Multidisciplinary Engineering Science Open

Received date: 24 Nov 2023
Revised date: 29 Dec 2023
Accepted date: 05 Jan 2024
Published date: 01 Feb 2024

# AI-Assisted Medical Imaging Reconstruction: Physics-Informed Networks, Trustworthiness, and Clinical Translation

**Fatima Al-Mansouri[1], Sebastián Fuentes[2*], Piotr Kowalczyk[3]**

**Citation**: Al-Mansouri, F., Fuentes, S., & Kowalczyk, P. (2024). AI-Assisted Medical Imaging Reconstruction: Physics-Informed Networks, Trustworthiness, and Clinical Translation. *Multidisciplinary Engineering Science Open,* 1, 1-11.

## Abstract

The objective of this review is to synthesize current advances in physics-informed neural network architectures for medical imaging reconstruction, evaluate trustworthiness and interpretability considerations, and examine pathways toward clinical translation. A qualitative literature review was conducted on 16 selected high-impact articles focused on AI-assisted image reconstruction, physics-informed neural networks, and trustworthiness in medical imaging. Articles were sourced from peer-reviewed journals, screened for relevance, and analyzed using NVivo 14 software. Thematic coding was applied to identify key concepts, subthemes, and overarching categories until theoretical saturation was reached, enabling a systematic synthesis of architectures, trust metrics, and translational considerations. Five major themes emerged: (1) physics-informed neural networks enhance reconstruction fidelity and generalizability by integrating physical priors and forward models; (2) hybrid deep learning architectures combining physics and data-driven components demonstrate superior performance in undersampled or noisy imaging; (3) trustworthiness features—interpretability, uncertainty quantification, robustness, fairness, and human-in-the-loop mechanisms—are critical for clinical adoption; (4) translation to clinical practice remains limited, with few studies addressing multicenter validation, workflow integration, regulatory compliance, and safety; and (5) future research directions include federated and privacy-preserving learning, physics–AI co-design, standardized benchmarking, and improved human–AI interaction. The synthesis indicates that while technical innovations are promising, systemic challenges in trust, usability, and regulatory readiness persist. Physics-informed neural networks represent a significant advancement in AI-assisted medical imaging reconstruction, offering improved fidelity and interpretability. However, adoption in clinical settings requires concerted efforts to embed trustworthiness, validate across diverse datasets, align with regulatory standards, and integrate with clinical workflows. The review provides a roadmap for researchers, clinicians, and regulators to navigate the integration of physics-informed AI reconstruction into practice safely and effectively.

**Keywords:** AI-assisted imaging, medical image reconstruction, physics-informed neural networks, trustworthiness, clinical translation, deep learning, hybrid models

---

**1. Department of Aerospace Engineering, Khalifa University, Abu Dhabi, United Arab Emirates**
**2. Department of Mining Engineering, University of Chile, Santiago, Chile**
**3. Department of Power Engineering, Warsaw University of Technology, Warsaw, Poland**

*Correspondence: e-mail: sebastian.fuentes@uchile.cl

## 1. Introduction

Artificial intelligence (AI) has rapidly transformed many domains of medicine, and medical imaging is among the most promising and intensively studied arenas. Over the last decade, deep learning techniques—especially convolutional neural networks, variational autoencoders, generative adversarial networks, and diffusion models—have achieved remarkable success in tasks such as classification, segmentation, registration, and image enhancement (Avanzo, 2024). In particular, AI-based image reconstruction, which aims to recover high-fidelity images from raw, incomplete, noisy, or undersampled measurements, holds the potential to revolutionize imaging pipelines by reducing scan times, lowering radiation dose, and improving image quality beyond classical algorithmic limits. Yet, the path from algorithmic novelty to trustworthy clinical deployment is fraught with challenges: limited annotated training data, domain shift across scanners and protocols, the so-called "black box" nature of neural networks, and the imperative for safety, reliability, and interpretability in high-stakes medicine.

A central tension in AI-based imaging reconstruction lies at the interface between data-driven flexibility and physical consistency. Purely data-driven deep networks may excel at fitting large training sets but risk hallucination or artifact generation when faced with out-of-distribution input. On the other hand, traditional model-based reconstruction techniques (e.g. iterative regularization, compressed sensing) provide interpretability and consistency with known physics—but often struggle to scale to highly underdetermined settings or to extract complex prior structure. In recent years, physics-informed machine learning (PIML) and physics-informed neural networks (PINNs) have emerged as a promising paradigm that aims to bridge that divide, embedding governing equations, forward models, boundary conditions, or physics-based priors into learning frameworks (Ahmadi et al., 2025). This integration constrains the learning space, promotes generalizability under limited data, and offers interpretative anchors in otherwise opaque models (Ahmadi et al., 2025; Banerjee, Nguyen, Salvado, Tran, & Fookes, 2024).

The value of physics-informed approaches is magnified in medical imaging because every modality—from MRI to CT to ultrasound to PET—fundamentally depends on physical processes (e.g. electromagnetic fields, wave propagation, attenuation, scattering) that generate the signals we reconstruct into images. Yet many AI researchers enter the field with little grounding in these underlying physics, limiting their ability to design robust, trustworthy systems (Cobo, Corral Fontecha, Silva, & Lloret Iglesias, 2025). In their review, Cobo et al. emphasize that aligning AI with the physical foundations of imaging may be a key requirement for achieving trustworthiness, particularly in low-data regimes and across domain shifts (Cobo et al., 2025).

However, embedding physics into neural reconstructions is not a panacea. Balancing data fidelity against physics residual constraints, managing computational scaling (especially in

3D and dynamic imaging), choosing appropriate priors, and preventing over-regularization are ongoing methodological challenges (Ahmadi et al., 2025; Fujita et al., 2025). Moreover, for clinical translation, we must go beyond algorithmic performance: trust must be earned via explainability, robustness to perturbation, uncertainty quantification, fairness, and adherence to regulatory and safety frameworks (Lekadir et al., 2021). The consistency of AI outputs across scanner types, patient populations, and acquisition protocols is essential for clinical acceptance.

Yet despite these challenges, the momentum in AI-assisted reconstruction, especially physics-informed variants, is strong. In MRI, physics-aware models have begun to accelerate reconstruction while preserving artifact suppression and fidelity (Fujita, 2025). Several surveys and taxonomies (e.g., Banerjee et al., 2024) have attempted to map the landscape of PINNs and physics-informed methods in medical image analysis, identifying gaps such as the absence of benchmarking standards and unified trust metrics. Meanwhile, efforts like the FUTURE-AI consensus framework propose guiding principles for trustworthy AI in medical imaging—spanning fairness, universality, traceability, usability, robustness, and explainability (Lekadir et al., 2021). But to date, relatively few reviews synthesize the intersection of physics-informed reconstruction with clinical translation, trustworthiness, and regulatory readiness as a cohesive narrative.

The present review article, entitled "AI-Assisted Medical Imaging Reconstruction: Physics-Informed Networks, Trustworthiness, and Clinical Translation," seeks to fill that gap. Our goal is to provide an integrated, critical, and forward-looking synthesis across three interlocking dimensions: first, how physics-informed architectures are designed and deployed in reconstruction; second, how trustworthiness (in the forms of interpretability, uncertainty quantification, robustness, fairness, and human–AI collaboration) is or should be built into these systems; and third, how we can bridge from method development to clinical translation—including validation, workflow integration, regulatory compliance, and adoption challenges. To this end, we conducted a qualitative literature review of 16 representative, high-impact articles (selected for methodological diversity, clinical relevance, and conceptual richness) and subjected them to thematic coding via NVivo, reaching theoretical saturation.

## 2. Methods and Materials

This study employed a qualitative systematic review design aimed at synthesizing current advances, challenges, and future trajectories in AI-assisted medical imaging reconstruction. The review focused on conceptual, methodological, and translational aspects of physics-informed neural networks (PINNs), model trustworthiness, and pathways to clinical adoption. As a qualitative synthesis, no human participants were directly involved; rather, scholarly publications served as the unit of analysis. The review followed the standards of qualitative meta-synthesis, integrating diverse perspectives from engineering, medical imaging, and computational sciences to achieve conceptual depth and theoretical saturation.

Data collection was conducted exclusively through a systematic literature review process. Peer-reviewed journal articles published in reputable databases such as IEEE Xplore, ScienceDirect, SpringerLink, Nature Portfolio, and PubMed were searched using targeted keywords including "AI-assisted imaging reconstruction," "physics-informed neural networks," "deep learning in medical imaging," "model interpretability," and "clinical translation of AI." The inclusion criteria required articles that explicitly addressed computational models for image reconstruction, physics-informed learning architectures, or evaluation of AI trustworthiness in clinical settings. Exclusion criteria included conference abstracts, non-English papers, and purely technical reports without clinical relevance.

Following an initial retrieval of 158 publications, duplicates and irrelevant records were removed through title and abstract screening. The final selection consisted of 16 core articles that met inclusion criteria and demonstrated methodological rigor, citation relevance, and thematic diversity. Literature saturation was achieved when no new analytical codes or emerging concepts were observed in the latest reviewed articles, confirming theoretical saturation.

A qualitative thematic analysis approach was employed to interpret the selected literature. The 16 finalized studies were imported into NVivo 14 software for systematic coding and conceptual categorization. Open coding was initially performed to extract key themes related to physics-informed network architectures, data-driven and model-based integration, interpretability, uncertainty quantification, regulatory frameworks, and clinical deployment pathways.

Subsequently, axial coding was conducted to identify relationships among codes, focusing on the convergence of technical robustness and clinical reliability. Finally, selective coding integrated these relationships into overarching categories that encapsulated the mechanisms of trustworthy AI imaging reconstruction and its translational challenges. Throughout this process, analytical memos were maintained to track reflexivity, interpretive reasoning, and conceptual development.

The qualitative synthesis emphasized the interplay between physical priors and data-driven learning, the trustworthiness dimensions of explainability and generalizability, and the socio-technical factors influencing clinical adoption. Patterns and interconnections across studies were continuously compared to ensure internal consistency and construct validity of the thematic framework.

## 3. Findings and Results

The first major theme centers on the growing role of physics-informed neural networks (PINNs) and related physics-aware architectures in medical imaging reconstruction, which combine data-driven learning with domain physical knowledge. These models embed governing equations (e.g. partial differential equations, conservation constraints, forward imaging models) directly into the learning objective or architecture to regularize and constrain the solution space (Raissi et al., as reviewed in PINNs literature; see Application surveys) (e.g., Banerjee et al., 2024). This approach mitigates overfitting, enhances robustness under limited or noisy data, and improves interpretability by ensuring consistency with known physical laws (e.g., enforcing data consistency layers, residual physics losses) (Banerjee et al., 2024; "Physics-informed machine learning for advancing computational …" (2025)). In medical imaging, PINNs (or hybrid physics-data models) have been applied for phase imaging (e.g. Transport of Intensity Equation, TIE) with demonstrable gains in noise resilience and reduced training data requirements (Li et al., 2022) and for tracer kinetic modeling in myocardial perfusion MRI where PINNs infer parameter maps subject to physiological conservation constraints (e.g., the compartmental models constrained by physics) (e.g., the myocardial perfusion MRI work) (see "Physics-informed neural networks for myocardial perfusion MRI quantification") (2022). Despite these successes, key methodological challenges persist, such as selecting appropriate physics priors, balancing loss weights between physics residual and data fidelity, computational scaling for 3D and time-resolved imaging, and domain adaptation across scanner protocols and modalities (Banerjee et al., 2024; the PIML review) (2025). As such, this theme explores architectures, training strategies, generalization behavior, and interpretability techniques within physics-augmented deep reconstruction frameworks.

The second theme encompasses the spectrum of deep learning architectures (beyond purely physics-informed ones) that have been developed or adapted for imaging reconstruction tasks. Over the past decade, convolutional neural networks (CNNs), generative adversarial networks (GANs), autoencoders, variational networks, and diffusion models have been tailored to reconstruct images from undersampled, noisy, or sparse measurements across modalities like MRI, CT, PET, and ultrasound (e.g., review of AI in advanced medical imaging) (Review and Prospect, 2023). Hybrid physics-data architectures, combining imaging-domain neural network modules with physical forward/inverse operators (e.g. physics-augmented U-Net blocks, residual physics layers) have become especially prominent, helping to marry the strengths of data-driven expressivity and domain constraints (see "Explicit Physics-Informed Deep Learning for Computer-Aided …" (MDPI) and other works). Deep compressed sensing and sparse-view reconstruction approaches leverage network learning to recover high-fidelity images from minimal measurements, often achieving better artifact suppression and contrast retention than classical iterative methods (Review of AI in advanced medical imaging, 2023). Transfer learning, domain adaptation, and meta-learning strategies are also being used to adapt pretrained models across modalities, scanner types, or imaging protocols, enabling models to generalize better with fewer retraining needs. Meanwhile, computational efficiency—both in network architecture (e.g. pruning, quantization, compact architectures) and in inference throughput—remains a critical design driver for translation to clinical scanners. This theme thus scrutinizes the design patterns, hybridization strategies, generalization tactics, and optimization tradeoffs in neural reconstruction models.

The third central theme addresses trustworthiness, explainability, and the interplay of reliability and fairness as required for clinical acceptability. A model's outputs may be technically accurate, but without clear transparency, uncertainty characterization, robustness assurances, and fairness safeguards, clinicians and regulators may distrust its use (Hasani et al., 2022). Transparent attribution methods (e.g. relevance propagation, saliency maps, latent feature interpretation) help elucidate how inputs influence outputs, thereby improving interpretability. Uncertainty quantification techniques (e.g. Bayesian neural networks, Monte Carlo dropout, aleatoric/epistemic decomposition) allow models to express confidence or uncertainty margins, which is especially critical in ambiguous or edge-case medical images (Trustworthy AI in Medical Imaging, PMC) (Hasani et al., 2022). Robustness analysis (noise, artifacts, adversarial perturbations, domain shift) is also key: trustworthy models should resist small input perturbations and maintain stable outputs under realistic variability. Bias and fairness issues must be considered: imaging AI approaches can reflect and amplify demographic, equipment, or sampling biases, necessitating bias-detection metrics and mitigation strategies (e.g., the "Bias in artificial intelligence for medical imaging" review) (Koçak et al., 2024). Ethical and accountability overlays—such as logging decision provenance, model audit trails, and governance frameworks—contribute to the accountability dimension. Finally, embedding human-in-the-loop mechanisms (e.g., interactive correction, expert oversight, decision-support loops) helps build user trust, calibrate AI assistance, and promote pragmatic adoption.

The fourth theme delves into translating AI reconstruction methods from lab prototypes to clinical deployment and the regulatory, workflow, safety, and adoption barriers inherent in that translation. Benchmarks, multicenter validation, and use of standardized imaging phantoms are vital to demonstrate generalization, reproducibility, and clinical equivalence (see the "Position statement on clinical evaluation of imaging AI" (Lancet D-digit) and translational reviews) (McCague et al., 2023). Integration into clinical workflows demands interoperability with PACS, DICOM standards, and seamless user interfaces so that radiologists can adopt AI outputs without disrupting routine practice. Safety risk management (e.g. automatic failure detection, uncertainty flags, fallback safe modes) is critical to prevent misdiagnosis or harm. Regulatory guidelines—such as FDA AI/ML device frameworks or CE marking—require traceability, post-market surveillance, version control, and explanation compliance; hence, developers must engineer explainability, auditability, and lifecycle monitoring into systems (the FUTURE-AI guideline) (Lekadir et al., 2021/2022). Ethical, legal, and reimbursement considerations also pose challenges: issues like patient consent for AI-augmented imaging, data ownership, liability for AI errors, and reimbursement models must be navigated. Moreover, economic cost–benefit analyses, hospital IT integration expenses, and return-on-investment calculations can make or break adoption decisions. Finally, clinician education—training radiologists and technologists in interpreting and supervising AI-enhanced reconstruction—becomes essential to create trust, understanding, and sustainable uptake.

The fifth theme projects ahead, highlighting future research frontiers and gaps in AI-assisted imaging reconstruction. A pressing direction is generalization across modalities (e.g. MRI, CT, PET, ultrasound) and multimodal fusion, enabling cross-domain transfer and shared priors. Co-design paradigms, in which physics simulators and neural networks are jointly optimized (e.g. differentiable simulators, hybrid optimization) may deepen synergy between physical and data models. Privacy-preserving and federated learning approaches (particularly for multi-institutional collaborations) will become critical for assembling large diverse datasets without compromising patient confidentiality (see the federated imaging review) (Koutsoubis et al., 2024). There is also a need for trust and performance benchmarking frameworks—public leaderboards, robust trust metrics, reproducibility standards—to unify comparisons across methods. The synergy of human and AI systems (hybrid intelligence, decision assurance loops, adaptive clinician-AI interfaces) represents another promising frontier. In addition, more research is required on scalable, real-time implementations and hardware acceleration, especially for 3D/4D imaging. Gaps remain in standardization of uncertainty propagation, explainability in highly nonlinear physics-augmented models, and in regulatory frameworks tailored to evolving AI. Addressing these gaps will be crucial to bridge the divide between method innovation and safe, trustworthy clinical impact (see the "unmet promise" translational gap discussions) (Bürger et al., 2024; "Physical foundations for trustworthy medical imaging," 2025).

## 4. Discussion and Conclusion

In our qualitative synthesis of 16 seminal works on AI-assisted medical imaging reconstruction, with particular attention to physics-informed networks, trustworthiness, and clinical translation, several convergent and divergent patterns emerged. First, we observed that physics-informed architectures are increasingly adopted to mitigate the overfitting and hallucination risks of purely data-driven models, especially in low-data or undersampled imaging regimes. Many reviewed studies embed differential equations, forward models, or physical priors either as penalty terms in loss functions or via hybrid network blocks (Banerjee, Nguyen, Salvado, Tran, & Fookes, 2024). The effectiveness of such embedding is often evidenced by improved reconstruction fidelity, noise robustness, and generalization across acquisition settings. Second, in the architectural domain, hybrid physics–data models—such as U-Net variants augmented with physics consistency layers or residual physics correction modules—outperform both traditional iterative solvers and naïve neural networks in competitive benchmarks, indicating that the synergy of domain knowledge and learnable components is a fruitful design direction. Third, across the studies, the importance of *trustworthiness* features—interpretability, uncertainty quantification, robustness to artifact and domain shift, fairness, and human-in-the-loop mechanisms—surfaced repeatedly as critical enablers (or bottlenecks) for real-world adoption. Fourth, the translation trajectory from algorithmic proof-of-concept to clinical deployment is still nascent: only a subset of works validate their methods on multicenter datasets, compare against clinical gold standards, or discuss regulatory, workflow, or safety issues. Finally, the future directions identified by the authors commonly include federated learning, physics–AI co-design, standardized benchmarking and trust metrics, and deeper human–AI synergy.

Interpreting these patterns in light of existing literature, we can see that the rise of physics-informed methods aligns with broader momentum in physics-aware AI. For example, Cobo, Corral Fontecha, Silva, and Lloret Iglesias (2025) argue that integrating physical constraints enhances both interpretability and robustness, especially in settings where training data are scarce. Their review of fundamental physics in imaging modalities underscores how domain ignorance often impedes AI model generalization (Cobo et al., 2025). Similarly, the comprehensive survey by Banerjee et al. (2024) frames physics-informed approaches in medical image analysis (PIMIA) as a means to balance expressivity and constraint, and highlights challenges such as choosing appropriate priors and benchmarking fairness. The consistency between our findings and these prior surveys reinforces that the field is coalescing around hybrid model strategies.

In the domain of trustworthiness, our results echo the growing consensus that “accuracy alone is insufficient” for clinical AI. The FUTURE-AI guideline (Lekadir et al., 2021/2025) posits that trustworthy medical AI must satisfy six principles: Fairness, Universality, Traceability, Usability, Robustness, and Explainability. In the works we coded, features such as uncertainty estimation, interpretability visualizations, and adversarial robustness tests can be mapped onto those principles. Kondylakis et al. (2025) further explore how instantiations of FUTURE-AI in medical imaging can be operationalized in design and evaluation. In trustworthy AI more broadly, the review by Hasani et al. (2022) and the article “Trustworthy Artificial Intelligence in Medical Imaging” emphasize the need to build relational and generalized trust via transparency, reliability, and mutual understanding between clinicians and models. Our synthesis confirms that trust features remain insufficiently addressed in many reconstruction studies. Furthermore, human-centered design considerations, such as the gap between algorithmic interpretability and clinician usability, have been pointed out in explainable AI reviews—Chen, Gomez, Huang, et al. (2022) highlight that many XAI methods in medical imaging neglect user validation or interface design. Our findings mirror that shortfall: few reconstruction works conduct empirical user studies around explanation or trust.

Regarding clinical translation, our coding revealed a mismatch between methodological sophistication and deployment readiness. Many studies restrict themselves to retrospective, single-center validations, small phantoms, or simulated data; only a handful engage multicenter datasets or protocol variability. This confirms the “translational gap” often lamented in AI medicine literature (Galić et al., 2023). The lack of discussion around regulatory compliance, user workflow, risk mitigation, and integration with PACS or DICOM ecosystems constrains clinical uptake prospects. Among the few that address such issues, authors often appeal to general AI in medicine translational principles (e.g. integration frameworks, validation pipelines, clinician education) rather than imaging-specific strategies. Galić et al. (2023) note that translation of AI to clinical practice entails not only model accuracy but rigorous validation, interoperability, ethics, and training—an agenda that many physics-informed reconstruction papers have not yet embraced.

In sum, the synthesis suggests that while physics-informed neural techniques are gaining traction and yield promising empirical performance in image reconstruction, the broader ecosystem of trustworthiness, human alignment, and translational scaffolding is still immature. Bridging these gaps will require holistic co-design of methods, metrics, workflows, and governance.

Our review has certain limitations. First, as a qualitative synthesis focused on 16 selected articles, our taxonomy and interpretive conclusions may miss insights from newer, unpublished, or domain-adjacent works. The selection bias toward high-impact or well-known papers could skew emphasis toward popular techniques, underrepresenting negative or null findings. Second, we rely exclusively on published descriptions, rather than replicating or independently benchmarking models; thus, our assessment of comparative performance and robustness is filtered through authors' own reporting and may be subject to optimism or publication bias. Third, our qualitative coding necessarily simplifies nuanced methodological differences—complex architectural divergences, hyperparameter sensitivity studies, and implementation details sometimes resist clean categorization, so fine-grained distinctions may be lost. Finally, because the field evolves rapidly, some of the insights in the reviewed works may already be outdated by more recent advances not captured in our review.

Future research should address several priority areas to drive maturation of AI-augmented imaging into clinical impact. First, the development and adoption of standardized benchmarking protocols and trust metrics for physics-informed reconstruction would enable more objective cross-comparison of methods; this includes metrics for uncertainty calibration, fairness across patient groups, and robustness to domain shift. Second, we advocate differentiable physics–AI co-design, in which physics simulators (or forward models) can be jointly optimized with neural networks rather than only incorporated passively; such coupling may yield more adaptive and efficient reconstructions. Third, in order to enable multi-institutional training and generalization, federated learning and privacy-preserving collaborative frameworks should be extended to physics-aware reconstructions, integrating quantification of uncertainty under heterogeneous data distributions (Koutsoubis, Waqas, Yilmaz, Ramachandran, & Schabath, 2024). Fourth, there is a need for human-centered explainability studies—moving beyond algorithmic attributions to interface prototypes, clinician usability testing, and iterative co-design (Chen et al., 2022). Fifth, longitudinal and prospective clinical validation studies—real-world imaging settings, variable scanners, patient diversity—must become the norm rather than the exception. Finally, the community should cultivate governance, auditability, and lifecycle monitoring frameworks embedding version control, explainability logs, and post-market surveillance consistent with FUTURE-AI principles and regulatory expectations.

In terms of practice implications, research groups designing reconstruction models should prioritize trust and usability from the outset, not as afterthoughts. Embedding uncertainty quantification modules, interpretability mechanisms, and local robustness tests is no longer optional but essential if translation is a goal. Clinicians, radiology departments, and hospital IT teams should engage early with developers to define integration paths—ensuring PACS compatibility, DICOM compliance, interface usability, fallback modes, and auditability. Adopting (or converging toward) consensus frameworks such as FUTURE-AI may help align development with regulatory and ethical norms (Lekadir et al., 2025; Kondylakis et al., 2025). Regulatory and standard bodies should consider developing imaging-specific trust and performance standards tailored to physics-informed AI, given the unique hybrid nature of these systems. Finally, institutions should invest in training programs for radiologists, technologists, and clinicians to interpret, interrogate, and manage AI-augmented reconstructions, cultivating a culture of safe oversight and mutual human–machine collaboration.

## Ethical Considerations

All procedures performed in this study were under the ethical standards.

### Acknowledgments

Authors thank all who helped us through this study.

## Conflict of Interest

The authors report no conflict of interest.

## Funding/Financial Support

According to the authors, this article has no financial support.

## References

Ahmadi, M., Biswas, D., Lin, M., Vrionis, F. D., Hashemi, J., Tang, Y., … & others. (2025). *Physics-informed machine learning for advancing computational medical imaging: integrating data-driven approaches with fundamental physical principles. Artificial Intelligence Review.*

Avanzo, M. (2024). The evolution of artificial intelligence in medical imaging. *Cancers, 16*(21), 3702.

Banerjee, C., Nguyen, K., Salvado, O., Tran, T., & Fookes, C. (2024). PINNs for medical image analysis: A survey. *arXiv preprint arXiv:2408.01026.*

Cobo, M., Corral Fontecha, D., Silva, W., & Lloret Iglesias, L. (2025). *Physical foundations for trustworthy medical imaging: a review for artificial intelligence researchers.* arXiv.

Fujita, S. (2025). Physics-informed deep learning reconstruction for ultrafast MRI. *Radiation Advances, 2*(3), umaf016.

Lekadir, K., Osuala, R., Gallin, C., Lazrak, N., Kushibar, K., Tsakou, G., … & Lambin, P. (2021). FUTURE-AI: guiding principles and consensus recommendations for trustworthy artificial intelligence in medical imaging. *arXiv preprint arXiv:2109.09658.*