%$) than IR ($\approx 45\%$), with several DLR protocols enabling $\geq 75\%$ reduction while preserving diagnostic quality.

DLR methods demonstrated a trend toward greater substantial dose reductions than traditional IR approaches while maintaining or even improving diagnostic image quality. DLR was generally associated with better performance than IR in terms of radiation dose mitigation. Among studies implementing DLR algorithms, dose reductions ranged up to 83% [25], with several studies reporting reductions well above 70% [27,34,35,40]. On average, DLR studies achieved a mean dose reduction of 58.4%, with a standard deviation of $\pm 21.2\%$, supporting the reproducibility of findings across studies of this technique in clinical

settings. In contrast, while effective, IR methods generally yielded more modest reductions, which were often limited by image noise and longer reconstruction times [4,28,36,47].

In abdominal and thoracic imaging, where dose accumulation is particularly concerning due to the frequency of surveillance imaging, DLR protocols achieved median reductions of up to 76% while preserving or improving diagnostic confidence. These figures reflect their enhanced performance in real-world clinical applications, such as cardiac and lung CT [26,29]. DLR reduced doses in abdominal CT by 54–76% [21,31,32,34,40,43] and in cardiac CT enabled a 43% reduction in coronary CTA, with the dose reduced to 0.8 mSv without stenosis misclassification [44]. Ultra-low-dose CT with sub-mSv doses (<1 mSv) was achieved in the evaluation of pulmonary nodules [29]. In contrast, while effective, IR methods generally yielded more modest reductions, often limited by image noise and longer reconstruction times [35,46]. For oncology follow-up, MBIR enabled a 75% dose reduction in metastatic liver surveillance [33].

In terms of image quality, DLR has superior noise reduction and higher SNR/CNR vs. IR [43]. IR improved diagnostic confidence, but with higher noise at extreme dose reductions [47]. Hybrid IR introduced artefacts in abdominal CT [43]. MBIR performance varied across scanners [21,43,46]. A strong conclusion was that DLR maintains diagnostic acceptability even at very low dose levels, including in challenging clinical cases such as colonography [25], coronary calcium scoring [26,39,44], urolithiasis [38], interstitial lung imaging [30], emphysema quantification [2], and abdominal oncology assessment [32,33,41,43]. In some cases, DLR was reported to provide improved lesion detectability or anatomical conspicuity compared with hybrid or model-based IR, as reported in comparative studies [25,27,30,37,42,44].

DLR enables high-quality LDCT for lung cancer screening [29]. In comparative designs where both methods were applied, several studies reported an advantage of DLR. For instance, refs. [27,40,41] demonstrated that DLR yielded better contrast-to-noise ratios and improved lesion detectability at significantly lower radiation doses than IR. These findings are particularly relevant for populations that require repeated imaging, such as patients with oncology or those undergoing chronic disease follow-up.

The importance of regional and institutional protocol standardisation is also evident, as significant dose variability often stems from site-specific decisions rather than patient or technical constraints. Practical approaches include harmonising acquisition parameters, using reference dose thresholds by anatomical region, and the routine incorporation of DRL into protocol optimisation workflows. However, despite the technical benefits reported for iterative and deep learning reconstruction techniques, several practical barriers to widespread clinical adoption remain. These include requirements for dedicated computational infrastructure and the associated implementation and maintenance costs, challenges related to integrating into existing clinical workflows, and the need for targeted staff training, particularly in resource-limited settings. Broader implementations of DLR will depend on continued regulatory endorsement, vendor-specific integration, and rigorous validation in large-scale, multi-centre clinical trials. DLR-based techniques represent the next evolution in low-dose CT imaging. Overall, DLR represents an evolving approach to dose optimisation in CT imaging, with studies suggesting potential benefits across a range of clinical applications, particularly in examinations with higher imaging frequency or radiation exposure.

Limitations and Biases in Current Research

Despite the promising results, several limitations emerged across the included studies. Many relied on small, single-centre samples with short study durations, which may limit generalisability. Patient BMI was frequently cited as a constraint, with some studies report-

ing lower BMI values compared to global averages. This may overestimate the apparent performance of DLR [27,31,32]. In addition, dose reduction percentages were derived from within-study comparisons using institution-specific reference protocols, which limits the direct comparability of quantitative dose reduction values across studies. Although most studies assessed image quality using objective quantitative metrics—such as image noise, SNR, and CNR—the choice of metrics, measurement methods, and scoring systems varied considerably, and subjective radiologist-based assessments were inconsistently applied. This methodological variability restricts direct cross-study comparisons and precludes quantitative synthesis. Nevertheless, within the scope of dose optimisation, these metrics and radiologist assessment were consistently used to support the conclusion that radiation dose reductions could be achieved without clinically relevant loss of diagnostic capability.

Further limitations relate to technological scope and external validity. The predominance of vendor-specific reconstruction software further limits cross-platform comparability, as most DLR studies were conducted on GE/Canon scanners ($n = 18/30$), which can introduce a degree of vendor bias into the evidence base and limit the generalisability of these findings to other major CT vendors, such as Siemens or Philips. The restriction of the review to studies published between 2020 and 2025 was intended to focus on contemporary reconstruction technologies currently implemented in clinical practice; however, this approach excludes earlier evidence on iterative reconstruction and may place greater emphasis on more recent deep learning-based implementations.

Methodological biases also emerged, predominantly selection bias due to retrospective designs and the exclusion of specific subgroups, such as obese or paediatric populations. Twelve studies reported some form of institutional collaboration or technical support from equipment manufacturers; however, only two studies reported direct manufacturer funding [23,24]. Although no consistent pattern of vendor-dependent bias was identified, and most studies were rated to have a low risk of bias according to the NIH Quality Assessment, the potential for optimism bias in studies with manufacturer involvement cannot be entirely excluded. A minority of studies presented moderate or high concerns, which were mainly related to limited blinding and insufficient reporting of inclusion criteria.

The certainty of evidence, as assessed by the GRADE, was high for most objective dose-reduction outcomes but decreased to moderate or low for subjective image quality measures, reflecting limitations inherent to non-randomised designs, heterogeneity in scanning protocols, and small sample sizes. Despite these constraints, the body of evidence demonstrates overall methodological robustness and internal consistency, providing a reliable foundation for advancing IR and DLR applications in CT dose reduction.

Further research would benefit from larger, multi-centric studies to improve generalisability across diverse populations and clinical settings. Greater standardisation of dose reporting metrics (CTDIvol, DLP, and effective dose) and reconstruction parameters across vendors may also facilitate reproducibility and cross-study comparability. From a practical perspective, DLR has been increasingly explored as a reconstruction option in clinical practice where available. However, its broader implementation remains dependent on local infrastructure, regulatory considerations, and further validation. Additionally, the integration of DLR with artificial intelligence-assisted diagnostics represents a promising direction for advancing in this field.

5. Conclusions

In 30 human adult studies (2020–2025), iterative reconstruction achieved ~24–50% dose reductions (mean $\approx 45\%$), while deep learning reconstruction achieved ~34–89% (mean $\approx 58\%$), with several DLR protocols enabling $\geq 75\%$ reductions while maintaining diagnostic image quality. Given heterogeneity, a narrative synthesis was appropriate.

Overall certainty ranged from high for dose-reduction and image quality outcomes to moderate–low for lesion detection, indicating that while the evidence strongly supports dose optimisation, deep learning-based reconstruction may be considered as part of dose optimisation strategies where available, with caution regarding diagnostic performance.

Author Contributions: Conceptualisation, S.C. and M.d.L.D.; methodology, S.C. and J.S.B.; investigation, S.C. and M.d.L.D.; data curation, S.C. and M.d.L.D.; formal analysis, S.C. and M.d.L.D.; writing –original draft preparation, S.C.; writing – review and editing, S.C. and M.d.L.D., M.F. and J.S.B.; supervision, J.S.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new datasets were generated. Template forms and extracted tables are available upon reasonable request from the corresponding author; no analytic code was used.

Acknowledgments: The author would like to thank the professors of the Doctoral Program in Occupational Safety and Health at the University of Porto.

Conflicts of Interest: The authors declare that they have no conflicts of interest.

Appendix A

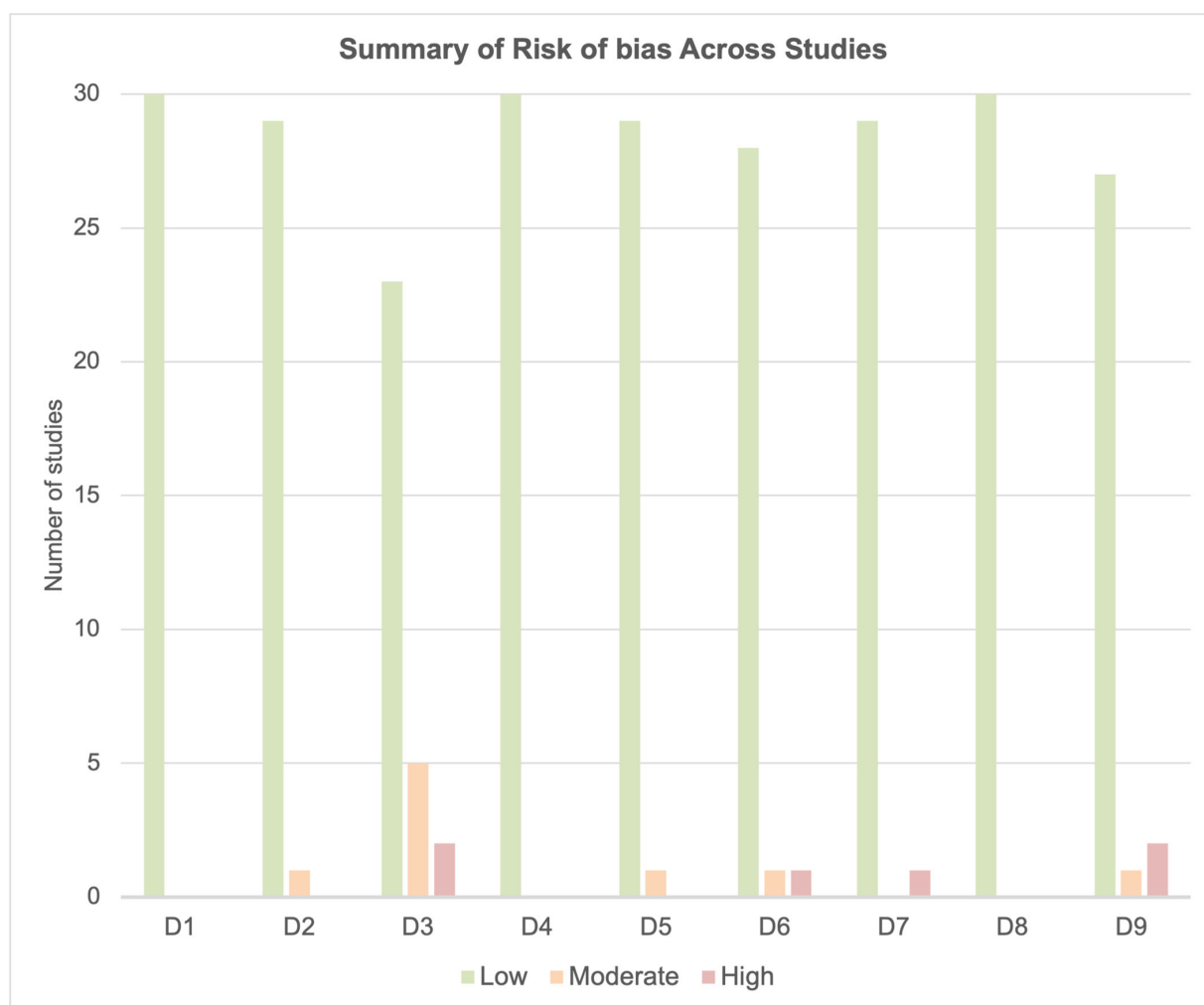


Figure A1. Summary of risk of bias across studies by domains.

Table A1. Database-specific strategies.

Database	Platform	Search String (Title/Abstract)	Filters Applied	Date
PubMed	NCBI	((“Computed Tomography”[All Fields] OR “CT Exam”[All Fields]) AND (“Dose Reduction”[All Fields] OR “Radiation Risk”[All Fields] OR “Radiation Dose Reduction”[All Fields]) AND (“Iterative Reconstruction”[All Fields] OR “Tube Voltage Modulation”[All Fields])) AND ((humans[Filter]) AND (2020/1/1:2025/3/22[pdat]) AND (english[Filter])) ((“Computed Tomography”[All Fields] OR “CT Exam”[All Fields]) AND (“Dose Reduction”[All Fields] OR “Radiation Risk”[All Fields] OR “Radiation Dose Reduction”[All Fields]) AND (“Automatic Exposure”[All Fields] OR “Tube Current Modulation”[All Fields])) AND ((humans[Filter]) AND (2020/1/1:2025/3/22[pdat]) AND (english[Filter])) ((“Computed Tomography”[All Fields] OR “CT Exam”[All Fields]) AND (“Dose Reduction”[All Fields] OR “Radiation Risk”[All Fields] OR “Radiation Dose Reduction”[All Fields]) AND (“Noise-Based Tube Current”[All Fields] OR “Innovation”[All Fields])) AND ((humans[Filter]) AND (2020/1/1:2025/3/22[pdat]) AND (english[Filter]))	Humans, English; 2020–2025	22 March 2025
Scopus	Elsevier	TITLE-ABS-KEY((“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Iterative Reconstruction” OR “Tube Voltage Modulation”))AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE,“ar”)) AND (LIMIT-TO (SRCTYPE,“j”)) AND LIMIT-TO (LANGUAGE,“English”) AND (LIMIT-TO (PUBSTAGE,“final”)) TITLE-ABS-KEY((“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Automatic Exposure” OR “Tube Current Modulation”)) AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE,“ar”)) AND (LIMIT-TO (SRCTYPE,“j”)) AND (LIMIT-TO (LANGUAGE,“English”) AND (LIMIT-TO (PUBSTAGE,“final”)) TITLE-ABS-KEY((“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Noise-Based Tube Current” OR “Innovation”)) AND PUBYEAR > 2019 AND PUBYEAR < 2026 AND (LIMIT-TO (SRCTYPE,“j”)) AND (LIMIT-TO (LANGUAGE,“English”) AND (LIMIT-TO (DOCTYPE,“ar”) OR LIMIT-TO (DOCTYPE,“re”))	Article, Journal, English; 2020–2025	22 March 2025
Web of Science	Clarivate	(“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Iterative Reconstruction” OR “Tube Voltage Modulation”) (Topic) and 2025 or 2024 or 2023 or 2022 or 2021 or 2020 (Publication Years) and Article (Document Types) and English (Languages) (“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Automatic Exposure” OR “Tube Current Modulation”) (Topic) and 2025 or 2024 or 2023 or 2022 or 2021 or 2020 (Publication Years) and Article (Document Types) and English (Languages) and Article (Document Types) (“Computed Tomography” OR “CT Exam”) AND (“Dose Reduction” OR “Radiation Risk” OR “Radiation Dose Reduction”) AND (“Noise-Based Tube Current” OR “Innovation”) (Topic) and 2025 or 2023 or 2021 or 2020 (Publication Years) and Article (Document Types) and English (Languages)	Article, English; 2020–2025	22 March 2025

Table A2. Risk of bias.

Ref.	Authors	Date	D1	D2	D3	D4	D5	D6	D7	D8	D9	Overall RoB
[2]	Jeong-A Yeom, Ki-Uk Kim, et al.	7.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[4]	Karolin J Paprottka, Karina Kupfer, et al.	11.2021	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[21]	Weitao He, Ping Xu, and Mengchen Zhang, et al.	9.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[22]	Sarah Prod'homme, Roger Bouzerar, et al.	3.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[23]	Ramandeep Singh, Subba R Digumarthy, et al.	3.2020	Low	Low	Low	Low	Low	Moderate	Low	Low	High	High
[24]	Yuko Nakamura, Keigo Narita, et al.	1.2021	Low	Low	Moderate	Low	Low	Low	Low	Low	High	High
[25]	Yanshan Chen, Zixuan Huang, et al.	3.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[26]	Liyong Zhuo, Shijie Xu, et al.	9.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[27]	Akio Tamura, Eisuke Mukaida, et al.	5.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[28]	Ali Chaparian, Mohamadhosein Asemanrafat, et al.	12.2021	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[29]	Huiyuan Zhu, Zike Huang, et al.	11.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[30]	Ruijie Zhao, Xin Sui, et al.	6.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[31]	Shumeng Zhu, Baoping Zhan, et al.	9.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[32]	Nieun Seo, Mi-Suk Park, et al.	2.2021	Low	Low	Moderate	Low	Low	Low	Low	Low	Low	Moderate
[33]	Peijie Lyu, Zhen Li, et al.	1.2023	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[34]	Tetsuro Kaga, Yoshifumi Noda, et al.	3.2022	Low	Low	Moderate	Low	Low	Low	Low	Low	Low	Moderate
[35]	E Hettinger, M.-L Aurumskjöld, H Sartor, et al.	3.2021	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[36]	Hayato Tomita, Kenji Kuramochi, et al.	6.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[37]	Xu Lin, Yankun Gao, et al.	3.2024	Low	Low	Low	Low	Low	Low	Low	Low	Moderate	Moderate
[38]	Abdul Rauf, Saqib Javed, et al.	10.2023	Low	Moderate	High	Low	Low	Low	Low	Low	Low	High
[39]	Angélique Bernard, Pierre-Olivier Comby, et al.	1.2021	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[40]	L E Cao, Xiang Liu, et al.	9.2020	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[41]	June Park, Jaeseung Shin, et al.	1.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[42]	Emilio Quaia, Elena Kiyomi, et al.	6.2024	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[43]	Sungeun Park, Jeong Hee Yoon, et al.	7.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[44]	Dominik C Benz and Sara Ersözlü, et al.	11.2022	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low
[45]	Lingming Zeng, Xu Xu, et al.	1.2021	Low	Low	Moderate	Low	Low	Low	Low	Low	Low	Moderate
[46]	Davide Ippolito, Cesare Maino, et al.	6.2021	Low	Low	Moderate	Low	Low	Low	Low	Low	Low	Moderate
[47]	A Sulieman, H Adam, et al.	5.2020	Low	Low	High	Low	Moderate	High	High	Low	Low	High
[48]	Yoshifumi Noda, Tetsuro Kaga, et al.	2.2021	Low	Low	Low	Low	Low	Low	Low	Low	Low	Low

Table A3. Summary of certainty of evidence (GRADE) for each outcome category across included studies.

Ref.	Authors	Main Outcome	Risk of Bias	Inconsistency	Imprecision	Indirectness	Publication Bias	Overall Certainty
[2]	Jeong-A Yeom, Ki-Uk Kim, et al.	Emphysema quantification (ULCT vs. SDCT)	Not serious	Not serious	Not serious	Not serious	Undetected	High
[4]	Karolin J Paprottka, Karina Kupfer, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[21]	Weitao He, Ping Xu, and Mengchen Zhang, et al.	CT enterography IQ + dose (IBD)	Not serious	Not serious	Not serious	Not serious	Undetected	High
[22]	Sarah Prod'homme, Roger Bouzerar, et al.	Stone detection on sub-mSv CT	Not serious	Not serious	Not serious	Not serious	Undetected	High
[23]	Ramandeep Singh, Subba R Digumarthy, et al.	Sub-mSv chest/abdominal CT DLIR vs. IR	Serious	Not serious	Not serious	Not serious	Suspected	Moderate
[24]	Yuko Nakamura, Keigo Narita, et al.	U-HRCT abdomen DLIR vs. IR/MBIR	Serious	Not serious	Not serious	Not serious	Suspected	Moderate
[25]	Yanshan Chen, Zixuan Huang, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[26]	Liyong Zhuo, Shijie Xu, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[27]	Akio Tamura, Eisuke Mukaida, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[28]	Ali Chaparian, Mohamadhosein Asemanrafat, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[29]	Huiyuan Zhu, Zike Huang, et al.	Sub-mSv LDCT for subsolid nodules	Not serious	Not serious	Not serious	Not serious	Undetected	High
[30]	Ruijie Zhao, Xin Sui, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[31]	Shumeng Zhu, Baoping Zhan, et al.	Abdominal LDCT with DLIR vs. routine dose IR	Not serious	Not serious	Not serious	Not serious	Undetected	High
[32]	Nieun Seo, Mi-Suk Park, et al.	ULDCT IR in follow-up of abscess	Not serious	Not serious	Not serious	Not serious	Undetected	High
[33]	Peijie Lyu, Zhen Li, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[34]	Tetsuro Kaga, Yoshifumi Noda, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[35]	E Hettinger, M.-L Aurumskjöld, H Sartor, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[36]	Hayato Tomita, Kenji Kuramochi, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[37]	Xu Lin, Yankun Gao, et al.	LD DECT enterography DLIR vs. ASIR-V	Not serious	Not serious	Not serious	Not serious	Suspected	High
[38]	Abdul Rauf, Saqib Javed, et al.	Dose reduction + image quality	Serious	Serious	Not serious	Not serious	Undetected	Low
[39]	Angélique Bernard, Pierre-Olivier Comby, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[40]	L E Cao, Xiang Liu, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[41]	June Park, Jaeseung Shin, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[42]	Emilio Quaia, Elena Kiyomi, et al.	ICU CT: DLIR vs. FBP/IR dose + IQ	Not serious	Not serious	Not serious	Not serious	Undetected	High
[43]	Sungeun Park, Jeong Hee Yoon, et al.	Liver CT: LD DLD vs. SD MBIR	Not serious	Not serious	Not serious	Not serious	Suspected	High
[44]	Dominik C Benz and Sara Ersözlü, et al.	CCTA dose + plaque metrics	Not serious	Not serious	Not serious	Not serious	Suspected	High
[45]	Lingming Zeng, Xu Xu, et al.	Half-dose liver CT DLIR vs. HIR	Not serious	Not serious	Not serious	Not serious	Undetected	High
[46]	Davide Ippolito, Cesare Maino, et al.	Dose reduction + image quality	Not serious	Not serious	Not serious	Not serious	Undetected	High
[47]	A Sulieman, H Adam, et al.	Dose metrics with IR package	Serious	Serious	Not serious	Not serious	Undetected	Low
[48]	Yoshifumi Noda, Tetsuro Kaga, et al.	Whole-body CT lesion detection + dose	Not serious	Not serious	Not serious	Not serious	Undetected	High

Table A4. Study-level linkage between included studies, their primary outcome, and GRADE certainty of evidence.

Ref.	Author	Outcome	GRADE Certainty
[2]	Jeong-A Yeom, Ki-Uk Kim, et al.	Emphysema quantification (ULCT vs. SDCT)	High
[4]	Karolin J Paprottka, Karina Kupfer, et al.	Dose reduction + image quality	
[21]	Weitao He, Ping Xu, and Mengchen Zhang, et al.	CT enterography IQ + dose (IBD)	High
[22]	Sarah Prod'homme, Roger Bouzerar, et al.	Stone detection on sub-mSv CT	High
[23]	Ramandeep Singh, Subba R Digumarthy, et al.	Sub-mSv chest/abd CT DLIR vs. IR	Moderate
[24]	Yuko Nakamura, Keigo Narita, et al.	U-HRCT abdomen DLIR vs. IR/MBIR	Moderate
[25]	Yanshan Chen, Zixuan Huang, et al.	Dose reduction + image quality	High
[26]	Liyong Zhuo, Shijie Xu, et al.	Dose reduction + image quality	High
[27]	Akio Tamura, Eisuke Mukaida, et al.	Dose reduction + image quality	High
[28]	Ali Chaparian, Mohamadhosein Asemanrafat, et al.	Dose reduction + image quality	High
[29]	Huiyuan Zhu, Zike Huang, et al.	Sub-mSv LDCT for subsolid nodules	High
[30]	Ruijie Zhao, Xin Sui, et al.	Dose reduction + image quality	High
[31]	Shumeng Zhu, Baoping Zhan, et al.	Abdominal LDCT with DLIR vs. routine dose IR	High
[32]	Nieun Seo, Mi-Suk Park, et al.	ULDCT IR in follow-up of abscess	High
[33]	Peijie Lyu, Zhen Li, et al.	Dose reduction + image quality	High
[34]	Tetsuro Kaga, Yoshifumi Noda, et al.	Dose reduction + image quality	High
[35]	E Hettinger, M.-L Aurumskjöld, H Sartor, et al.	Dose reduction + image quality	High
[36]	Hayato Tomita, Kenji Kuramochi, et al.	Dose reduction + image quality	High
[37]	Xu Lin, Yankun Gao, et al.	LD DECT enterography DLIR vs. ASIR-V	High
[38]	Abdul Rauf, Saqib Javed, et al.	Dose reduction + image quality	Low
[39]	Angélique Bernard, Pierre-Olivier Comby, et al.	Dose reduction + image quality	High
[40]	L E Cao, Xiang Liu, et al.	Dose reduction + image quality	High
[41]	June Park, Jaeseung Shin, et al.	Dose reduction + image quality	High
[42]	Emilio Quaia, Elena Kiyomi, et al.	ICU CT: DLIR vs. FBP/IR dose + IQ	High
[43]	Sungeun Park, Jeong Hee Yoon, et al.	Liver CT: LD DLD vs. SD MBIR	High
[44]	Dominik C Benz and Sara Ersözlü, et al.	CCTA dose + plaque metrics	High
[45]	Lingming Zeng, Xu Xu, et al.	Half-dose liver CT DLIR vs. HIR	High
[46]	Davide Ippolito, Cesare Maino, et al.	Dose reduction + image quality	High
[47]	A Sulieman, H Adam, et al.	Dose metrics with IR package	Low
[48]	Yoshifumi Noda, Tetsuro Kaga, et al.	Whole-body CT lesion detection + dose	High

References

- Smith-Bindman, R.; Wang, Y.; Chu, P.; Chung, R.; Einstein, A.J.; Balcombe, J.; Cocker, M.; Das, M.; Delman, B.N.; Flynn, M.; et al. International Variation in Radiation Dose for Computed Tomography Examinations: Prospective Cohort Study. *BMJ* **2019**, *364*, k4931. [CrossRef] [PubMed]
- Yeom, J.A.; Kim, K.U.; Hwang, M.; Lee, J.W.; Kim, K.I.; Song, Y.S.; Lee, I.S.; Jeong, Y.J. Emphysema Quantification Using Ultra-Low-Dose Chest CT: Efficacy of Deep Learning-Based Image Reconstruction. *Medicina* **2022**, *58*, 939. [CrossRef] [PubMed]
- Shin, H.J.; Chung, Y.E.; Lee, Y.H.; Choi, J.Y.; Park, M.S.; Kim, M.J.; Kim, K.W. Radiation Dose Reduction via Sinogram Affirmed Iterative Reconstruction and Automatic Tube Voltage Modulation (CARE KV) in Abdominal CT. *Korean J. Radiol.* **2013**, *14*, 886–893. [CrossRef] [PubMed]
- Paprottka, K.J.; Kupfer, K.; Riederer, I.; Zimmer, C.; Beer, M.; Noël, P.B.; Baum, T.; Kirschke, J.S.; Sollmann, N. Impact of Dose Reduction and Iterative Model Reconstruction on Multi-Detector CT Imaging of the Brain in Patients with Suspected Ischemic Stroke. *Sci. Rep.* **2021**, *11*, 22271. [CrossRef]
- Baskan, O.; Erol, C.; Ozbek, H.; Paksoy, Y. Effect of Radiation Dose Reduction on Image Quality in Adult Head CT with Noise-Suppressing Reconstruction System with a 256 Slice MDCT. *J. Appl. Clin. Med. Phys.* **2015**, *16*, 285–296. [CrossRef]
- Ulyanov, D.; Vedaldi, A.; Lempitsky, V. Deep Image Prior. In Proceedings of the 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), Salt Lake City, UT, USA, 18–23 June 2018; pp. 9446–9454. [CrossRef]
- Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [CrossRef]
- Page, M.J.; Moher, D.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. PRISMA 2020 Explanation and Elaboration: Updated Guidance and Exemplars for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n160. [CrossRef]
- Mendeley. Com/Reference-Manager. Available online: <http://www.mendeley.com> (accessed on 6 December 2025).
- Ouzzani, M.; Hammady, H.; Fedorowicz, Z.; Elmagarmid, A. Rayyan—A Web and Mobile App for Systematic Reviews. *Syst. Rev.* **2016**, *5*, 210. [CrossRef]
- SCISPACE. Available online: <http://www.scispace.com> (accessed on 5 June 2025).
- Rozema, R.; Kruitbosch, H.T.; van Minnen, B.; Dorgelo, B.; Kraeima, J.; van Ooijen, P.M.A. Structural Similarity Analysis of Midfacial Fractures—A Feasibility Study. *Quant. Imaging Med. Surg.* **2022**, *12*, 1571–1578. [CrossRef]
- Rozema, R.; Kruitbosch, H.T.; van Minnen, B.; Dorgelo, B.; Kraeima, J.; van Ooijen, P.M.A. Iterative Reconstruction and Deep Learning Algorithms for Enabling Low-Dose Computed Tomography in Midfacial Trauma. *Oral. Surg. Oral. Med. Oral. Pathol. Oral. Radiol.* **2021**, *132*, 247–254. [CrossRef]
- Feldle, P.; Grunz, J.P.; Kunz, A.S.; Pannenbecker, P.; Patzer, T.S.; Pichlmeier, S.; Sauer, S.T.; Hendel, R.; Ergün, S.; Bley, T.A.; et al. Influence of Spectral Shaping and Tube Voltage Modulation in Ultralow-Dose Computed Tomography of the Abdomen. *BMC Med. Imaging* **2024**, *24*, 49. [CrossRef] [PubMed]
- Boubaker, F.; Puel, U.; Eliezer, M.; Hossu, G.; Assabah, B.; Haioun, K.; Blum, A.; Gondim-Teixeira, P.A.; Parietti-Winkler, C.; Gillet, R. Radiation Dose Reduction and Image Quality Improvement with Ultra-High Resolution Temporal Bone CT Using Deep Learning-Based Reconstruction: An Anatomical Study. *Diagn. Interv. Imaging* **2024**, *105*, 371–378. [CrossRef] [PubMed]
- Alsaihati, N.; Solomon, J.; McCrum, E.; Samei, E. Development, Validation, and Application of a Generic Image-Based Noise Addition Method for Simulating Reduced Dose Computed Tomography Images. *Med. Phys.* **2025**, *52*, 171–187. [CrossRef] [PubMed]
- Tsuboi, K.; Kanbe, T.; Matsushima, H.; Ohtani, Y.; Tanikawa, K.; Kaneko, M. Three-Dimensional CT Imaging in Extensor Tendons Using Deep Learning Reconstruction: Optimal Reconstruction Parameters and the Influence of Dose. *Phys. Eng. Sci. Med.* **2023**, *46*, 1659–1666. [CrossRef]
- Legeas, O.; Bourhis, D.; Garetier, M.; Pennaneach, A.; Meriot, P.; Ognard, J.; Ben Salem, D. Quantitative and Qualitative Optimisation of Dosimetry in Computed Tomography Explorations of the Temporal Bone Using Two Iterative Reconstruction Algorithms. *Neurosci. Inform.* **2021**, *1*, 100017. [CrossRef]
- Emoto, T.; Nagayama, Y.; Takada, S.; Sakabe, D.; Shigematsu, S.; Goto, M.; Nakato, K.; Yoshida, R.; Harai, R.; Kidoh, M.; et al. Super-Resolution Deep-Learning Reconstruction for Cardiac CT: Impact of Radiation Dose and Focal Spot Size on Task-Based Image Quality. *Phys. Eng. Sci. Med.* **2024**, *47*, 1001–1014. [CrossRef]
- Kim, D.; Lee, H.; Shin, D.S.; Lee, Y. Feasibility Study of Hybrid Scanning Technique Parameters on Dose Reduction and CT-Image Quality. *Radiat. Phys. Chem.* **2025**, *226*, 112179. [CrossRef]
- He, W.; Xu, P.; Zhang, M.; Xu, R.; Shen, X.; Mao, R.; Li, X.H.; Sun, C.H.; Zhang, R.N.; Lin, S. Deep Learning-Based Reconstruction Improves the Image Quality of Low-Dose CT Enterography in Patients with Inflammatory Bowel Disease. *Abdom. Radiol.* **2024**, *50*, 3907–3916. [CrossRef]

22. Prod'homme, S.; Bouzerar, R.; Forzini, T.; Delabie, A.; Renard, C. Detection of Urinary Tract Stones on Submillisievert Abdominopelvic CT Imaging with Deep-Learning Image Reconstruction Algorithm (DLIR). *Abdom. Radiol.* **2024**, *49*, 1987–1995. [\[CrossRef\]](#)
23. Singh, R.; Digumarthy, S.R.; Muse, V.V.; Kambadakone, A.R.; Blake, M.A.; Tabari, A.; Hoi, Y.; Akino, N.; Angel, E.; Madan, R.; et al. Image Quality and Lesion Detection on Deep Learning Reconstruction and Iterative Reconstruction of Submillisievert Chest and Abdominal CT. *Am. J. Roentgenol.* **2020**, *214*, 566–573. [\[CrossRef\]](#)
24. Nakamura, Y.; Narita, K.; Higaki, T.; Akagi, M.; Honda, Y.; Awai, K. Diagnostic Value of Deep Learning Reconstruction for Radiation Dose Reduction at Abdominal Ultra-High-Resolution CT. *Eur. Radiol.* **2021**, *31*, 4700–4709. [\[CrossRef\]](#) [\[PubMed\]](#)
25. Chen, Y.; Huang, Z.; Feng, L.; Zou, W.; Kong, D.; Zhu, D.; Dai, G.; Zhao, W.; Zhang, Y.; Luo, M. Deep Learning-Based Reconstruction Improves the Image Quality of Low-Dose CT Colonography. *Acad. Radiol.* **2024**, *31*, 3191–3199. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Zhuo, L.; Xu, S.; Zhang, G.; Xing, L.; Zhang, Y.; Ma, Z.; Wang, J.; Yin, X. Ultralow Dose Coronary Calcium Scoring CT at Reduced Tube Voltage and Current by Using Deep Learning Image Reconstruction. *Eur. J. Radiol.* **2024**, *181*, 111742. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Tamura, A.; Mukaida, E.; Ota, Y.; Nakamura, I.; Arakita, K.; Yoshioka, K. Deep Learning Reconstruction Allows Low-Dose Imaging While Maintaining Image Quality: Comparison of Deep Learning Reconstruction and Hybrid Iterative Reconstruction in Contrast-Enhanced Abdominal CT. *Quant. Imaging Med. Surg.* **2022**, *12*, 2977–2984. [\[CrossRef\]](#)
28. Asemanrafat, M.; Chaparian, A.; Lotfi, M.; Rasekhi, A. Impact of Iterative Reconstruction Algorithms on Image Quality and Radiation Dose in Computed Tomography Scan of Patients with Malignant Pancreatic Lesions. *J. Med. Signals Sens.* **2022**, *12*, 69–75. [\[CrossRef\]](#)
29. Zhu, H.; Huang, Z.; Chen, Q.; Ma, W.; Yu, J.; Wang, S.; Tao, G.; Xing, J.; Jiang, H.; Sun, X.; et al. Feasibility of Sub-MilliSievert Low-Dose Computed Tomography with Deep Learning Image Reconstruction in Evaluating Pulmonary Subsolid Nodules: A Prospective Intra-Individual Comparison Study. *Acad. Radiol.* **2024**, *32*, 2309–2319. [\[CrossRef\]](#)
30. Zhao, R.; Sui, X.; Qin, R.; Du, H.; Song, L.; Tian, D.; Wang, J.; Lu, X.; Wang, Y.; Song, W.; et al. Can Deep Learning Improve Image Quality of Low-Dose CT: A Prospective Study in Interstitial Lung Disease. *Eur. Radiol.* **2022**, *32*, 8140–8151. [\[CrossRef\]](#)
31. Zhu, S.; Zhang, B.; Tian, Q.; Li, A.; Liu, Z.; Hou, W.; Zhao, W.; Huang, X.; Xiao, Y.; Wang, Y.; et al. Reduced-Dose Deep Learning Iterative Reconstruction for Abdominal Computed Tomography with Low Tube Voltage and Tube Current. *BMC Med. Inform. Decis. Mak.* **2024**, *24*, 389. [\[CrossRef\]](#)
32. Seo, N.; Park, M.S.; Choi, J.Y.; Yeom, J.S.; Kim, M.J.; Chung, Y.E.; Ku, N.S. A Prospective Study on the Use of Ultralow-Dose Computed Tomography with Iterative Reconstruction for the Follow-up of Patients Liver and Renal Abscess. *PLoS ONE* **2021**, *16*, e0246532. [\[CrossRef\]](#)
33. Lyu, P.; Li, Z.; Chen, Y.; Wang, H.; Liu, N.; Liu, J.; Zhan, P.; Liu, X.; Shang, B.; Wang, L.; et al. Deep Learning Reconstruction CT for Liver Metastases: Low-Dose Dual-Energy vs Standard-Dose Single-Energy. *Eur. Radiol.* **2024**, *34*, 28–38. [\[CrossRef\]](#)
34. Kaga, T.; Noda, Y.; Mori, T.; Kawai, N.; Miyoshi, T.; Hyodo, F.; Kato, H.; Matsuo, M. Unenhanced Abdominal Low-Dose CT Reconstructed with Deep Learning-Based Image Reconstruction: Image Quality and Anatomical Structure Depiction. *Jpn. J. Radiol.* **2022**, *40*, 703–711. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Hettinger, E.; Aurumskjöld, M.L.; Sartor, H.; Holmquist, F.; Svärd, D.; Timberg, P. Evaluation of Model-Based Iterative Reconstruction in Abdominal Computed Tomography Imaging at Two Different Dose Levels. *Radiat. Prot. Dosim.* **2021**, *195*, 205–211. [\[CrossRef\]](#) [\[PubMed\]](#)
36. Tomita, H.; Kuramochi, K.; Fujikawa, A.; Ikeda, H.; Komita, M.; Kurihara, Y.; Kobayashi, Y.; Mimura, H. Effects of Model-Based Iterative Reconstruction in Low-Dose Paranasal Computed Tomography: A Comparison with Filtered Back Projection and Hybrid Iterative Reconstruction. *Acta Med. Okayama* **2022**, *76*, 511–517. [\[CrossRef\]](#) [\[PubMed\]](#)
37. Lin, X.; Gao, Y.; Zhu, C.; Song, J.; Liu, L.; Li, J.; Wu, X. Improved Overall Image Quality in Low-Dose Dual-Energy Computed Tomography Enterography Using Deep-Learning Image Reconstruction. *Abdom. Radiol.* **2024**, *49*, 2979–2987. [\[CrossRef\]](#)
38. Rauf, A.; Javed, S.; Chandrasekar, B.; Miah, S.; Lyttle, M.; Siraj, M.; Mukherjee, R.; McLeavy, C.M.; Alaaraj, H.; Hawkins, R. The Use of Artificial Intelligence and Deep Learning Reconstruction in Urological Computed Tomography: Dose Reduction at Ghost Level. *Urol. Ann.* **2023**, *15*, 417–423. [\[CrossRef\]](#)
39. Bernard, A.; Comby, P.O.; Lemogne, B.; Haioun, K.; Ricolfi, F.; Chevallier, O.; Loffroy, R. Deep Learning Reconstruction versus Iterative Reconstruction for Cardiac CT Angiography in a Stroke Imaging Protocol: Reduced Radiation Dose and Improved Image Quality. *Quant. Imaging Med. Surg.* **2021**, *11*, 392–401. [\[CrossRef\]](#)
40. Cao, L.; Liu, X.; Li, J.; Qu, T.; Chen, L.; Cheng, Y.; Hu, J.; Sun, J.; Guo, J. A Study of Using a Deep Learning Image Reconstruction to Improve the Image Quality of Extremely Low-Dose Contrast-Enhanced Abdominal CT for Patients with Hepatic Lesions. *Br. J. Radiol.* **2021**, *94*, 20201086. [\[CrossRef\]](#)
41. Park, J.; Shin, J.; Min, I.K.; Bae, H.; Kim, Y.-E.; Chung, Y.E. Image Quality and Lesion Detectability of Lower-Dose Abdominopelvic CT Obtained Using Deep Learning Image Reconstruction. *Korean J. Radiol.* **2022**, *23*, 402–412. [\[CrossRef\]](#)

42. Quaia, E.; Kiyomi Lanza de Cristoforis, E.; Agostini, E.; Zanon, C. Computed Tomography Effective Dose and Image Quality in Deep Learning Image Reconstruction in Intensive Care Patients Compared to Iterative Algorithms. *Tomography* **2024**, *10*, 912–921. [[CrossRef](#)]
43. Park, S.; Yoon, J.H.; Joo, I.; Yu, M.H.; Kim, J.H.; Park, J.; Kim, S.W.; Han, S.; Ahn, C.; Kim, J.H.; et al. Image Quality in Liver CT: Low-Dose Deep Learning vs Standard-Dose Model-Based Iterative Reconstructions. *Eur. Radiol.* **2022**, *32*, 2865–2874. [[CrossRef](#)]
44. Benz, D.C.; Ersöz, S.; Mojon, F.L.A.; Messerli, M.; Mitulla, A.K.; Ciancone, D.; Kenkel, D.; Schaab, J.A.; Gebhard, C.; Pazhenkottil, A.P.; et al. Radiation Dose Reduction with Deep-Learning Image Reconstruction for Coronary Computed Tomography Angiography. *Eur. Radiol.* **2022**, *32*, 2620–2628. [[CrossRef](#)] [[PubMed](#)]
45. Zeng, L.; Xu, X.; Zeng, W.; Peng, W.; Zhang, J.; Sixian, H.; Liu, K.; Xia, C.; Li, Z. Deep Learning Trained Algorithm Maintains the Quality of Half-Dose Contrast-Enhanced Liver Computed Tomography Images: Comparison with Hybrid Iterative Reconstruction: Study for the Application of Deep Learning Noise Reduction Technology in Low Dose. *Eur. J. Radiol.* **2021**, *135*, 109487. [[CrossRef](#)] [[PubMed](#)]
46. Ippolito, D.; Maino, C.; Pecorelli, A.; Salemi, I.; Gandola, D.; Riva, L.; Franzesi, C.T.; Sironi, S. Application of Low-Dose CT Combined with Model-Based Iterative Reconstruction Algorithm in Oncologic Patients during Follow-up: Dose Reduction and Image Quality. *Br. J. Radiol.* **2021**, *94*, 20201223. [[CrossRef](#)] [[PubMed](#)]
47. Sulieman, A.; Adam, H.; Elnour, A.; Tamam, N.; Alhaili, A.; Alkhorayef, M.; Alghamdi, S.; Khandaker, M.U.; Bradley, D.A. Patient Radiation Dose Reduction Using a Commercial Iterative Reconstruction Technique Package. *Radiat. Phys. Chem.* **2021**, *178*, 108996. [[CrossRef](#)]
48. Noda, Y.; Kaga, T.; Kawai, N.; Miyoshi, T.; Kawada, H.; Hyodo, F.; Kambadakone, A.; Matsuo, M. Low-Dose Whole-Body CT Using Deep Learning Image Reconstruction: Image Quality and Lesion Detection. *Br. J. Radiol.* **2021**, *94*, 20201329. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.