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REVIEW

Charting the path forward: CT image quality assessment - an in-depth review

Siyi Xun[1] · Qiaoyu Li[2] · Xiaohong Liu[3] · Pu Huang[4] · Guangtao Zhai[3] · Yue Sun[1] · Peter H.N. de With[5] · Mingxiang Wu[6] · Tao Tan[1]

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Abstract

Computed Tomography (CT) is a frequently utilized imaging technology that is employed in the clinical diagnosis of many disorders. However, clinical diagnosis, data storage, and management are faced with significant challenges posed by a huge volume of non-homogeneous CT data in terms of imaging quality. As a result, the quality assessment of CT images is a crucial problem that demands consideration. The history, advancements in research, and current developments in CT image quality assessment (IQA) have been examined in this paper for the first time. In this review, we collected and researched more than 500 publications related to CT-IQA published before 2024, providing visualization analysis of keywords and co-citations in the knowledge graph of these papers. This paper also discusses the research branches derived from the field of CT-IQA as well as the prospects and obstacles to its development. At present, Artificial intelligence (AI)-based CT-IQA is becoming a notable trend. It helps improve the accuracy of CT scanning equipment and the performance of CT system reconstruction algorithms, and provides a new idea for CT image processing algorithms. In the future, the rigorously validated and fully regulated AI-based CT-IQA model will become a powerful tool for medical image quality control.

Keywords Computed Tomography · Image Quality Assessment · Artificial Intelligence · *CiteSpace*

1 Introduction

Computed Tomography (CT) is one of the imaging modalities that is most frequently utilized in clinical practice (Rubin 2014). CT images are crucial for the clinical diagnosis of disorders of the neurological system, cardiovascular system, chest and abdominal organs, bones, and joints because of its rapid imaging speed and high contrast between bones and soft tissues. As a result, CT imaging is a crucial tool for routine physical examinations and disease screening.

Consequently, a significant volume of CT images is produced every day. Massive non-homogeneous CT images, however, make clinical diagnosis as well as the management and storage of medical data more challenging (Dash et al. 2019). It is easy for low-quality images to impede clinical diagnosis, leading to incorrect diagnoses. It is also very difficult to identify images of minimal acceptable quality that are sufficient for clinical use or research settings. Simultaneously, variations in quality has a significant impact on the acceptance of CT images across various medical facilities. Poor-quality images may lead to additional radiation exposure for patients, increase the risk of recurrent cancer, and waste societal resources. Therefore, CT image quality assessment (IQA) is of great significance.

CT-IQA refers to the process of determining the extent of image distortion by examining and analyzing the fundamental characteristics of CT images (contrast, clarity, etc.) and other factors affecting their quality (patient position, artifacts, etc.). It is a crucial area of research in computer vision, medical image processing, and related disciplines. The development of CT-IQA can be divided into three distinct phases: (1) Subjective Assessment Dominance Period (1990-2000): Early stage evaluations relied primarily on radiologists' expertise, with outcomes constrained by individual variability and time-intensive workflows; (2) Emergence of Objective Algorithms (2000-2015): Advances in computing technology and digital image processing facilitated standardized assessments through pixel statistics, information theory, structural feature-based algorithms, and quantitative metrics for imaging systems, although these methods suffered

Siyi Xun and Qiaoyu Li contributed equally to this work.

Extended author information available on the last page of the article

from high computational complexity and limited correlation with human visual perception; (3) Artificial intelligence (AI)-Driven Innovation Era (2016-present): Deep learning models have demonstrated potential in artifact correction and low-dose imaging optimization, while confronting challenges in generalizability, model explainability, and ethical debates regarding clinical deployment.

To date, despite the exponential growth of CT-IQA research, no comprehensive review has systematically synthesized fragmented technical advancements (e.g., artifacts, imaging system and processing algorithm optimization, AI-driven automated assessment) with broader clinical and ethical challenges (e.g., radiation risks, model explainability, accountability). This study presents the inaugural systematic review of the CT-IQA domain, integrating bibliometric analysis (conducted via *CiteSpace*) with critical technological milestones to comprehensively map its historical evolution, current research landscape, and future trajectories. The work also identifies emerging opportunities and unresolved challenges for advancing CT-IQA methodologies in clinical and technical contexts. To our knowledge, this represents the first systematic review dedicated to CT-IQA, filling a critical gap in three decades of interdisciplinary research. By establishing this review, we aim to provide scientific evidence and theoretical foundations for developing standardized assessment frameworks, advancing explainable AI-based evaluation models, standardizing clinical practices, and promoting precision medicine. Figure 1 illustrates the process of CT image collection and quality assessment. By employing the visualization graph analysis of literature linked to CT-IQA, we describe the historical timeline of CT-IQA using key turning points in the field's development as anchor points. Additionally, we identify emerging branches in the field through co-occurrence and co-citation analysis among studies. Finally, we examine current limitations and future directions for the CT-IQA domain.

The remainder of the paper is structured as follows. Section 2 introduces developments in the field of CT imaging and IQA. In Section 3, we use *CiteSpace* to analyze the retrieved papers and summarize them based on the development process, key branches, and future trends. Section 4 discusses the aforementioned review. Section 5 presents our conclusions.

2 Background

2.1 CT imaging's development

CT imaging technology has been widely employed in many different fields since its introduction in the 1970s. Researchers have improved the performance of CT scanners from various perspectives in the past few decades (Kalra et al. 2004). Table 1 displays the technical characteristics and development process of the five-generation CT scanners. From the early low-resolution, lengthy scanning times to the contemporary high-speed, high-resolution, and low-radiation-dose equipment, CT imaging is constantly evolving.

Different CT imaging machines have varying resolutions, noise levels, contrast, radiation doses, and scanning speeds due to the quantity and arrangement of detectors, the focus, and the energy of X-ray sources. As a result, the quality of

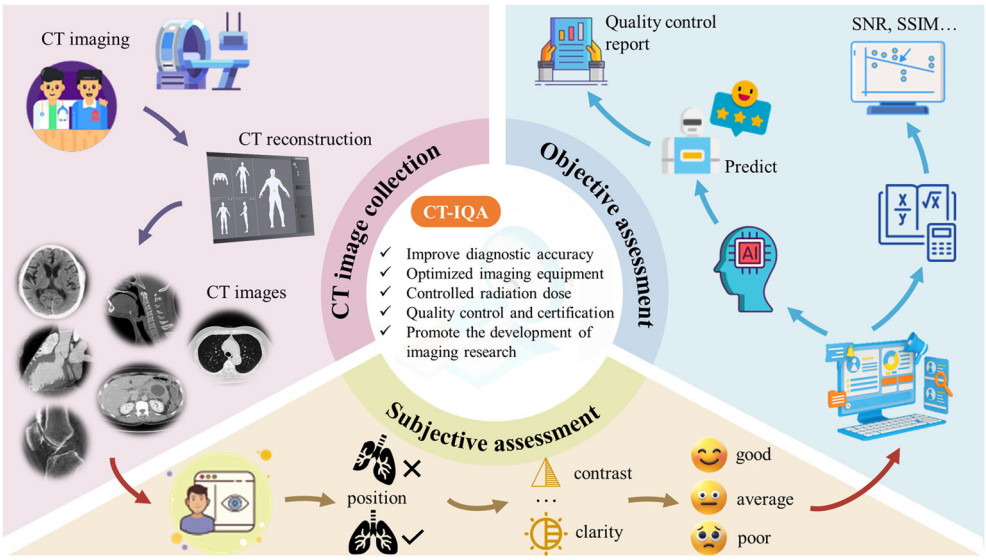


Fig. 1 Schematic representation of the CT image acquisition and quality assessment workflow development

Table 1 Five-generation CT scanners' technical characteristics and development process

Development	Technical characteristics
1970s-1980s: First-generation CT scanners	The human body was scanned by rotating X-ray sources and detectors. Afterwards, two-dimensional slices were combined into three-dimensional images using computer methods that have a low resolution and a lengthy scan duration.
1980s-1990s: Second-generation CT scanners	Improved resolution and faster rotation speed. Spiral CT technology was introduced to accelerate full-body scans.
1990s-2000s: Third-generation CT scanners	Multi-row detector technology was introduced, allowing simultaneous acquisition of multiple slices. This significantly reduced scanning time and enhanced spatial resolution.
2000s-2010s: Fourth-generation CT scanners	Increased detector rows further improved resolution and scanning speed. Advanced image reconstruction algorithms were developed, enabling precise visualization of internal anatomical structures.
Since 2010s: Fifth-generation CT scanners	More sophisticated radiation dose control technology as well as higher resolution were implemented. Furthermore, portable CT scanners have been developed, enabling imaging in non-clinical environments.

the CT images generated by the scan differs. The quality of CT images has significantly increased with ongoing technological advancements, making these systems essential tools in contemporary medicine and playing a significant role in clinical diagnosis.

2.2 Image quality assessment

IQA is one of the key technologies in digital image processing field. By analyzing and exploring the features of images, it can evaluate the degree of image distortion (i.e., image quality) (Okarma 2019). Depending on the subject of IQA judgment process, it can be divided into subjective assessment and objective assessment.

2.2.1 Subjective assessment

Subjective assessment is based on visual perception and human perceptual judgment, where observers evaluate image quality through visual inspection. The general workflow of subjective assessment experiment includes: 1) Preparing the data set; 2) Inviting observers to score images; 3) Deriving final quality scores through statistical aggregation of observer ratings. The assessment results are generally represented by the Mean Opinion Score (MOS) or Differential Mean Opinion Score (DMOS) (Streijl et al. 2016).

The International Telecommunication Union has established standardized protocols for subjective assessment methods. Double Stimulus Impairment Scale (DSIS), Double Stimulus Continuous Quality Scale (DSCQS), and Single Stimulus Continuous Quality Evaluation (SSCQE) are the three most widely used methods (Mantiuk et al. 2012). Table 2 summarizes the key characteristics of these methods.

2.2.2 Objective assessment

Although subjective assessment accurately captures the image quality, it is costly and often subject to subjective factors. Therefore, numerous objective assessment methods for assessing image quality have been developed. IQA can be categorized into Full Reference IQA (FR-IQA), Reduced Reference IQA (RR-IQA), and No Reference IQA (NR-IQA) depending on whether a reference image is used as the assessment standard (Joy and Sarma 2014).

Traditional objective assessment developed algorithms based on mathematical theory to explore the relationships between images of different quality. Researchers developed different assessment methods from perspectives such as pixel statistics, information theory, and structural information. Table 3 displays typical metrics of objective assessment.

Table 2 Subjective assessment methodologies for medical image quality: DSIS, DSCQS, and SSCQE

Method	Meaning
DSIS	Observers compare distorted and reference images, rating impairment severity on a 5-level scale.
DSCQS	Observers blindly rate distorted and undistorted images on a continuous scale. The DMOS quantifies quality degradation, with lower values indicating minimal perceptual differences.
SSCQE	Observers provide real-time ratings for test images over a continuous period. Final scores combine rating magnitude and temporal dynamics.

Table 3 Common objective assessment methods and metric descriptions

Metric	Description
HaarPSI (Reisenhofer et al. 2018)	The Haar wavelet decomposition coefficient is used to measure local similarity between the ideal image and the image that needs to be assessed.
LPIPS (Zhang et al. 2018)	Deep features from neural networks are used as perceptual metrics to measure the perceptual similarity between two images.
MS-SSIM (Wang et al. 2003)	The assessment score is derived by combining structural similarity results at multiple scales (resolutions).
MSE (Das et al. 2004)	The mean squared error between true and predicted pixel values quantifies the difference between the observed and reference images.
SSIM (Hore and Ziou 2010)	The degree of image distortion is determined by an in-depth assessment of the sample image's brightness, contrast, and structure.
PSNR (Hore and Ziou 2010)	Measuring the ratio between the maximum possible signal power and the distorting noise power in reconstructed signals or images.
VIF (Sheikh and Bovik 2005)	Based on the idea of natural scene statistics and image signal extraction by human visual system, information entropy and mutual information are utilized to assess image quality.
VSI (Zhang et al. 2014)	The gradient modulus and chrominance features are utilized to build additional complementary features, and the image saliency feature map is used to calculate the image distortion.

With the advancement of AI, researchers have proposed and refined numerous AI-based techniques and metrics for IQA in recent years. AI-based image quality assessment mainly simulates the human visual system through AI models to achieve automatic and accurate results. The AI-based image quality assessment process usually includes data preparation, model training, evaluation, and deployment.

Kang et al. (2014) achieved accurate NR-IQA by using a 5-layer Convolutional Neural Network (CNN). To improve performance, Bosse et al. (2017) employed end-to-end networks by sharing the same architecture for both FR-IQA and NR-IQA during training. To determine the final assessment result, Bianco et al. (2018) separated the input images into sub-regions and summed the predicted scores of each region. Deep learning-based NR-IQA methods promote the development of IQA and even outperform FR-IQA results as deep learning technology advances.

2.2.3 Medical image quality assessment

Medical imaging is an important branch of the digital image domain. Numerous studies have extended natural image IQA techniques to medical IQA (Li et al. 2018; Chow and Rajagopal 2017; Oszust et al. 2020). These techniques, however, have limitations due to the unique nature of medical imaging. Lei et al. conducted medical IQA across various modalities using deep learning and machine learning techniques (Lei et al. 2022; Liu et al. 2020). Mason et al. (2019) examined 10 FR-IQA methods, while Stepien and Oszust (2022) analyzed NR-IQA methods for Magnetic Resonance Imaging (MRI) to investigate the effect of IQA methods on MRI images. Furthermore, Kastryulin et al. (2023) assessed 35 distinct IQA techniques in MRI, including both full-reference and no-reference methods, based on criteria such as noise, contrast, and artifact presence.

However, there is no flawless image that can be regarded as the "gold standard" in medical IQA. Therefore, many researchers believe that the most effective IQA method for medical imaging is NR-IQA (Chow and Paramesran 2016). Currently, assessing quality solely based on the information and characteristics of the medical image itself is still a major challenge in medical IQA.

2.3 IQA metrics

2.3.1 CT imaging system evaluation

Modulation Transfer Function (MTF) and Noise Power Spectrum (NPS) are two important concepts in evaluating CT imaging systems (Friedman et al. 2013). They describe the detail retention capability and noise distribution characteristics of the system, respectively, both of which are key indicators for evaluating and optimizing CT imaging.

MTF reflects the ability of an imaging system to retain information at different resolutions. The system can deliver better detail (high MTF) or loss of detail (low MTF), depending on its performance. The MTF measures the CT system's ability to capture detail, which directly affects the accuracy of the clinician's lesion assessment (e.g., detecting early tumor margins).

NPS reflects the type and spatial frequency distribution of image noise. In CT images, low-frequency noise (large mottled particle noise) causes the overall image to be blurred, which is more likely to interfere with the observation of large structures (such as organ contours). High-frequency noise (uniform fine particle noise) leads to detail loss and is more likely to affect small structures (e.g., blood vessel branches).

NPS can help engineers optimize CT equipment, for example, by reducing low-frequency noise to make liver tumors easier to identify, and controlling high-frequency noise to improve the detection rate of small lung nodules.

If the MTF of the imaging system is high, it can transmit more details and the impact of noise is relatively small; on the contrary, if the MTF is low, noise interference becomes more pronounced. Therefore, evaluating an imaging system requires joint consideration of MTF and NPS performance.

2.3.2 Algorithm evaluation

The basic goal of objective assessment is to design computational models that can accurately and automatically evaluate image quality. The ultimate goal is to use computers to replace the human visual system for viewing and recognizing images. Therefore, the performance of objective assessment methods is usually measured by comparing the difference and correlation between model results and MOS.

Three primary metrics are used to evaluate the performance of objective assessment algorithms: Spearman rank order correlation coefficient (SRCC), Pearson linear correlation coefficient (PLCC), and Root mean square error (RMSE). SRCC assesses the monotonicity of IQA algorithm predictions by measuring the linear correlation between the rank-ordered data of two target arrays. PLCC quantifies the precision of the predictions made by the IQA algorithm and characterizes the linear correlation between two sets of data. RMSE quantifies the absolute error between the two sets of data to assess the expected consistency of their results. The calculation formulas are as follows:

$$SRCC = 1 - \frac{6\sum_{i=1}^{N} d_i^2}{N(N^2-1)} \tag{1}$$

$$PLCC = \frac{\sum_{i=1}^{N}(s_i - \bar{s})(p_i - \bar{p})}{\sqrt{\sum_{i=1}^{N}(s_i - \bar{s})^2 \sum_{i=1}^{N}(p_i - \bar{p})^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(s_i - p_i)^2} \tag{3}$$

where s_i and p_i are the MOS and predicted quality scores respectively, $\bar{s}$ and $\bar{p}$ are the average values of the MOS and predicted quality scores respectively, N represents the number of samples, and d_i^2 represents the squared difference between the MOS and predicted quality score of the i-th image.

These metrics assess the performance of objective assessment methods from various perspectives. Likewise, they are applied to evaluate AI-IQA models. In real-world applications, combining multiple metrics for joint analysis is essential to achieve a comprehensive model assessment.

3 In-depth domain analysis

The primary source of information for our visual analysis of the "CT image quality assessment" topic was the *Scopus* database search results. We focused on essential terms such as "CT", "medical image", and "Image Quality Assessment (IQA)" in the retrieval process. Simultaneously, to improve the quality and applicability of the visual analysis graph, we removed unrepresentative paper categories and disregarded publications unrelated to the aforementioned keywords. This methodology resulted in the creation of an extensive dataset that contained 554 research articles from 1994 to 2024.

Given the limitation of *CiteSpace* (Chen 2004, 2006; Chen et al. 2010; Chen 2012) in integrating results from diverse databases, our review process incorporated significant findings from additional repositories, namely *Google Scholar*, *IEEE Xplore*, *PubMed*, *Semantic Scholar*, and *Springer*, to ensure a comprehensive overview of pertinent fields. Furthermore, we conducted a meticulous comparison between the references in the selected papers from the aforementioned databases and the co-occurrence atlas produced by *CiteSpace*. This was undertaken to manually validate the scientific accuracy and comprehensiveness of the atlas.

This study employed the bibliometric analysis tool *CiteSpace 6.2.R6 Advanced*, utilizing its multidimensional visualization and quantitative analysis capabilities alongside insights from our investigative process, to systematically examine the origin and development of the CT-IQA field. The analysis aimed to identify key trends in its evolution, clarify the domain's knowledge structure, and determine the presence of any paradigm shifts. To accomplish these objectives, we used keywords and citation bibliographies as nodal points for the analysis. To exhibit more simply and intuitively, we merged keywords with the same meaning, eliminated the display of irrelevant words, and merged the same literature with different citation formats during the analysis process. A supplementary glossary of key *CiteSpace* terms is included in the appendix.

3.1 CT-IQA development

In order to explore the development of CT-IQA in the last 30 years, we built a keyword co-occurrence network[1] and

[1] The Keyword Co-occurrence Network is a network based on the frequency of co-occurrence of keywords in literature. If two or

drew a map of co-occurrence keywords for the published information of the dataset (refer to Fig. 2). This graphical representation helped to analyze the growing research focus in the CT-IQA field from a longitudinal perspective. Based on Fig. 2, we summarized the time zone evolution of the CT-IQA research (Fig. 3). We then performed burst detection on the keywords, the sensitivity threshold was 1.0, and the minimum burst duration was one year. This process identifies 24 keywords (designated as 'burst keywords') that exhibit significant fluctuations, as shown in Fig. 4. These burst keywords are represented as red dots in Fig. 2, where keywords such as 'methodology' and 'imaging' were manually identified as data noise due to terminology generalization, and their nodes were hidden in the graph. According to the representative key development nodes shown in the figure, we analyzed and summarized the development of CT-IQA. In the analysis process, we focused on Frequency (Freq), Betweenness Centrality (BC), and Burst Strength (BS).

3.1.1 The dawn of CT-IQA

CT imaging was first introduced in 1972 and progressively implemented. People's awareness of CT image quality grew as a result of the ongoing advancements in CT imaging technology and equipment. In 1994, Soares et al. (1993) published the first study assessing the quality of X-ray-based computed tomography images. They also examined the effects of various attenuation correction techniques on the noise characteristics of reconstructed single photon emission computed tomography (SPECT) images. Later, Suleiman et al. (1995) used the phantom for the first time to investigate how radiation exposure affects the quality of CT and X-ray images at various locations of the United States. Radiation safety and quality control in Asia and East Asia are examined by Oresegun et al. (1999). Since then, scientists began to assess, investigate, and improve the quality of CT images from various angles and domains, including imaging technology and image processing methods.

3.1.2 Artifacts in CT-IQA

In 2001, the first burst word "artifacts" began to appear in the field of CT-IQA (Fig. 4. Line 7, Freq=43, BC=0.06, BS=4.84, 2009-2014). The high betweenness centrality of artifact research connected the problem of algorithm optimization and clinical application. Artifacts are abnormal changes in density that appear in an image. They are one of the important factors affecting the quality of CT images. In the 2000s, the popularity of fourth-generation multi-slice spiral CT scanners and the emergence of energy spectrum CT led to physical artifacts such as X-ray hardening. In early artifact research, researchers mostly focused on verifying the relevance of artifacts to clinical use. Dey et al. (2008) studied the effects of artifacts on Dual-Source CT (DSCT) image quality and found that artifacts do not significantly affect final clinical use if properly identified. However, low-quality images with artifacts could no longer meet the growing demand for high-quality CT images from clinicians and researchers. With the popularity of Iterative Reconstruction (IR) algorithms, algorithmic artifacts such as IR texture distortion began to appear. Therefore, researchers began to explore the causes of CT artifacts and their reduction techniques (Boas et al. 2012), leading to a surge in related studies (2009-2014). The "negative indicator" role of artifacts also promoted the advancement of CT-IQA. How to fine-tune parameters and algorithms by quantifying artifacts to produce high-quality CT images became a key research focus (Nikolaev et al. 2017). After 2014, with the emergence of deep learning and its application in artifact correction (Gjesteby et al. 2017), CT-IQA officially entered the era of "predictive evaluation", while its research paradigm continued to be shaped and challenged by new artifacts. Meanwhile, the quantitative assessment of the influence of artifacts on the quality of CT images and the application of the Metal Artifact Reduction (MAR) algorithm are also constantly being explored (Lustermans et al. 2024; Cordeiro and Laureano 2025). Currently, quantifying and analyzing novel artifacts introduced by emerging technologies (e.g., AI reconstruction), such as CT image distortion caused by Generative Adversarial Networks (GANs), should become a new research priority.

3.1.3 IQA revolution in CT imaging systems

Then came "iterative reconstruction" (Fig. 4. Line 11, Freq=60, BC=0.03, BS=3.6, 2013-2014) and "computed tomography scanner" (Fig. 4. Line 2, Freq=64, BC=0.05, BS=15.27, 2005-2017) exhibit the highest burst strength and the longest burst period. These two burst keywords represent the core components of the CT imaging system, building its technical framework through algorithmic and hardware perspectives. The scanner acts as the "producer" of CT data, while the reconstruction algorithm serves as the "translator", collaboratively defining the performance boundaries of CT systems (e.g., resolution, noise).

The long-term explosion of CT scanners from 2005 to 2017, and continuous hardware iterations necessitated IQA research to address multi-generation device differences. As a result, researchers investigated how various CT scanners affected CT image quality. For early traditional CT scanners, Flohr et al. (2005) assessed Z-axis flying focus technology

more keywords appear simultaneously in the same literature (i.e. "co-occurrence"), they are considered to be related semantically or thematically. This network is used to quickly locate the core topics, technical hotspots and evolutionary trends in the field.

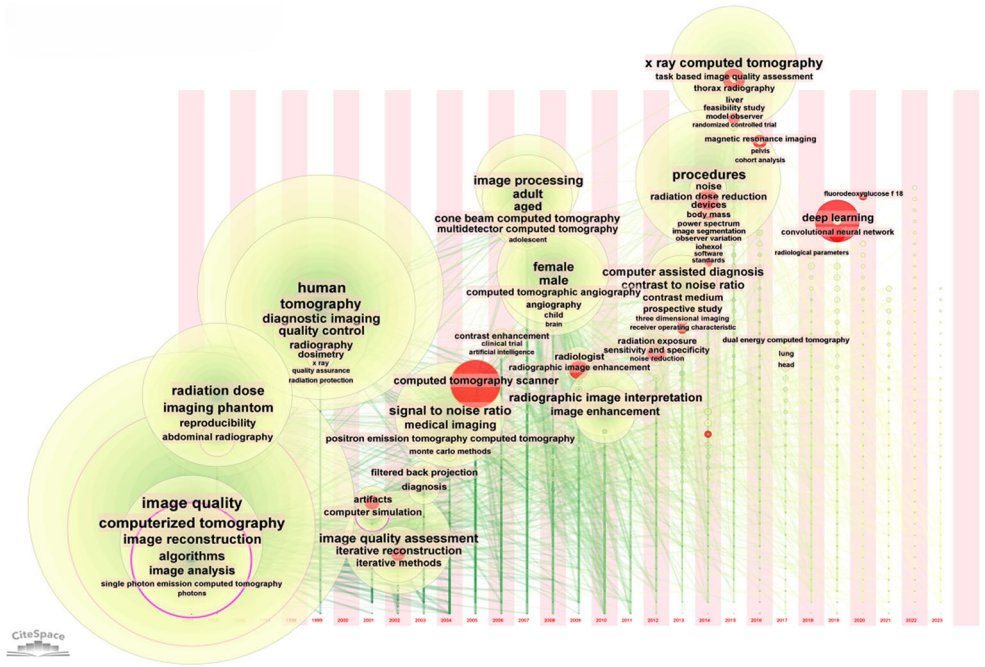


Fig. 2 Map of co-occurrence keywords in the CT-IQA research from 1994 to 2023. The horizontal axis of the graph map indicates the years, is segmented into annual intervals, and depicted as alternating pink and white color blocks. Nodes in this diagram represent keywords, symbolized by circles, with the size of each circle corresponding to the keyword's frequency of occurrence. Keywords are centrally displayed within each circle in black font on a pink background. Additionally, a purple ring encircles keywords demonstrating high centrality, and a red dot signifies keywords with notable bursts. The presence of connections between nodes is derived from the co-occurrence relationship among keywords. Specifically, when two keywords simultaneously appear within the publication information of an article, a connecting line is formed. The gradation of the line's color (from darker to lighter shades) illustrates the evolution of the co-occurrence relationship over time (from the earlier part to the later part)

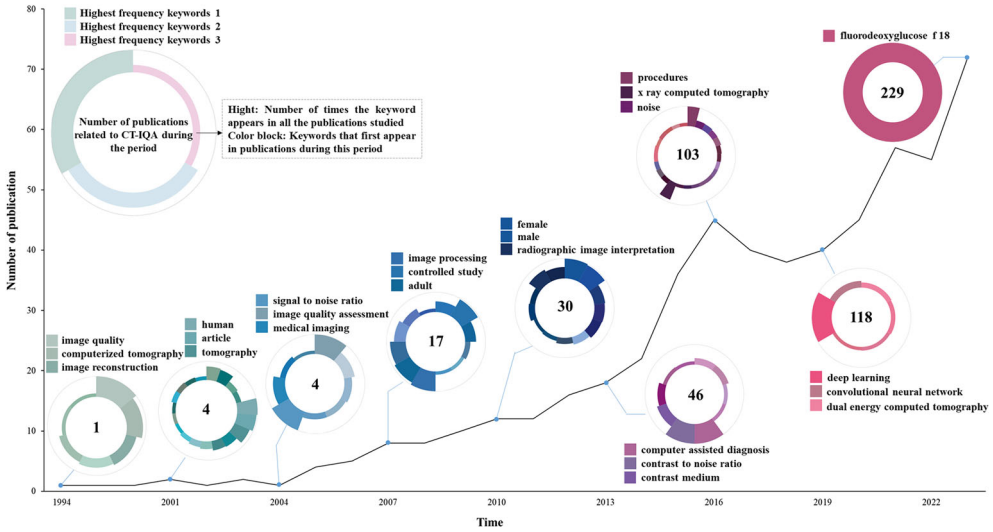


Fig. 3 A time-zone diagram representing the evolution of CT-IQA research from 1994 to 2023. The horizontal axis indicates the year, and the vertical axis displays the number of publications associated with CT-IQA. The circlesrepresent the time and frequency of keyword occurrences in the research dataset. For each period of discovery, only the top three keywords with the highest frequencies are labeled within the circle

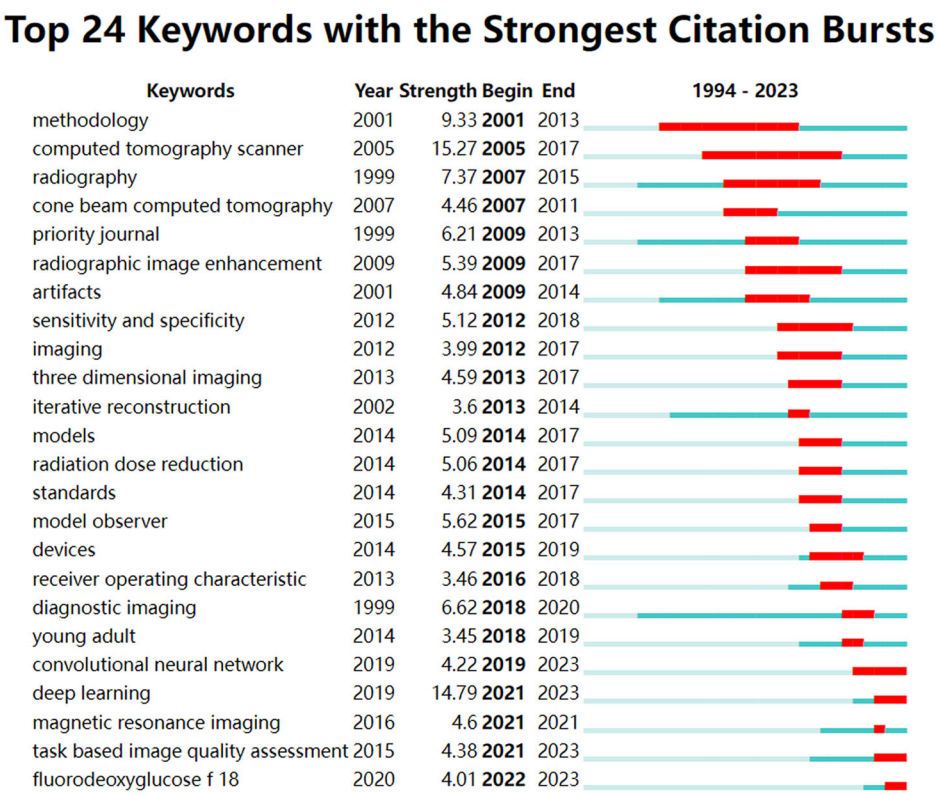


Fig. 4 Keywords with the strongest citation bursts. Columns from left to right indicate: (1) Detected Burst Term, (2) First Appearance Year, (3) Burst Intensity, (4) Burst Start Year, (5) Burst End Year. The sixth column provides a visual representation of the term's burst from 1994 to 2023, with the entire blue line depicts the period from 1994 to 2023. The starting point of the dark blue line represents the year of the term's initial appearance, while the starting point of the red line indicates the year of the burst's initiation. The light blue time period has not yet occurred

in Multi-detector row CT (MDCT) and found that the technology could effectively suppress artifacts and improve CT image quality during reconstruction. Xu et al. (2012) assessed Cone Beam CT (CBCT) image quality and guided technical updates to ensure quality standards. These studies revealed the direct impact of traditional hardware optimization on IQA and established benchmarks for subsequent technical iterations. For the new CT scanners, Patzer et al. (2023) performed quantitative and qualitative IQA on shoulder images using a Photon Counting Detector (PCD) CT scanner. The investigation showed that PCD-CT has potential as a key clinical imaging method for shoulder trauma assessment. Although emerging devices like PCD-CT demonstrated unique clinical value, systematic consensus on quality differences and advantages across anatomical sites remains lacking.

Meanwhile, for CT image reconstruction algorithms, Vardhanabhuti et al. (2013) assessed the image quality of three traditional reconstruction techniques: Filtered Back Projection (FBP), Adaptive Statistical Iterative Reconstruction (ASIR), and Model-Based Iterative Reconstruction (MBIR). The outcomes demonstrated the superior noise reduction and enhanced image quality of MBIR. Vaishnav et al. (2014) compiled the latest research on task-based CT iterative reconstruction IQA techniques and assessed the dose reduction achieved by relevant IR algorithms. They extended IR assessment from simple quality assessment to dose-efficacy balance analysis. However, traditional IR methods were time-consuming and prone to texture distortion. Current bibliometric analysis of our dataset indicates that deep learning-based reconstruction algorithms have become mainstream, as further analyzed in Section 3.2.2.

For the overall assessment of CT imaging systems, Allert and DiBianca (2005) conducted a comprehensive assessment from multiple angles (e.g., contrast, spatial resolution) and developed an automated assessment program based on this framework. Wilson et al. (2013) provide an IQA technique for CT systems, enabling precise measurement of tube current modulation and IR performance. However, single-time-point system assessment has limitations, as CT device performance may degrade over time. To address this, Roa et al. (2015) studied quality control techniques by analyzing six CT scanner models from four manufacturers over six years. Greffier et al. used imQuest software (Greffier et al. 2020) to assess four CT systems and the effects of FBP and two generations

of IR algorithms on image quality. Their study integrated hardware and algorithms into a unified framework, achieving multi-dimensional assessment of CT imaging systems. These studies are expected to improve CT image quality and system performance. Future research should focus on dynamic quality assessment and maintenance by combining imaging parameters, device service duration, and reconstruction algorithms.

3.1.4 IQA of CT image processing algorithm

Since the advent of CT imaging, research priorities have expanded beyond hardware development. The keyword "radiographic image enhancement" first surfaced in 2009 and continued to grow rapidly until 2017 (Fig. 4. Line 6, Freq=26, BC=0.02, BS=5.39, 2009-2017). Its low frequency and prolonged burst period indicate that there is a long-term clinical need but the relevant research is relatively scattered. Radiographic image enhancement refers to quality improvement through post-processing techniques such as contrast enhancement and noise reduction. As a key component in developing image processing algorithms, CT-IQA evaluates enhanced images to guide algorithm optimization, verify performance, and ensure output quality. By actively intervening in image quality, radiographic image enhancement makes CT-IQA gradually shift from assessing raw images based on physical parameters to assessing processed image based on post-processing technology, which changes the research paradigm of CT-IQA.

Image enhancement is an important CT image processing technology. Noël et al. (2013) studied an iodine contrast enhancement tool for CT images, evaluating its performance through subjective assessment and the Contrast-to-Noise Ratio (CNR). However, single metrics like CNR cannot fully capture enhancement effects on complex anatomical structures. Al-Ameen et al. (2015) improved the ratio-restricted adaptive histogram equalization and proposed a simplified contrast enhancement technique. They evaluated this method against other enhancement techniques using the Universal Image Quality Index (UIQI), SSIM, and Feature Similarity Index (FSIM), validating its effectiveness through multidimensional metrics. Sim et al. (2018) proposed a contrast enhancement technique for non-contrast CT. They evaluated the technique by integrating the SSIM, PSNR and entropy assessment model with multiple objective indicators and subjective visual assessments. The clinical efficacy of this technique for diagnosing brain diseases was also validated. From single index validation to multidimensional assessment, researchers verified the effectiveness of the proposed enhancement technique through different assessment methods. These techniques improved the contrast and sharpness of CT images and provide improvements for low-quality CT images.

Another crucial post-processing method for CT images is denoising. To balance computational efficiency and quality enhancement, Zhu and Ding (2017) proposed a parallel denoising technique that dynamically adjusts parameters through IQA feedback. For high precision requirements of industrial CT imaging systems, Lee (2019) proposed a Total Variational (TV) denoising technique. They used NPS, CNR, and coefficient of variation to validate its efficacy. Clinical needs of special populations (e.g., children) drove the refinement of denoising techniques. Watanabe et al. (2020) investigated the performance of reconstruction and denoising techniques in pediatric abdominal CT images, inviting radiologists to conduct quality assessments. Zhang et al. (2024) proposed a denoising model DnST based on the Swin Transformer architecture. By introducing the perceptual loss function and the residual mapping mechanism, and designing a new perceptual PSNR index, a comprehensive optimization of noise suppression, structure preservation and lesion sensitivity was achieved in low-dose CT images. Sadia et al. (2024) systematically reviewed the denoising algorithms of low-dose CT images and focused on the latest progress of deep learning techniques, providing a theoretical framework for constructing a robust and explainable intelligent CT denoising system.

Furthermore, image fusion, artifact removal, and other popular post-processing methods for CT images have been comprehensively described (Zaidi et al. 2008; Cao et al. 2024). IQA serves as an essential tool to verify and optimize these algorithms. In recent years, deep learning applications in CT post-processing algorithms have emerged as a new trend. By combining the dual advantages of traditional post-processing algorithms and AI models, this integration further advances end-to-end image processing and quality assessment, thereby driving the development of CT-IQA.

3.1.5 CT-IQA meets AI model

In the past five years, "convolutional neural network" and "deep learning" have emerged within the CT-IQA research community. Among them, Deep learning (DL) exhibited a burst strength of 14.79 (Fig. 3. Eighth circle, Figure 4. Line 21, Freq=55, BC=0.01, BS=14.79, 2021-2023). The high frequency and BS values underscore DL's profound impact on CT-IQA, shifting traditional physics-driven assessments toward data-driven implicit modeling and end-to-end frameworks. This transition follows a technical trajectory: "CNN exploration-Clinical integration-Large model transition", fundamentally reshaping the CT-IQA paradigm.

Naeemi et al. (2016) used CNN to pioneer the exploration of big data's impact on CT-IQA, catalyzing subsequent research into deep learning applications in this field. This groundbreaking study set the stage for a paradigm shift toward deep learning-based CT-IQA. Building on this, Wang

et al. (2022) compared the performance of 9 different objective assessment metrics in CT images, and proposed a combined IQA model based on genetic algorithm. Hayashi et al. (2020) further leveraged deep learning to analyze CT images across varying noise levels, demonstrating AI's potential in clinical diagnosis.

As we mentioned, the NR-IQA method is currently regarded as an effective approach for medical IQA. Li et al. (2018) broke through the limitation of traditional NR-IQA that relied on manual features and conducted a pioneering investigation into deep learning-based NR-IQA for CT images. Pal et al. (2021) proposed a cross-domain NR-IQA method by integrating self-supervised regularization into CNN, promoting the shift toward unsupervised/weakly supervised paradigms in CT-IQA. To address the lack of labeled data, Gao et al. (2019) used traditional FR-IQA metrics as supervision, and employed PSNR/SSIM as priors to train an NR-IQA model. Subsequently, Gao et al. (2021) incorporated prior information from pre-restored images into CNN and proposed a novel NR-IQA method named PR-IQA. Furthermore, Lee et al. (2022) proposed Depth Detector IQA (D2IQA), which automatically quantifies CT image quality with performance comparable to FR-IQA metrics. This indicates that the application of DL models in CT-IQA are gradually mature.

Technology maturity drives the penetration of assessment scenarios to clinical critical tasks, Xia et al. (2023) explored the impact of different denoising techniques on chest CT images for COVID-19 diagnosis, demonstrating feasibility in public health emergencies. Duan et al. (2020) proposed an IQA model based on CT image statistics, enabling real-time quality monitoring during reconstruction. This achieved a paradigm shift toward clinical real-time quality monitoring.

Currently, large models have ushered in a new era of CT-IQA. Chen et al. (2023) proposed the IQAGPT model, integrating vision-language model with ChatGPT to generate quality text reports with semantic interpretation while predicting CT image quality scores. At the same time, users can interactively refine assessments via ChatGPT. Preliminary results have demonstrated the feasibility of the model, which is very exciting.

Table 4 summarizes AI-based CT-IQA models. Deep learning-based CT-IQA methods leverage neural networks to automatically learn image feature representations, effectively capturing complex patterns and latent relationships. This capability enables high-performance prediction models adaptable to diverse scenarios, significantly advancing CT-IQA development. AI has ushered in a transformative era for CT-IQA, with large models further expanding its research frontiers. However, our review reveals that most existing AI-based CT-IQA models rely on stacked CNN architectures trained on 2D synthetic datasets. Future research should prioritize exploring real 3D CT image quality assessment by integrating advanced models such as GANs, attention mechanisms, and Vision Transformers.

3.1.6 IQA for CT-relevant modalities

In conducting our investigation, we came across a number of IQA studies of CT-related imaging modalities. For example, the burst word "fluorodeoxyglucose f 18" was observed (Fig. 3. Ninth circle, Figure 4. Line 24, Freq=11, BC=0, BS=4.01, 2022-2023). In Positron Emission Tomography-Computerized Tomography (PET/CT), it is frequently utilized as a tracer. The short-term burst of related research with limited frequency reflects growing demand for multi-modal imaging assessment. Consequently, CT-IQA methods should evolve from single-modality assessment to multi-modality collaborative frameworks to address continuous advancements in imaging technology.

For PET/CT, Yin et al. (2015) examined the effectiveness of 13 widely used IQA methods and suggested a subjective assessment database for PET/CT images, providing the data basis for follow-up studies. Qi et al. (2023) developed an AI-based quality assessment system for PET/CT, enabling rapid image quality analysis and comprehensive report generation. Gross and Kupinski (2005) investigated SPECT imaging system IQA and parameter adjustments for detection tasks. Greffier et al. (2021) assessed four Dual-Energy Computed Tomography (DECT) platforms' image quality and spectral performance. Dillenseger et al. (2017) assessed CBCT systems across diverse imaging protocols using qualitative and quantitative methods.

Multi-modal CT image fusion compensates for single-technique limitations and enhances diagnostic comprehensiveness. However, temporal synchronization of multi-modal data and cross-device compatibility constrain clinical implementation. Future research should prioritize developing advanced image fusion algorithms, utilizing deep learning for multi-modal quality feature extraction, and designing unified evaluation metrics. Emerging challenges include highly integrated evaluation of multi-probe, multi-energy-spectrum, and multi-modal imaging, driven by diversified radioactive tracers and PCD-CT adoption. Foundation models with robust feature extraction capabilities will enable innovative solutions in this domain (Zhang and Metaxas 2024; He et al. 2024; Sun et al. 2024).

The evolution of CT-IQA mirrors the profound shift in medical imaging from experience-driven to data-driven methodologies. In early CT development, quality assessment relied on human visual assessments and basic physical metrics, establishing a linear quality assessment framework based on phantom testing. As CT imaging proliferated, researchers shifted focus to technological advancements in artifact recognition and system optimization, gradually enhancing objective quantification via image processing

Table 4 Summary and comparison of some AI-based automated CT image assessment models

Refs	ROI	Method	Loss	Scale	Data	Performance
Naeemi et al. (2016)	Thorax, Abdomen	CNN	N/A	Phantom: 1-6 Patient: 1-5	Private dataset: 690 Phantom: 81 Patient: 100	Acc = 0.9380
Wang et al. (2022)	Thorax	Genetic algorithm	N/A	1-5	LIDC-IDRI: 266 Train: 190; Test: 76	SRCC = 0.9209
Hayashi et al. (2020)	N/A	AlexNet	N/A	1-3	Private dataset: 90 Train: 63; Test: 27	Acc = 0.9260
Li et al. (2018)	Thorax	AlexNet	N/A	1-5	Mayo CT data: 1500 Train: 1350; Test: 150	PLCC = 0.9953 SRCC = 0.9952
Pal et al. (2021)	Thorax, Abdomen	CNN	Self-supervised, L2, Heatmap	1-6	Mayo CT data Abdomen: Train 9198, Test 3315 Thorax: 3185	Compare with GSSIM (Abdomen, Thorax) PLCC = 0.9830, 0.9170 SRCC = 0.9710, 0.9060 KROCC = 0.8570, 0.7430
Gao et al. (2019)	Thorax	CNN	N/A	1-3	Mayo CT data: 900 Train: 720; Test: 180	PLCC = 0.9602 SRCC = 0.9548
Gao et al. (2021)	Thorax, Abdomen	CNN	L1	1-5	Mayo CT data: 700 Train: 420 Val: 140 Test: 140	BF, NLM, BM3D PLCC = 0.8770, 0.8731, 0.8653 SRCC = 0.8296, 0.8302, 0.8184 RMSE = 10.3906, 10.5805, 10.8607
Lee et al. (2022)	Abdomen	Cascade R-CNN, ResNet-50	CrossEntropy, L1	0-10	2016 Low Dose CT Grand Challenge dataset: 9228 Train: 6390; Val: 1598 Test: 1240	PLCC = 0.9132 SRCC = 0.9058
Xia et al. (2023)	Thorax	CNN	CrossEntropy	1-2	COVID-CT-MD Train: 374 Val: 175	Ori, AD1, AD2, TV1, TV2 AUC = 0.9350, 0.9150, 0.8950, 0.9450, 0.9500 Sen = 0.9500, 1.0000, 0.9100, 1.0000, 0.9500 Spe = 0.9200, 0.8300, 0.8800, 0.8900, 0.9500
Duan et al. (2020)	Head, Thorax, Abdomen, Hip	SVM	N/A	1-2	Private dataset: 690	Head, Thorax, Abdomen, Hip SRCC = 0.7769, 0.8661, 0.8040, 0.9094
Chen et al. (2023)	Abdomen	VLM, ChatGPT	CrossEntropy, MSE	1-5	2016 AAPM Grand Challenge Dataset: 1000 Train: 800; Test: 200	PLCC = 0.7540 SRCC = 0.7480

Acc: Accuracy; AD: Anisotropic Diffusion; AUC: Area under the ROC Curve; BF: bilateral filtering; BM3D: Block-matching and 3D filtering; KROCC: Kendall Rank Order Correlation Coefficient; N/A: Not Applicable; NLM: Non-local mean filtering; Ori: Original; Refs: References; ROI: Regions of interest; Sen: Sensitivity; Spe: Specificity; TV: Total Variation; Val: Validation

algorithms. The advent of artificial intelligence, particularly deep learning, has revolutionized the IQA paradigm, enabling CT-IQA to transition from physical feature analysis to data-driven modeling. This progression is now advancing toward standardized, interpretable intelligent quality control systems within multi-modal fusion.

3.2 Research branches derived from CT-IQA

The cited papers chosen for this review synthesizes the relevant studies on CT-IQA, completely broadening the scope and depth of the field. To investigate future trends, we constructed a Document Co-citation Network[2] using *CiteSpace* and analyzed the knowledge structure of citations from the past five years. Specifically, we visualized references within the dataset and applied clustering algorithms[3] to nodes in the co-citation network (Fig. 5). The clustering results map the knowledge network structure in the domain and reveal core research themes and sub-domain differentiation characteristics. We applied the "log-likelihood ratio" algorithm to assign cluster labels, with keywords extracted from titles of highly cited papers, reflecting the focused research topics in the field. During clustering, clusters were filtered based on low modularity values (Q)[4] (loose connections within clusters), low silhouette values (S)[5] (mixed cluster topics), low size value (limited studies), or low citation burst. Figure 5 reveals four densely interconnected node subsets, corresponding to core research clusters (overall Q value=0.8801). From this analysis, four dominant research themes emerged. Themes include: "phantom study", "artificial intelligence deep-learning reconstruction algorithm", "dose reduction opportunity", "virtual monoenergetic reconstruction".

To summarize key branches in the CT-IQA domain, we detected the burst of the co-citation. With a sensitivity threshold of 1.0 and a minimum duration of 2 years, 11 references with the strongest reference bursts were found (see Fig. 6), denoted as red dots in Fig. 5. The literature with high burst citations can indicate the research hotspots of each period. Burst citations typically align with major technological advancements, with its co-citation clusters mapping technology diffusion pathways. Our investigation prioritized both domain-specific highly cited publications and detected citation bursts as critical analytical focal points.

3.2.1 Phantom study in CT-IQA

Phantom study (Fig. 5. Cluster #0, S value=0.982, Size=77, Average year=2012) investigate CT imaging systems by mimicking human bodies through standardized simulated body models. As the largest cluster, phantom study has become a mature and cohesive research field in the early days. Phantom scans generate CT images can be used to assess the effectiveness of CT devices, conduct performance benchmarking, and validate protocols while minimizing human radiation exposure risks. To investigate the imaging quality and resolution characteristics of CT imaging systems under various dosage levels, reconstruction methods, and contrast parameters, the three most-cited publications in this cluster all utilize phantom-generated CT images (Yu et al. 2013; Leipsic et al. 2010; Richard et al. 2012).

Underlying these technical advancements is the continuous innovation within phantom research itself. Through analyzing the other articles in cluster #0, we found that phantom research has evolved alongside scientific and technological progress. The reliability and fidelity of the phantom studies have steadily evolved from the first basic simulation of natural tissues and organs to the more intricate and realistic simulation. Based on this, a wide range of illnesses and lesions (such as cancers, vascular stenosis, etc.) have been identified, which has been useful in assessing how well imaging equipment can identify and diagnose lesions (Wilby et al. 2021). Phantom study has gradually advanced toward multi-modal imaging due to the development of multi-modal medical imaging technology, allowing for a more accurate assessment of the benefits, drawbacks, and complementarity of each modality (Filippou and Tsoumpas 2018). However, most existing models are designed for static and homogeneous scenes, and lack the ability to simulate dynamic physiological processes (such as respiratory motions, blood perfusion) and disease-specific anatomical variations, limiting their clinical validation utility.

Phantom study provides rigorously controlled experimental frameworks for CT imaging technologies, algorithms, or parameters across diverse imaging performance testing, validation, and optimization scenarios. This provides a scientific foundation for clinical translation and implementation, aids in quality control and improvement, and improves image quality and system reliability. The development of intelligent dynamic phantoms and the integration of pathological features into model development will advance CT-IQA innovations. In addition, phantom studies pose minimal radiation

[2] Document Co-citation Network is constructed based on the frequency of pairwise document co-citations. If references A and B are jointly cited by multiple publications, they form a co-citation relationship, indicating thematic relevance within the knowledge domain.

[3] Co-citation clustering is defined by analyzing co-citation relationships between documents (i.e., two documents cited together by a subsequent publication). Frequently co-cited documents form thematic clusters.

[4] Modularity (Q value): A metric evaluating cluster significance. Generally, $Q > 0.3$ indicates a significant clustering structure.

[5] Silhouette (S value): The average silhouette score of a cluster. $S > 0.5$ suggests reasonable cluster quality, while $S > 0.7$ indicates high-confidence clustering.

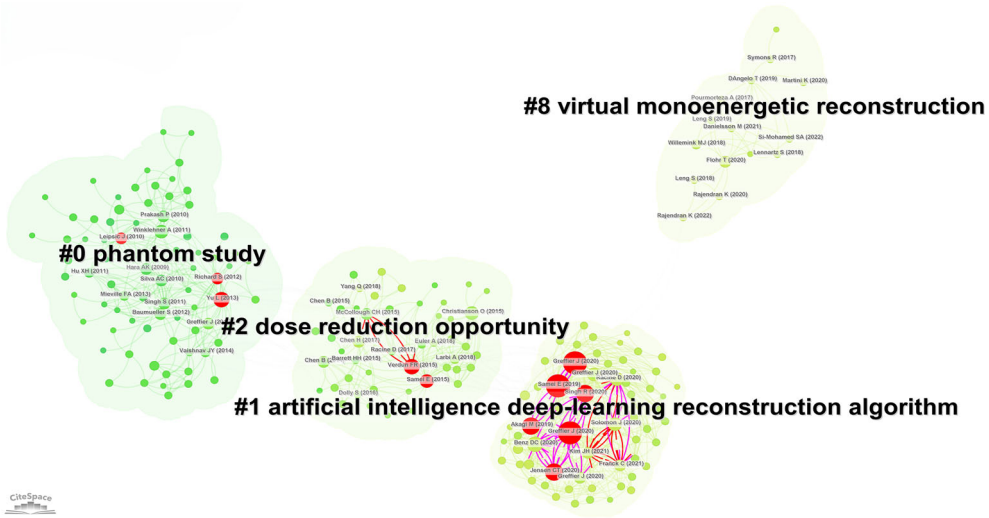


Fig. 5 Cluster graph depicted the development of CT-IQA (The nodes in this graph represent references, denoted by circular shapes, and grey text denotes the author and year information of frequently co-citation. The four core clusters in the figure are categorized in ascending order of scale as follows: #0 phantom study, #1 artificial intelligence deep-learning reconstruction algorithm, #2 dose reduction opportunity, #8 virtual monoenergetic reconstruction. Purple lines signify pre-existing connections among various nodes, while red lines indicate newly established connections)

exposure risk, positioning low-dose imaging as a critical research frontier.

3.2.2 CT-IQA of artificial intelligence deep-learning reconstruction algorithm

With the continuous development of AI, researchers are using deep learning algorithms and neural networks to automatically extract and learn features from large-scale datasets. This enables the generation of higher-quality and more accurate reconstructed images, enhancing CT image quality. As we mentioned, CT-IQA is an important way for optimizing CT image reconstruction algorithms. Therefore, CT reconstruction algorithms based on AI and deep learning (Fig. 5. Cluster #1, S value=0.97, Size=62, Average year=2019) have correspondingly promoted the development of CT-IQA. The high S value and a recent average publication year (2019), indicates that the field has emerged as an active research frontier. This paradigm shift has been systematically validated in recent key studies.

Greffier et al. (2020) evaluated the potential of the hybrid IR algorithm and the deep learning image reconstruction (DLIR) algorithm for optimizing image quality and radiation dose. Singh et al. (2020) compared the image quality and performance of the two algorithms on chest, abdomen, and pelvic CT scans, focusing on clinically significant lesion detection. Akagi et al. (2019) added MBIR for comparison. Multiple studies have shown that compared with traditional reconstruction methods, DLIR can reduce noise, improve spatial resolution detectability without changing noise texture, and has good lesion detectability, while demonstrating superior performance in noise reduction, contrast enhancement, and other objective assessment metrics. In addition, Jensen et al. (2020) conducted quantitative and qualitative evaluations of DLIR in enhanced abdominal tumor CT. Their findings confirmed DLIR's effectiveness in improving CT image quality. However, as DLIR intensity increases, recon-

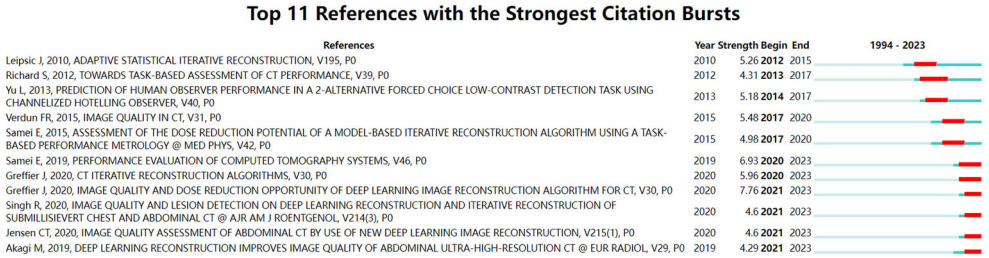


Fig. 6 References with the strongest citation bursts (same explainability as Figure 4, except that this figure shows nodes as references)

structed images exhibit gradual blurring. It is worth noting that current algorithms lack adaptability to emerging detector technologies (e.g., PCD-CT) and fail to address motion artifacts from breathing or cardiac activity, limiting the performance of image reconstruction and quality assessment. Wang et al. (2024) demonstrated that DLIR in low-dose chest CT significantly reduced the radiation dose while ensuring image quality comparable to that of conventional-dose CT, and had the same effect on disease diagnosis. Klemenz et al. (2024) utilized DLIR to enhance the image quality of CT pulmonary angiography, further confirming the potential of DLIR in the optimization of CT image quality.

Despite persistent technical limitations, the role of AI-driven reconstruction algorithms in advancing CT-IQA is unequivocally established. In the future, combining the physical imaging characteristics of the novel detector with real-time biological signals to achieve end-to-end quality optimization for next-generation CT systems can help AI reconstruction and clinical CT-IQA deep integration. Simultaneously, when analyzed alongside Fig. 6, analysis reveals that the papers that have maintained high bursts up to this point are all associated with the deep learning reconstruction algorithms. This further underscores the immense potential for deep learning advancement in CT-IQA.

3.2.3 Dose reduction in CT-IQA

The amount of X-ray radiation that a patient receives during CT imaging is referred to as the radiation dose. Contrast, resolution, noise levels, and other aspects of CT image quality are influenced by the radiation dose. High doses increase cancer risks and may damage cells and tissues, whereas excessively low doses compromise scan quality. This contradiction directly gives birth to the need for dynamic balance between radiation dose and image quality, which drives technological innovation. Our analysis revealed that "dose reduction" (Fig. 5. Cluster #2, S value=0.946, Size=48, Average year=2016) permeated practically every step of CT-IQA's development. The ultimate goal of researchers is to reduce patient radiation exposure while maintaining image quality, preserving human health, and reducing healthcare costs.

To achieve this goal, both hardware innovation and software optimization are required. On the one hand, researchers have developed detectors with improved detection efficiency and reconstruction algorithms better aligned with hardware characteristics to generate low-dose and high-quality CT images. To balance image quality and radiation risks, medical professionals and technicians need to continuously optimize scanning parameters based on patient weight and scan location.

On the other hand, researchers are exploring methods to enhance low-dose CT images into high-quality outputs via advanced post-processing algorithms. Samei and Richard (2015) compared the dose-performance of MBIR and ASIR, demonstrating that MBIR could halve the CT dose using projected data while maintaining image quality. By simulating CT images across varying radiation doses and anatomical structures, AI technology can predict the optimal dose threshold and generate interpretable clinical risk assessment reports, thereby ensuring the dose-to-quality balance of CT images.

3.2.4 Virtual monoenergetic reconstruction in CT-IQA

With the constant advancement of CT equipment technology, contemporary CT scanners are now able to provide dual-energy imaging, that is, simultaneous scanning employing two distinct energy levels. Virtual monoenergetic reconstruction (Fig. 5. Cluster #8, S value=1, Size=15, Average year=2019) is based on this type of dual-energy imaging. It simulates imaging at a single energy level by processing raw data from CT scanners using specialized algorithms. This enhances CNR, reduces beam hardening and metal artifacts, enhances the ability to detect anomalous structures, and improves overall image quality, giving physicians access to more useful data. Despite its small size, the cluster achieves the S value and has a recent average publication year. This indicates that the field represents an emerging research direction; however, more research is required to validate its clinical translation potential.

However, this technology remains constrained by traditional detectors' physical limitations-the advent of PCD-CT marked the unlocking of multienergy imaging potential. The top three most-cited papers in this cluster focus on PCD-CT. This leap stems from a paradigm-shifting innovation in detector technology. PCD-CT employs photon-counting detectors to count and measure the energy of each incident X-ray photon, enabling direct acquisition of multienergy X-ray data without requiring separation via multiple energy thresholds as in DECT. Compared to DECT, PCD-CT has greater resolution and contrast while avoiding electronic noise interference (Flohr et al. 2020). Consequently, PCD-CT can minimize radiation exposure, optimizes contrast agent utilization, and enables quantitative imaging (Willemink et al. 2018).

At present, PCD-CT is expected to replace or complement conventional DECT. Leng et al. (2019) summarized the principles, current advancements, and clinical application of PCD-CT. Their work provides a comprehensive overview through phantom, animal, and clinical case studies. With

the increasing maturity of PCD-CT technology, researchers have compared and explored the differences in radiation dose and image quality between PCD-CT and traditional energy integration detector CT (EID CT) in phantom and different scanning structures, verifying the characteristics of low dose and high quality of PCD-CT imaging (Bhattarai et al. 2024; Spampinato et al. 2024; Marth et al. 2024). Furthermore, ultra-high resolution PCD-CT (Tóth et al. 2024) and high-pitch mode PCD-CT (Pannenbecker et al. 2024) have also demonstrated significant advantages in various types of imaging. Following rigorous multi-scenario validation, PCD-CT's benefits-including high resolution, low radiation dose, multienergy imaging, enhanced soft-tissue contrast, and reduced noise-are anticipated to revolutionize clinical diagnosis, enhancing diagnostic accuracy and elevating clinical imaging standards.

3.3 Prospective

Finally, in order to make a scientific prediction about the direction of future development, we applied Structural Variation Analysis (SVA) to clustered themes (the principle is shown in Chen (2012)) and analyzed structural changes in co-cited clusters. Our analysis focused on a 5-year citation span, prioritizing recent co-citations. After identifying critical nodes through betweenness centrality and burst detection, the analysis generates key connections in purple and red (Fig. 5). Purple lines link studies with high BC values, indicating technical foundations on which the field has long relied. Red lines connect nodes where at least one exhibits high burst strength, with red line-dense regions typically marking technological inflection points or emerging research frontiers. The convergence of these connections may catalyze paradigm shifts. This framework enables analysis of whether the CT-IQA knowledge structure has undergone a paradigm shift and prediction of future trends.

In cluster #2, we observed that Viry et al. (2018) established novel associations between CT-IQA, reconstruction techniques, and dose by citing papers McCollough et al. (2015) and Verdun et al. (2015) to investigate the potential of various reconstruction algorithms in dose reduction. However, this link existed in isolation, lacking supporting purple or complementary links. Consequently, the isolated link failed to drive a paradigm shift, prompting the exclusion of further analysis.

In cluster #1, there are three sub-clusters (labeled 1, 2, and 3, from left to right). Sub-cluster 1 consists of purple links, paper (Samei et al. 2019) serves as the central node in subcluster 1, and papers (Greffier et al. 2020) and (Akagi et al. 2019) are co-cited in papers (Greffier et al. 2021; Harun et al. 2021; Greffier et al. 2021). The impact of various parameters and deep learning reconstruction algorithms on CT image quality is investigated, and a link between various reconstruction algorithms and CT system assessment guidelines is established. The findings demonstrate the significance of reconstruction algorithms in CT system assessment.

Within sub-cluster 2, researchers investigated diverse perspectives related to the two concepts of "deep learning" and "reconstruction algorithm", as well as five highly cited papers (Greffier et al. 2020; Singh et al. 2020; Jensen et al. 2020; Greffier et al. 2020; Benz et al. 2020). The purple links means that this sub-cluster has become an important technical pathway. The performance comparison of several deep learning reconstruction techniques with conventional algorithms was examined in papers (Jensen 2022; Fair et al. 2022; Li et al. 2022; Greffier et al. 2022) by citing these highly cited papers. Park et al. (2022) examined the variation in image quality between standard-dose CT reconstructions and low-dose CT images denoised using deep learning methods.

Four highly cited papers (Solomon et al. 2020; Franck et al. 2021; Racine et al. 2020; Kim et al. 2021) in subcluster 3 examined the performance of DLIR and contrasted it with two significant conventional reconstruction techniques, FBP and ASIR. The coexistence of purple and red links signifies that this subcluster simultaneously serves as a knowledge hub and an emerging research frontier. Papers (Yang et al. 2023; Nagayama et al. 2023; Barca et al. 2023) cited these works as a basis for their comparative analysis of deep learning reconstruction algorithms and conventional reconstruction techniques. Nagayama et al. (2023) developed a DLIR algorithm especially for Coronary Computed Tomography Angiography (CCTA) and compared it with four conventional techniques. The outcomes demonstrated that the DLIR method may reduce artifacts and reconstruction time while enhancing image quality.

Sub-clusters 2 and 3 delve into the core theme of DLIR, while sub-clusters 1 has emerged through diverse citation linkages. Despite the emergence of correlation links, their sparsity suggests that knowledge development in the DLIR domain remains characterized by incremental advancements, with no significant paradigmatic shift identified, necessitating further investigation. Current DLIR research focuses on the develop of novel algorithms and their performance comparison with conventional algorithms.

Therefore, we examined the trajectory and evolution of the co-citation connection in link walkthrough[6] the backdrop of the literature co-citation graph. By tracing citation pathways, we can map the gradual evolution of CT-IQA and shifting research priorities, revealing critical advancements, emerg-

[6] Link walkthrough tracks citation pathways between nodes through dynamic user interactions, mapping knowledge flow trajectories across documents. Critical pathways bridging different clusters (research sub-fields) frequently catalyze technological convergence or interdisciplinary integration.

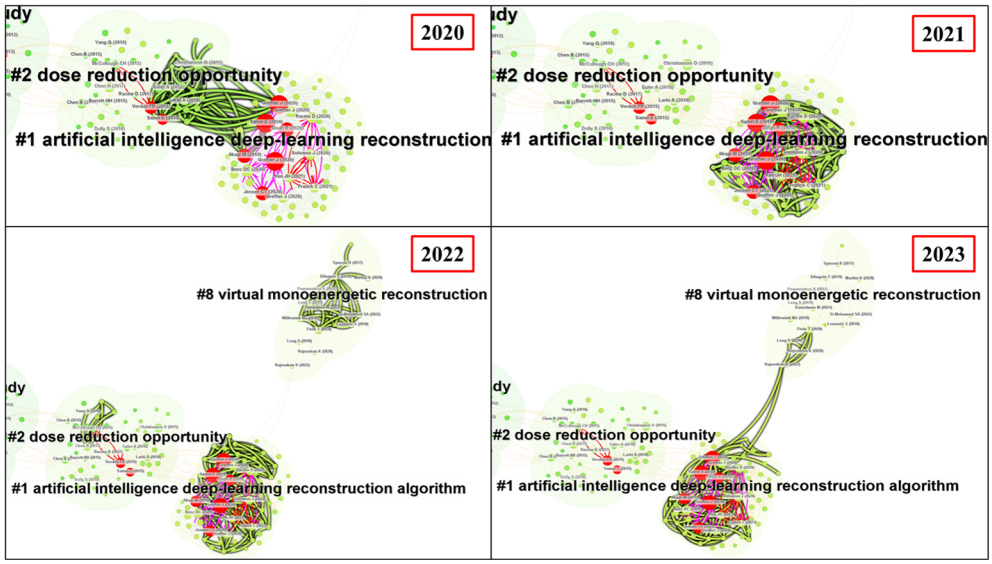


Fig. 7 Link-walkthrough of the co-cited graph from 2020 to 2023 (the green connection line in the figure is the link-walkthrough path)

ing trends, and thematic associations. A link-walkthrough schematic from recent years is shown in Fig. 7.

Reconstruction techniques based on AI and deep learning began offering new prospects for dose reduction in 2020 and a large number of related studies subsequently integrated into CT-IQA research. Clusters #1 and #2 generated significant associations, prompting researchers turned their attention to cluster #1. As we discussed in Section 3.2.4, researchers initiated investigations into virtual monoenergetic reconstruction in 2022. PCD-CT and related technologies began converging with DLIR in 2023. As a result, academics will increasingly focus on developing novel CT imaging techniques, advanced reconstruction algorithms, and efficient CT-IQA frameworks. Spanning dose reduction to imaging innovation, AI now drives the entire CT-IQA technology chain.

Simultaneously, we observed that AI-driven CT-IQA has gained sustained momentum and is poised to emerge as a prominent research frontier. This trend is strongly supported by the emergence of key terms and co-citation papers in Figs. 4 and 6. Studies demonstrate that AI-based CT-IQA models outperform numerous conventional methods. Current evidence suggests accelerated research in this field, which is expected to proliferate and establish itself as a prominent research frontier.

4 Discussion

In the 1970s, CT imaging technology began to be used in clinical diagnosis. This prompted society to pay attention to the quality of CT images. CT-IQA could assist relevant personnel in performing quality assurance and enhancement. Researchers have raised standards for equipment performance and image processing algorithms as a result of the advancement of digital imaging technology, and CT-IQA is encountering both new opportunities and challenges.

During the early stages of CT-IQA development, medical imaging experts or physicians subjectively assessed medical images using their professional knowledge and personal experience. The results of subjective assessment were inconsistent, the process was time-consuming, labor-intensive, and prone to individual biases (e.g., workload, mood, or clinical experience). To address this, the medical community began establishing image quality norms and standards to improve the accuracy of subjective assessments. Simultaneously, objective CT-IQA methods began to emerge. Objective algorithms automatically perform assessments, producing reliable and repeatable results and converting image quality into quantifiable metrics for simple comparison and analysis. However, objective algorithms require handling large datasets and complex computations. Moreover, due to the complexity of the human visual system, existing algorithms still cannot fully simulate the subjective assessment.

The use of AI technology in CT-IQA has grown significantly in recent years, enabling tasks such as assessing reconstruction algorithms, identifying artifacts, and evaluating body positioning. The automatic assessment of CT image quality can be achieved by training the AI model, improving both efficiency and objectivity. Simultaneously, AI continuously optimizes its assessment models through iterative learning, enhancing result alignment with clinical reality. Based on existing research and analysis, AI-based CT-IQA techniques are advancing rapidly and have become a critical direction in medical imaging.

4.1 Challenge

4.1.1 Data

AI models require a large amount of high-quality annotated data to learn. Similarly, traditional objective assessment methods also need data to verify their effectiveness. However, publicly accessible CT-IQA data sets remain scarce currently. Most existing datasets are generated by introducing noise to CT scans through simulation. Although simulated data of varying quality levels can generate large amounts of training samples, they cannot fully replicate complex clinical lesions and pathological conditions, nor accurately capture physiological variations between different patients.

Therefore, constructing real-world CT-IQA datasets remains an ongoing challenge. On the one hand, manual processes such as cleansing, screening, standardizing, and labeling proprietary datasets are resource-intensive and time-consuming. On the other hand, curating specialized medical imaging datasets requires rigorous ethical approval and robust privacy safeguards, as data security and patient confidentiality must be prioritized. Furthermore, datasets must be designed to address potential biases and ensure equity (e.g., avoiding overrepresentation of specific populations), as such biases can compromise assessment accuracy and exacerbate healthcare disparities. These multifaceted barriers underscore that data scarcity and governance are key limitations hindering the advancement of CT-IQA.

4.1.2 Performance

AI models require complex training and optimization procedures. Due to the complexity and diversity of clinical contexts, most existing IQA models struggle to handle heterogeneous, multi-center data and have not been extensively clinically validated and tested. Consequently, these models exhibit limited robustness, poor generalization capability, and challenges in scaling to real-world applications. In clinical settings, CT-IQA models must assess image quality in real time to support rapid clinical decision-making. However, complex AI models often require substantial computational resources, potentially limiting their deployment in resource-constrained healthcare facilities. Additionally, CT-IQA models require periodic updates to adapt to evolving clinical practices and technological advancements. However, each update requires re-validation and regulatory certification, increasing the complexity and cost of technical maintenance.

4.1.3 Ethics and law

In the context of healthcare, AI models struggle to explain their IQA decision-making processes, making the models challenging to apply in the real world. Three potential risks arise from this challenge:

(1) Clinical risk and trust crisis caused by lack of explainability. Current mainstream deep learning models implicitly learn CT image quality features through hundreds of millions of parameters, but their IQA decision-making process lacks transparency, resulting in clinicians unable to verify their logic. From a technical perspective, poor explainability causes AI models to face two major clinical problems: misdiagnosis/missed diagnosis and cross-center reproducibility barriers. From an ethical perspective, whether opaque AI models can be accepted for clinical use and whether patients can provide informed consent are critical issues that cannot be ignored.

(2) The dilemma of law and responsibility caused by the ambiguity of the accountability system. When an AI-IQA system causes a clinical accident, the liability chain is far more complex than that of traditional medical devices. On the one hand, defining accountability among stakeholders-developers (for model flaws), healthcare institutions (for adopting AI technology), and physicians (for over-reliance on AI at the expense of clinical judgment)-remains challenging. On the other hand, traditional medical malpractice laws primarily focus on human clinicians' actions; however, as AI-driven evaluations become standard practice, existing legal frameworks fail to address accountability gaps. Establishing clear responsibility definitions and enforcing legal oversight mechanisms has become a critical challenge requiring multidisciplinary attention.

(3) Dual challenges of regulation and promotion. Rigorous testing by regulators and multi-center certification can ensure the safety and effectiveness of CT-IQA models, but these processes prolong the development, deployment, and rollout of AI systems. Additionally, the rapid iteration of AI models demands adaptive regulatory frameworks for dynamic oversight. At the same time, the absence of globally harmonized certification standards for AI medical devices hinders the widespread adoption of these technologies.

4.2 Opportunity and direction

4.2.1 AI-based CT-IQA models

The emergence of large model (Ray 2023), cloud computing (Saiyeda and Mir 2017), foundation model (Rasoolzadeh et al. 2024), universal network (Lin et al. 2024; Zhang et al. 2024) and big data (Chen and Lin 2014) have introduced transformative capabilities for medical imaging. These technologies enable efficient processing and scalable storage of massive medical image datasets, while providing high-performance computational capabilities to develop and deploy complex deep learning architectures. Such advancements empower AI models to transcend traditional limita-

tions in data utilization and algorithmic performance within the CT-IQA domain.

It is worth noting that the continuous development of large models plays an important role in the field of CT-IQA. On the one hand, large models possess vast parameter spaces and extensive training datasets, enabling autonomous learning of intricate patterns. By integrating data from different medical centers and scanning devices for finetuning, these models can provide more accurate and robust quality assessments. In addition, as they process more data sets, they can gradually adapt to personalized scenarios, providing customized IQA strategies for different patients' physical conditions and scanning devices. On the other hand, large models can handle multi-modality data (e.g., text, images, video). This capability can be extended to CT-IQA, combining CT image data with other modality data (e.g., medical records, MRI or PET images) for cross-modality quality assessment. In addition, the semantic understanding ability of large models can provide higher explainability for CT-IQA. For example, models can not only give quality scores, but also explain in natural language the causes of suboptimal image quality and propose corrective measures.

At the same time, to address the ethical-legal dilemmas of AI application in CT-IQA, it is essential to establish a three-stage "Technology-Constraint-Application" strategy: (1) *Technology stage.* Relying on existing interpretable AI frameworks and guidelines (Ieee 2024) embedding explainability into model development (Alvarez Melis and Jaakkola 2018; Lipton 2018; Salahuddin et al. 2022). For example, using interpretable tools (e.g., attention maps) to visualize the model's focus areas (e.g., artifacts, noise); combining medical image quality criteria (e.g., noise levels, contrast thresholds) to generate verifiable quantitative interpretations; designing clinician-friendly interfaces that display the key rationales behind AI assessment. (2) *Constraint stage.* Through implementing comprehensive audit logs, emergency plans, and misjudgment response mechanisms, establish an AI medical device regulatory framework based on the responsibility traceability system. At the same time, promoting specialized legislation to clarify liability attribution, data privacy protection, and patients' right to informed consent (Bostrom and Yudkowsky 2018; Cath 2018). (3) *Application stage.* In addressing regulatory and adoption challenges, privacy-preserving federated learning frameworks are adopted to integrate heterogeneous data, establish a real-time performance monitor-feedback-iterative closed-loop system, and enable a gradual transition from auxiliary screening to critical diagnostic scenarios, thereby accumulating clinical trust. Currently, accelerating the formulation of unified technical standards and ethical review guidelines will facilitate global deployment of the technology.

To date, legal frameworks remain in gradual adaptation to emerging AI technologies (Mazurowski 2019; Angus 2020). When AI-IQA systems cause errors, accidents, or injuries, ethical and legal responsibilities need to be further explored. Addressing these challenges requires global interdisciplinary collaboration among engineers, clinicians, legal experts, ethicists, and policymakers to resolve the technical, legal, and ethical complexities of AI in CT-IQA, ensuring both the safe deployment and responsible scaling of this technology. There is every reason to believe that AI-driven models will assume an expanding role in CT-IQA, ultimately driving transformative advances in medical imaging.

4.2.2 Scanners and post-processing algorithms

Furthermore, during the course of our investigation, we discovered that CT radiation dose requirements vary across clinical applications. The quality of CT images exhibits a dose-dependent relationship, with fidelity directly correlated to exposure levels. For instance, while low-dose CT screening improves early cancer detection rates (Gao et al. 2021), it generally produces suboptimal image resolution. Conversely, high-dose CT, despite entailing non-negligible radiation risks, proves essential for precision-demanding scenarios such as routine diagnosis, surgical planning, interventional therapy. It is challenging to raise the quality of low-dose CT images on a large scale. Therefore, optimizing scanner hardware capabilities (scanning speed, resolution, and dose control technology), advancing reconstruction algorithms for noise suppression and artifact reduction, and developing intelligent post-processing pipelines leveraging deep learning will become crucial research areas.

4.2.3 Standardized CT-IQA system

In order to establish a standardized CT-IQA system, researchers should also strive to organically combine subjective assessment, objective assessment, and AI assessment methods. The results of the subjective assessment should be used further to guide the development of objective assessment and AI assessment methods. In data-scarce scenarios or clinically inexperienced settings, reasonable objective assessment methods can provide foundational priors to AI assessment. AI assessment models can also rely on its own automatic and efficient characteristics to assist subjective assessment and provide reference benchmarks for subjective assessment.

Further, it is also important to establish unified assessment standards for different assessment methods, as well as a reasonable assessment process and method. This enables a thorough and comprehensive assessment of CT image quality.

5 Conclusion

This paper systematically reviews the development history, current research priorities, and emerging trends in CT-IQA. CT-IQA has evolved from the early subjective assessment to the AI-driven automatic assessment, undergoing paradigm shifts from technological innovation to clinical deployment. With the maturity of AI technologies, AI-driven CT-IQA demonstrates significant clinical translational potential, which can significantly improve CT-IQA efficiency, optimize healthcare resource allocation, and provide accurate assessment suggestions for medical institutions. However, critical challenges persist, including limited data availability, insufficient explainability, and ethical legal gaps in clinical implementation. By improving CT system reconstruction algorithms, establishing credible CT image post-processing algorithms, advancing the resolution and scanning speed of CT equipment, and building standardized CT-IQA workflows, CT-IQA is expected to achieve more extensive applications in medical imaging. In the future, AI-IQA models with rigorous clinical validation and comprehensive supervision will deliver high-efficiency image quality assessment tools for clinical workflows, while driving AI-driven advancements in medical technology.

Appendix

CiteSpace

CiteSpace is an academic paper visualization analysis tool grounded in the principles of knowledge graph and scientometrics. It utilizes detailed information from collected paper as nodes (including keywords, references, authors, institutions, and countries), and co-occurrence relationships as connections to generate knowledge graphs. These graphs visually represent the structure, patterns, and distribution of knowledge within a field. Through interactive manipulation of the knowledge graphs produced by *CiteSpace*, such as identifying nodes with high frequency and high betweenness centrality, searching for nodes with significant bursts, clustering co-occurring nodes, adding timelines to co-occurrence graphs, and incorporating structural variation analysis, an in-depth visual analysis is facilitated. *CiteSpace* is applicable to a wide range of academic fields, aiding researchers in uncovering and exploring the knowledge structure, development trends, and research hotspots of their fields of interest. It also provides valuable insights into predicting future trends in these fields. The key terms based on which *CiteSpace* software technology is used for visual analysis and their descriptions are shown in Table 5 below.

Table 5 CiteSpace software key terms and their description

Terms	Description
Node	In a knowledge graph, nodes are the basic units that represent entities or concepts. In *CiteSpace*, nodes can be authors, institutions, countries, keywords, terms, categories, references, cited authors, cited journals, and so on. Nodes are connected by edges (relationships) to form the structure of the graph.
Keyword co-occurrence	Keyword co-occurrence refers to two or more keywords that appear simultaneously in the same document. In the knowledge graph, this co-occurrence relationship can be used to reveal possible correlations between these keywords.
Co-Citation	When two or more documents are cited by the same document, they are considered to be co-cited. In the knowledge graph, the co-citation relationship can be used to reveal the similarity, correlation or common research area between literatures.
Frequency	In the knowledge graph, frequency usually refers to the number of times a node occurs in the whole graph. Nodes with high frequency usually indicate importance or significance.
Betweenness Centrality	Betweenness centrality is a measure of how well a node is connected to other nodes in a network. Nodes with high betweenness centrality play an important role as bridges in information propagation because they are located on short paths in the network.
Burst Detection	Burst detection is used to identify events or relationships that occur with an unusually high frequency within a designated time frame. In the knowledge graph, it helps to discover concepts that cause concern or change in a specific time period.
Clustering	Clustering refers to the method of grouping nodes within a graph based on certain similarities or connectivities. This process aids in deciphering substructures and groups within the knowledge graph, thereby underlying patterns and associations.
Cluster Label	A cluster label is a descriptive label for a cluster or group that generalizes the topic or feature of the nodes in the cluster.
Structural Variation Analysis (SVA)	SVA involves examining alterations in the structure of a graph, encompassing the identification of changes in nodes and edges, and comprehending the implications of these alterations on the graph's entirety. This approach is instrumental in apprehending the dynamic characteristics and evolving trends of the knowledge graph.

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Data Availability No datasets and materials were generated or analysed during the current study.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

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Authors and Affiliations

Siyi Xun[1] · Qiaoyu Li[2] · Xiaohong Liu[3] · Pu Huang[4] · Guangtao Zhai[3] · Yue Sun[1] · Peter H.N. de With[5] · Mingxiang Wu[6] · Tao Tan[1]

✉ Xiaohong Liu
xiaohongliu@sjtu.edu.cn

✉ Mingxiang Wu
szmxwu@outlook.com

✉ Tao Tan
taotanjs@gmail.com

[1] Faculty of Applied Sciences, Macao Polytechnic University, R. de Luís Gonzaga Gomes, Macao 999078, China

[2] Faculty of Languages and Translation, Macao Polytechnic University, R. de Luís Gonzaga Gomes, Macao 999078, China

[3] Shanghai Jiao Tong University, 800 Dongchuan Road, Shanghai 200240, China

[4] Shandong Province Key Laboratory of Medical Physics and Image Processing Technology, School of Physics and Electronics, Shandong Normal University, 1 University Road, Jinan 250358, Shandong, China

[5] Department of Electrical Engineering, Eindhoven University of Technology, Postbus 513, Eindhoven 5600 MB, Nederland

[6] Department of Radiology, Shenzhen People's Hospital, 1017 Dongmen North Road, Luohu District, Shenzhen 518001, Guangdong, China