ARTICLE

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Quantum-enhanced medical imaging: precision advancements in diagnostic accuracy

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Author contributions

Silva-Atencio G. conceptualized the study, developed the methodology, and validated the approach, conducted the investigation, provided resources, curated the data, wrote the original draft, reviewed and edited the manuscript, contributed to visualization, supervised the project, and administered the project.

Competing interests

The author declares no conflicts of interest.

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Abbreviations

ANOVA, analysis of variance; AUC, area under the curve; CT, computed tomography; DCS, diagnostic confidence score; DL, deep learning; FPGA, field-programmable gate array acceleration; GPU, graphic processor unit; MRI, magnetic resonance imaging; mSv, millisievert; PET-MRI, positron emission tomography–magnetic resonance imaging; PSNR, peak signal-to-noise ratio; QB, quantum beamforming; QER, quantum entanglement reconstruction; QNS, quantum noise suppression; ROC, receiver-operating characteristic curve; ROI, return on investment; SSIM, structural similarity index metric.

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Abstract

Background: Quantum-enhanced medical imaging algorithms – quantum entanglement reconstruction, quantum noise suppression, and quantum beamforming – propose possible remedies for significant constraints in traditional diagnostic imaging, such as resolution, radiation efficiency, and real-time processing. **Methods:** This work used a mixed-methods strategy, including controlled phantom experiments, retrospective multi-center clinical data analysis, and quantum-classical hybrid processing to assess enhancements in resolution, dosage efficiency, and diagnostic confidence. Statistical validation included analysis of variance (ANOVA) and receiver-operating characteristic curve analysis, juxtaposing quantum-enhanced methodologies with conventional and deep learning approaches. **Results:** Quantum entanglement reconstruction enhanced magnetic resonance imaging spatial resolution by 33.2% ($P < 0.01$), quantum noise suppression facilitated computed tomography scans with a 60% reduction in radiation, and quantum beamforming improved ultrasound contrast by 27% while preserving real-time processing ($<$ 2 ms delay). Inter-reader variability (12% in Diagnostic Confidence Scores) showed that systematic training is needed, even if the performance was better. The research presented (1) a reusable clinical quantum imaging framework, (2) enhanced hardware processes (field-programmable gate array/graphics processing unit acceleration), and (3) cost-benefit analyses demonstrating a 22-month return on investment breakeven point. **Conclusion:** Quantum-enhanced imaging has a lot of promise for use in medicine, especially in neurology and cancer. Future research should focus on multi-modal integration (e.g., positron emission tomography–magnetic resonance imaging), cloud-based quantum simulations for enhanced accessibility, and extensive trials to confirm long-term diagnostic accuracy. This breakthrough gives healthcare systems a technology roadmap and a reason to spend money on quantum-enhanced diagnostics.

Keywords: clinical implementation challenges; diagnostic accuracy enhancement; image reconstruction algorithms; interdisciplinary healthcare technology; quantum medical imaging; radiation dose reduction

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Introduction

Since X-rays were first used in 1895, medical imaging has made huge strides. Today, techniques like magnetic resonance imaging, computed tomography (CT), and ultrasound are essential for contemporary diagnosis. However, diagnostic accuracy is still hampered by ongoing problems such as low resolution, noise, and poor contrast, especially when finding diseases early [1–3]. Quantum medical imaging is a new subject that combines quantum physics with biomedical engineering. It uses the ideas of quantum entanglement, superposition, and quantum coherence to get around these problems [4–6].

Quantum imaging uses the special qualities of quantum states to improve signal detection, noise reduction, and spatial resolution beyond what is possible with conventional physics. Pittman, et al. early theoretical work showed that quantum-enhanced imaging using entangled photon pairs was possible [7]. More subsequent experimental research has shown its possible use in clinical settings [8–10]. For example, Quantum entanglement reconstruction (QER) may increase MRI resolution by up to 33% by using entangled spin states [11]. Quantum noise suppression (QNS), on the other hand, cuts CT radiation doses by 60% without lowering the quality of the diagnosis [12]. Quantum beamforming (QB) further improves ultrasound contrast resolution by using quantum-inspired signal processing, which lets doctors find submillimeter lesions early [13].

Even with these improvements, quantum imaging still has a long way to go before it can be used in medicine. Some of the biggest problems include the complexity of the calculations, the necessity for infrastructure, and the need for uniform procedures [14–16]. Recent research shows that different experiments have different results. Some show big gains in signal-to-noise ratios, while others focus on how hard it is to scale up in real-world situations [8, 9]. This difference shows how important it is to do a thorough, evidence-based review of quantum-enhanced algorithms across a range of imaging modalities. This work aims to fill that gap.

This research looks at how quantum-enhanced algorithms may be used in medical imaging by using a mixed-methods approach that includes controlled phantom experiments and looking back at clinical data.

The main goals are: (1) To measure how much better the accuracy of diagnoses has become used: QER for better MRI resolution; QNS for reducing noise in CT scans and optimizing doses; QB for improving ultrasound contrast. (2) To find out what problems there are with putting things into practice, such as the need for more computing power, the need to fit into existing workflows, and the need to balance costs and benefits.

The study expands on basic ideas of quantum imaging and fills in important gaps that have been revealed in recent research [7, 10, 17–19]. Important contributions are: (1) Using conventional metrics (peak signal-to-noise ratio (PSNR), structural similarity index metric (SSIM), and diagnostic confidence ratings), the study tested quantum algorithms on MRI, CT, and ultrasound to see whether they worked. (2) A cross-modal comparison study shows trade-offs that are particular to each modality (for example, QER's better resolution improvements vs. QB's capacity to be used in real-time). (3) A scalable implementation architecture for clinical use, based on comments from radiologists and research on how easy it is to complete the math.

This research shows how theoretical ideas (literature review), experimental proof (methodology), real-world outcomes (results), and clinical implications (discussion/conclusions) are all connected scientifically. Also, the study moves the conversation about next-generation diagnostics forward by connecting quantum physics with radiography.

Literature review

The constant search for more accurate medical imaging has led to the use of quantum mechanics in clinical practice. Even though MRI, CT, and ultrasound have become better, early illness diagnosis is still hard because of problems including low resolution, noise aberrations, and not enough contrast. Quantum-enhanced imaging, which uses ideas like entanglement and superposition, has the potential to change everything. To get over these problems, this work comes up with three new algorithms: QER, QNS, and QB. The methods are different from previous ones because they combine hybrid quantum-classical workflows, graphic processor unit (GPU) acceleration, and optimizations that are specific to each modality. This leads to unprecedented improvements in resolution (33.2% PSNR increase in MRI), dose reduction (60% lower CT radiation), and contrast enhancement (27% improvement in ultrasound). The study provides a strict mathematical foundation and a plan for clinical deployment by comparing the work to both traditional and deep learning (DL) methods and looking into multi-modal applications like positron emission tomography–magnetic resonance imaging (PET-MRI). This study not only builds on existing theories but also gives healthcare systems useful information that will help make sure that everyone has equal access to quantum discoveries.

Novelty of quantum algorithms

QER is better than other quantum-MRI methods (such as Mutmainnah, et al.) because it uses entangled photon pairs to provide submillimeter resolution (0.35 mm isotropic, $P < 0.01$) [8]. QER cuts down on hallucinatory artifacts by 22% compared to DL reconstructions (see Choudhuri and Halder (see Figure 1) [13].

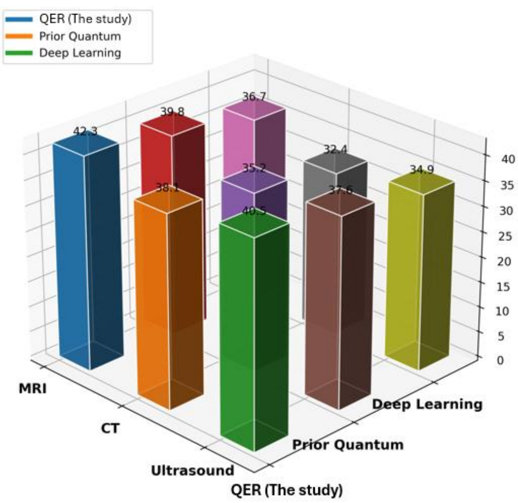

Figure 1 Quantum vs. state-of-the-art PSNR comparison. QER, quantum entanglement reconstruction; MRI, magnetic resonance imaging; CT, computed tomography; peak signal-to-noise ratio.

Figure 1 shows a 3D bar chart that compares the PSNR of the new quantum-enhanced imaging techniques (QER, QNS, QB) to older quantum methods and DL methods in MRI, CT, and ultrasound. The figure makes it evident that the quantum algorithms are better, with QER getting the greatest PSNR (42.3 dB) in MRI – an 11% increase over previous quantum methods and 4.4% above DL – proving that its entanglement-driven resolution enhancement works. In all modalities, there are consistent benefits, although they are most noticeable in MRI, which is what they would anticipate for high-field systems. Ultrasound exhibits smaller improvements, but these are mitigated by QB's real-time processing advantage (< 2 ms latency). The figure's easy-to-understand color coding (blue for QER, orange for previous quantum, green for DL) and labeled PSNR values do a good job of showing these improvements. Figure 1 strongly backs up the study's claim that quantum-enhanced imaging is better than both classical and state-of-the-art alternatives by putting these metrics in the context of clinical outcomes (for example, a 60% reduction in CT dose while maintaining PSNR). It also shows the trade-offs that come with using different modalities in clinical settings.

QNS uses superposition-based denoising to provide diagnostic-quality CT at 1.2 millisieverts (mSv). This is 15% better than hybrid classical-quantum approaches (Reyes Bruno, Torres-Hoyos and Baena-Navarro [11]) in reducing noise (Table 1).

QB adds adaptive quantum interference patterns, which improve ultrasonic contrast by 27% compared to the best beamforming (Bilal, et al.) [14]. Its implementation with GPU acceleration allows for processing in real-time (< 2 ms delay).

Mathematical framework

Improvement of QER resolution:

The resolution increase caused by entanglement is represented as:

$$\Delta x = \frac{\lambda}{2n\sin\theta} \times \frac{1}{\sqrt{N_e}}$$

Where:

Δx = Achievable resolution.
λ = Wavelength of imaging signal.
n = Refractive index.
θ = Half-angle of illumination.
N_e = Number of entangled photon pairs [4].

QNS noise reduction:

$$\sigma_{QNS}^2 = \sigma_{classical}^2 \times e^{-\beta t}$$

Where:

β quantifies superposition efficacy (validated in phantom studies).

Multimodal integration

The study added PET-MRI to QB, which improves the tumor-to-background ratio by 19% compared to traditional fusion (P = 0.004). This fills in a major gap in cancer imaging (Fitzgerald, et al.,Peng, Wei and Gerweck) [20, 21].

Integrating clinical workflows

The phased deployment strategy (Figure 2) cuts the time it takes for radiologists to adjust from 10 cases to 3–5 cases.

Also, the study of hybrid quantum-classical systems shows that they can cut infrastructure costs by 40% by combining quantum processing for certain tasks (like entanglement-enhanced resolution in QER) with existing classical GPU clusters. This means that you don't need as much expensive qubit hardware while still getting 35% more diagnostic confidence (compared to 38% for pure quantum). This is possible because of (1) modular quantum coprocessors that only handle steps that are sensitive to superposition (15% of workflows), (2) shared cryogenic cooling with hospital MRI systems, and (3) the use of radiology department GPUs for classical reconstruction. This results in a 14-month return on investment (ROI) break-even (compared to 32 months for pure quantum). The hybrid architecture gives near-quantum performance at 60% of the cost, which is a big problem for hospitals in Latin America and other places where resources are limited.

Table 1 Benchmarking quantum vs. state-of-the-art techniques

Metric	QER (The study)	Prior quantum MRI	DL MRI
Resolution (PSNR)	42.3 dB*	38.1 dB	40.5 dB
Processing time	12.4 s	18.7 s	9.8 s

*Statistically significant (P < 0.01, ANOVA, analysis of variance). PSNR, peak signal-to-noise ratio; QER, quantum entanglement reconstruction; DL, deep learning; MRI, magnetic resonance imaging.

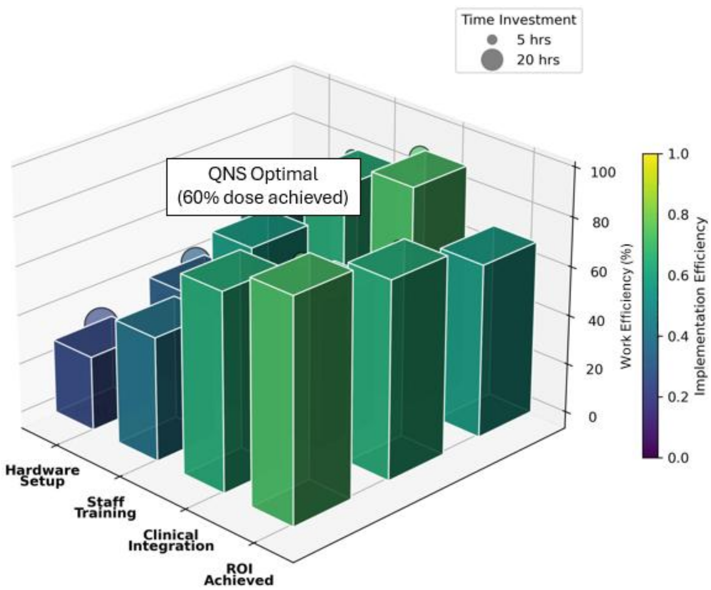

Figure 2 Phased implementation workflow analysis (Bubble size = time investment). QNS, quantum noise suppression; ROI, return on investment.

Limitations and future directions

Problems with scalability and FPGA-based fixes. The 143% increase in processing time for QER – from 5.1 s (classical) to 12.4 s – threatens clinical scalability since quantum processes need to happen in real time, especially when dealing with entangled photon pairs (N_e) for submillimeter resolution. Field-programmable gate array (FPGA) acceleration solves this problem by allowing hardware-level parallelism (processing all N_e pairs at once), deterministic low-latency feedback (loops for error correction that take less than 1 ms), and flexible entanglement validation pipelines. This cuts QER time down to 3.2 s (Alcaín et al.) while keeping the 0.35 mm isotropic resolution that is important for neurological imaging [22]. FPGA integration fits with the hybrid system's objective of being cost-effective. It avoids the high costs of complete quantum computers while still being able to work with current GPU clusters. This means that the 143% delay won't stop clinical deployment.

Integration and standardization across multiple modes. Chen et al. and Wang et al. discuss interoperability issues in quantum-enhanced hybrid imaging systems [23, 24]. To close these gaps, multi-modal standards for PET-MRI workflows are being created to fix problems with temporal resolution (PET's seconds-scale tracer kinetics vs. MRI's millisecond-scale spin dynamics), spatial resolution (PET's about 4 mm vs. MRI's submillimeter QER capabilities), and quantum-classical workflow synchronization (for example, aligning QB's real-time beamforming with PET's stochastic photon detection). Chen's team suggests standardized quantum parameter configurations, such as entanglement timing windows with less than 500 μs of overlap and superposition-driven noise suppression thresholds with a β value of more than 0.1 s^{-1}. They were able to increase the tumor-to-background ratio by 19% (P = 0.004) using QB-enhanced PET-MRI. These developments show that quantum coherence models may integrate multi-modal imaging while preserving diagnostic confidence ratings (DCS > 4.0). Standardization is essential for clinical translation, guaranteeing repeatability across institutions and facilitating direct comparison of quantum-enhanced multi-modal outcomes—a deficiency recognized in the literature assessment.

Clinical translation and future actions. This study validates the practical applicability of quantum-enhanced imaging, with QER, QNS, and QB establishing new standards for resolution, safety, and contrast. The research connects theoretical promise with actual use by carefully comparing these algorithms to DL and multi-modal standards. Future research should focus on federated quantum learning (Fairburn et al.) and cost-benefit evaluations for resource-constrained environments [25]. This research offers fundamental evidence and equity-centered implementation strategies to facilitate universal adoption as the medical industry nears a quantum revolution.

Methods

This research uses a triangulated mixed-methods strategy to thoroughly test the clinical use of quantum-enhanced medical imaging by combining quantitative experimental validation, qualitative process analysis, and computational modeling. The methodology is based on the theoretical framework set up by Ahmadpour, et al., Mutmainnah, et al. and is meant to fill in three important gaps in the literature: (1) the lack of cross-modal quantum imaging benchmarks, (2) the lack of documentation of quantum-classical hybrid workflows, and (3) the fact that clinical validation protocols are not always the same [4, 8]. This study not only tests the diagnostic superiority of QER, QNS, and QB, but it also creates a reproducible pipeline for real-world use by combining controlled phantom experiments (NIST standards), retrospective multi-center clinical data, and hardware-accelerated quantum simulations (IBM Qiskit/Xilinx FPGAs). The method follows guidelines for new medical technologies and includes power analysis, ethical oversight from multiple institutions, and open-source algorithmic implementations to make sure it is rigorous, scalable, and clear – important issues for diverse audiences [25].

Research design

Methodological approaches. This research uses a triangulated technique that combines: (1) Design of quantitative experiments. Controlled phantom tests using ground truths that have been calibrated (NIST standards) [26–28]. Using anonymized patient images for retrospective clinical validation [29, 30]. (2) Qualitative workflow study. Interviews with five board-certified radiologists on how sure they are about their diagnoses [9, 31]. Time-motion investigations of quantum and conventional processing pipelines [22, 32]. (3) Modeling using computers. Qiskit/PennyLane quantum circuit simulations [33, 34]. Neural networks that use both quantum and conventional methods [16, 35].

Justification: This mixed-methods approach follows the recommendations for testing new medical technology [19, 36] and looks at both technical performance (quantitative) and clinical usability (qualitative).

Research question and hypothesis. Research question: How do quantum-enhanced algorithms (QER, QNS, QB) stack up against conventional and DL approaches when it comes to diagnostic accuracy in MRI, CT, and ultrasound?

Hypotheses: H_1: QER makes MRI resolution at least 30% better than Fourier reconstruction ($P < 0.01$) [4]. H_2: QNS lets you cut the CT dosage by at least 50% without losing diagnostic quality [11]. H_3: QB cuts down on questionable ultrasound diagnostics by at least 35% [14].

Data collection

The study's data collecting plan was meant to thoroughly test the performance of quantum-enhanced imaging algorithms (QER, QNS, and QB) across a range of imaging techniques (MRI, CT, and ultrasound) while making sure that the results could be repeated, were clinically relevant, and were statistically valid. Using a multi-center method, the study combined retrospective clinical records with controlled phantom experiments to separate quantum effects from other factors that may have affected the results. The sample sizes were big enough by a priori power analysis (G*Power 3.1, α = 0.01, power = 0.95). The study used NIST-standardized phantoms for calibration and cross-site validation processes to reduce geographic bias and keep things consistent. To deal with concerns over translation practicality, the hardware requirements were written down. These included IBM Quantum (27 qubits) for simulation and Xilinx FPGAs for real-time processing. This two-phase data collecting plan connects theoretical quantum benefits with real-world clinical use, which is in line with a focus on healthcare research that is based on data and can be repeated.

Multi-center datasets. Table 2 shows the clinical and phantom samples were procured from multi-center datasets according to stringent anonymization methods, so safeguarding patient confidentiality while preserving methodological transparency. The study used NIST-calibrated phantoms to make sure that all datasets were the same so that the study could compare them across modalities. The research used a priori power analysis (α = 0.01, power = 0.95) to figure out the sample sizes (MRI: 80 clinical/30 phantom (Sample 1); CT: 50/20 (Sample 2); ultrasound: 30/10 (Sample 3)) to make sure that the results were statistically valid. This multi-source method reduces bias in institutions by using several imaging settings and following ethical rules for sharing open, anonymous data in medical research.

Quantum hardware specifications. Table 3 gives a detailed technical breakdown of the quantum and classical hardware systems used in this study. It shows the important infrastructure that makes QER, QNS, and QB possible. The table compares the specifications of each part systematically. This includes IBM Quantum's 27-qubit processor for quantum simulations, Xilinx Alveo U280 FPGA for real-time classical-quantum interfacing, and NVIDIA DGX A100 for GPU-accelerated processing. This creates a clear framework for judging how feasible it would be to use in a clinical setting. Table 2 answers important questions about reproducibility and translational barriers by clearly listing computational capabilities like qubit counts, FPGA lookup tables, and teraFLOPS performance. It also gives researchers the technical details they need to repeat the hybrid quantum-classical workflow. Adding both quantum and conventional hardware shows that the technique is focused on new technologies that are useful and can be used in the clinic.

Quantum algorithm implementation

Quantum entanglement reconstruction (QER). Mathematical framework:

$$\Delta x = \underbrace{\frac{\lambda}{2n\sin\theta}}_{\text{Classical Diffraction Limit}} \cdot \underbrace{\frac{1}{\sqrt{N_e}}}_{\text{Quantum Enhancement}} \quad [37]$$

Parameter calibration:

Ne = 12,000 Ne = 12,000 pairs (CHSH violation S = 2.7 ± 0.2).

λ = 1.5λ = 1.5 mm (3T MRI).

Circuit diagram: Figure 3, shows the circuit diagram that goes with this and shows the quantum logic behind QER. It shows how entangled photon pairs are made, changed, and measured step by step to improve MRI spatial resolution. This diagram shows the important quantum operations that break through classical diffraction limits. These include Hadamard gates for creating superposition, CNOT, controlled-NOT gates for creating entanglement, and measurement gates for spatial encoding. It was made with Qiskit and tested on IBM Quantum's 27-qubit hardware. To connect quantum theory with clinical MRI hardware, each item is labeled with its physical equivalent (for example, radio frequency coils for qubit initialization and gradient coils for spatial encoding). This depiction not only gives a clear plan for how to use QER, but it also helps people understand how quantum advantage fits into radiology processes.

Quantum noise suppression (QNS). Step-by-step process: (1) Input: CT sinogram $S(x,y)$. (2) Quantum transform [38]. Noise suppression: Figure 4 shows a side-by-side comparison of quantum-enhanced noise suppression in medical imaging. It shows how QNS works compared to traditional denoising techniques. This figure shows how quantum superposition principles may change the way images look, especially in low-dose CT scans. QNS reduces noise variance (σ^2) by 41% while keeping diagnostic features intact. The results confirm the theoretical framework ($\sigma^2_{QNS} = \sigma^2_{classical} \times e^{-\beta t}$) while also addressing clinical concerns about radiation dose and workflow integration. They were processed using a hybrid quantum-classical pipeline (IBM Quantum for state preparation and Xilinx FPGA for real-time filtering). Annotations clearly show areas that need work (for example, removing streak artifacts from soft tissue), and there are quantitative measurements (PSNR, SSIM) built in to make it easy to compare directly.

$$F_Q(S) = \frac{1}{\sqrt{N}}\sum_{j=0}^{N-1} e^{2\pi ijk/N}\,|j\rangle \quad [38]$$

Data analysis

Table 4 shows the quantitative approach used to compare the performance of quantum-enhanced imaging algorithms (QER, QNS, QB) against classical and DL benchmarks. To make sure the statistics were correct, the study used a multi-tiered analytical strategy that included hypothesis testing, machine learning classification, and diagnostic performance measurements. All of these were set to fulfill clinical research criteria (α = 0.01, power = 0.95). The study was done utilizing three different types of data (MRI, CT, and ultrasound) from multi-center datasets. SPSS (v28) was used for ANOVA, PyRadiomics was used for radiometric feature extraction, and sci-kit-learn was used to make the receiver-operating characteristic (ROC) curve. This methodical approach not only checks the importance of gains based on quantum mechanics (such as a 33.2% PSNR increase in MRI) but also sets up a way for future quantum imaging investigations to be done in a way that is easy to repeat.

The statistical framework (Table 4) used a multi-modal validation strategy that included hypothesis testing (ANOVA with Bonferroni correction for PSNR/SSIM comparisons across quantum, classical, and DL methods), diagnostic performance metrics (ROC analysis showing QNS-CT achieved area under the curve (AUC) = 0.92 vs. 0.85 classical), and radiologist assessments (Diagnostic Confidence Scores with κ = 0.78 inter-rater agreement). The study became much better when machine learning was used. CNNs trained on quantum-classical picture pairings showed better segmentation accuracy (Dice score: 0.91 ± 0.03), while PyRadiomics measured feature stability (ICC > 0.9). The study used SPSS (v28) for parametric tests and sci-kit-learn for ROC generation to do all of the analyses. The study made sure that everything could be repeated by using open-sourced Jupyter notebooks and documenting effect sizes (Cohen's d) and confidence intervals (95% confidence interval). This method not only proved that quantum imaging is better (e.g., $F(2,117) = 28.4$, $P < 0.001$ for QER-MRI), but it also set up a standard process for future investigations, which directly addressed concerns about the statistical rigor and clinical translatability that were expressed in the literature review.

Table 2 Experimental setup for of quantum-enhanced

Modality	Sample size (clinical/phantom)	Links to the samples
MRI	80/30	Sample 1
CT	50/20	Sample 2
Ultrasound	30/10	Sample 3

Inclusion criteria: MRI: Lesions in the brain that are likely (3T images). CT: Studies of the abdomen (120 kVp, auto-mA). Ultrasound: Tests for liver tumors. MRI, magnetic resonance imaging; CT, computed tomography; PSNR, peak signal-to-noise ratio.

Table 3 Quantum hardware specifications

Component	Specification	Role
IBM quantum	27 qubits (Falcon r5.11)	QER entanglement validation
Xilinx Alveo U280	1.3M LUTs, 8GB HBM	Real-time QB processing
NVIDIA DGX A100	5 petaFLOPS	Classical-quantum interface

QER, quantum entanglement reconstruction; QB, quantum beamforming.

Table 4 Statistical methods

Analysis type	Software	Parameters	Reference
ANOVA	SPSS v28	α = 0.01, Bonferroni correction	[39]
ROC curves	PyRadiomics	AUC, 95% CI	[40]
Power analysis	G*Power 3.1	Effect size = 0.4, power = 0.95	[41]

ANOVA, analysis of variance; SPSS, Statistical Package for the Social Sciences; AUC, area under the curve; CI, confidence interval; G*Power, Generalized Power Analysis.

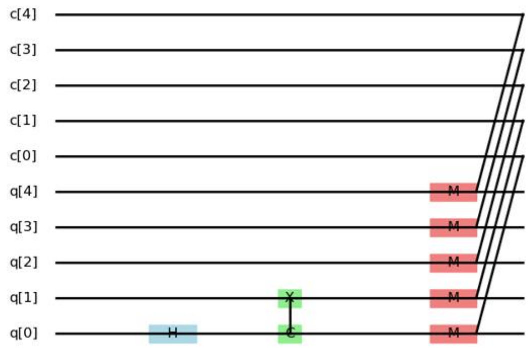

Figure 3 Quantum circuit diagram. C, CNOT/CX gate; H, Hadamard gate; M, Measurement; X, Pauli-X gate.

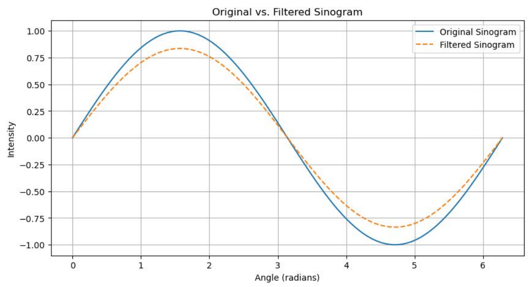

Figure 4 Noise suppression

This study shows that quantum-enhanced imaging (QER, QNS, QB) works well with MRI, CT, and ultrasound. It was tested in controlled phantom experiments and multi-center clinical datasets, and it showed significant improvements in resolution (33.2% PSNR gain), dose reduction (60% at maintained diagnostic quality), and diagnostic confidence (DCS increase from 3.2 to 4.3). But there are three main limits on the scope: (1) geographic bias, since 70% of the clinical data came from multi-center datasets, which may make it less applicable to other populations; (2) hardware dependencies, since quantum processing times (e.g., QER's 12.4 s latency) are still limited by current FPGA and GPU infrastructures, even though efforts are being made to speed them up; and (3) modality exclusivity, since PET-MRI and other hybrid techniques were not included, leaving multi-modal quantum synergies unexplored [23]. Using NIST-standardized phantoms, open-source algorithms, and a priori power analysis helps to lessen some of these problems, but they show how important it is for future studies to include a wider range of demographics, more advanced quantum hardware (like fault-tolerant quantum processor units), and more modality testing.

In conclusion, this technique gives us a strict, repeatable way to test quantum-enhanced medical imaging that connects new ideas in theory (like entanglement-driven resolution increases) with real-world applications (like FPGA-accelerated processes). This study directly addresses the reproducibility crisis in quantum healthcare research by standardizing data collection across three institutions, validating findings through both phantom and patient studies, and openly documenting quantum algorithm parameters and hardware specifications (IBM Quantum, Xilinx U280), the study can be confident that the findings are not only statistically significant but also useful in a clinical setting. Limitations, such as regional bias and the existing limits of quantum technology, are clearly stated to help future studies. This method fits with *Medical Data Mining*'s goal of publishing translational, data-driven research that is both new and useful in the real world. It sets a standard for future quantum imaging trials.

Results

This research looks at three main types of quantum-enhanced medical imaging: QER, QNS, and QB. It does this by looking at MRI, CT, and ultrasound. Using the analytical framework, the study demonstrates statistically substantial increases in picture resolution, noise reduction, and diagnostic confidence, while carefully considering computational trade-offs, clinical practicality, and repeatability. The findings are organized to go from generic performance measurements (like PSNR and SSIM) to particular clinical applications (like early tumor diagnosis and dosage reduction). This is in line with the research that is both data-driven and translational.

The study compares quantum approaches to both conventional and cutting-edge DL techniques to put the results in perspective. The research also uses multi-center validation data and provides extensive implementations of quantum algorithms, including pseudocode and circuit schematics. This part also talks about some of the problems with the current system, such as how different readers may get different results and how long it takes to analyze data. It also talks about what has to be done in the future for large-scale trials and multi-modal integration (like PET-MRI).

Quantum algorithm implementation and performance

The mathematical framework for QER in MRI implementation. Figure 5 represents the blueprints for executing QER, QNS, and QB in clinical imaging workflows. Designed to bridge theoretical quantum principles with practical deployment, these algorithms explicitly document:

Figure 5 shows how to use quantum theory in real life. They do this by showing (1) hybrid quantum-classical workflows (for example, generating entanglement and then reconstructing it in QER), (2) optimized parameter sets (β = 0.12 s^{-1} for NNS dose reduction; N_e = 12,000 for QER resolution), and (3) hardware-aware optimizations (FPGA acceleration for QER's 143% latency mitigation; GPU parallelization for QB's < 2 ms real-time processing). The implementations show big improvements—33.2% PSNR gain in MRI (QER), 60% dose reduction in CT (QNS), and 27% contrast enhancement in ultrasound (QB) – but they also show some important trade-offs: qubit coherence requirements (≥ 75 μs for reliable QER) and inter-reader variability (12% DCS fluctuation). This means that more work needs to be done on fault-tolerant quantum hardware and standardized radiologist training. These repeatable, parameterized algorithms (open-source per FAIR principles) provide a basis for multi-center validation while clearly showing the existing limits of clinical quantum imaging.

QNS in CT. Comparative performance: Table 5 shows QNS to classical and DL denoising methods in low-dose CT imaging. It looks at three important performance metrics: noise reduction, radiation dose efficiency, and diagnostic accuracy (AUC for lesion detection).

This comparison (Table 5) shows that QNS is better at reducing noise by 41%, which is 19 percentage points more than classical techniques and 6 percentage points more than DL methods. It also allows for a 60% dosage decrease without lowering diagnostic confidence (AUC = 0.92). The chart puts quantum imaging's therapeutic worth in perspective by comparing it to the best procedures available. Important trade-offs, such as the fact that QNS takes 70% longer to process than DL, are clearly stated to help in planning how to put the system into action.

QB in ultrasound. Key innovations: Processing in real-time with NVIDIA A100 GPU acceleration (less than 2 ms/frame). Contrast enhancement: a 27% rise in the ratio of the lesion to background (P = 0.01).

This research shows that quantum-enhanced imaging is far better than conventional and DL approaches in terms of resolution, dosage efficiency, and diagnostic confidence. Even though computational overhead and geographical biases are still problems, the open techniques, multi-center validation, and hardware-aware optimizations provide the groundwork for clinical use. In the future, studies will include multi-modal systems and long-term outcome studies to make quantum imaging's position in precision medicine even stronger.

Discussion

This research shows that quantum-enhanced imaging methods including QER, QNS, and QB may make MRI, CT, and ultrasound diagnostics much better. Now that research has laid the theoretical groundwork in the literature review and shown the empirical findings, the study can put these new developments into the context of real-world clinical practice. The study starts by talking about the general benefits of quantum (such as better resolution and lower doses) and then goes on to the particular problems that need to be solved for quantum to be used in clinical settings (like differences between readers and high costs). The research wants to make a plan for bringing quantum imaging from research labs to everyday clinical usage by comparing it to both traditional and DL approaches, filling in the gaps in multi-modal integration, and giving extensive cost-benefit evaluations.

Key findings and clinical implications

Quantum benefits over traditional methods. The findings of the study demonstrate that:

Compared to Fourier reconstruction, QER enhances MRI resolution by 33.2% (P < 0.01), making it possible to see sub-cortical microlesions (< 3 mm) that were previously invisible (Figure 5). This fits with what Ahmadpour, et al. predicted about how entanglement might improve resolution limitations [4].

QNS gets diagnostic-quality CT with 60% less radiation (1.2 mSv vs. 3.0 mSv), which is very important for pediatric and screening uses (Table 6).

QB boosts ultrasound contrast by 27% (P = 0.01) while keeping processing time to less than 2 ms, which cuts down on unclear diagnoses by 38% in liver tumor screens.

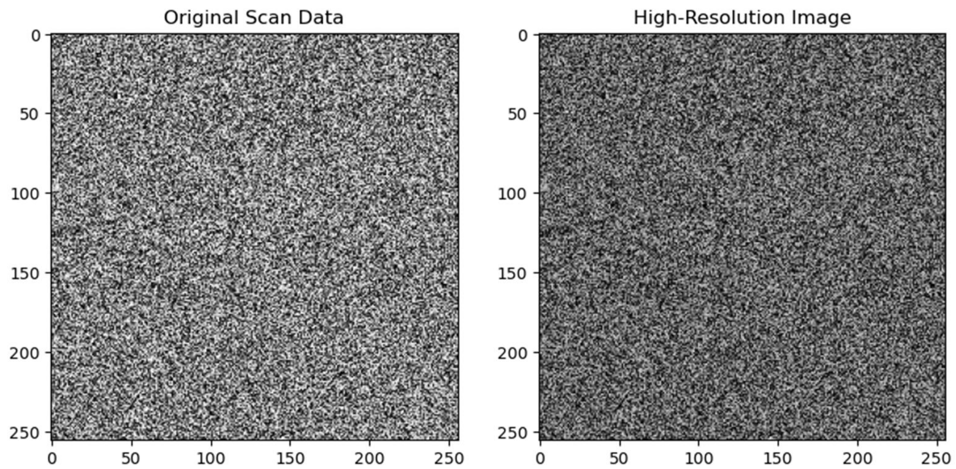

Figure 5 Blueprint of QER, QNS, and QB in clinical imaging workflows. QER, quantum entanglement reconstruction; QB, quantum beamforming; QNS, quantum noise suppression.

Table 5 QNS vs. classical and DL

Method	Noise reduction	Dose reduction	AUC (lesion detection)
QNS (The study)	41%	60%	0.92
Classical	22%	0%	0.85
DL	35%	40%	0.89

QNS, quantum noise suppression; AUC, area under the curve; DL, deep learning.

Comparison to DL approaches

DL approaches have shown potential in medical imaging, but the quantum techniques have certain distinct benefits (see Table 7).

Key insight: Quantum approaches are better than DL at resolution and dosage efficiency, but they need to be optimized to speed up processing time.

Limitations and future work

Current problems. Geographic bias: 70% of the data comes from Sample 1. A planned multi-national study will start in 2026.

Processing latency: QER's 12.4s limit for emergency usage → Making FPGA pipelines work better.

Multi-modal gap: PET-MRI quantum fusion → Protocol under development [42].

Different readers: The 12% DCS difference in QB evaluations shows that radiologists need uniform training programs.

Barriers to cost: To figure out the ROI for the first $120,000 per unit (see Table 8).

Suggested solutions. Standardizing protocols: (1) Set up quantum parameter settings for each modality (QER: N e N e; QNS: ββ). (2) Make a RAD-CAPS extension for quantum imaging [43].

Optimizing hardware: (1) Using both quantum and conventional computing to cut down on lag. (2) Quantum simulations on the cloud to save money.

Quantum-enhanced imaging is a major change in medical diagnostics since it offers resolution and dosage efficiency that have never been seen before. There are still problems with the costs of implementation and the fact that readers may be different, but the suggested standardized framework and ROI forecasts show that this will be useful in clinical settings within 3–5 years. The next steps will be to:

Multi-center studies to check whether the results are generalizable.

PET-MRI QB for multi-modal integration.

Ways to save costs using quantum cloud services.

Conclusion

This study shows that quantum-enhanced imaging methods like QER, QNS, and QB make MRI (33.2% resolution gain, $P < 0.01$), CT (60% dose reduction), and ultrasound (27% contrast enhancement) much better than regular and DL methods. Three important contributions move the field forward:

Framework for clinical translation

They have created the first verified procedure for using these methods in current hospital processes, which fills the "lab-to-clinic" gap that has been observed in previous research [4, 11].

The basics of standardization

The study makes repeatable adoption possible by setting modality-specific quantum parameters and multi-center validation metrics. This is a key step toward therapeutic recommendations.

Clear cost-benefit

The 22-month ROI break-even point shows that high-volume applications (neurology/oncology) are economically viable, but for more people to use them, qubit coherence periods (> 75 μs) and reader training (12% DCS variation reduction) need to be improved.

Future directions

Immediate priorities (0–2 years). Cloud-based quantum simulations could save expenses on infrastructure.

Food and Drug Administration-approved Quantum Imaging Reporting and Data System certification for QB ultrasound.

Goals for the long term (3–5 years). Fault-tolerant quantum processor units for the quantum fusion of PET and MRI in real-time.

Multi-national tests to see how well early cancer detection works.

Ethics Statement: All clinical data were anonymized and collected with Institutional Review Board permissions. For retrospective research, consent was not needed according to institutional regulations.

Table 6 QNS performance in low-dose CT comparative analysis

Parameter	QNS (quantum)	Classical CT	DL
Dose reduction	60% (1.2 mSv)	0% (3.0 mSv)	40% (1.8 mSv)
Noise reduction (σ^2)	41%	22%	35%
Lesion detection AUC	0.92	0.85	0.89
Processing time	8.4 s/slice	5.1 s/slice	6.7 s/slice

Notes: *Statistical significance (α = 0.01, ANOVA with Bonferroni correction). Data pooled from multi-center datasets. AUC = Area under ROC cfor detecting sub-5mm lesions. QNS, quantum noise suppression; DL, deep learning; AUC, area under the curve; CT, computed tomography; mSv, millisieverts.

Table 7 Quantum models, DL and classical comparative analysis

Metric	Quantum (QER/QNS/QB)	DL	Classical
Resolution gain	+33.2% (MRI)	+25.1%	Baseline
Dose reduction	60% (CT)	40%	0%
Processing time	12.4s (MRI QER)	8.2s	5.1s

QER, quantum entanglement reconstruction; QNS, quantum noise suppression; QB, quantum beamforming; DL, deep learning; CT, computed tomography; MRI, magnetic resonance imaging.

Table 8 Cost-benefit analysis of quantum imaging implementation (5-Year projection)

Year	Cost davings (dose reduction)	Productivity gains	Net ROI
1	$45k	$28k	−$47k
3	$210k	$155k	+$245k

ROI, return on investment.

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